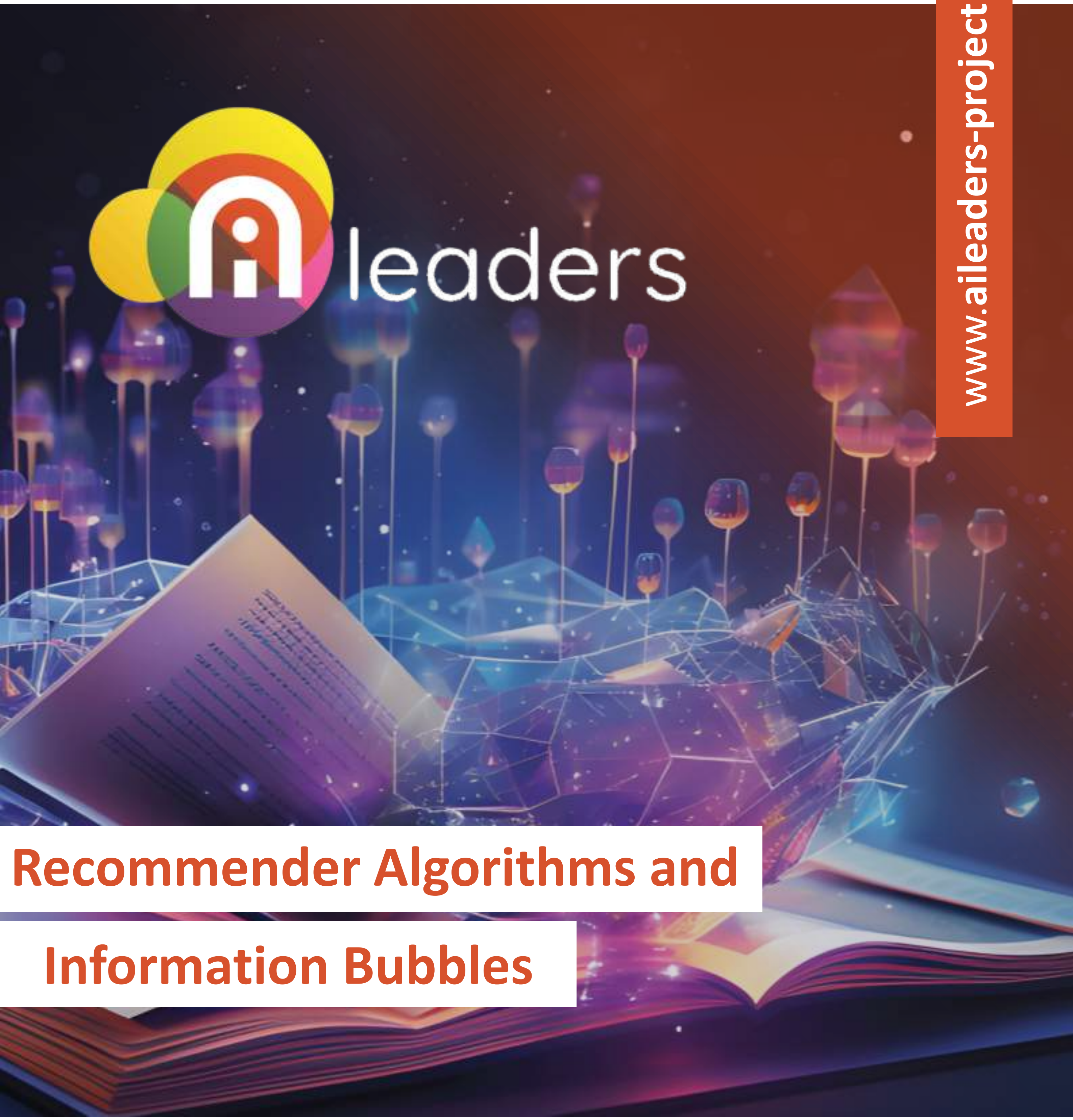

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Recommender Algorithms and Information Bubbles

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CASE STUDY: 07

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 into two parts. First, the case emphasises the role of algorithmic recommendation in shaping information distribution and the associated risks for society in general. In order to introduce the concept of information bubbles, it analyses 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 relate 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 can lead to discrimination. Students are then encouraged to explore and propose solutions.

