Recommendations Drive Engagement

Here we discuss how to make content relevant by making the right recommendations, eventually, increase engagement.

Recommendation

To recommend well, you must understand the total inventory available to each user, gather implicit and explicit signals about your users, and use those signals to anticipate user behavior (**prediction**) and determine importance (**relevancy**) of each inventory to each user. An effective recommendation system must, therefore, include a prediction algorithm that can assign a numerical "**relevancy score**" to each *inventory-user pair*.

As a product grows and more content is produced, most users will subscribe to more content and spend more time on the platform – thereby increasing the number of connections. The *amount of content consumed* will ultimately be a strong indicator of long-term retention and engagement of the user.

Inventory and Connections

Unlike a social platform such as Facebook, Snapchat or Instagram, which includes user-generated as well as professional content, a platform such as Netflix generally makes its entire inventory available to each subscriber. Thus, inventory is the same for each user, and consumption and engagement depend heavily on how users interact with recommendations, search, browsing, and subscriptions to specific programming or channels.

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Signals (Variables)

A product's signals (content profile / content characteristics) comprise all available information on users and their content preferences and can help you predict whether a given user will engage with a given piece of content. Examples of signal categories are given in the table below; note that some categories include hundreds of individual types of signals and that this list is not comprehensive.

Category	Signals	Notes
Type of content	Original or licensed	Strategically, it may make sense to promote original content over licensed.
Details of content	Informational, entertaining or educational; language; length; detailed content (actors, animals etc.); movie, show or documentary	Detail of content helps determine user interests.
Recency of content	New or old content	New content is more likely to have higher engagement.
Content watched and searched	Order of content; type of content; time of day; searched	Content watched helps personalize content.
Engagement of content	Explicit feedback (upvotes, ratings, click etc.); Implicit feedback (time spent, browsing); change with time; comparative engagement	The more a user engages with a piece of content, the more valuable it is.
User information	Demographics; connectivity; device characteristics	Understanding personas helps identify patterns across users and improve recommendations

Prediction and Relevance

Because users' past behavior is predictive of their future behavior, a machine learning model can use signals like those above to determine to a certain degree of confidence whether a given user will watch a specific content and produce a relevancy score specific to each content-user pair. When each piece of content in your inventory has such scores, your sorting algorithm can then place them in the order they will appear to each user.

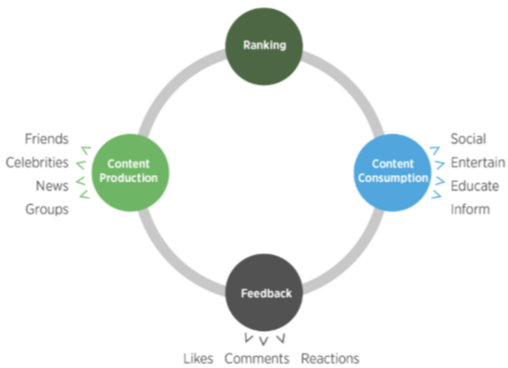
These predictions are challenging for multiple reasons. Watching a piece of content for a few minutes does not reveal whether the user liked it; perhaps they did not, perhaps they simply got distracted and forgot to return. Even completing an episode or more does not necessarily indicate they enjoyed it. A high rating, on the other hand, is more instructive. It's important to take care in determining which signals will inform your relevancy scores, and to what extent. Choosing and properly weighting each function is as much art as science, and can be quite complex: How much should a partial viewing weigh? How important is recency? Clicking on a video?

In addition, the relevancy score for each post-user pair should reflect not only the predictions derived from your signals but your product's optimization function. Based on your company's mission, you may decide to optimize for time spent, for example, or for number of sessions or click-through rate. According to Netflix, their business objective is to maximize member satisfaction and month-to-month subscription retention, both of which correlate with maximizing consumption of video content. Therefore, Netflix optimizes its algorithms to give the highest scores to titles a user is most likely to watch and enjoy. Ultimately, a recommendation is effective when it optimizes for your overall goals for the product.

Engagement

In most cases, if your product is growing well, users are retained at high levels and you have good indicators of stickiness, your product is in great shape. But it could also be the case that people are not returning often enough, are not producing or consuming enough content, or are not spending enough time using the product. These are indicators of low engagement. For social products (such as Facebook and Instagram) in particular, time spent in the product is the simplest indicator of whether your product is engaging. The higher the time spent, the higher the engagement. True product-market fit happens when a product is highly engaging.

