ON customer lifetime value in ecommerce


Julien Kervizic Follow
Dec 12, 2018 · 16 min read ★

The **customer lifetime value** (CLV) is an estimate of all the future profits to be accumulated from a relationship with a given customers. It is used in the business to measure the performance of retention strategies and to provide insights into how much should be spent in customer acquisition.

Decomposing Customer Lifetime value

The formula for customer lifetime value, can then be decomposed as the product of multiple metrics:

CLV = Lifetime * Purchase Frequency * AOV * Profit Margin

The simplified formula describe above has a few caveats such as not taking into account any discounting and that profit margin is constant with respect to both time and average order value. For the sake of explaining the drivers of customer lifetime value, these can be however safely ignored.

Taking a simple example of an e-commerce website customer, ordering some shoes online. Customers on the platform have an expected lifetime of two years, and tend to order shoes about twice per year and at average order value of $100, the business profit margin for these type of purchase is about 25%. Based on these information we can compute the expected CLV of the customer: 2*2*100*25%= $100

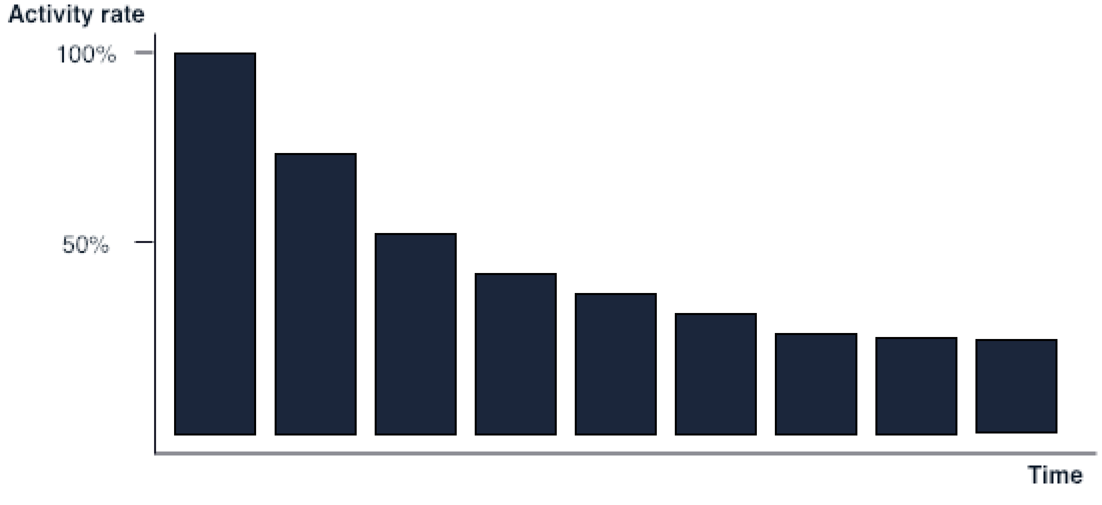
Lifetime

Lifetime relates to the expected duration a given customer will stay active on your platform, as such metrics that relates to **activity rate** and **churn** provide good performance measures as to how the metrics should be directionally improving.

Different metrics and charts allow us to track how we are performing with respect to keeping our customers engaged and retained with our platform and offering.

Activity rate

When looking at an aggregate level, getting an understanding of a how we are tracking with respect to lifetime expectancy can be done through the use of activity rate decay curve.



