CASE STUDY

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Recommender
Algorithms

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| 01 Abstract

| Type of OER (Case study, Simulation, Scenario exercise, …)

This OER is a **case study on recommender algorithms and information bubbles**, and how it **relates to algorithmic recommendation practices in advertising.** The case is essentially divided in two parts. First, the case emphasizes the role of algorithmic recommendation in shaping information distribution and the associated risks for society in general. To introduce the concept of information bubbles it analyzes the case of YouTube's recommendation system, explaining its mechanics through a practical exercise comparing different variables. Class discussions focus on YouTube's content recommendations and related challenges as well as possible solutions. Through the first part, students are also invited to think about how information bubbles and issues with recommender systems may related to advertising practices. The second part of the case focuses on algorithmic recommendation used for online advertising, explaining how these types of algorithms work using Amazon as an example. Then, the case shifts to possible issues with algorithmic advertising, including examining the case of Facebook ads and how it led to discrimination. Students are then encouraged to explore and propose solutions.

| Goal or Purpose

The goal of this case study is to illustrate how recommender algorithms have become an essential part of how we consume information and content in our society and to highlight the problems and challenges that arise from the widespread use of this technology. Then, the case study makes connections between recommender algorithmics in general and the ones used for online advertising, raising awareness on uses that may be problematic and invites student to explore potential solutions.

| Expected Learning Outcomes

- The student will be able to **identify** ethical challenges and regulatory considerations in AI-driven personalization for society at large and **connect** this with practices related to advertising.
- The student will be able to **evaluate** the impact of personalization practices on information ecosystems.
- The student will be able to **propose** possible solutions to mitigate the negative effects of recommender algorithms on our society and that prioritize fairness and inclusivity.

| Suggested Methodological Approach

This case works best as problem-based learning in which instructors should guide a discussion with students once they have familiarized themselves with concepts and technology. Topics for discussion and potential concerns are provided, but instructors should encourage students to think on their own and identify other potential concerns they may have. The YouTube case should work as material that can introduce the problem that can be correlated with specific challenges and the Tournesol case provides a possible solution. For this last one, students should be encouraged to discuss if the solution can be effective and to come up with enhancements, improvements or even other possible solutions.

| Keywords
Recommender algorithms, Information Bubbles, Algorithmic advertising, information and data literacy, bias

02

INTRODUCTION TO THE CASE STUDY

Recommender Algorithms an Information Bubbles.

Introduction: The Role of Recommender Algorithms

Recommender algorithms have become a crucial component of modern digital platforms, influencing consumer choices in sectors such as e-commerce, entertainment or news consumption. While recommender algorithms **enhance user experience and increase engagement**, they also raise **significant ethical and legal concerns** related to privacy, bias, manipulation and mis- and dis- information.[1]

In relation to dis and mis- information, recommender algorithms are of concern because of how they can affect the health of our **information ecosystems**, and by extension, **democracy** itself. For citizens to make the right choices in both their private and public lives, it is essential that they have access to the right information to empower them to make decisions for themselves based on the reliable information they have access to.

A related concern is that **information bubbles**[2], or situations in which algorithms only expose users to certain instances of information but not to others may not only affect the quality of information we received but may also contribute to confirm our biases by not exposing us to other points of view and isolating us in a reality of our own. There are fears that information bubbles can become so extreme that they may even lead some people to radicalization and extremism.[3]

This case study explores the ethical challenges surrounding recommender algorithms in our society.

