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ETHICAL IMPLICATIONS OF FILTER BUBBLES AND PERSONALIZED NEWS-STREAMS

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1. Abstract

In the days of traditional media, be it print, radio, or television, every consumer of a product received the same information. However, with the transition to the online world, personalization, tailoring information to the individual's interests, became a possibility. Starting with the advent of personalized search *(Pitkow et al., 2002)*, which was introduced by Google as a feature of its search engine in 2004, interest-based advertising and personalized news became both features, improving the relevance of the information to a specific user, and ethical problems – how can information only I receive influence me? The issue is even more complicated when talking about social media and personalized news – how can we ensure algorithms are transparent and indiscriminate? The present research is focused on bringing to attention possible ethical dilemmas and solutions to filter bubbles brought on by news personalization.

2. Keywords

filter bubbles, personalized news, information filtering, fake news, news algorithms, social media

3. Introduction

Even though discussions regarding the personalization of content served to consumers on the internet started in the late ’90s, there were not many mainstream analyses into the ethical implications of such manipulation of content until the introduction of the term “filter bubble” by Eli Pariser. “***The filter bubble*** *tends to dramatically amplify confirmation bias—in a way, it’s designed to. Consuming information that conforms to our ideas of the world is easy and pleasurable; consuming information that challenges us to think in new ways or question our assumptions is frustrating and difficult.*” (Pariser, 2012, p. 51). The filter bubble is supposed to be a safe space, a way for us to avoid unfriendly thoughts and unpleasant facts. But by design, it does more to insulate us than it does to create a more open world. When a filter bubble is in place, we spend a lot of our waking hours navigating through information that doesn’t challenge us and will never challenge us. All media and products (not just our own) are shaped by this process, and the more we learn about it, the more we learn that it’s bad for consumers. “*The era of personalization is here, and it’s upending many of our predictions about what the Internet would do.*” (Pariser, 2012, p. 15), but to understand how personalized websites work, we first need a description of their fundamentals.

“*Nearly all major websites, from Google to The New York Times, use at least some personalization to drive the content displayed for a particular user, and what is deemed “relevant” to one visitor may not appear at all for another*” (Valentine & Wukovitz, 2013, p. 27). This exposes the biases that can come with implementing good social science into online services. This has serious implications for our democracies. It is reasonable to believe that Facebook and Google are in the best position to improve their services by knowing their users better and curating a more relevant online experience for them. But it is not clear that they are capable of doing this without the biases that come with them, and without feeling their biases when they do. If users trust these companies to improve their online experience based on the research that they're already engaged in, they are likely to be less likely to provide extra information, rather than better information.

This is an incredibly diverse, nonlinear world, full of layers upon layers of sites and services that we assumed to be separate and autonomous, but that are the visualizations of the complexity of our digital networks, fully interconnected. These layers are built by us and programmed through technology to address our preferences and interest, to serve content that is tailored just for us. The result of these layers is a dynamic, intuitive world of individual preferences, which operates according to complex rules, which may not be intuitive to consumers of information. They may not be intuitive to the designers who make them, or even to the programmers who build the algorithms that compile these rules in the age of machine learning, where the same algorithms may take decisions that we might not be able to explain: "*It is extremely difficult to reverse engineer a Neural Network. We have reached a point where even the creator of an algorithm does not understand it completely*" (Nielly, 2020). The classic curricula for software developers, creators of code and algorithms, often do not include ethics courses, and often "software embeds moral and cultural values and inevitably nudges society toward these values". (Narayanan & Vallor, 2014, p. 24)

4. The ethics of algorithm-personalized news streams

The constant usage of algorithmic personalization for any kind of interfaces, "*such as curated feeds in online news, raises new questions for designers, scholars, and critics of media*". (Kizilcec, 2016) What are their purpose and the role of the user in this technologized society? To what extent are they necessary, or do they limit our free imagination and call for weirder choices? And why are they ever-proliferating, especially at the time when television, social media, and other platforms are expected to be more grounded and involved in their users' lives? Algorithmic platforms in many cases are working to challenge the monopoly that traditional media used to hold over digital information. This raises the question of whether human interests trump information interests in the process of shaping information curation and even production, which would in turn have implications for the use of algorithmic information in the digital information economy.

Pariser points out three dynamics of the "filter bubble" which make online filtering potentially damaging: users are "alone" in their "filter bubble," it is invisible, and users do not choose to enter the bubble themselves. (Pariser, 2012) All of these can lead to "self-selection" in which some ideas are blocked from "sustained presence," and many of the ones passed through do not reach a critical mass, allowing their proponents to repeat their views without much serious challenge. Research showed that people often select the information they agree with, that reinforces their beliefs, even when presented with opposing views. (Liao & Fu, 2013) Individuals appeared to have little need for information that contradicted their existing beliefs. Thus, people seem to show little motivation to consume contrary information when engaging in "active thinking". It is not clear whether the tendency to prefer information that reinforces individualistic attitudes was a byproduct of the self-defensive nature of these beliefs or the result of active reasoning strategies or a combination of both.

