



**The CENTRE for EDUCATION
in MATHEMATICS and COMPUTING**

Recommendation Algorithms

A CS and Society resource addressing economic and cultural issues within the realm of digital technology and computing

This resource will:

- explain how recommendation algorithms decide what content to suggest, and
- challenge you to consider how these algorithms could be improved and safeguarded.

Your Experiences

Recommendation algorithms are all around you, quietly influencing what you see and do. Discuss your experiences with a partner using **inside-outside circles**.



Do you listen to music recommendations from platforms like Spotify? How similar are the recommendations to music you already like?



On entertainment platforms like Netflix, how do you decide what to watch? Do other household profiles suggest similar titles?



When shopping on a site like Amazon, are you interested in the items it recommends? Are you influenced by ratings and reviews?



After watching a series of suggested videos on platforms like YouTube, have you ever seen something you strongly disliked?

Form two concentric circles, with each student facing a discussion partner. After each question, rotate the outer circle one position to form new partnerships.



Surprising Statistics

35%

The amount of **Amazon's** total revenue coming from the purchase of recommended products.

40%

The amount of **Spotify** streams coming from suggested playlists and personalized mixes.

70%

The amount of **YouTube's** total watch time coming from the recommended content list.

80%

The amount of **Netflix** streaming hours coming from personalized recommendations rather than searches.

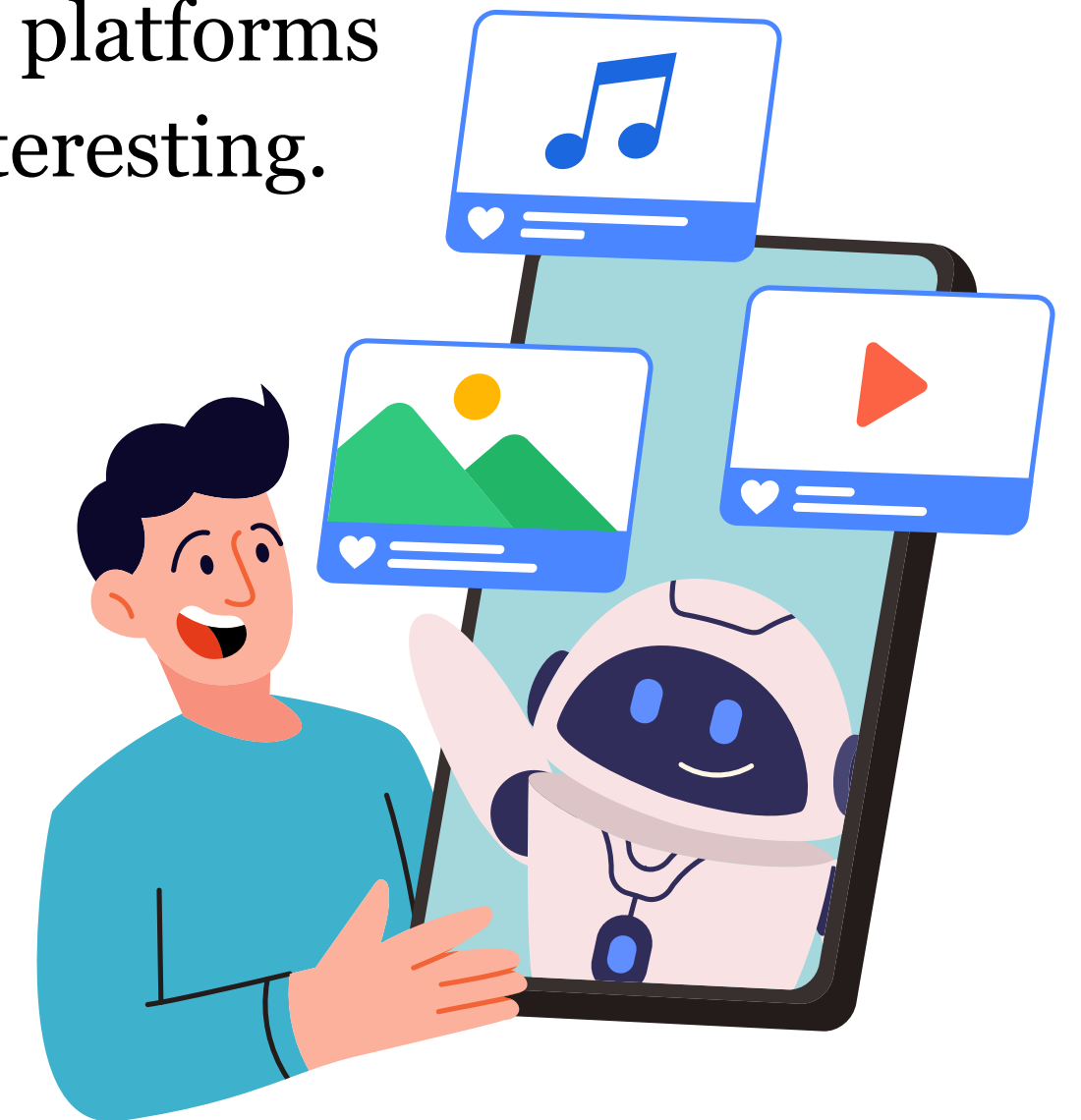


Recommendation Algorithms

Many online systems and services make money from our engagement. The longer we stay on a platform, the more opportunities there are to show us advertisements or sponsored products. Recommendation algorithms help keep us glued to the platforms by continually presenting us with content we are likely to find interesting.