Goal/Purpose

The goal of this case study is to illustrate how recommender algorithms have become an essential part of how we consume information and contents in our societies as well as to highlight the problems and challenges that arise from the widespread use of 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 inviting students to explore potential solutions.

Expected Learning Outcomes

01 The student will be able to **identify** ethical challenges and regulatory considerations in AI-driven personalisation for society at large and c**onnect** this with practices related to advertising.

02 The student will be able to **evaluate** the impact of personalisation practices on information ecosystems.

03 The student will be able to **propose** possible solutions to mitigate the negative effects of recommender algorithms on our societies and that prioritise fairness and inclusivity.

Suggested Methodological Approach

This case works best as problem-based learning in which the instructors should guide a discussion with students once they have familiarised themselves with the concepts and technology. Topics for discussion and potential concerns are provided, but the 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 the latter one, students should be encouraged to discuss whether 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

Introduction

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, as well as mis- and disinformation[1].

In relation to dis and misinformation, 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 life and public life, it is essential that they have access to the right information that can 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 receive but 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 radicalisation and extremism.[3]

This case study explores the ethical challenges surrounding recommender algorithms in our societies. Recommender algorithms use **machine learning and artificial intelligence** to analyse user behaviours and suggest personalisesd 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 personalised recommendations.**

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

YouTube’s Recommendation System - How does it work?

One of the most scrutinised recommendation systems is **YouTube’s algorithm.** YouTube’s recommender algorithm is a **complex AI-driven system designed to maximise 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 **personalised recommendations**.

What drives YouTube’s Recommender Algorithm?[7]

01 Data Collection and Processing:

YouTube tracks user interactions, including watch history, search history, likes, dislikes, comments, and shares, as well as subscriptions and notification preferences, watch time, and session duration.

02 Ranking and Prediction Models:

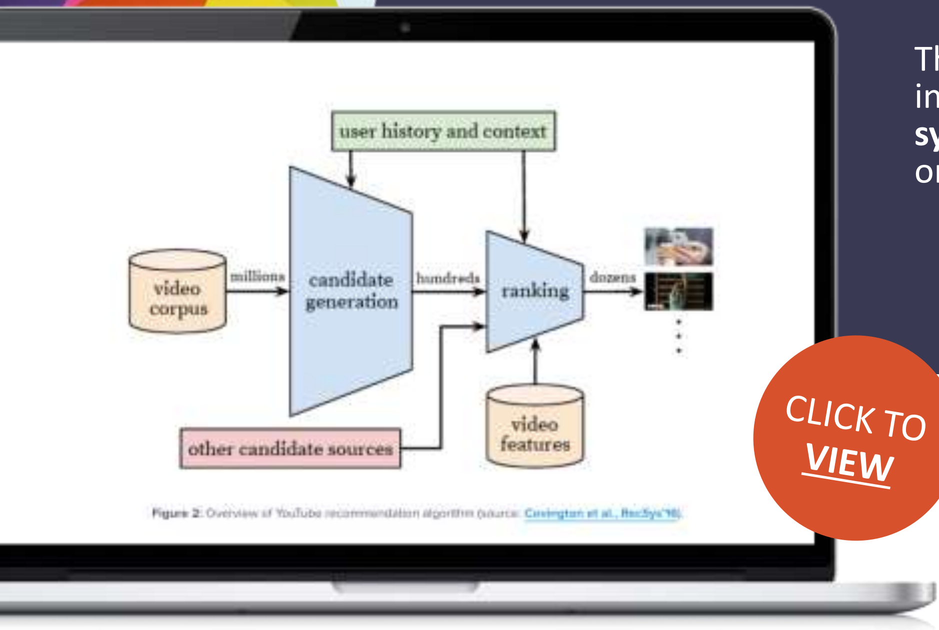
Ranking and Prediction Models: The algorithm uses **deep learning models to analyse past behaviour** and **predict what a user is likely to watch next**. It evaluates different factors, such as how often users click on a recommended video; how long users engage with a video (watch time); and likes, shares,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