There are also divergent opinions – a 2017 study on news personalization concluded that "*except for small effects of implicit personalization on content diversity, we found no support for the filter-bubble hypothesis*" (Haim et al., 2017, p. 1), finding that even though explicit personalization of news, while analyzing Google News, had almost no effect on content diversity, even though some news outlets were over-represented, mainly outlets of conservative nature and others under-represented. When studying the effects of personalized communication, even though concluding that "*there is little empirical evidence that warrants any worries about filter bubbles*" (Zuiderveen Borgesius et al., 2016), found the following issues of concern: polarization as a consequence of self-selected personalization, political learning as impacted by self-selected personalization, and effects of pre-selected personalization, and noted that these issues are currently not of urgency only because the technology is insufficient. Others have suggested that users are empowered by such algorithms, and not enslaved by them – the consumer is "*responsible for defining her tastes and preferences*". (Culén & Ren, 2007, p. 834)

The tendency of algorithms to favor the extreme right and conservative sources of information has also been noticed in a study on YouTube videos, being able to "*identify the existence of an extreme right filter bubble, in terms of the extent to which related channels, determined by the videos recommended by YouTube, also belong to extreme right categories. Despite the increased diversity observed for lower related rankings, this filter bubble maintains a constant presence*." (O'Callaghan et al., 2013, p. 9)

Other researchers identified that transparency brings trust in algorithmic interfaces, but *“designing for trust requires balanced interface transparency—not too little and not too much.”* (Kizilcec, 2016), with *“numerous aspects of algorithmic systems that could be disclosed in an effort to advance a journalistic truth-telling process that increasingly hinges on the norm of transparency”* (Diakopoulos & Koliska, 2017, p. 14). This is an issue because usually “*the criteria on which filtering occurs are unknown; the personalization algorithms are not transparent*” (E. Bozdag & Timmermans, 2011, p. 2), the users not even knowing if the information being presented to them is manipulated or malformed in any way. There are multiple opportunities for regulators to enhance the degree of disclosure by providing a more responsive and personal service, clarifying limitations and disclosure requirements, and ensuring that all stakeholders have an opportunity to provide input on the development of new algorithms. Finally, we consider there should be a set of rules for the design of a transparent algorithmic framework that can build on the level of algorithmic transparency identified as needed. We propose two approaches to implementation of algorithmic transparency. First, we suggest an algorithmic transparency advisory board to provide users and developers with advice on algorithms' expected privacy and security properties, ethical assumptions, and design tradeoffs. Second, we propose a centralized algorithmic audit process that provides auditors with specific tools to audit algorithmic decision criteria, decisions, and outcomes across an entire pipeline.

While research has been done in the limitations of the transparency ideal in algorithmic accountability, (Ananny & Crawford, 2018), attempts to create a framework to detect, quantify, and overcome the online filter bubble have been considered, but not yet finalized. (Garimella, 2017).

Some researchers have suggested that recommender systems should aim to provide users with information about novel items and use serendipity as a way to improve, "*as a performance measure for algorithms*", (Maccatrozzo, 2012) concluding that "*by drawing on concepts of recommendation novelty and recommendation serendipity, […] perceived recommendation serendipity has a strong positive effect, both on perceived preference fit as well as on the perceived enjoyment of the users*." (Matt et al., 2014, p. 15). Such approaches might be worth investigating in not only product recommendations but news and information curation, to reduce the bias of filter algorithms. To promote diverse exposure to information and limit the effect filters have on the individuals' consumption of media, others have proposed strategies: develop systems that enforce more diverse exposure to users, news aggregators with a threshold for "counter-attitudinal stories", encourage users to read more diverse information and participate in perspective-taking. (Resnick et al., 2013, p. 97) Others suggest that we should have ethics of algorithms, "*a definition of networked information algorithms (NIAs) as assemblages of institutionally situated code, practices, and norms with the power to create, sustain, and signify relationships among people and data through minimally observable, semiautonomous action.*" (Ananny, 2016).

Whether we should be surprised by the immense social and political consequences of enabling the efficient construction of such networks, and which information can be considered 'private', depends to a large extent on the level of user data sharing involved, and what the implications are for individual users of these and future networks. Moreover, users' individualistic search-engine behavior might also be assumed to favor a social network structure that over-emphasizes personalization, and which makes it possible for each user to be seen as being "the most important person in his/her network." "*Even leaving* *aside concerns about individual and social consequences of possible 'filter bubbles', the user profiling required to achieve this personalization raises numerous ethical issues around privacy and data protection*." (Koene et al., 2015, p. 7)

5. Conclusions

Since personalization is based on users' behavior, this might mean that they are systematically privileging some kinds of information, search engine terms, and possibly categories over others. This comes at the price of over-personalizing the information we are shown. This, in turn, comes at the expense of the diversity of viewpoints we encounter. It also raises many ethical issues: at the most basic level, personalization tends to create filter bubbles that allow people to get their information only from people similar to themselves. This might allow for a perception of consensus among group members.

Moreover, since people tend to favor information that supports their own point of view, personalization tends to favor the accessibility of one narrow range of views over others. There is a strong possibility that if our news is filtered by personalization algorithms, we will not be exposed to diverse viewpoints and thus will not be able to develop a more coherent view of our world.

The presentation of a limited number of view points is not only a threat to news consumption but can be seen as a "serious threat to our democracy" (E. Bozdag & van den Hoven, 2015, p. 249), thus further research is needed both in exploring the effects of filter bubbles and in developing tools to balance the exposure users have to personalized content, and even proposing possible software design solutions to combat filter bubbles. (V. E. Bozdag, 2015, p. 65)

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