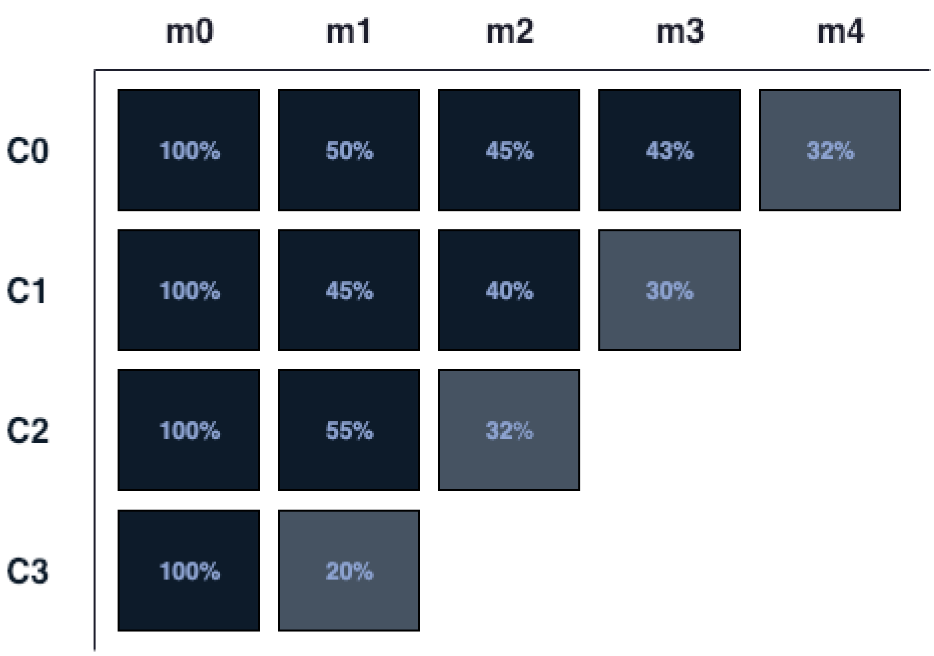
On the X axis of the decay curve is the time since acquisition of the customers or since the first time a specific event happened, on the Y axis the % of customers that are active in that given period. The decay curve therefore represents the % of customers that would be active at a certain tenure on an e-com site. The activity metrics is normally tied to what is of interest for the analysis, for e-commerce the main metrics of interest is purchases.

Given the initial drop-off that a lot of company faces due to early life churn, there often tends to be a segmentation of customer lifetime value between customers that are acquired and churn quickly after acquisition and those that tend to be retained after this initial period.

Cohort Consideration

The concept of cohort is very important to understanding how to track retention's performance over time. With that and e-commerce in mind, a cohort is defined as a group of customers joining a service or first performing an action, typically an order at a given period of time. A cohort could be for instance, all the customers having made their first purchase on a specific e-commerce website on January 2018.

Having cohort defined this way is quite helpful in order to get a better understanding as to what part of a retention's performance might be due to a mix effect in the tenure of the customer base.



Within a triangle chart, each of the rows represent a specific cohort of customer. Each of the column on the other hand represent a time frame relative to the starting day of each customer within the cohort, here above represented in month.

Let say that C0 represent customer having first ordered in January 2018 and C1 would represent customer having first ordered in February 2018 and so on. M0 would for them represent their first month of activity on the platform since each of them would have at least made their first order they would be considered active that month, therefore all the cohort is considered active and the activity rate within that cell is 100%. The next month -ie: m1, would be the period starting on Feb 1 for customers having first purchased on the first of January, but since that month is relative to the first purchased dateit would be Feb 15 for those having first purchase on the 15 of Jan.

The diagonal values in the table is supposed to represent one given period in time. For instance in the example above the diagonal that is greyed out show represents the period from the first of May (1st Jan + 4 months) to the 30th of June (31st Jan + 5 Months). In the chart above we can see that all the values within the diagonal are exhibiting lower activity rate than the previous cohorts's value at the same lifestage, this can be an indication that a specific event happened during that period that impacted the activity rate.

Other Metrics

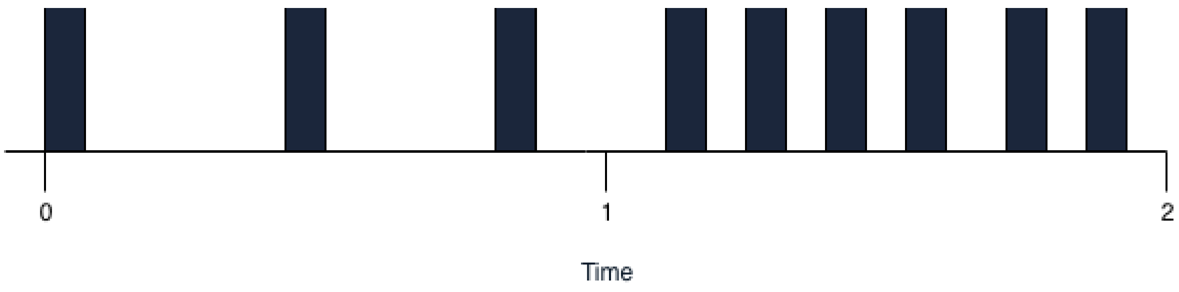
While metrics such as repurchase rate can provide a a good operational measure for early life retention and how quickly we are able to re-engage acquired customers.