Recommendation Algorithms

Decision-making systems designed to suggest relevant items, content, or actions based on what they know, or can guess, about us.



Types of Recommendation Algorithms

Content-Based Filtering

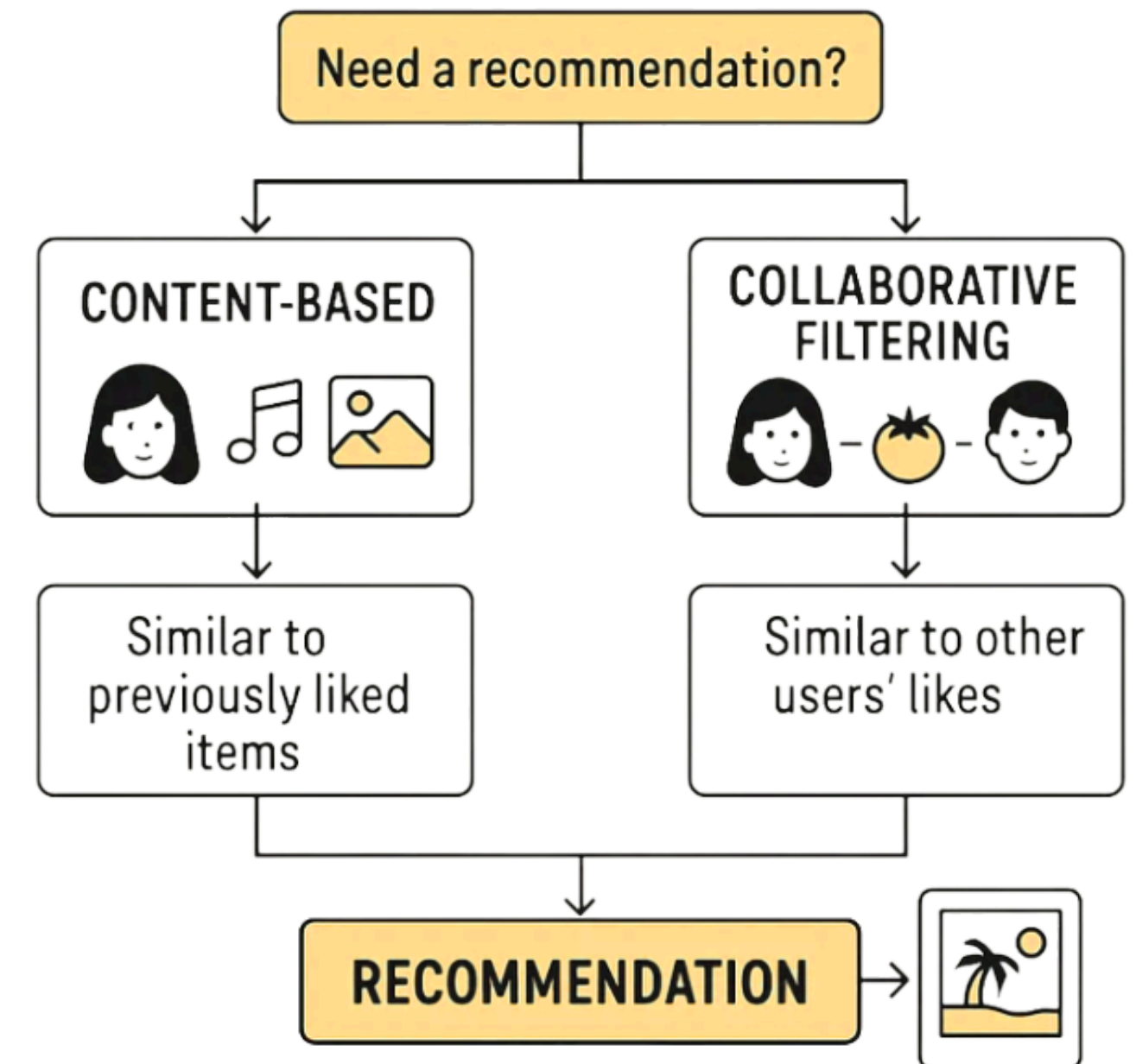
- Classifies content according to *attributes* such as movie genre, clothing style, or music artist.
- Recommends content with *similar attributes* to what you have already engaged with.

Collaborative Filtering

- Identifies other *users* with common interests who engage with similar content as you.
- Recommends content that these *similar users* have already engaged with.

Hybrid

- A combination of both content-based and collaborative.



<https://generativeai.pub/why-the-internet-feels-so-personal-the-power-of-recommender-systems-de029159a12b>



Mathematics at Work

Collaborative filtering algorithms work with lots of data. This data is stored in an **engagement matrix** – a table containing a row for each user and a column for each content item. When a user engages with an item, the corresponding cell is filled in with a number measuring the level of engagement. An empty cell means the user has not yet seen the item. The algorithm looks for similarities between users and/or items to predict the values of empty cells. A high prediction suggests that a user will strongly engage.