03 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 to display to the user** (from 1 to 10). 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 contents.**

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 one experiences on this platform:

CLICK TO **VIEW**

See for Yourself How YouTube'sAlgorithm Works

The 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 one sees on YouTube. **Click on the following image** to access the simulation:

CLICK TO **VIEW**

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) seems to be **well-aware of the issues** with its 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 contents** served to users and to **encourage exploration.** YouTube also encourages users to take breaks to prevent over-engagement with specific types of contents. YouTube has also **tweaked** its algorithm to **consider new and trending contents** in order to **enhance the discoverability** of diverse contents.

YouTube also uses fact-checking to **mitigate the effects of dis- and misinformation** on its platform, restricts the monetisation of misleading contents, and has made further adjustments to its algorithms in order to **reduce the spread of harmful contents.** Users have also been given more control over their **recommendation settings**, allowing them to clear watch history or mark contents as "Not interesting" in an effort to **refine their recommendations**.

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

Third-party Interventions

To address issues associated with recommender algorithms, a range of third-party solutions are being explored, many of which focus on **content-agnostic "soft interventions"** such as **"virality circuit breakers"** that temporarily halt the algorithmic boosting of fast-spreading posts, or the introduction of **"targeted friction"** and the use of prompts and pop ups that encourage users to read an article before sharing.

Beyond that, legislation like the EU´s Digital Services Act (DSA) also aims to give users more autonomy by requiring large platforms to offer at least one recommender system alternative that is not based on user profiling. **Under the law,** large platforms are required to actively monitor and take measures to mitigate **what the DSA calls** "systemic risks" **or threats that the algorithms, or their use, can pose to the rights of people, or to democracy itself, among others.**

Beyond demanding changes to platforms such as YouTube, there are projects focusing on user-driven collaboration to improve the experiences of users that interact with recommender systems, seeking to give them some control over what they see online. One example of this is **Project Tournesol,** an open-source platform which provides a tool for collaborative decisionsq.[11] **The main aim of the Tournesol project is to collaboratively identify top videos of public interest by eliciting contributors' judgements on content quality to build a large open database of video quality judgements.**
The immediate effect of this database **is to improve what videos are recommended by Youtube, using the inputs of thousands of people who use the platform. Tournesol** also provides users with **a browser extension** that allows users to **display videos recommended by the community** directly on their 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 the Creative Commons Licence, hoping that this will also help improve research on recommender algorithms.

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

Other Examples

[CaptainFact](), a web-based tool that allows for collaborative verification of Internet videos overlaying them with trustworthy sources. Another example is [Climate Feedback](), which uses a network of credentialed scientists to annotate online articles for accuracy, ranking them through a credibility score.

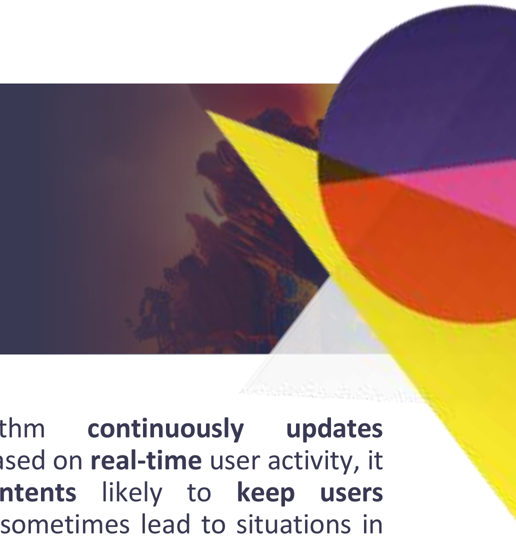
CLICK TO VIEW

Overall, initiatives such as these seek to **shift power towards communities and experts** to **collectively assess and contextualise information,** offering **counterbalance to purely engagement-driven recommender algorithms**.