Purchase Frequency

The purchase frequency relates to how often a customer buys in a given unit of lifetime.

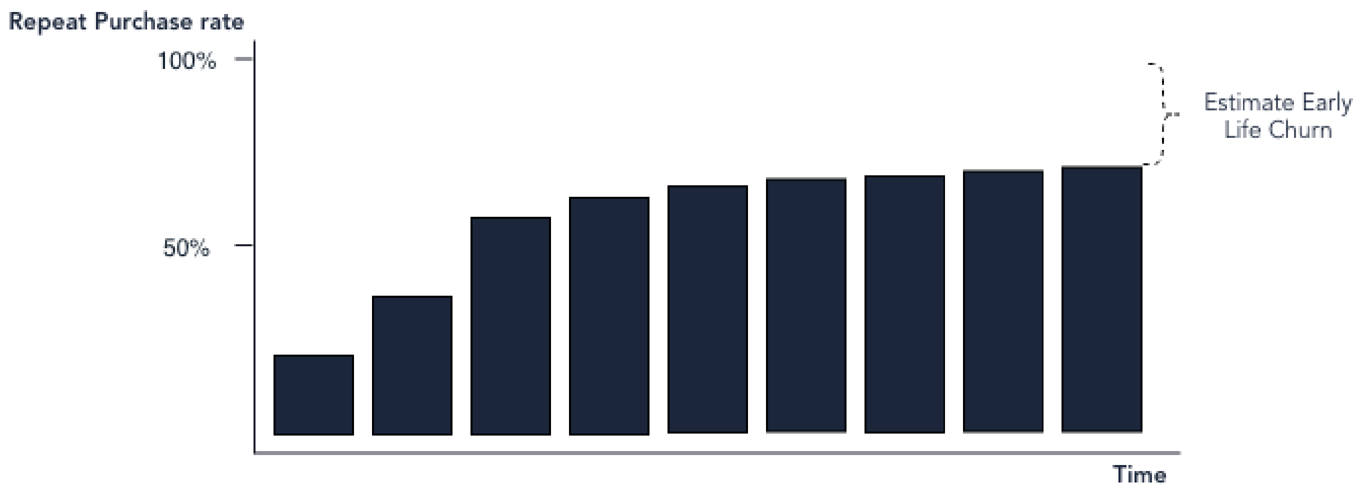
Customers with high purchase frequency tend to have an overall better retention profile, looking at it from a different perspective, the purchase frequency is a measure of activity and retention within each of the periods considered. If we were to look at an activity metrics' period infinitely small, the purchase frequency metrics wouldn't be needed and instead be traded off for a real-time activity rate.

Metrics such as time between purchase and repeat purchase rate can be combined with the purchase frequency metrics to provide a holistic view of how we are performing on a more operational perspective.



For customers who haven't churned and have a consistent purchasing pattern, the time between purchase can provide a good approximation as to the purchase frequency without having to wait the full period needed to calculate the purchase frequency.

> Purchase Frequency ≈ Purchase Frequency Time Interval / Time Between Purchases



Tracking the repeat purchase rate allows us to get an understanding early as to how we are performing with respect to early life churn and take action early on. It also allows us to handle a first intermediate goal to keep the customers for one more action, this generally help improves the overall retention metrics as a customer that has been more engaged as some point tend to be more likely to make one more re-order.

Infrequent purchases can still be an issue for tracking a customer lifetime value, take the example of a car purchase. The life expectancy of a car is about 8 years. Waiting for a car repurchase to understand how we are performing would not allow for remedying any issues that may arise, additional checkpoints based on different criteria would in this case be needed to get a measure of intermediate performance.

That is not to say that not focusing on getting these customers to have a higher purchase frequency is not something that might be beneficial, take for instance a car dealership that is able to convert a customer from a car purchase into a car lease, long term car leases last an average of 3 years, compared to an average 8 years for a car's life expectancy.