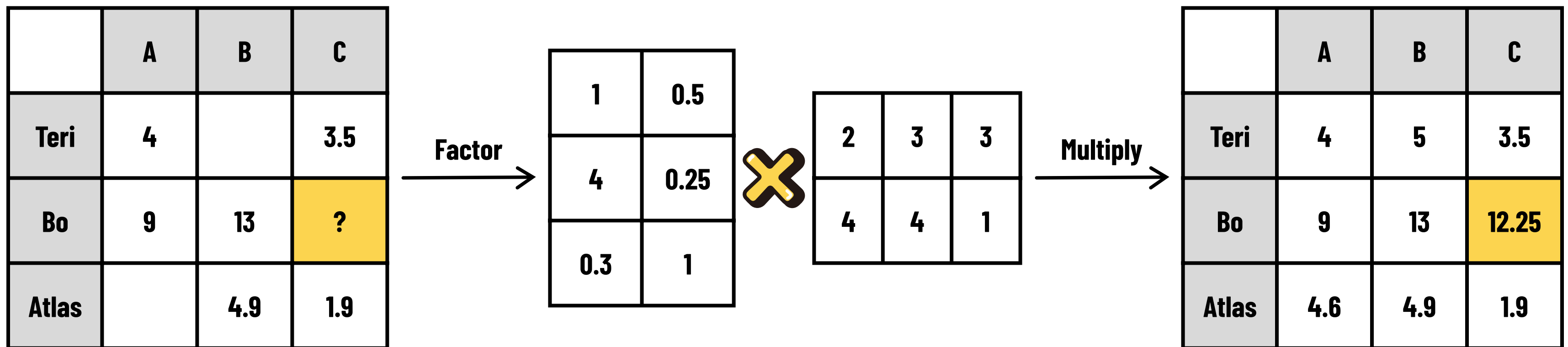
Platforms can have millions of users and millions of content items, but users typically only interact with a small fraction of them. This results in engagement matrices that are huge with mostly empty cells – called **data sparsity**. This type of matrix makes it hard for algorithms to find the patterns they need to make good predictions.

	A	B	C
Teri	4		3.5
Bo	9	13	?
Atlas		4.9	1.9



Mathematics at Work - Continued

Matrix factorization uses techniques from linear algebra to address the data sparsity problem. A large and mostly empty matrix can be broken down (factored) into two smaller and more densely filled matrices: one exposing user patterns and the other, patterns among content.



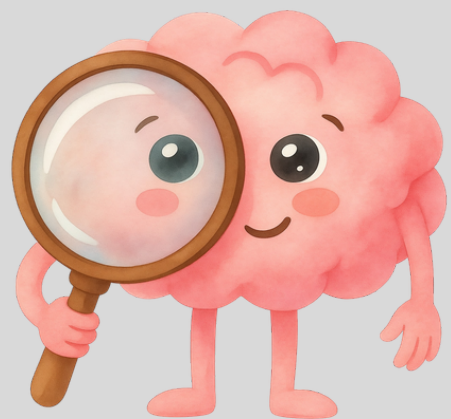
A user's future engagement can then be predicted by multiplying the two matrices together.