Discussion

Where Do Potential Problems Come From?

YouTube's algorithm has been criticised for creating **information bubbles** or **content rabbit holes** such as the ones discussed in our Introduction to the case.



The problem is that it seems that recommender algorithms either continuously feed one particular type of contents or are increasingly polarising for users, which leads to potential misinformation and ideological echo chambers.

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

Talking about the Issues

Using the experience with YouTube's algorithm we now can discuss the **potential societal problems** associated with the use of recommender algorithms that determine what people see online in general, and with information bubbles in particular.

Potential Societal Problems

01 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 utilised and shared.

02 Bias and Discrimination:

- **Bias Reinforcement.** Algorithms may reinforce existing biases by promoting contents that align with past behaviour, limiting exposure to diverse perspectives.
- **Concerns about Fairness.** Historical biases in training data can result in unfair treatment of certain demographic groups.

03 Manipulation and Exploitation:

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

04 Misinformation and Radicalisation:

- Recommender algorithms can **amplify misleading or sensational contents** due to their high engagement potential.
- Recommender algorithms **may also hide important information** from users, decreasing the quality of information they receive, but also raising concerns about possible **exclusion** or **discrimination.**
- Studies have shown that **such algorithms contribute to the spread** of conspiracy theories and extremist ideologies.

The Impact 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 can also 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 contents or products. A prime example is **Amazon**, which uses its own algorithm to recommend people products they may want to buy.

Amazon's algorithm bases product recommendations on **correlations between products** and not on similarities between user profiles and their purchasing behaviour. This allows Amazon to avoid analysing purchase 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."[13]

How Recommender Algorithms serve ads

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

To match ads with users, platforms use techniques such as **content-based filtering, which recommends ads similar to previously viewed contents, and collaborative filtering**. Many systems also use hybrid models and deep learning to refine ad recommendations further. Google, Amazon, or Meta 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 optimises ad delivery over time. Platforms such as Google[14], Facebook[15], and Amazon[16] use these methods to maximise ad effectiveness while keeping users engaged.

12 https://www.pssi.cz/download/docs/8209_764-blog-private-companies-and-disinformation.pdf
13 See: https://www.amazon.science/the-history-of-amazons-recommendation-algorithm
14 Google ads explained by Google: https://business.google.com/es/google-ads/
15 You can listen to how it works from Amazon's own scientists: https://www.youtube.com/watch?v=GSQj27ps854
16 This is how Meta's one works: https://www.facebook.com/business/news/good-questions-real-answers-how-does-facebook-use-machine-learning-to-deliver-ads#:~:text=How%20does%20Facebook%20decide%20which,results%20of%20our%20ad%20auction

Potential Issues: Advertising and Discrimination

An issue with algorithms that recommend ads is that, in general, recommender algorithms can **actively discriminate against people,** because they are **not neutral at all;** they are **socio-technical systems** that can perpetuate societal biases, because **algorithms are designed by humans and trained on historical data** that can be inaccurate, incomplete, or skewed, which can **lead to "automation bias"** against marginalised groups based on race, gender, or sexual orientation.[17]