This means that over the time it takes for a car to be end of life there has been close to 3 leases setup or close to 2 times more occurrence for the car dealership to have to earn the customers' business, and potentially enter in negotiation with that customer. The expected gain from negotiating each of these transaction would have been however much smaller than for negotiating a car purchase. Let's assume for a moment that the cost of the lease is purely proportional to the life expectancy of the car, that for each negotiation the customer can expect to obtain a discounted rate θ over the value of the transaction and that entering each negotiation or potentially switching to a better offer has a fixed cost κ.

Then the expected gain for negotiating rates for a lease during the lifetime of a car would be:

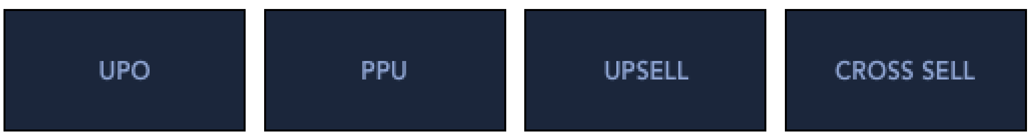
$$E(\text{negotiating}) = ((1\text{-}\theta)^{*}\text{Car Value}) — (8/3)\kappa$$

Compared to to the expected gains when it comes to purchase:

$$E(\text{negotiating}) = ((1\text{-}\theta)^{*}\text{Car Value}) — \kappa$$

When switching costs are significant we can see that there is less gain to be made from negotiating, making users less likely to switch. By forcing more frequent purchases, Car dealerships have the opportunity to either offer a lower discount rate on the car value or benefit from higher retention rate from their customer both factors increasing their lifetime value.

Average order value



Metric such as the number of units per order, price per unit, up-sell rate and cross-sell rate provide operational metrics for tracking how we are impacting AOV.

AOV as a metrics can be decomposed into a units per order and price per Unit metrics:

> AOV = Unit / Order * Price / Unit

Decomposing the metrics we can see that we have a **unit per order** metrics that ‘s directly associated with the basket size and that can be impacted by activities such as **cross-sell** and **increased selection** and a price per unit metrics that can be impacted by activities such as **revenue management** and **upsell.**

Other type of management of AOV for e-commerce website tend to rely on minimum order quantity, free shipping threshold and volume based discounts.

Profit Margin

At an aggregate level, the calculation of profit margin is fairly simplistic: the ratio of profits, defined as revenues minus costs, to revenue.

$$\text{PROFIT MARGIN} = \frac{\text{REVENUE-COST}}{\text{REVENUE}}$$

Starting with an overall ratio that provides a sense of direction allows to provide an initial steer towards what appears to be best use of capital, but there is definitively a need to go deeper in this calculation.

For this we need to rely on a process of attribution and of allocation of costs and revenues. Costs and Revenues should be attributed at the level they are incurred and allocated at a finer grain based ***activity based drivers.***

Activity based drivers are factors that contribute to the cost or revenues in question. For example if you are looking at an order the value of the order is related to the number of units in the order, to a certain extent if you are paying on a per parcel the cost is also associated to these units, better activity based drivers for cost in this case would be the weight or dimensions of these items.

Segmentation

First Order Attribution

Traffic Origin

Having a better understanding of how customer lifetime varies by their traffic source, allows us to make more informed decision towards where to place our marketing spend. Google analytics allows to tie an order to its originating traffic channel based on last click order attribution [X]. It represents a first step to gain visibility on the different customer segment and how they relate to Custer Lifetime Value, enabling a more efficient marketing spend.

Demographic and Interest based Targeting

Demographic and interest trickling down from advertising settings can also be used to get a grasp of Customer Lifetime value per target advertising segments. Looking at segments with cost per acquisition and customer lifetime value allows to optimize the targeting settings and shift the marketing budget towards customers segments having the highest return on investment (CLV/CPA).

First Order Content

First order content can help to get a better grasp at customer lifetime value based on the proposition offered to them. In case of significant category expansion, it can help get a grasp of the lifetime value of customers acquired because of the new category and how the category expansion impacted customers that could have been acquired without the category expansion.

RFM

RFM stands for recency, frequency and monetary value, it is a method of behavioral segmentation typically used in database and direct marketing for providing a measure of value of each segment of the customer base.

