Filter bubbles

Adaptive Decision Support Systems

Filter bubbles

Internet filters look at the things you seem to like – actual things you've done, or the things people like you like – and try to extrapolate.

They are prediction engines, constantly creating and refining a theory of who you are and what you'll do and want next.

Together, these engines create a unique universe of information for each of us – what I've come to call a filter bubble

Pariser, 2011: page 9

Filter bubbles

By filtering all but the top predicted items, recommenders isolate us from a diversity of viewpoints, content, and experiences

They provide a very myopic view of the world and thus make us less likely to discover and learn new things

Auto propaganda that indoctrinates us with our own ideas

At a societal level, this causes increased polarization and an obstruction of information flows

Today we'll discuss…

Dahlgren (2021): two types of filter bubbles:

The "technological" filter bubble

- What it does and how it comes about

The "societal" filter bubble

- The presumed consequences for the individual and for society

Bursting the filter bubble

- An overview of techniques that have been tried

What is a filter bubble?

The “technological” filter bubble explained

Technological bubble

Leysen et al. (2022): A technological filter bubble is:

...a decrease in the **diversity** of a user's **recommendations** over **time**...

...in any dimension of diversity...

...resulting from the **choices** made by different recommendation stakeholders.

—> Auto propaganda that indoctrinates us with our own ideas

Diversity

Structural (source) diversity: diversity of information suppliers (also: source fairness)

Topic diversity: depends on domain and granularity

Viewpoint diversity: same topic, different perspectives (includes misinformation)

Latent diversity: as determined by the algorithm (as discussed last week)

Choices over time

Affects the diversity of a user's recommendations

- Not consumption
- At the individual level

This happens over time

- Pariser: it happens because the system iteratively "refines its theory of who you are and what you'll want next"

Involves decisions of multiple stakeholders

- User choices, platform policies, supplied content

Detour: traps

Recommender systems' makers describe their purpose as 'hooking' people

- Enticing them into frequent or enduring usage
- Entrenched paradigm: "captology" and persuasive tech

When asked how to deal with the cold start problem:

> *"If you're in your first week of listening to us, we're like, 'Fuck that! Play the hits!' Play the shit you know they're going to love to keep them coming back. Get them addicted."*

Detour: traps

How?

By having recommendations everywhere

- Recommenders are persuasive by design

By focusing on behavior rather than ratings

- Optimize for consumption, not liking

By focusing on Top-N metrics

- Present items with the highest chance of being followed

Example studies

Leysen: literature probe of papers about filter bubbles:

All papers consider some type of diversity

Most studies do not consider time

- Comparison between (groups of) users
- Comparison between different algorithms

Only 4 studies meet all criteria of technological filter bubbles

Groups of users

Haim et al. (2018): expressing a preference for a topic on Google News makes that topic appear more often

- This reduces structural diversity
- Nechustai et al. (2019) find no difference, though

Bakshy et al. (2015): considerable polarization in Facebook news

- But most users are exposed to alternative ideologies

Hussein et al. (2020): some users are recommended misinformation on YouTube despite no prior interest

Algorithms

Möller et al. (2018): Recommend articles based on source article: considerable differences between algorithms

- But more diverse than news curated by an editor

Liu et al. (2021): Big differences in political diversity between CF and CBF

Baracskay et al. (2021): Big differences in recommendation diversity between music streaming apps

- Recommendation diversity is usually lower than the diversity of the input playlist

Algorithms

Created 3 playlists of 15 songs: low, medium, high diversity

Fed to 5 streaming services: Spotify, Pandora, Apple Music, Youtube Music, and Last.fm.

Created 15 lists with first 20 recs for each playlist+service

For each list (including input lists), calculated average latent cosine similarity between all pairs of songs

Algorithms

Input playlist diversity		Recommendation output					
		Spotify	Pandora	Apple	YouTube	Last.fm	Average
Low	0.51	0.681	0.606	0.448	0.446	0.427	0.522
Medium	0.289	0.538	0.282	0.313	0.239	0.236	0.322
High	0.084	0.217	0.195	0.101	0.092	0.266	0.174
Average		0.479	0.361	0.287	0.259	0.31	

Diversity over time

Nguyen et al. (2014): MovieLens users' recommendation diversity over time

- Topic diversity of recommendations decreased over time

Bountouridis et al. (2019): Simulated effect of algorithms in a BBC dataset

- Unexpectedness of recommendations decreased over time, except for "Most Popular" and UserKNN (increase!)