The Role of Recommender Algorithms

Recommender algorithms use **machine learning and artificial intelligence** to analyze user behavior and suggest personalized content. Companies such as Amazon, Netflix, YouTube, and Facebook employ **sophisticated recommendation systems to enhance user engagement** and **drive revenue**. These systems rely on **data** such as **user interactions, browsing history, and preferences to curate personalized recommendations.**

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[1]In his book, Filterworld, journalist Kyle Chayka discusses the prominent role of recommender algorithms in our society, for good or ill. Here is an interview about Chayka's work: https://www.theverge.com/24094338/kyle-chayka-filterworld-algorithmic-recommendation-tiktok-instagram-culture-decoder-interview

[2]Here is a TED talk on information bubbles, also known as filter bubbles: https://www.ted.com/talks/eli_pariser_beware_online_filter_bubbles?language=en

[3]Further reading: In Gonzalez v. Google, a case before the Supreme Court of the United States, the possibility that recommender algorithms can lead to terrorist radicalization was discussed. Students can access a podcast on the case: https://www.techpolicy.press/a-deep-dive-into-gonzalez-v-google/ Further information on the case: https://www.oyez.org/cases/2022/21-1333

[4]How Netflix recommends you things to watch: https://www.youtube.com/watch?v=nq2QtatuF7U

[5]Here is an explainer on how Spotify's recommendation algorithm works: https://www.youtube.com/watch?v=pGntmcy_HX8&t=37s

[6]How Tik Tok figures you out: https://www.youtube.com/watch?v=nfczi2cI6Cs

03

RECOMMENDER ALGORITHMS

| YouTube’s Recommendation System

How does it work?

One of the most scrutinized recommendation systems is **YouTube’s algorithm.**

YouTube’s recommender algorithm is a **complex AI-driven system designed to maximize user engagement** by **suggesting videos** tailored to individual preferences often based on **previous viewing history.** It relies on a combination of **deep learning techniques, user data analysis, and content evaluation** to provide **personalized recommendations**.

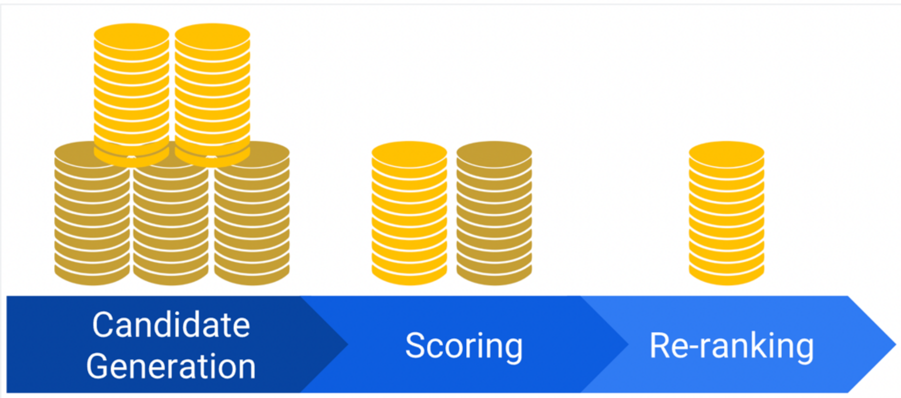
What drives YouTube’s Recommender Algorithm?[7]

1.**Data Collection and Processing:** YouTube tracks user interactions, including watch history, search history, likes, dislikes, comments, and shares, subscriptions and notification preferences, watch time and session duration.

2. **Ranking and Prediction Models:** The algorithm uses **deep learning models to analyze past behavior** and **predict what a user is likely to watch next**. It evaluates different factors, such as: how often users click on a recommended video; how long users engage with a video (watch time); and likes, shares, and comments (engagement metrics).

3. Recommendation Process. YouTube uses a recommendation process that can be outlined as follows:

- **Candidate Generation:** The system first filters millions of videos to create a smaller set of relevant recommendations.
- **Scoring:** Another model **scores and ranks the candidates in order to select the set of items** (on the order of 10) **to display to the user**. Since this model evaluates a relatively small subset of items, the system can use a more precise model relying on additional queries.
- **Re-ranking.** The system must take into account **additional constraints for the final ranking**. For example, the system **removes items that the user explicitly disliked** or **boosts the score of fresher content.**



Source: https://developers.google.com/machine-learning/recommendation/overview/types