	Recency	Frequency	Monetary Value
uid1	1	5	9
uid2	4	6	3
uid3	2	2	5

RFM segmentation works by assigning a score for each of these metrics to each of the different customers with the highest score typically representing the most desired outcome (ie: most recent, most frequent, highest value).

RFM segmentation has previously been used as a mean to estimate customer lifetime value. Taking information from within a specific RFM segment, rather than the overall population, to compute estimates helps embed more granular behavioral information into these estimates and better align the result to a direct marketing strategy.

Applications of Customer Lifetime value

Customer Acquisitions

Customer Lifetime value also directly impacts and determines the amount that should be spend in customer acquisition.

It would not be a good business model if your **Cost per Acquisition (CPA)** was greater than your **CLV**. Getting a good grasp of the relation between CPA and CLV at customer level allows to understand which profile of customers are not profitable or profitable enough and help steer customer acquisition towards the right customer profiles.

In most cases firms would be looking at getting back the money invested in customer acquisition within a certain time.

$$\text{Payback Period} = \text{CPA} / \text{Annual Profit}$$

The payback period provides and estimate for how long it takes to recoup the investment made in customer acquisition.

Optimizing Retention Offers

Having the right understanding of the drivers of customer lifetime values and their expectations at customer level, allows to provide the right visibility in balancing the cost of offering a retention offer with the expected remaining lifetime value of the customer. Discount levels can be tailored to the value of keeping a customer on the service based on its actual likelihood to churn for a given offer.

Telecom companies are a good example of how a retention strategy is impacted by CLV. Telecom companies spend a decent amount of money on customer acquisition, a huge amount of money in fixed assets (spectrum, towers …) and tend to have low variable costs. When a customer calls to cancel his plan / subscription the telecom operator is faced with a trade-off, what does he need to do to retain the customer without being "gamed" by it. Not counting the reputational aspect that also dictates their retention strategy, the operator need to essentially maximize at that time:

$$\max\{(p)\,\theta(x)\,\text{CLV} + (1\text{-}p)\,\text{CLV}\}$$

With p being the probability that you would actually leave the operator and not just call to seek a discount and theta θ being the discount function that would retain you on the service.

Obtain Financing

Since through the calculation of CLV, we are able to estimate our future expected earnings for each customer that we acquire the valuation of a business is essentially a factor of two variables:

1. The CLV that the business is expected to achieve in each of the future periods
2. It's ability to acquire new customers.

These factors are precisely why tech startups that exhibit strong growth and retention/engagement metrics tend to be valued at such skyrocketing rates. Despite often not showing any form of profit or revenue, the business model of most tech startups is based of high fix costs, low variable costs and to manage the top-line, a default revenue model exists through advertising, making the risk of not being able to generate revenue limited.

Impacting Customer Lifetime value

As we have seen before there are a couple drivers, metrics and chart that can be used to understand and track the performance of our customer lifetime value metrics but there are also a couple actions that can be performed to increasing your customer's lifetime value, improvement on the cost structure stretching the offering as well as implementing effective retention and communication strategies.

Cost Structure improvements

As we have seen previously in the different factors contributing to the lifetime value, profit margins are a definite driver for customer lifetime value. Profit margin being define as (Revenue — Cost)/Revenue, we can see that improving our cost structure has direct benefits upon the CLV.

Retention strategies

Proper on-boarding can help reduce early life churn, understanding what are the issues faced by your customer or the cause of their potential dissatisfaction in the early days of the relationship with your company and remedying it, as is a subsequent discount on their first re-order.

Managing customers who are have a high risk profile, be it obtained through a **propensity model** or some decision rules, will help manage your overall churn rate. The type of offers that are provided to customers who are classified as at risk should be carefully managed, especially around triggering events. Specific event triggers should be managed as close to real-time as possible in order to be most impactful. Platforms such as Salesforce marketing cloud offer the ability to send near real-time contextual messages through their trigger send end points.

If your business model allows it, setting up a subscription offering is also effective at retaining and increasing the purchase frequency of certain types of customers.

Stretch offering

Increasing selection and on-time availability

Amazon Flywheel

Increasing selection is one of the core pillars of amazon flywheel, it generally has a direct impact on conversion rate. Imagine going to a store and not having what you are looking for; you are not going to buy. Increasing selection makes it less likely that this event happens. But having selection is not everything to maximize lifetime value you also need those items to be purchasable (for a moment excluding out of stock email address collection). Increasing the selection of purchasable items on your store your be the goal.