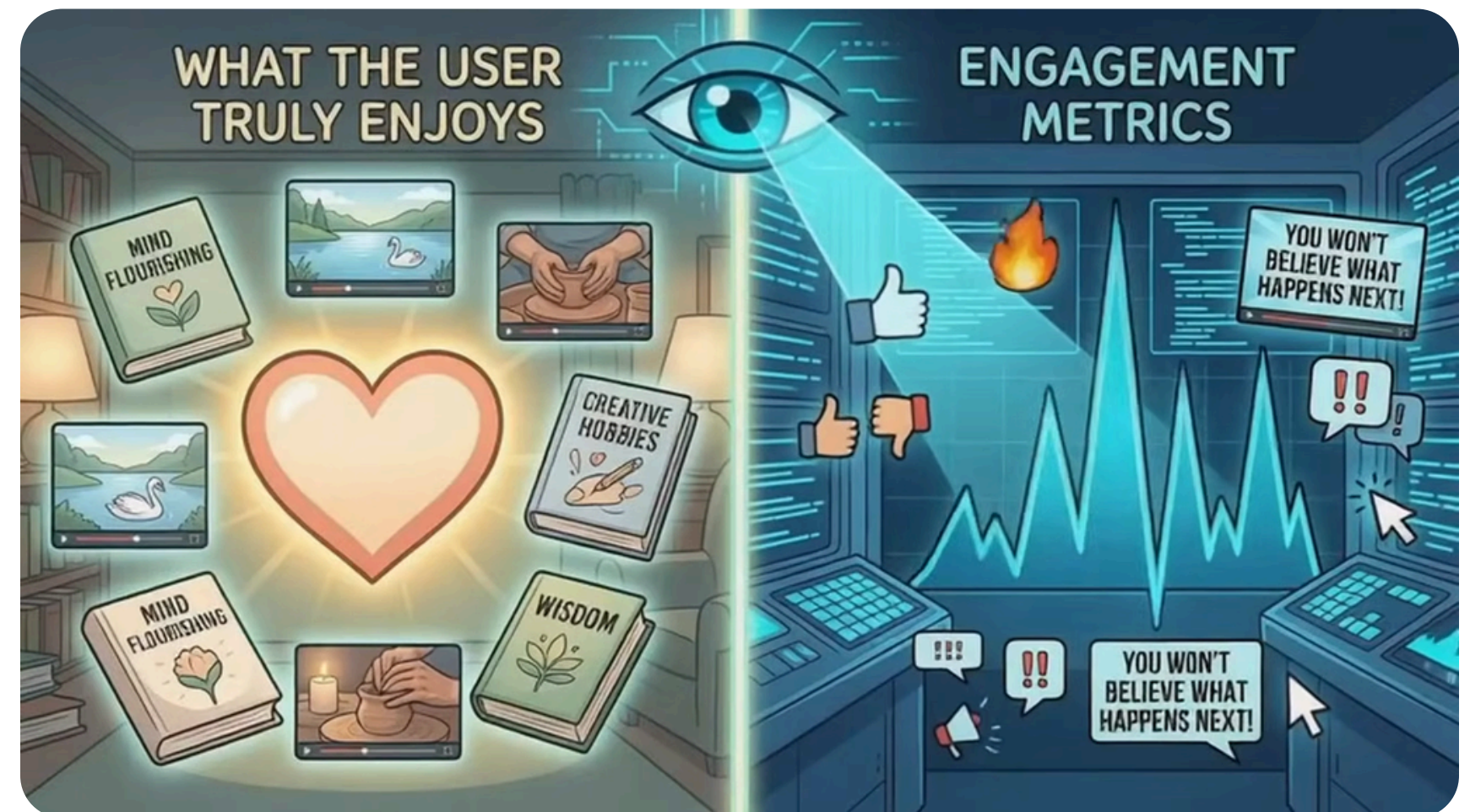
Deconstructing the Algorithms

It may seem like platforms such as Netflix and YouTube can read our minds when they predict our preferences, but there is no magic here. The following video breaks down the mechanics behind these impressive algorithms. After watching, complete the infographic found under additional materials.

VIDEO

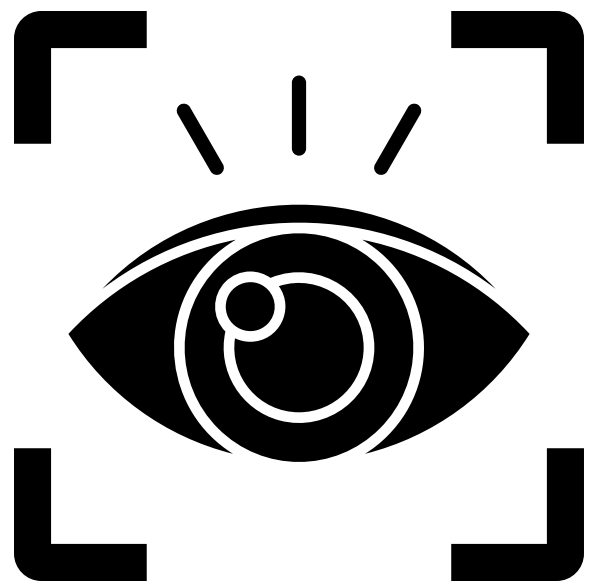


Can you spot the signs? What evidence is there that this is an AI-generated video?



Artwork Personalization

Not only are recommendation algorithms sophisticated in *what* they choose to present, but also in *how* they choose to present it. For example, different Netflix users may see different artwork for the exact same show. By combining user data with insights from psychology, Netflix's algorithms make predictions about which types of images are more likely to catch users' attention.



NOSTALGIA



SUSPENSE



HORROR



Artwork Personalization - Continued



Discuss! Which graphic is most likely to engage ...

- A user who watches nature documentaries?
- A user who watches comedies about friends?
- A user who watches sci-fi mysteries?

Which graphic is most likely to engage **you**? Why?

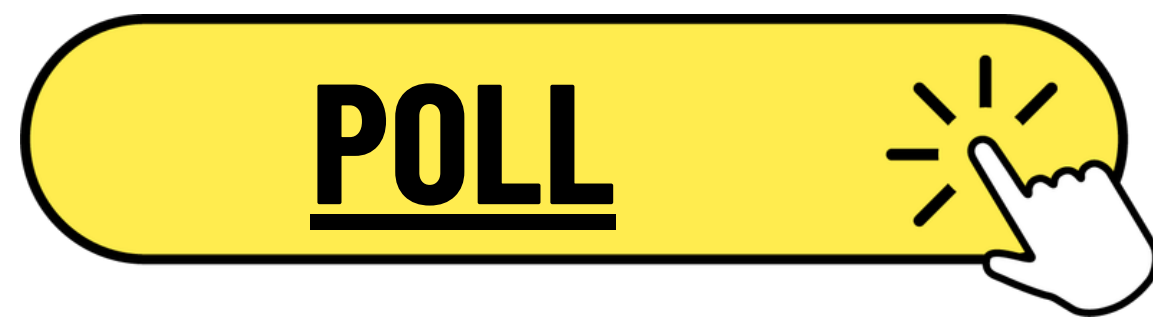
<https://netflixtechblog.com/artwork-personalization-c589f074ad76>



Novelty vs. Familiarity

Do users prefer the safety of familiarity or the excitement of novelty? The answer is *both at the same time*. To maximize user engagement, recommendation algorithms aim for content that is similar enough to previous preferences to be comfortable, yet different enough to spark interest.