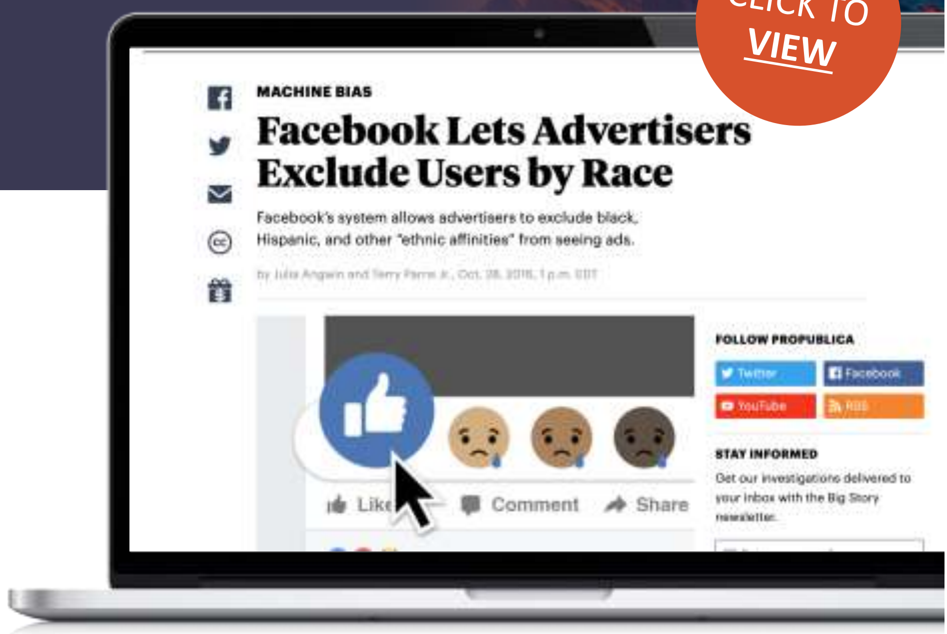
This can be **particularly harmful in targeted advertising**, because advertising interests coupled with optimisation techniques can be used to **exclude specific demographics from seeing opportunities for housing, employment, or credit**, even without intention. Even if the way in which technology "decides" what ads are shown or not shown seems neutral, it is far from it and can end up perpetuating historical discrimination against vulnerable persons, which is something known as "disparate impact." [18]

Disparate impact resulting from online advertising practices has been documented on several occasions. What follows is one of the most well-known proven instances in relation to Facebook's advertising practices.

ProPublica's Research on Online Advertising and Exclusion

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

CLICK TO VIEW



17 See: Noble, S. U. (2018). Algorithms of oppression: How search engines reinforce racism. New York University Press.
18 https://www.law.cornell.edu/wex/disparate_impact#:~:text=A%20disparate%20impact%20policy%20or,by%20the%20Wex%20Definitions%20Team%5D

Discussion

Talking about the Issues

01 Can you identify similar challenges to those **identified with YouTube's algorithm?**

02 What potential **problems** do you think may arise from **personalised advertising or product recommendations?**

What can we do?

As we can see, **recommender algorithms in advertising** are designed to personalise contents by analysing 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 do not fit common behavioural patterns might receive fewer relevant recommendations, which practically reduces their access to opportunities.

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

What solutions would you propose?

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 for us to understand how algorithmic recommendation works and what the issues associated with it are. 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 contents people consume as well as 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 make sure that students make the connection between the generalised use of algorithms for content recommendation in society and their uses in contemporary advertising practices, which is what the second part focuses on.

Part Two 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 customise the case study, then Part Two can be an open canvas, where the instructor may decide to further focus on recommender algorithms used for news dissemination, 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 eCommerce in the case of Amazon. Instructors could also choose to focus on its use in finance and banking, health care, transportation (Google Maps or Uber), or other areas other than 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 as well as, ideally, to get them to avoid the pitfalls and propose solutions.** Thus, this case study should be particularly useful whenever you want to give a **general context of how technology is changing society**, the **responsibilities of a business leader** that deals with digital transformation and technological advancement, or in any class where you want to introduce material that helps **think critically about the technology we use today.**

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 explaining how recommender algorithms work and to identifying 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 a 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.

There are quite a few **technical terms** used throughout the case study. The footnotes often contain links to videos or accessible texts that explain these terms. It is recommended that the **instructor becomes familiar with these terms beforehand** in preparation for using the case study.

