How to make the most of your budget thanks to algorithmic segmentation

Margot Miller

Adikteev is known in the industry for our superior customization and client-first approach to retargeting, but what if we told you there were even greater opportunities for customization with Adikteev? For some clients, we've developed custom algorithms to help meet their very specific needs. Learn more about how we use advanced machine learning technology to develop custom re-engagement campaigns.

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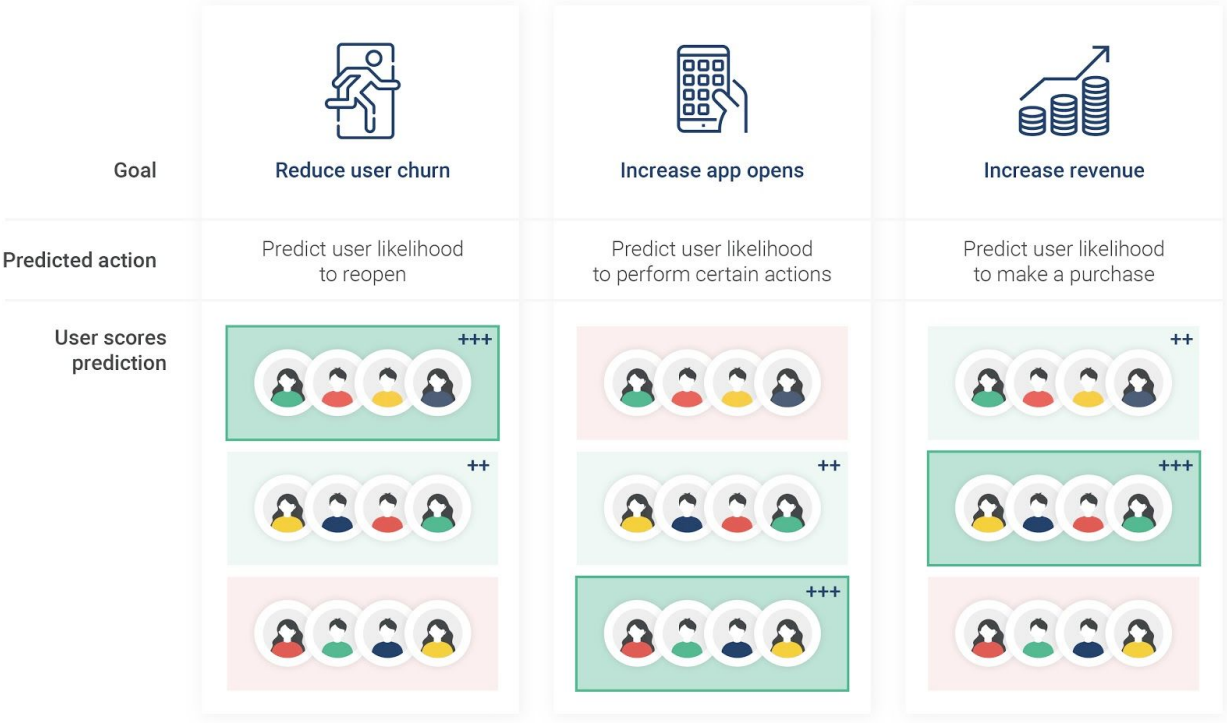
What is algorithmic segmentation

Algorithmic segmentation is the usage of machine learning technologies to generate user-level predictions, or scores. Scoring users creates more refined audience segments, which increases marketing performance by adapting advertising strategies to user scores. Marketers who have already implemented a robust retargeting structure can get even more granular by predicting user behavior.