What is your appetite for novelty versus familiarity? Explore your personal tastes using the following poll.



Filter Bubbles

When the novelty vs. familiarity scale tips too heavily towards familiarity, you may find yourself in a filter bubble.

Filter Bubble

When recommendation algorithms primarily serve you content that fits your existing interests, isolating you from diverse topics, opinions, and new ideas.

For example, Spotify might suggest new pop music, but not any country music. Or YouTube might show videos about the economic impacts of data centers, and ignore videos about environmental impacts.

Filter bubbles can hinder the development of a balanced perspective, and reinforce existing biases.

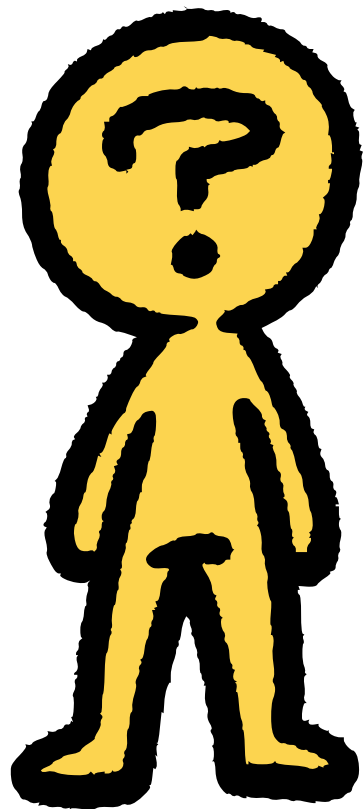
LEARN MORE



Feed Audit

In the *Feed Audit* activity found under additional materials, create a poster that illustrates what may be lurking both inside and outside of your filter bubble.

*Do any of your classmates have a filter bubble similar to yours?
Does anyone have a filter bubble that is quite different?*



Echo Chamber

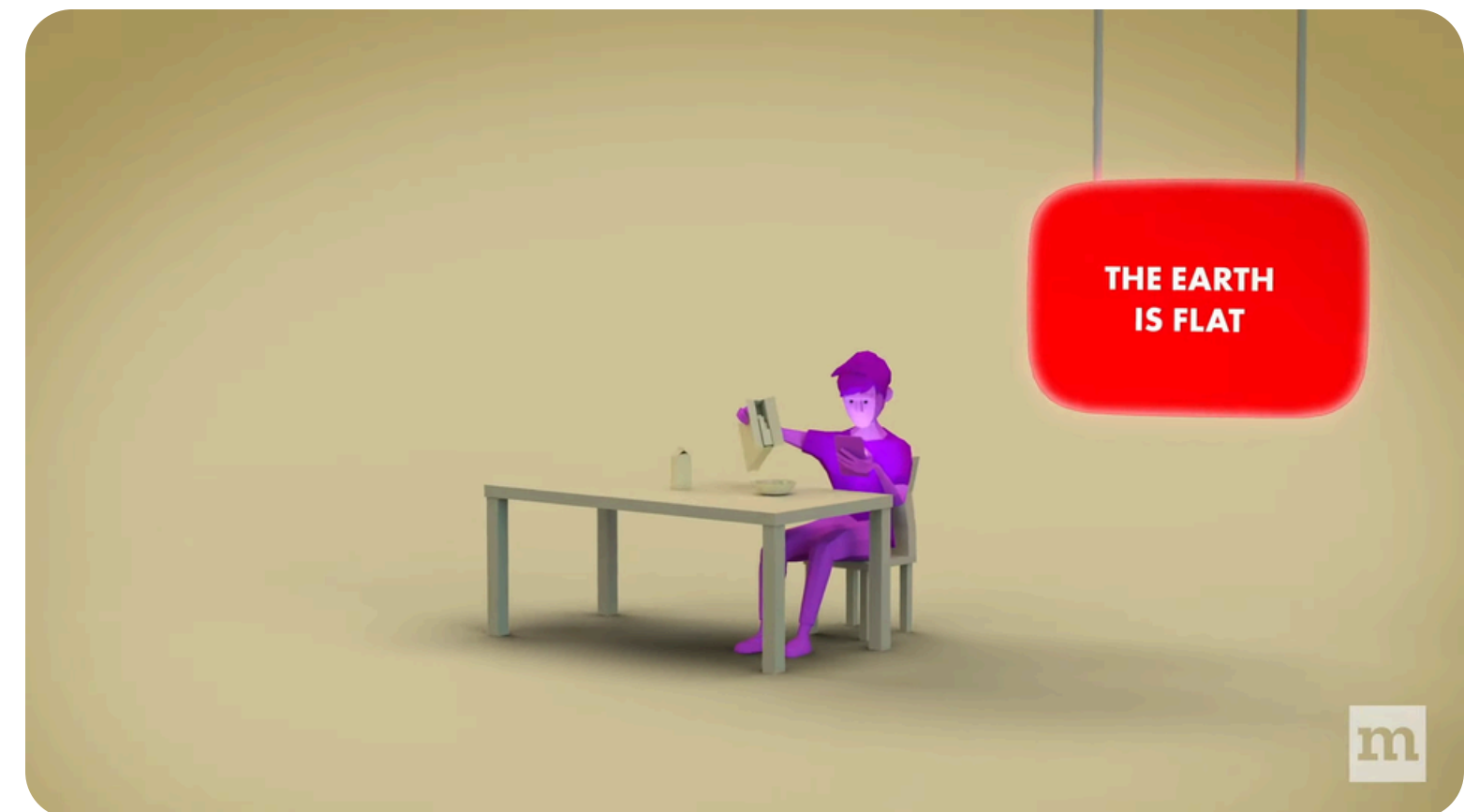
A community of people in the same filter bubble. Echo chambers reinforce shared opinions and beliefs and differing or opposing views are rarely expressed.



