madduck insights

INTRODUCING

The most accurate LTV Prediction in the market!

We know that handling and basing decisions on LTV can be a pain sometimes, especially when there is prediction involved. This is why we solved the whole LTV problem for you: you can now take all your UA and pricing decisions based on the most accurate LTV prediction on the market!

The only thing you need is to paste your AppStore token on madduck insights: **no SDKs, no code, no meetings! Signup & paste your token under 2 minutes, get your LTVs in 30 seconds.**

WHAT is LTV?

Lifetime Value (LTV) is the amount of revenue a customer generates a business over the life of his/her relationship with it. LTV is especially critical for subscription businesses since the revenue is not a one-time affair for them. To know if a subscription business is profitable on a customer basis, one must compare the Customer Acquisition Cost (CAC) to LTV. The LTV:CAC ratio measures the return on investment for each dollar your brand spends to acquire a new customer.

To summarize, LTV is the holy grail of the subscription business and can be constantly improved, package by package, country by country. Refer to our Developer's Guide to Subscription Business to know more about the importance of LTV and its "incorruptibility" as opposed to revenue.

WHY
predict it?
(when you can just look at the realized LTV)

Realized LTV shows past user behavior and although it is valuable information to measure profitability, it would be misguided to use it to make decisions for new user acquisition or evaluate your A/B tests: you need to predict future LTV for those decisions.

However a predicted LTV is only useful when it is based on most recent cohorts (to mirror current trends) and when it is available fast (which implies limited data). This is what we do and we do it without compromising accuracy.

The way to
PREDICTION

Recent Cohort Base (RCB):

We assume that the last 3 months is the ideal timeframe that reflects the current state of any mobile app. We also assume that in Apple's world, a cohort is determined by the following characteristics: package duration, price, introductory offer type, introductory offer duration and introductory offer price. As a result, we define a Recent Cohort Base as a group of users who share the above characteristics in the last three months.

Data we use:

We use four main raw Apple reports to handle churn and renewal figures to calculate retention rates within a daily timestamp throughout the Recent Cohort Base. This enables us to provide retention rates without any time limitation associated with fixed cohort definitions: in short, **when you have to wait four weeks to see your weekly packages' retention rates on Apple dashboards, we are able to use them as soon as it becomes available** (i.e. 7 days for a weekly package).

STEPS

1

Realized Retention Rates

We lay the foundation of our prediction by calculating realized LTV figures for target apps in each country with the abovementioned RCB characteristics on a daily basis and extract the realized retention rates from the beginning to date. Afterwards, we transform them into a single retention rate array in order to use it as the projection's origin.

2

Extrapolation

To make an extrapolation, we look for packages with the same characteristics across the history of the app and use its data as a "fingerprint"; if the same characteristics are impossible to find, the most similar package is used as a basis. This fingerprint serves as a trend indicator and definitely not used as direct data points since we believe that any use of data points before RCBs misleads estimations.

3

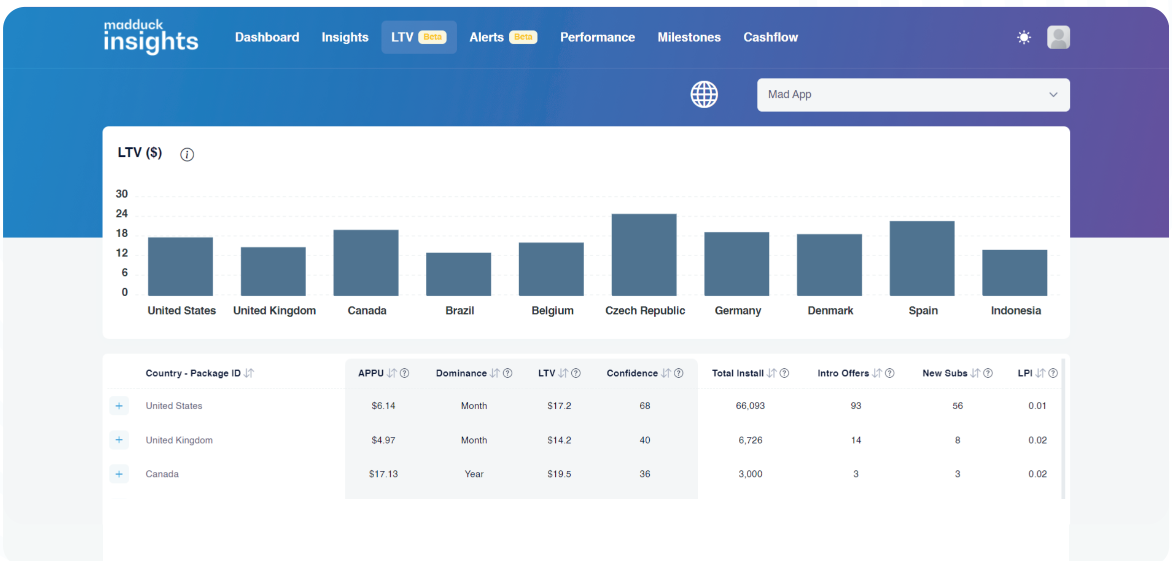
Projection:

We use the beta-geometric (BG) distribution as a basis to project retention rates beyond the extrapolations. This model was published in several different papers by valuable educational institutions such as London Business School, Wharton College etc. Evidently, we set some different parameters in order to modify the distribution's fitting for the mobile app domain's dynamics .

Like in most prediction models, the biggest concern in using this model is the availability of data. We solved this problem by using a similarity algorithm: we basically cluster cohorts with similar behaviors and subscription products with similar characteristics in order to increase data points and extend the calculation base.

And voila!

On insights LTV screens, you can clearly see realized, extrapolated and projected retention rates so that you are in total control of your LTV figures. On top of that, we also provide a **Confidence Level** for each estimation.

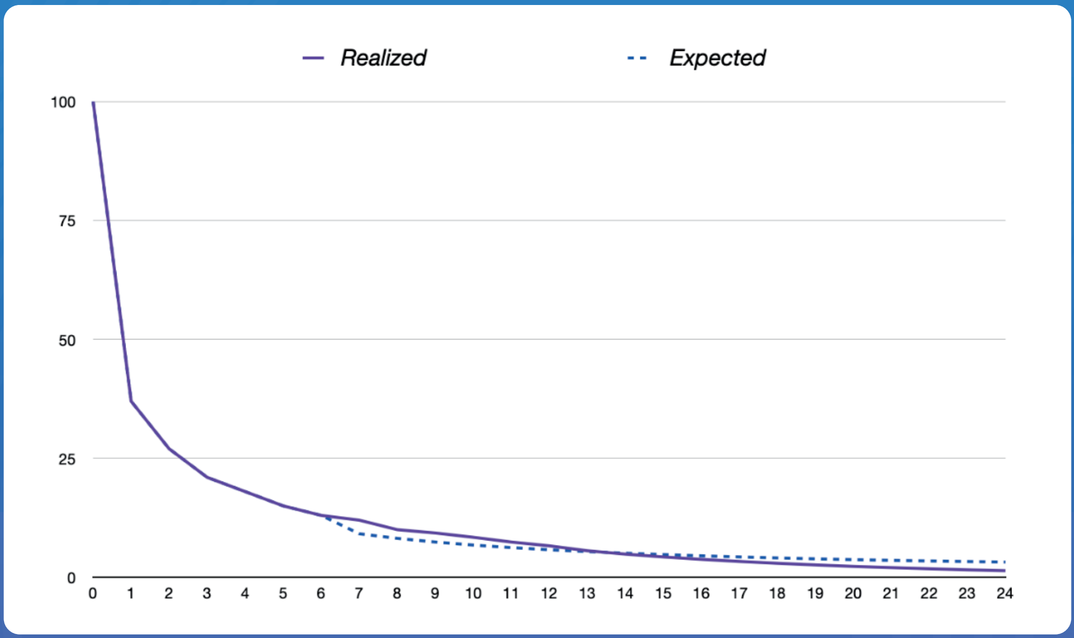


The Proof

Recently, one of our customers with > $500K MRR, asked us to prove the reliability of our LTV forecasting. Here's what we did:

- We used a monthly package that had unchanged characteristics from Aug.22;
- We set up our algorithm to act as if we were in 31.12.22 and noted the predicted retention rates for the 8 months to come (until 31.08.23) along with the algorithm's confidence level (89%)
- We traveled forward in time to now and calculated realized retention rates at 31.08.23 for the cohorts that activated until 31.12.22 and compared the results

Retention For: Madduck App's Weekly Package



We were simply blown away: our confidence level of 89% delivered an accuracy of 98% 8 months into the future. We repeated the same process for following months (i.e. acted as if we were 31.01, 28.02 etc) and the results were pretty much the same: we hit an average accuracy rate of 97,6% overall.

Connect your AppStore token now and never worry about measuring your **LTV** again!

Signup Now

Any questions?

Get in touch!

https://madduck.com/contact-us/