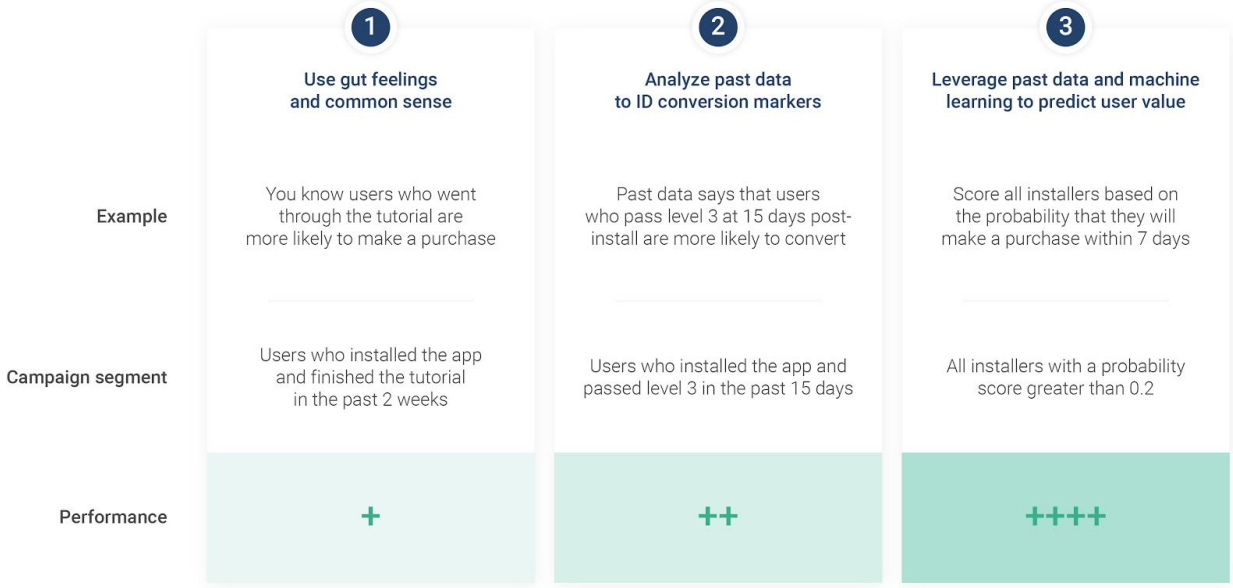
Instead of implementing basic rule-based filtering or using past data to define audience segments, **integrated machine learning predictions** give each user a score based on the probability that they will or will not perform a pre-defined in-app action.

As a marketer with experience in retargeting, you might have a variety of goals that can't really be met with basic campaign strategies. For example, if you're looking to increase revenue, it's possible to develop a **custom algorithm** that predicts the likelihood that a user will make a purchase. If you'd like to reduce user churn, it's possible to predict which users are not likely to open your app. If you want to increase app opens, it might be useful to predict which users will perform certain actions.



Why algorithmic segmentation

Leveraging these **prediction-based audience segments** helps improve conversion rates, and makes your media budget more efficient. Instead of dedicating a specific amount of the budget to a large number of less relevant users, that same amount can be used to target a smaller number of high performing users, streamlining marketing spend. In addition, by targeting **the most relevant users possible**, users who are not likely to convert aren't bombarded with ads they're not interested in. They won't become tired, annoyed or frustrated with your brand and can be targeted in more appropriate ways.



In addition, algorithmic segmentation may help mitigate some of the uncertainty around the future of re-engagement on iOS. At the moment, iOS 14 has reached **nearly 80% adoption**, signaling that the likelihood of running campaigns on Apple devices will soon be greatly reduced. Focusing marketing budgets on high performing user segments identified by machine learning could improve performance and make up for losses incurred by the depreciation of IDFA.

As you can imagine, user-level scoring requires **user-level data**, which can be a challenge with the upcoming privacy changes on iOS. In parallel to the App Tracking Transparency framework, Apple introduced the IDFV (ID for Vendor) which is a user identifier that is common across all apps of the same publisher. Also, your app might be using another type of user ID (for instance if your app requires to log in). This ID will provide another

channel to continue to enable user scoring and help minimize the effect of losing the IDFA.

How to implement algorithmic segmentation

There are a few different options for implementing algorithmic segmentation on an app.

Companies with large, in-house data science teams can implement it themselves, as long as they have enough time and team members to dedicate to the task. In theory, the benefits of running **homegrown algorithmic segmentation** are superior transparency and increased agility when it comes to changing direction.

However, it's rare that a company has the personnel or time to spare to develop a robust algorithmic segmentation model on its own. With the amount of data required, the time it takes to develop the model, the frequency of calibration to ensure the model is functioning properly, and then ultimately the generation of analyses and recommendations for optimization, it's a large undertaking that can be a drain on resources. In most cases, an in-house data science team has **many other app-related challenges** to work on, and industrializing a machine learning model to integrate it into a business workflow is not a simple task.