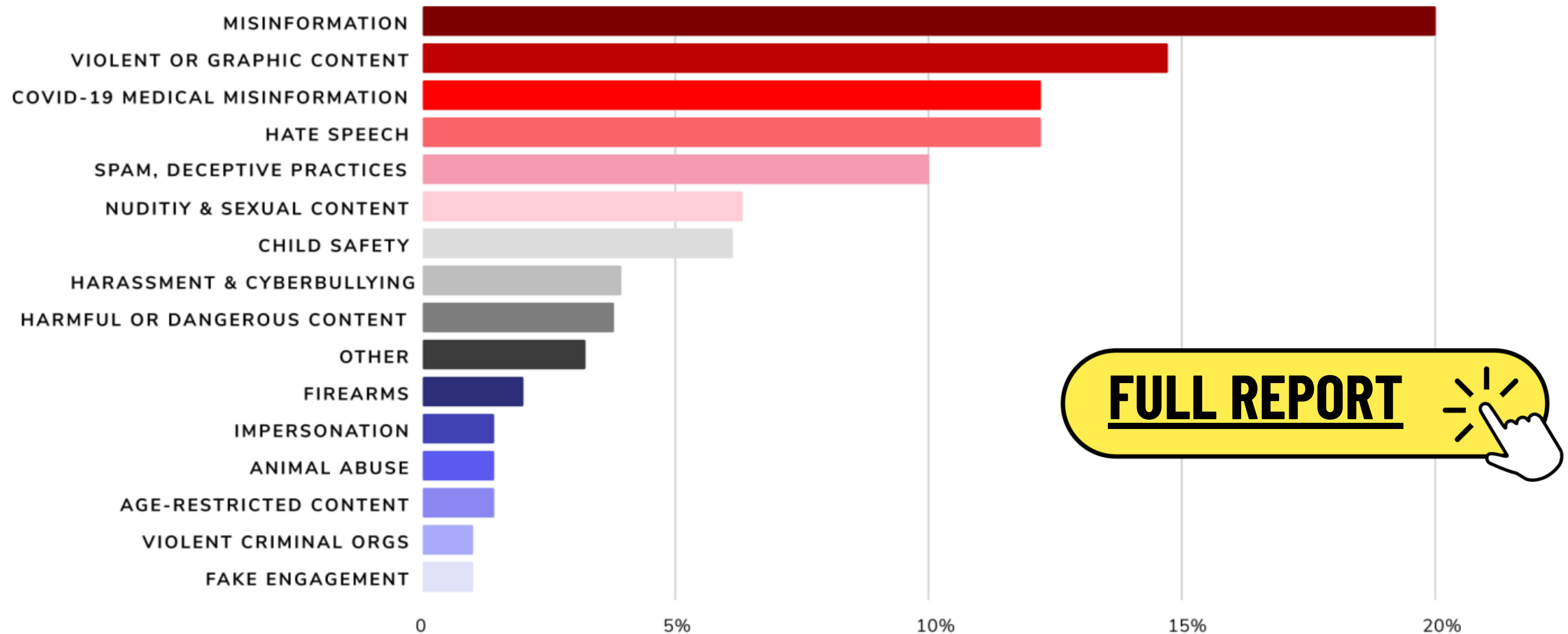
Mozilla Foundation

The Mozilla Foundation is a non-profit organization whose mission is to ensure that AI technologies help, rather than harm, humanity. In 2019, Mozilla launched a public awareness campaign called #YouTubeRegrets, in which stories were solicited from people whose lives were negatively impacted by YouTube's recommendation algorithms.

Over 35,000 YouTube users submitted examples of YouTube recommendations that they regretted watching.