[7]See: https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/45530.pdf

This is **roughly** what happens inside **YouTube's recommender system**[8]**,** which determines what you experience on their platform:

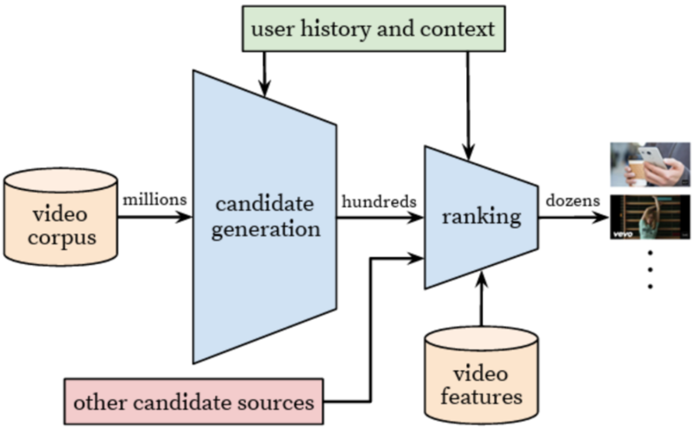
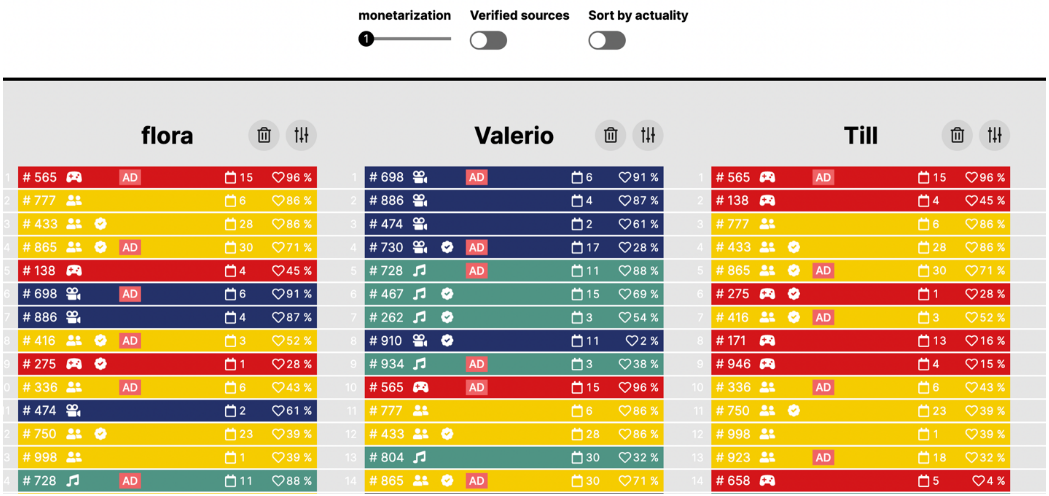


Figure 2: Overview of YouTube recommendation algorithm (source: [Covington et al., RecSys'16](https://)).

See how YouTube's Recommender Algorithm works for Yourself:

Project **DataSkop** from **Platform Dynamiken** [9]has built a simulation of the YouTube Recommender system using **donated data** from volunteer users. This will allow us to **discuss and understand how the different variables** affect the list of videos we see on YouTube. **Click on the following image** to access the simulation:



[8]https://blog.youtube/inside-youtube/on-youtubes-recommendation-system/
[9]https://dataskop.net/recommender-sim/?en

WHAT PLATFORMS ARE DOING

YouTube's Efforts

As a company, YouTube, and its parent, Google, seem to be **well-aware of the issues** with their recommender algorithms. The company has made efforts to solve these issues.

For example, YouTube introduced features such as "Up Next" to **increase the diversity of content** served to users and to **encourage exploration.** YouTube also encourages users to take breaks to prevent over-engagement with specific types of content. YouTube has also **tweaked** its algorithm to **consider new and trending content** in order to **enhance discoverability** of diverse content.