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:

01 In groups, ask students to explore their individual **Netflix**[19], **Spotify**[20], **TikTok**[21] (or similar) profiles and take note of the top ten TV shows/songs they see on the app.

02 Ask group members to compare what they see and to discuss what similarities and differences they see. **Why do they think the particular contents are shown to them?**

03 Ask group 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 One

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**.

Potential Societal Problems

01 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 utilised and shared.

02 Bias and Discrimination:

- **Bias Reinforcement.** Algorithms may reinforce existing biases by promoting contents that align with past behaviour, limiting exposure to diverse perspectives.
- **Concerns about Fairness.** Historical biases in training data can result in unfair treatment of certain demographic groups.

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

Potential Societal Problems

03 Manipulation and Exploitation:

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

04 Misinformation and Radicalisation:

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

For the discussion on Part One, instructors should explore "what platforms are doing" as well as "third-party interventions" (see page 5). Instructors can frame the discussion around possible solutions using the following prompts for discussion:

Who will fix it and how?

Questions:

01 Do you think **YouTube** is making enough effort to solve the **problem of information bubbles** inside its own platform?

02 What **barriers** or **conflicts of interest** do you see in **YouTube's** own efforts?

03 What do you think about **Tournesol's** solutions? Do you see any **potential for positive impact**? What are its **limitations**?

04 What strategies can platforms, policymakers, and technologists implement to **make recommender systems more balanced, transparent, and resistant to bias** while still **keeping users engaged**?

05 What solutions **would you propose?**

For Part One

The instructor must **make sure 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.**

Students should also be invited to evaluate the proposed solutions by contrasting the identified problems (see pages 6 and 7) to evaluate if solutions are sufficient and to get ideas of what kinds of solutions should be proposed.

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

01 How do algorithmic advertising systems **contribute to discrimination**, particularly in areas such as job recruitment, housing, and financial services? Can you think of examples from the real world that illustrate these risks?

02 What role **do recommender algorithms play** in shaping **the way in which advertisements are targeted** to users?

03 How can recommender algorithms lead **to the exclusion of certain demographic groups from access to opportunities**?

04 How does the personalisation of ads through recommender algorithms create "**advertising filter bubbles**," and in what ways might this **reinforce economic or social inequality**?