Diversity over time

Tomlein et al. (2021): Misinformation on YouTube

- Even after watching misinformation, you still get alternative viewpoints (especially if you also watch debunking videos)
- However, misinformation increases over time in "What to watch next" (watching debunking videos reduces this)

Lu et al. (2020): Effect of a more diverse algorithm in a news website

- Topic diversity increased over time

Consequences

The “societal” filter bubble explained

Consequences

Seaver (2018) on **Captivation**: Recommendation technology blurs the line between persuasion and coercion

- Many persuasive tech people are now actively working against it

Algorithmic recommendation has become inescapable for contemporary users of the Web

- Everything is a trap!

Consequences

You become trapped in a you loop, and if your identity is misrepresented, strange patterns begin to emerge, like reverb from an amplifier

Pariser, 2011: page 125

Personalization algorithms can cause identity loops, in which what the code knows about you constructs your media environment, and your media environment helps to shape your future preferences

Pariser, 2011: page 233

Consequences

Outcomes (Pariser, 2011):

- narrower self-interest
- overconfidence
- dramatically increased confirmation bias
- decreased curiosity
- decreased motivation to learn
- fewer surprises
- decreased creativity and ability to innovate
- decreased ability to explore
- decreased diversity of ideas and people
  decreased understanding of the world
- skewed picture of the world

Backlash

People's initial reaction to the filter bubble: backlash

Loss Aversion: losses loom larger than gains

Fear of Missing Out: the fear that others might be having rewarding experiences from which one is absent

The joy of getting recommendations may be spoiled by our worry of missing out on other enjoyable items that were not recommended

Backlash

The algorithm does not care about items that are missed (especially with ranking accuracy)

- Goals is to find the best Top-N items

For the user, missed items may decrease their satisfaction with the system (decision confidence)

- And even their satisfaction with their choices (regret)

Embracing the bubble

People's long-term reaction to the filter bubble: conformity

Recommender systems are persuasive

- users are prone to agree with predicted ratings and to follow a recommender's advice

Lanier (2010): "positive feedback loop"

- Users will unknowingly make themselves "fit in" with the system better (make themselves more easily targetable)

Embracing the bubble

Pariser (2010): items that are "easy" to like or consume

- Predict "rate-ability"

If we embrace the Filter Bubble, we run the risk of getting locked in by the algorithm

- If so, recommenders do not just inhibit discovery and learning, they actively work against it

For society

When I considered what it might mean for a whole society to be adjusted in this way, [personalisation] started to look more important, [since] the filter bubble is a centrifugal force, pulling us apart

Pariser, 2011: page 12 + page 9

Pariser's argument is mostly political (as he focuses on news)

- Jaron Lanier takes a broader "personal identity" perspective

For society

Temporal Discounting

- We choose guilty pleasures that provide instant gratification over substantive educational experiences of long-term value.

Boyd (2009): “the psychological equivalent of obesity”

- Recommended content is the cerebral equivalent of junk food


OPINION

Critiques

Is the filter bubble real?

Critiques

1. Technological bubbles may not cause societal bubbles

    Even a strong reduction in diversity may not result in societal impacts

2. We often seek supporting information, but seldom avoid challenging information

    People are selective in information search, but will engage when challenged

3. We prefer like-minded people, but interact with others too

    Same as #2

Critiques

4. A digital choice does not necessarily reveal a preference

    But this might actually exacerbate the problem

5. Mostly tested on politics, which is only a small part of our lives

    Would this also happen in other domains? Are the consequences bad there too?

6. Different media can fulfill different needs

    We don’t just get their recommendations from a recommender system

Before we adjourn

Groups!

Send me an email

Proposed topic: “[decision domain] for [user group]”

- Why is this topic interesting to you?
- How can ADSS help here?
- How will you recruit participants?

Scheduled weekly meeting time

Whether you want to submit an IRB

- Required for potential publication, otherwise not

Do this by today!

Questions…