What drives engagement? It is valuable to create a simple framework to understand what drives engagement in your product. Social products such as Facebook, Instagram, Tiktok, etc. *have a production/consumption framework to drive engagement.* In this framework, *users produce content which is then shown to others, creating delightful experience. Consumers of the content provide feedback in terms of upvotes, comments, reactions, likes, sharing, etc., which makes users want to produce content again. This production/consumption loop creates* ***engagement, which can be measured by users coming back frequently (number of sessions), consuming more content (number of views) and spending more time on the site.***



1. Creating high quality inventory easily,
2. Showing users with the most relevant content in the right order at the right time,

There are multiple approaches to increasing engagement:

making it easier for users to create different types of content,

helping connect users with the most relevant content,

showing them the right content in the right order at right time,

making sure people are able to consume content easily on any device and any network condition, etc.

In addition, as more individuals, influencers, Key Opinion Leaders (KOL) and businesses produce content, there is a greater likelihood that users will see engaging and relevant content they love.

It's also important that you design your product to make it easier for people to interact with its content, as this strengthens the ***positive feedback loop***.

Another engagement model is the e-commerce model. For example, eBay connects sellers to buyers. In this model, you can increase engagement by

focusing on the quality of the inventory available, the quantity of unique listings, the relevance of items shown to the buyer, the value of the listings,

connecting the right content to the right buyer in the right order at the right time, simplifying the buying process,

building trust at every step of the experience, etc. Optimizing each part of the funnel should increase overall engagement.

Metrics to track

These metrics will help you understand connections on your platform.

Consider **segmenting** them by country, language, type (news, movies, etc.), original vs. licensed, format (text, video, etc.) and/or platform (iOS, Android, desktop).

Inventory available: The more overall inventory available via recommendations, search and browse, the more likely it is users will find something they want.

Consumption of available inventory: Know how much a user is consuming relative to their available recommended inventory.

Number of connections: The more a user is connected to relevant content, the more likely they are to consume content.

Metrics in a broad range

Note that many of these metrics are specific to companies that fit the production/consumption paradigm.

Time spent/DAU This metric is a strong indicator of whether your product is engaging. Again, this depends heavily on the specific product and expected engagement. Market share of time spent is also a good indicator of whether you are doing well from a market perspective.

Number of sessions Number of sessions in a given day is another good indicator of whether your product is engaging. An increase in this metric is also the earliest indicator of whether you are achieving product-market fit. (Similarly, a decrease in number of sessions is the earliest warning sign that something is going wrong.)

Time spent/session Both number of sessions and time spent/session are levers to grow overall time spent. It is valuable to understand whether you can more easily increase overall time spent by increasing the number of sessions or by increasing time spent/session.

Inventory available for companies that have news feeds (ByteDance, Instagram, Facebook, LinkedIn, etc.), users can consume content only if there is inventory for them to see. Knowing how much inventory is available and how it is distributed helps you understand how content can be monetized.

Content consumption (number of <completed> views) The metric of time spent is often skewed by types of content that are inherently time-consuming, such as videos. Therefore, it is helpful to understand how many pieces of content people consume relative to the inventory. Are some people inventory-constrained and thus unable to consume content?

Production of content How much content does each user produce every day, week and month? How many of them produce content on a regular basis? The total production of a product is based on the number of users who produce content and the amount that each produce. For ecosystems in the production/consumption paradigm, the production of high-quality content is the most important metric for an engaging ecosystem.

Feedback on content Key feedback metrics to track are likes, comments and reactions. Likes are a weaker form of feedback than comments. Regardless, all feedback is important to the ecosystem. Without it, production will decrease, which will ultimately lead to a drop in consumption.

Engagement Considerations

Possible segmentations Consider segmenting your metrics by country, device, age, gender, phone year class, connectivity class, platform, age in product, content format (video, picture, text, etc.) and content type (social, entertainment, informational, educational, etc.).

Leading and lagging indicators Imagine you start out using a product multiple times per day (multiple sessions) and spending a lot of time with it. Over time, you start getting bored with the product and your usage drops off - but you are still an engaged user in many ways, visiting the product many times per week and more than twenty times per month. At this point, DAU, WAU and MAU have not yet changed.

Eventually, however, as you use the product fewer times per week, you will continue to register as a WAU and MAU but less as a DAU. Over time, you will no longer be a WAU, and then not a MAU, either. And chances are, you are not alone; many other users are likely getting bored, too. At an aggregate level, *these types of behavioral changes* first *manifest* in engagement metrics such as the number of sessions. It's likely that as your use of the product changes, first you will consume fewer items of content, then you will have fewer sessions and read fewer stories each time. A drop in number of sessions is the earliest leading indicator for a drop in DAU. Similarly, a drop in DAU is a leading indicator of a drop in WAU and ultimately, MAU.

Takeaways

To recommend well, you must understand the total inventory available to each user, gather implicit and explicit signals about your users, and use those signals to predict user behavior.