voyantis

The Full LTV Optimization Guide

Voyantis empowers growth and user acquisition teams of top brands to acquire ROI positive users at scale and unlock new profitable audiences.

The principles of what we are presenting are relevant for all business models. The main difference lies in the mechanics and mathematics of how to predict the LTV value, but not how to leverage it.

Mathematically the problems split into "Transactional" (IAP) where it's more about predicting whether a user would pay (and how much), and "Contractual" (subscription, and funny enough, ads monetization). This is where it's more about predicting retention and engagement.

Here are the contents of this guide:
A quick breakdown of the different types of LTV data:

- Predictive LTV: Forward-thinking modeled data
- Historical LTV: Data stemming from customer's interactions with the brand
- Residual (Future) LTV: Predicted revenue yet to be generated from customer
- A simple (and efficient) way to categorize users
- Using LTV data for marketing optimization
- Best practices when building predictive models
- Questions to ask before onboarding a new predictive solution for user acquisition

Gone are the days of optimization based on short-term conversion windows–LTV-based optimization is now the name of the game.

LTV data presents tremendous business value. It can assist in the discovery of audience potential, optimization of revenue forecasts, identification of the highest value customers and calculation of their worth.

There are many different ways to calculate LTV, and in most cases, they include the following:

1. Define the target audience with all the specifications like gender, demography, etc.
2. Purchase Frequency Curve based on your transactional and historical data.
3. Get Customized Lifetime Value Forecast.

Here's a quick breakdown of the different types of LTV data:

Predictive LTV: Forward-thinking modeled data

Since LTV is a forward-thinking concept, it is, by nature, predictive data based on the brand's relationship with a customer over their lifetime interaction with the company.

Since this is modeled data, it is important to keep in mind that the modeling is only as good as the data utilized to model the results. The more data, the better. For cohorts based on new tactics or small sample sizes, modeling error is likely to increase.

Historical LTV: Data stemming from customer's interactions with the brand

This refers to the actions and average revenue per user to date, or so far in their lifetime during the course of their relationship with the brand.

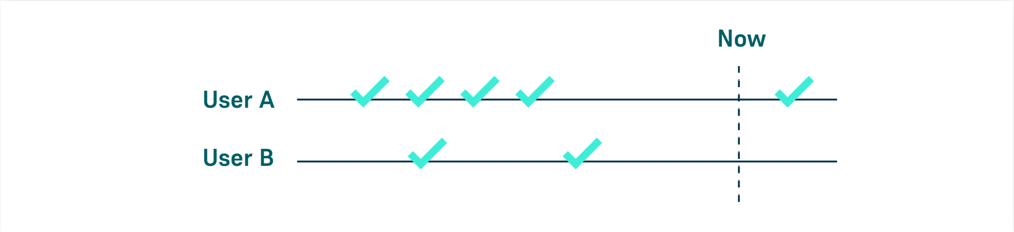
When using historical LTV, the key thing to keep in mind is understanding that different cohorts may be influenced by different time frames. This can be accounted for by defining a set cohort window, for example the first 360 lifetime days, and excluding users who have had less than 360 lifetime days, or by defining a cohort by acquisition month, for example users acquired in January 2020.

Residual (Future) LTV: Predicted revenue yet to be generated from customer

This is the opposite of historical LTV, as it refers to the revenue that has yet to be generated by the customer. This can be useful for retention campaigns to determine how much spend should be focused on retaining those users.

Predictive LTV = Historical LTV + Predicted Future LTV

Here's a visual representation of LTV data.



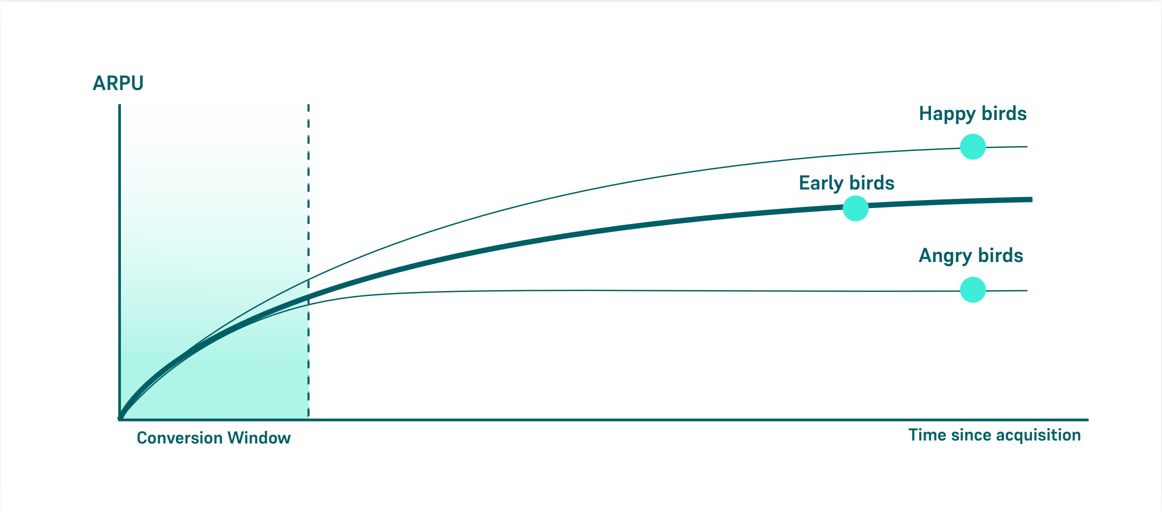
You can see that User A has higher historical LTV. Conversely, User B has higher residual LTV, and furthermore will have a higher total LTV. If prediction is done right, they will have a higher predictive LTV. because they take more time before making purchases, and these purchases are usually of a higher value. User A conducts purchase events within conversion windows.