Customer Experience

> We see our customers as invited guests to a party, and we are the hosts. It's our job every day to make every important aspect of the customer experience a little bit better. — Jeff Bezos

Customer Experience is a proxy for the perception a given customer has for your brand or company. A lot of components go into it and in general covers all the interactions that happen between the customer and your company, but for e-commerce companies some of the main drivers for good customer experiences are:

- A working and usable websites
- Quality products with reliable description
- Quick, trackable deliveries with right estimates
- Great customer service

Looking at a single paragraph of an Amazon job post for a Customer Experience PM provides us wit the key keywords to driving good customer experience:

> meet customer expectations.

Membership programs

Membership programs of some form can improve customer lifetime value by making customers more retentive, or increase their frequency and average order values. Amazon's prime program is an example of that, but other types of membership or loyalty program can help towards your goal of increasing CLV. *Miles* loyalty programs in the airline and hotels

Communication Strategy

> Communications is at the heart of ecommerce and community — Meg Whitman

Unless ignored, every communication has an impact on customer lifetime value. Communication with the customer should be carefully managed in order to generate uplifts and not reversals.

Nudges

Push notification, email , sms or even snail mail are different means of nudging a a customer to make a purchase, managing the communication as to not induce fatigue, unsubscribe or have your communication completely ignored is what you should strive towards if you want to be able to increase CLV through customer communication.

Each communication to the customer is an opportunity to generate an uplift in value for that customer, but needs a careful management of the decision rules and contact policies towards the customers.

Behavioral Retargeting

Retargeting based on *passive* behavior such as Abandoned Cart emails or Catalog Retargeting on Facebook based on Lurking views can help uplift lifetime value by converting intent into active purchasing behaviour.

Facebook for instance allows to retarget an audience with the same products that they have browsed on your website, through the creation of a catalogue sales campaign.

Relevancy

Personalization allows to increase the relevancy of communication towards the customers and bring a higher likelihood of converting a communication into an actual purchase. Personalization also helps increase overall engagement and decrease some of the negative impacts of communication by providing content and offers customers care about.

Forecasting vs. Planning

Forecast or Plan?

Depending on your current situation it might be preferable to forecast or plan for customer lifetime value. By forecasting we mean a prediction that is based on a statistical method or an algorithm, by planning we mean making a set of decision of how this evolution will be driven over time.

Forecast tend to be preferable when a few conditions are met

- We need to understand the CLV of multiple customer segments
- There is enough historical data available to understand the evolution of CLV
- There is no structural changes to CLV and its evolution in customer lifetime value is incremental and can be estimated through forecasting models ie: there is no big project that would impact significantly the CLV of the customers.

Forecasting lifetime value tends to be more, it is possible to forecast what would be CLV using even simple techniques like SQL queries.

Planning is to be preferred when some conditions are met:

- We need to plan lifetime value for a limited number of customer segments
- There is limited data available related to how the CLV is evolving over time and the computation of lifetime value needs to be more assumption based
- There are structural changes expected in the lifetime value

When not all of these conditions are being met a mix of planning and forecasting might be needed in order to properly capture the planned evolution of the metrics.

Evolution

Some approach to how customer lifetime value have been proposed such as taking it into account as an option value.

Wrapping up

Customer Lifetime value can be impacted through a few levers that can easily be tracked and impacted. Getting an understanding of what the lifetime value of our customers is important in order to optimise our acquisition and retention strategy as well as providing a way to value the business that is operated. The lifetime value can be improved by improving the cost structure, implementing a retention strategy, stretching the offers and service being offered and handling a proper communication strategy. Looking only at the actual customer lifetime value might however not provide the right level of information to capture improvement or the evolution of lifetime value over time. Capturing these expected changes would allow to make better informed decision with respect to investment in either acquisition, retention or in valuing the business.

. . .

More from me on Hacking Analytics:

- One the evolution of Data Engineering
- Principles of e-commerce Personalization
- ON the attribution and decomposition of mix and rate effects
- Experimental Design and How to Avoid blowing everything up
- Hacking up a reporting pipeline using Python and Excel

Startup Analytics Data Science Ecommerce Marketing