YouTube also uses fact-checking to **mitigate the effects of dis and misinformation** on its platform, restricts monetization of misleading content and has made further adjustments to its algorithms to **reduce the spread of harmful content.**

Users have also been given more control over their **recommendation settings**, allowing them to clear watch history or mark content as "Not interested" in an effort to **refine their recommendations**.

YouTube also makes the effort to **explain how their algorithm works to raise awareness** about how what users see is decided[10].

THIRD-PARTY INTERVENTIONS

Project Tournesol

Tournesol is an open-source platform which provides a tool for collaborative decisions.[11] The main aim of the Tournesol project is to **collaboratively identify top videos of public interest by eliciting contributors' judgements on content quality** and with the goal of **building a large open database of video quality judgements**.

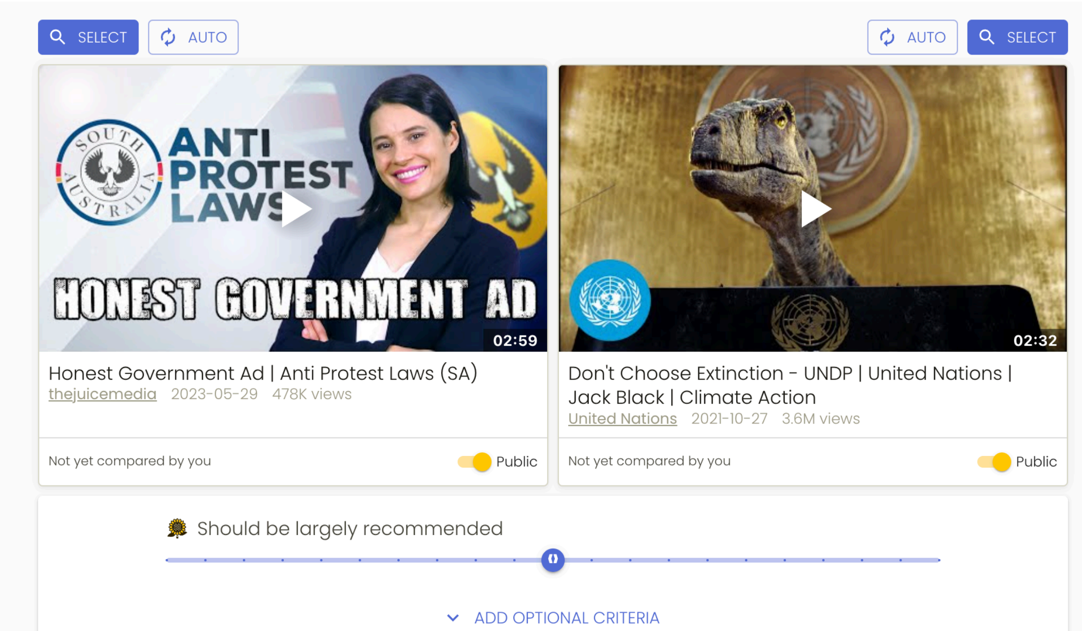
The immediate effect of this database**, Tournesol creators say, is to improve the recommendations of thousands of people using the platform.** The long-term effect is to facilitate and improve future research projects by making this database available.

Tournesol also provides users with **a browser extension** that allows users to **display videos recommended by the community** directly on the YouTube home page.

Tournesol encourages **transparency, knowledge sharing** and **media literacy** by making its algorithm and all source code **open source** and released as **Free Software.** They also make their database **open and free to use** under a Creative Commons License.