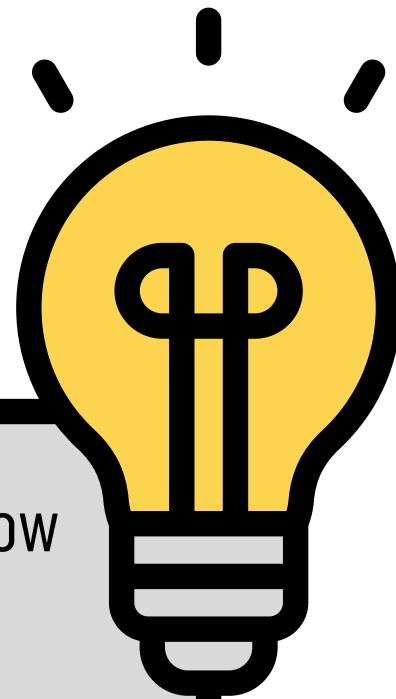


Mozilla Foundation - Findings



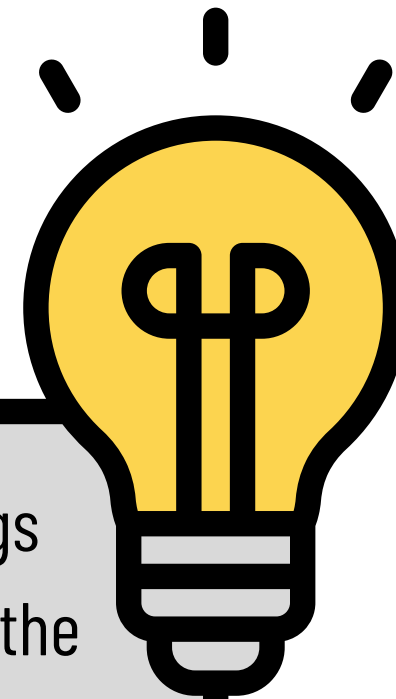
Mozilla Foundation - Advice

To the creators
of YouTube:



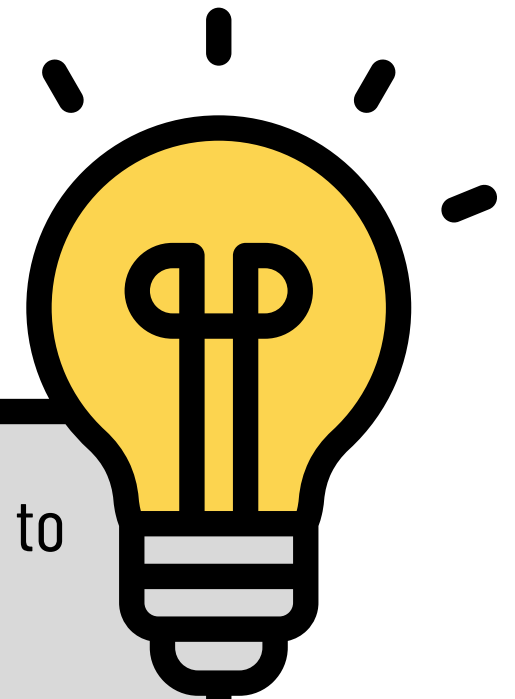
Be transparent about how your recommendation systems work, including insight into problem areas.

To the users
of YouTube:



Check your data settings to make sure you have the right controls in place for yourself and your family.

To the legal
policy makers:



Create policies tailored to the specific issues and risks associated with content recommendations.

Based on what you now know about recommendation algorithms, what additional advice would you give to the creators, the users, and the policy makers?



Decision Time

Are recommendation algorithms good, bad, or a mix of both?

In the following poll, share what you feel is the best feature and the worst feature of recommendation algorithms.

POLL



Further Resources

Uncover more of the mathematics behind how recommendation algorithms make predictions.



Dig more into the benefits and dangers of recommendation algorithms.



Learn more about how recommendation algorithms work.



Join the Mozilla Foundation community.



Additional Materials

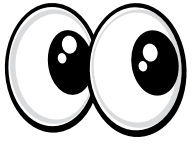
Recommendation Algorithms

Besides what you watch, Netflix knows ...

*

*

*



The algorithms see people as

The algorithms try to show you things _____

not necessarily things that you _____



Signs of Engagement:

1

2

3

4

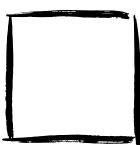
5

What Drives
Engagement?

OVER

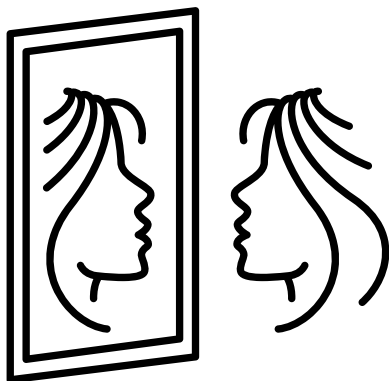
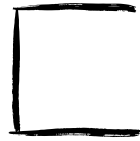
Having no information about you is the _____

Your first



clicks on a new platform

are worth more than the next



The algorithms don't just

what you already like, they

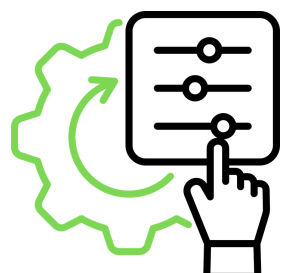
what you like next

Ways to recalibrate the algorithms:

*

*

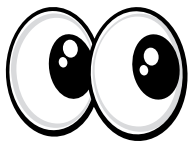
*



Recommendation Algorithms

Besides what you watch, Netflix knows ...

- * When you pause and when you rewind
- * What time you watch
- * Whether or not you finish a title



The algorithms see people as clusters of behaviours

The algorithms try to show you things you will engage with

not necessarily things that you will like



Signs of Engagement:

1

clicking

2

watching

3

scrolling

4

sharing

5

commenting

outrage, conflict, and novelty

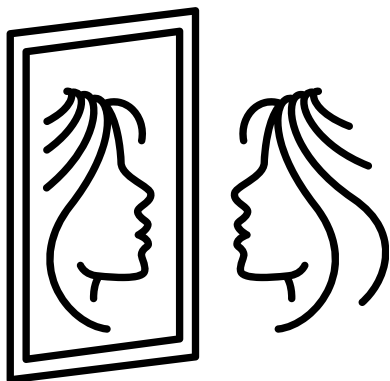
What Drives
Engagement?