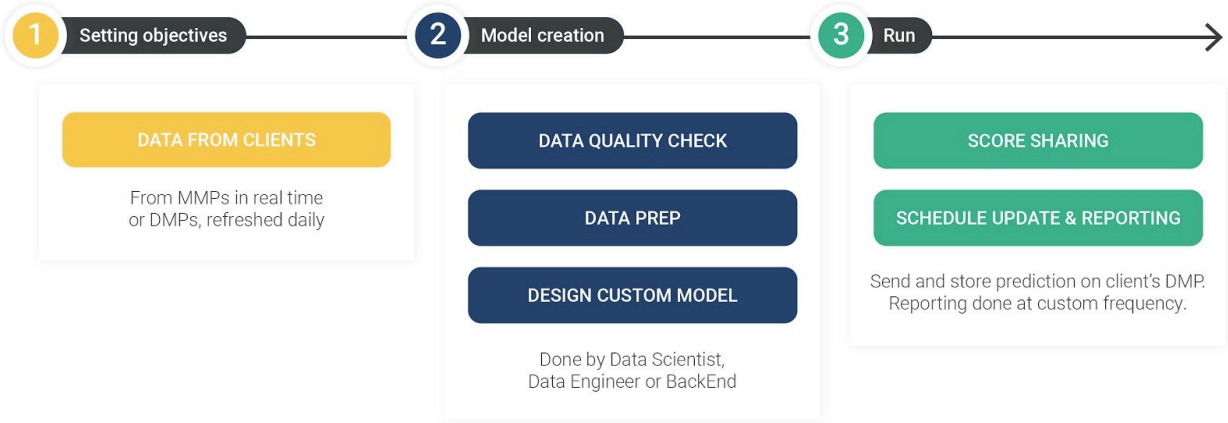
Another option is to outsource algorithmic segmentation to an experienced partner. By doing this, companies can avoid spreading themselves too thin, and in turn receive more positive outcomes. Also, ML-based segmentation built by a retargeting partner is often more powerful and comprehensive: the algorithm is developed by ad pros who know how to **create the best segments** according to ad KPIs. Retargeting partners such as Adikteev have been in the **audience segmentation game** for quite some time, offering algorithmic segmentation to clients who are not able to dedicate an entire data science team to a single endeavor.

With that being said, outsourcing algorithmic segmentation requires a high level of transparency and trust from retargeting partners to ensure **accurate results and appropriate optimizations**. We pride ourselves on our clarity and openness when it comes to our partners, and we're not interested in becoming a black box. Here's what the process of developing and deploying a custom segmentation model looks like at Adikteev.

Algorithmic segmentation @ Adikteev

When developing an algorithmic segmentation model, our first step is getting clarity about the client's business goals and deciding on which actions we'll be predicting. As mentioned, this could be the likelihood that a user will make a purchase, sign up for a

subscription or anything else that might be relevant to the app. Then, we need to collect about **7-14 days worth of historical in-app data**. This can be done through the client's tracking partner or shared from a DMP.



Once we receive the data, our analysts check for the presence of abnormalities or inconsistencies to ensure the data is correct and not corrupted. Then, our Data Science team can build **the first training dataset** to calibrate the machine learning models. When the dataset is built, we analyze a few days of historical data, and then we use a train/test split of 70% vs. 30% during the model learning phase.

All automated tasks such as training dataset enrichment, machine learning model refresh and prediction (or "user score" updates) are scheduled to run at **a specific frequency** such as daily or weekly. We also add a layer of monitoring to ensure the data received regularly is correct, that the models are being correctly refreshed, and that the accuracy of the models and the predictions remains high. We want to maintain a consistently high performance level for the model in order to train it again if necessary.

Once the model is up and running, all app users will receive a score, which is refreshed at a certain frequency such as daily. As mentioned before, the score represents the probability that a user will complete the desired conversion. The client can then define **dynamic user segments** by grouping users based on their scores and decide how much of their budget to dedicate to each segment.

Using algorithmic segmentation outside the Adikteev DSP

Previously, algorithmic segmentation was only available on our proprietary DSP. Adikteev is proud to announce that its algorithmic segmentation capabilities can now be leveraged **on any channel**. This includes social channels such as Facebook, Snap and TikTok, other DSPs, and CRM tools and push notifications such as Braze.

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With **Klust**, Adikteev's algorithmic segmentation service, app publishers can dramatically increase campaign reach and impact. Klust makes it easier to **scale your algorithmic segmentation**, taking your strategy all the way from concept to deployment on any platform.

Essentially, algorithmic segmentation is just an extension of our already highly customizable service. We're using the same technology to identify the most high value users and help optimize your retargeting budget. The possibilities are endless, no matter the vertical: it's all up to your goals and budget. Our clients currently using algorithmic segmentation have seen a 20% increase in in-app purchase rates, and **a 20% to 60% increase in revenue** overall.

At Adikteev, we never stop innovating, and our custom models are just one piece of the ever-evolving puzzle of **predictive segmentation**. In the coming months, we'll be releasing more content about how we can better serve our clients' diverse needs and keep up-to-date with changes in the industry. Stay tuned for big news from Adikteev!