[10]For an overview of these efforts see: https://developers.google.com/machine-learning/recommendation/overview/types
[11]Read more about Tournesol: https://tournesol.app/about

You can **try Tournesol** yourself by **clicking on the following image**:



04

ALGORITHMS AND ADVERTISING

| RECOMMENDER ALGORITHMS, INFORMATION BUBBLES AND BUSINESS PRACTICES

The Impacts of information Bubbles on Businesses:

For businesses, social media is an excellent way to connect with customers online, share information about their products, engage the public, and develop a brand reputation. The ease and speed of social media has made it possible to reach out to a much wider audience than previously possible. At the same time, it also brings new risks to businesses, as they equally can become targets of disinformation, which is readily consumed by a significant number of people online.[12]

Other types of companies, very different from YouTube, use algorithms to recommend users content but also products. A prime example is **Amazon**, who uses its own algorithm to recommend people the products they may want to buy.

Amazon's algorithm bases product recommendations on **correlations between products** not on similarities between user profiles and their buying behavior. This allows Amazon to avoid analyzing buying histories across their entire customer database. Instead "Amazon researchers used a **relatedness metric based on differential probabilities**: item B is related to item A if purchasers of A are more likely to buy B than the average Amazon customer is. The greater the difference in probability, the greater the items' relatedness."

| RECOMMENDER ALGORITHMS AND ADVERTISING

How Recommender Algorithms serve us ads

Recommender algorithms serve advertising by **analyzing user data to deliver personalized ads**. These algorithms collect **data from browsing history, purchase behavior, content engagement, and demographic information** to build **user profiles.** Based on these profiles, **ads are targeted to users most likely to find them relevant**.

To match ads with users, platforms use techniques such as **content-based filtering, which recommends ads similar to previously viewed content**, **and collaborative filtering**. Many systems also use hybrid models and deep learning to refine ad recommendations further. Google[13], Amazon[14] or Meta[15] use proprietary algorithms to deliver ads.

Once an ad is displayed, algorithms continuously track interactions, such as clicks or conversions, to improve future recommendations. This creates a feedback loop that optimizes ad delivery over time. Platforms like Google, Facebook, and Amazon use these methods to maximize ad effectiveness while keeping users engaged.

Talking about the Issues

- Can you identify similar challenges as those **identified with YouTube's algorithm?**
- What potential **problems** do you think may arise from **personalized advertising or product recommendations?**

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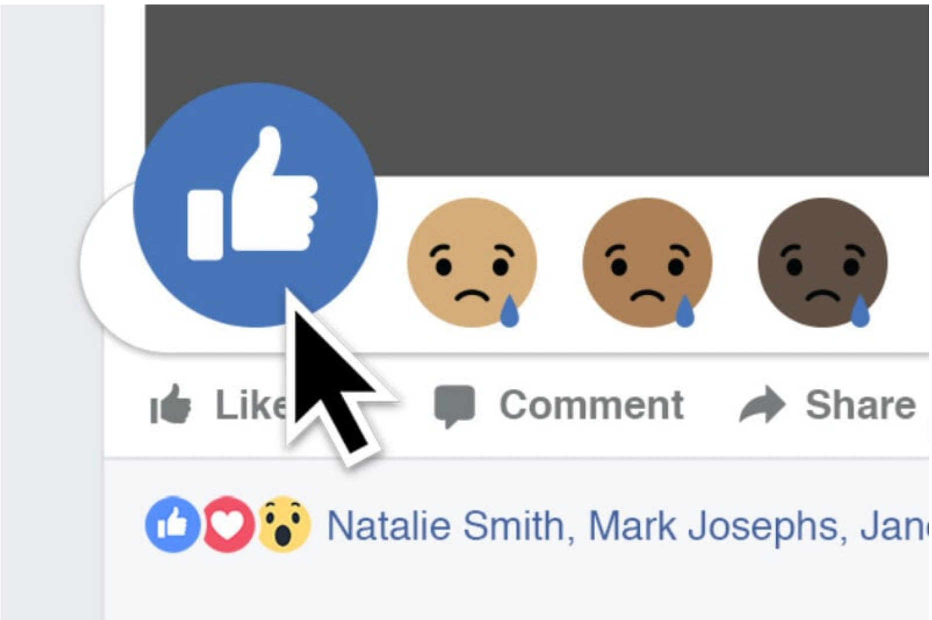
[12] https://www.pssi.cz/download/docs/8209_764-blog-private-companies-and-disinformation.pdf
[13] Google ads explained by Google:
[14] You can listen to how it works from Amazon's own scientists: https://www.youtube.com/watch?v=GSQj27ps854
[15] This is how Meta's one works:

ADVERTISING AND DISCRIMINATION

ProPublica's Research on Online Advertising and Exclusion

In 2016, ProPublica, a Journalistic organization documented how Facebook's ad system excluded users from certain advertisements based on their race, an illegal practice under the law.

Click on the image below to read about the case:



DISCUSSION

What can we do?

As we can see, **recommender algorithms in advertising** are designed to personalize content by analyzing user data and predicting preferences. While this improves ad relevance and engagement, it can also lead to **unintended consequences such as user** exclusion as the **ProPublica case** shows.

These algorithms **may reinforce biases** by limiting exposure to diverse products, services, or job opportunities, disproportionately impacting certain groups. Additionally, users who don't fit common behavioral patterns might receive fewer relevant recommendations, reducing their access to opportunities.

How can advertisers and platforms **balance personalization with inclusivity** to ensure that recommender systems serve a broader and more equitable audience?

What **solutions** would you **propose?**

05

GUIDELINES FOR INSTRUCTORS

GUIDELINES FOR INSTRUCTORS

On the Case Study

The case study aims to provide instructors with specific examples of algorithmic recommendation used by relevant technology companies in order to explore what role they play in society and in shaping our information ecosystem. The practices of well-known companies such as YouTube, Amazon or Meta are explored in order to understand how algorithmic recommendation works and what are the issues associated with it.

The case study is essentially divided into two parts. The first one is devoted to recommender algorithms in general, exploring their role in determining what information and content people consume and related issues, such as information bubbles. Apart from exploring the issues and possible solutions, throughout the examples and hands-on demonstrations during the case, the instructor should ensure that students make the connection between the generalized use of algorithms for content recommendation in society and their uses in contemporary advertising practices, which is what the second part focuses on.

Part 2 is shorter because part one should provide students with enough context and knowledge to fill in the blanks and because part two could be substituted for other relevant uses of algorithmic recommendation in society. If instructors decide to customize the case study, then part 2 can be an open canvas, where the instructor may decide to further focus on recommender algorithms used for news dissemination, for platforms similar to YouTube or other social media such as Instagram or Tik Tok, or to fuel business models such as the ones pursued by Netflix, Spotify, or for eCommerce in the case of Amazon. Instructors could also choose to focus on its use in finance and banking, healthcare, transportation (think Google Maps or Uber) or other areas apart from advertising.

The Case Study is especially adept at exploring the potential challenges and risks of using recommender algorithms in society and is most helpful when used to raise awareness about these issues in order to get students to think critically about the technologies that have become an essential part of our economy and the way we conduct business online and ideally, to get them to avoid the pitfalls and propose solutions.

On Resources

Throughout the material, instructors and students will find resources that will help them learn about what is being discussed in the case study. Several videos contribute to explain how recommender algorithms work and to identify known issues or risks associated with their use. There are also links with longer readings that allow for more in-depth knowledge about the topics discussed here. Some of the resources, particularly those represented by a clickable image in the case study, are essential components, as they are hands on demonstrations of the concepts discussed in the case study. When this is the case, there is clear prompt inviting the instructor and students to **click on the image** that will take them to the resource.

Video materials and readings are short in duration, meaning that the instructor can choose to either assign them as prep work before coming to class to work on the case study, or, if the course structure permits it, to be also watched and read while working with the case study inside the classroom.

Talking about the Issues

Where do Potential Problems Come From?