OVER

calm, resolution, and familiarity

Having no information about you is the cold start problem

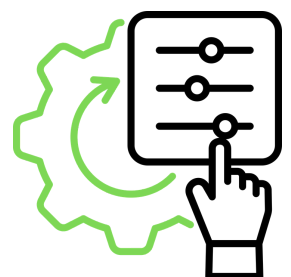
Your first 3 clicks on a new platform
are worth more than the next 100



The algorithms don't just
reflect
what you already like, they
shape
what you like next

Ways to recalibrate the algorithms:

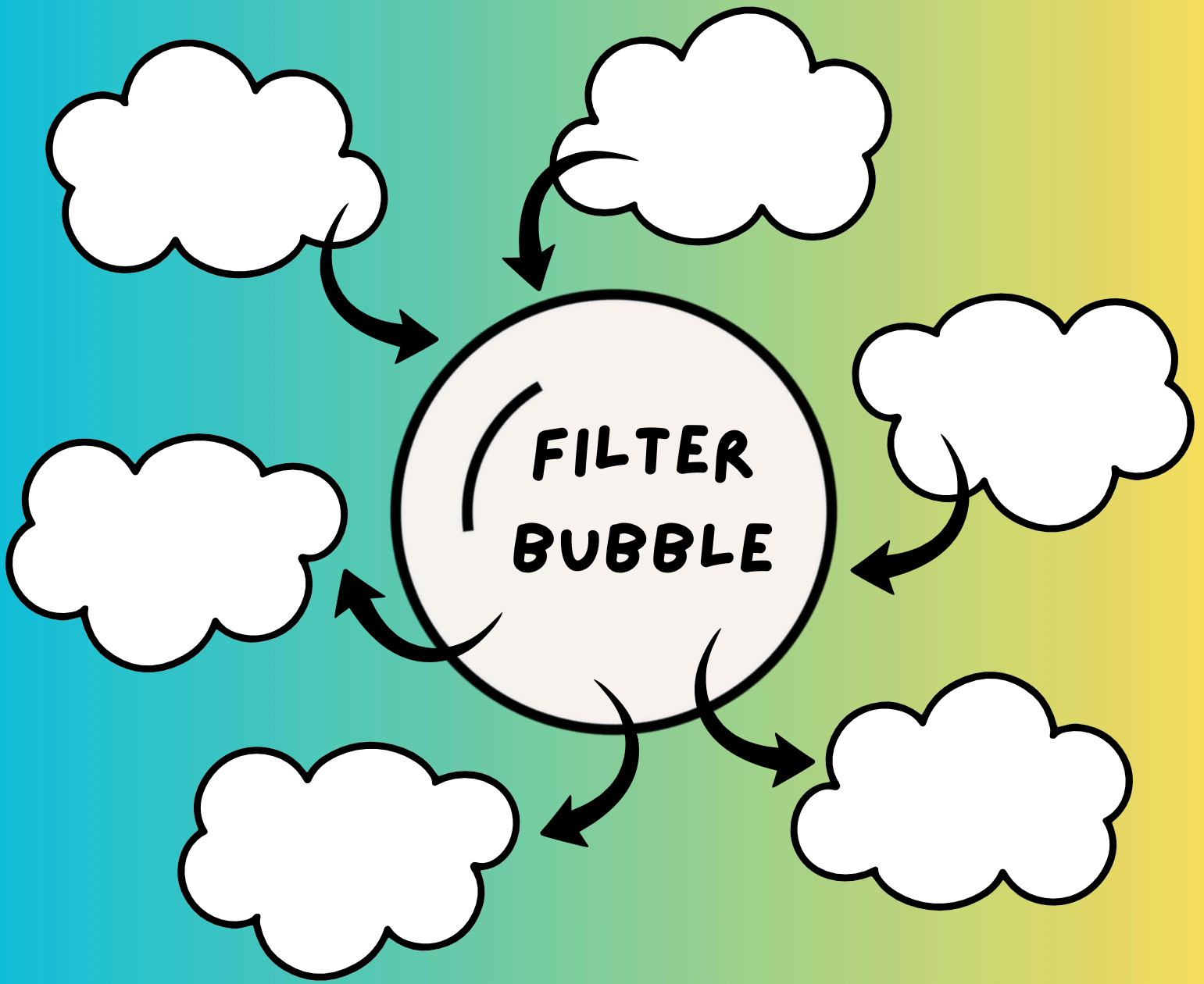
- * skip past bait items without clicking
- * watch items you like all the way through
- * deliberately search for something specific



Feed Audit

Take a look at your feed from an online platform that you use regularly.
For example: TikTok, YouTube, Spotify, Netflix, ...
Examine your personalized recommendations to find your filter bubble.

What topics, opinions, genres, and experiences are **inside** your bubble?



What topics, opinions, genres, and experiences are **outside** your bubble?