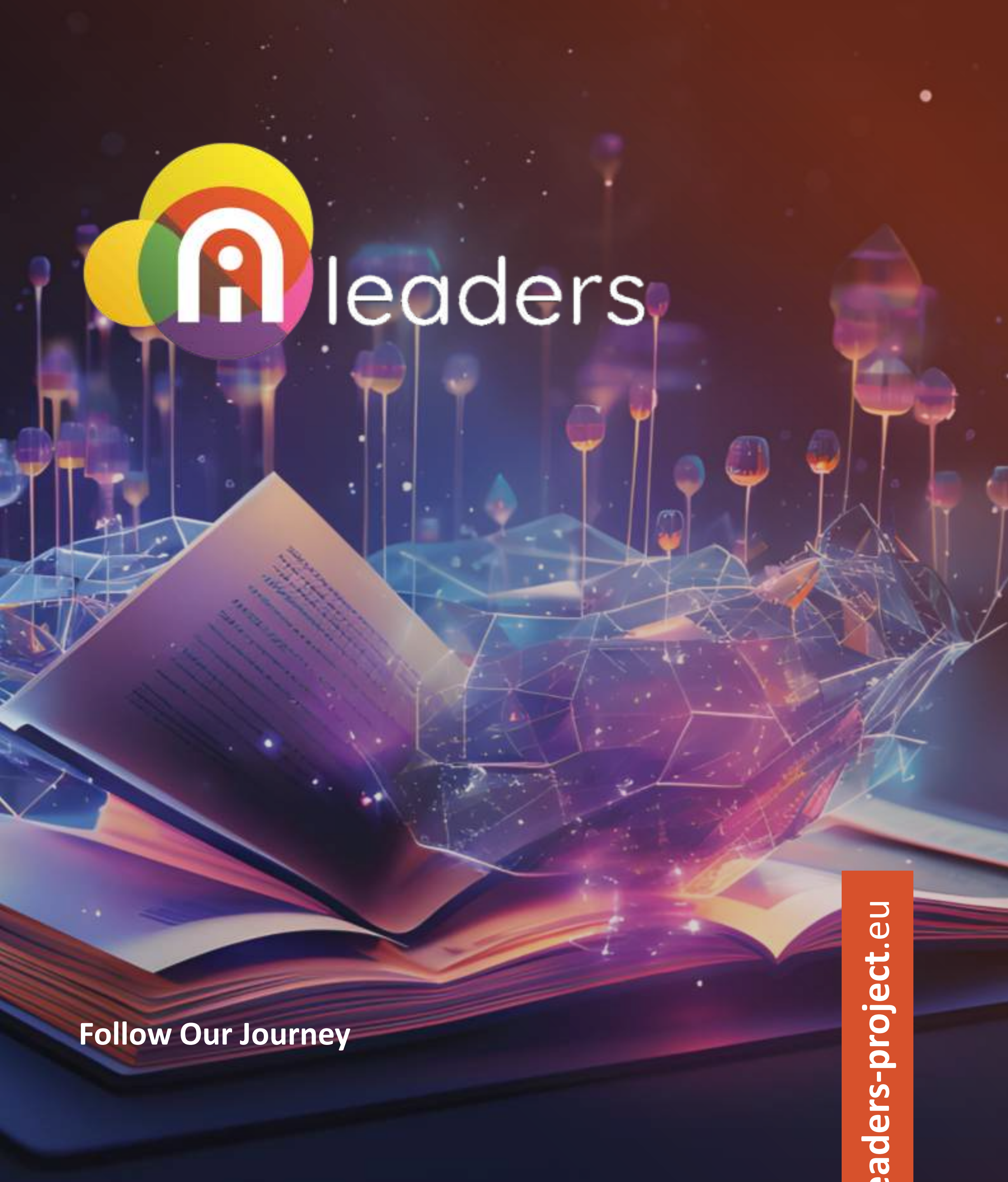
05 To what **extent should companies be held accountable for algorithmic discrimination** in ad targeting, and what policies or regulations could promote fairness in algorithmic advertising?

06 What are the **ethical trade-offs between maximising ad relevance** for engagement and profit and ensuring inclusivity in online advertising?

07 How can companies **balance these competing priorities**? How can they **address potential biases**?

Further Reading

- Jannach, D., Zanker, M., Felfernig, A., & Friedrich, G. (2010). Recommender systems: An introduction. Cambridge University Press. https://www.cambridge.org/core/books/recommender-systems/C6471B59388D8A9F684C49C198691B53
- Chayka, K. (2024). Filterworld: How Algorithms Flattened Culture. Doubleday. https://www.penguinrandomhouse.com/books/695902/filterworld-by-kyle-chayka/
- Noble, S. U. (2018). Algorithms of oppression: How search engines reinforce racism. New York University Press. https://nyupress.org/9781479837243/algorithms-of-oppression/
- Selbst, A., boyd, d., Friedler, S., Venkatasubramanian, S. &Vertesi, J. (2018). Fairness and Abstraction in Sociotechnical Systems (August 23, 2018). 2019 ACM Conference on Fairness, Accountability, and Transparency (FAT*), 59-68, Available at SSRN: https://ssrn.com/abstract=3265913
- Kourabi, F., & Tapp, A. (2021). The ethical challenges of recommender systems. arXiv. https://arxiv.org/abs/2105.05265
- Sweeney, L. (2013). Discrimination in online ad delivery. Communications of the ACM, 56(5), 44-54. https://doi.org/10.1145/2447976.2447990



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