A simple (and efficient) way to categorize users

Now that we went over the different types of LTV data, let's go over the different types of users. As you can imagine, we juggle many data sets for our clients. In doing so, we came up with a great way to distinguish between the different types of users that can be targeted in user acquisition campaigns, to achieve maximum results.

Here's how we break users down at Voyantis:

- **"Early birds"** refers to users that are easy to target because they exhibit purchase events within conversion windows. When optimizing campaigns for purchase/value optimization the early birds do get acquired, but the CAC for this audience is high. In most cases, the growth marketer does not know how many of the early bird users will continue to make purchases over time.
- **"Happy birds"** (a term we happily coined and have yet to trademark) are a subset of early birds, which will purchase a few more times outside of the conversion window, thereby making them high LTV users.
- **"Angry birds"** (not to be confused with the addictive game) are a subset of early birds. They are users who purchase early on within the conversion window, but won't purchase again.
- **"Late bloomers"** refers to users who are more likely to make a purchase later on in their user journey. There are many perks associated with targeting late bloomers, including lower acquisition costs, diversification opportunities, higher long-term ROAS, increased loyalty, and more purchases over time.



In this graph, the early birds are the combination of angry birds and happy birds.

In addition to driving acquisition, LTV data can also be used to help focus and optimize retention campaigns. Custom audiences and lookalike models can also be built from LTV data to target highly valuable users.

Using LTV data for marketing optimization

Now here's the big question: How can LTV data be used to achieve maximum results in user acquisition campaigns?

Target your best next users based on historical data

When LTV is used as a metric, it can be used to target the best of the best customers. By matching demographic data with affinities, interests, and more, you can create whole new audiences with the same background as your current cream-of-the-crop customers.

This is especially handy when trying to reach late bloomers, because overlooking this segment leaves a lot of money on the table due to lower acquisition costs, and greater ROAS. Targeting late bloomers also opens up campaign diversification opportunities, by covering a larger portion of the customer journey and, therefore, acquiring new audience groups that previously might have been missed. Scalability will be increased, without suffering from diminishing returns on ad spend.

Optimize search campaigns using LTV data

LTV data can be used in a variety of ways to optimize campaigns and unlock greater returns. LTV-based campaigns allow for segmentation and action driven by actual revenue and expense. For instance, optimizing paid search by keyword is a particularly strong use case.

Double down on high potential campaigns

For paid search, LTV data can also be used to identify favorable CAC:LTV ratios, and to identify high-potential campaigns. For the latter, it is best to focus on opportunities where the average bid position is below 1.5 in order to identify the cases with the greatest opportunity.

Optimize retention campaigns by zeroing in on user interactions

LTV data isn't just about driving acquisition. It can also be used to help focus and optimize retention campaigns. For example, it can be used to measure how often users return to apps after initial installation, or continue interacting with the brand after promotional periods pass.

Activate high value lookalike campaigns

The data can also be utilized to build custom audiences and lookalike models, to optimize towards highly valuable customers. On Facebook, this would need to be approached by first creating a customer value Custom Audience, to serve as a source audience, which you can read more about here.

Regardless of the application, it's important to remember that optimization towards LTV is not done as a one-off activity and is part of a feedback loop. Ideally a monthly repeating process can be set up to review new customers acquired via the campaigns being tested against and track whether these users are on track to maintain their estimated CAC:LTV ratio.

Best practices when building predictive models

Whether on Google, Facebook, Snap, or any other ad network—predictive modeling can help brands build a user acquisition strategy based on criteria such as payback period and future ROAS to unlock new opportunities that current ad network solutions can't deliver by default. There are some best practices that one must keep in mind when building predictive models.

- **Conduct continuous testing on the models:** When building data models, it's not only important to build the best system possible, but also to perform ongoing testing to ensure its effectiveness, and keep it trained on the most relevant data.
- **Compare the profit prediction power of multiple KPIs:** Different KPIs offer their own set of trade-offs across different vertices, such as viability, accuracy, and speed to produce recommendations. Test multiple KPIs, to determine which ones are best suited for your goals.
- **Segment users to homogenous groups:** This serves as a great way to improve conversion rate, but also a proven method to reduce noise and improve the predictive power of your model.
- **Don't forget the time factor:** Remember that the lifecycle of your app/campaign/audience/creative can also influence the ability of your model to make accurate predictions.

Questions to ask before onboarding a new predictive solution for user acquisition

(You can read more about this on our blog.)

1. What's your current media spend and by how much do you expect it to grow?
2. What metrics does the new solution use to predict LTV?
3. How many internal engineering, product, and operations resources will you need to implement and use the solution?
4. Is the new solution made for your business model and martech stack?
5. Are we talking about offline insights or actual all-in-one analytics and optimization?
6. Which 3rd party enrichment data does the solution provide?
7. How quickly does the solution generate actionable predictions that can be used to optimize existing campaigns?
8. Who's the targeted persona that the platform is built for?
9. How does the solution deal with (and solve) iOS 14.5-related issues?

Building an LTV data-driven strategy, especially from the ground up, can appear as a massive undertaking. However, with the right strategies, team, tools, and technologies in place, LTV data can easily be utilized to achieve maximum results, with exponential ROAS both in the long and short term.