YouTube's algorithm has been criticized for creating **information bubbles** or **content rabbit holes** like the ones discussed in our introduction to the case. The problem is that it seems that recommender algorithms continuously feed either one particular type of content or increasingly polarizing or extreme content to users, leading to potential misinformation and ideological echo chambers.

Since the algorithm **continuously updates recommendations** based on **real-time** user activity, it **only prioritizes content** likely to **keep users engaged**, which can sometimes lead to situations in which only **similar content is repeatedly recommended** over and over.

For the introduction.

The instructor should introduce the following preliminary exercise to encourage reflection on the topic at hand and to ensure that all students are on the same page.

Preliminary exercise:

- In groups, ask students to explore their individual **Netflix**[16]**, Spotify**[17]**, TikTok** [18](or similar) profiles and take note of the top ten tv shows/songs they see on the app.
- Ask group members to compare what they see with their peers and to discuss what similarities and differences they see. **Why do they think the content shown to them?**
- Ask groups members to discuss **how they think this relates to the ads they see on their feeds** in social media such as **Instagram** or **YouTube.**

For part 1

Using the experience with YouTube's algorithm the instructor should be able to discuss **potential societal problems** associated with the use of recommender algorithms that determine what people see online in general, and of information bubbles in particular. The instructor should lead the **class discussion around the following important topics,** but they should also encourage students to **introduce and discuss concerns of their own**.

1. Privacy Concerns:
    - **Invasions of Privacy.** Recommender algorithms rely on vast amounts of user data, often collected without explicit user consent.
    - **Lack of Awareness and Lack of Transparency.** Users may not be fully aware of how their data is utilized and shared.
2. Bias and Discrimination:
    - **Bias Reinforcement.** Algorithms may reinforce existing biases by promoting content that aligns with past behavior, limiting exposure to diverse perspectives.
    - **Concerns about Fairness.** Historical biases in training data can result in unfair treatment of certain demographic groups.

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[16]How Netflix recommends you things to watch: https://www.youtube.com/watch?v=nq2QtatuF7U
[17]Here is an explainer on how Spotify's recommendation algorithm works: https://www.youtube.com/watch?v=pGntmcy_HX8&t=37s
[18]How Tik Tok figures you out: https://www.youtube.com/watch?v=nfczi2cI6Cs

3. Manipulation and Exploitation:

- **Algorithms that pursue profit first, healthy information ecosystems second.** Businesses can design algorithms to prioritize profit-driven content over user well-being, encouraging excessive consumption or unhealthy behaviors.
- **User Manipulation.** Some platforms use persuasive design techniques to maximize engagement, often at the cost of user autonomy.

4. Misinformation and Radicalization:

- Recommender algorithms can **amplify misleading or sensational content** due to its high engagement potential.
- Studies have shown that **such algorithms contribute to the spread** of conspiracy theories and extremist ideologies.

For part 2

The instructor must **ensure that students make the connections between more general recommender algorithms,** the issues related to **information bubbles**, the problems described just above and the use of **recommender algorithms in advertising.**

For leading the discussion, instructors may ask the following questions:

- How do algorithmic advertising systems **contribute to discrimination**, particularly in areas like job recruitment, housing, and financial services? Can you think of examples from the real-world that illustrate these risks?
- What role **do recommender algorithms play** in shaping **the way advertisements are targeted** to users?
- How can recommender algorithms lead **to the exclusion of certain demographic groups from opportunities**?
- How does the personalization of ads through recommender algorithms create "**advertising filter bubbles**," and in what ways might this **reinforce economic or social inequality**?
- To what **extent should companies be held accountable for algorithmic discrimination** in ad targeting, and what policies or regulations could promote fairness in algorithmic advertising?
- What are the **ethical trade-offs between maximizing ad relevance** for engagement and profit and ensuring inclusivity in online advertising?
- How can companies **balance these competing priorities**? How can they **address potential biases**?

06

ANNEXES

Further reading

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