Philosophical Perspectives on Recommender Systems: Ethical Implications, Biases, and Their Impact on Autonomy and Privacy

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Abstract. Recommender Systems (RSs) assist users in navigating overwhelming amounts of digital information by offering personalized suggestions. While invaluable, these systems raise concerns about biases, fairness, as well as user privacy and autonomy. This work examines these issues, highlighting both the benefits and risks, and calls for strategies to mitigate potential harms.

Keywords: Recommender Systems · Personalization · Decision Making · Bias · Fairness

1 Introduction

With the abundance of digital content and variety of choices made on a daily basis [15], Recommender Systems (RSs) simplify decision-making by filtering relevant items based on user behavior and preferences. Originating in the 90s with systems like Tapestry [5], GroupLens [14], Bellcore [7], and Ringo [17], RSs are now integral to daily life. Nevertheless, despite their utility [8, 16], ethical challenges such as algorithmic bias [2], filter bubbles [13], and privacy erosion [9] arise frequently within RSs. This paper investigates RSs' impact on human autonomy, decision-making, and fairness, emphasizing the need for ethical algorithm design and robust regulations.

RSs typically involve three key actors: users, items (often with providers behind them), and the platform (see Fig.1). The recommendations can be created based on the user behavior feedback data collected by the platform, which can be either explicit feedback (e.g., ratings and likes), or implicit feedback (e.g., browsing history, content consumption). Recommendation processes might differ depending on the application domain, however, certain issues like bias, privacy and fairness concerns are universal and should not be overlooked when implementing a recommendation mechanism. Additionally, understanding these challenges often calls for an interdisciplinary approach.

2 Recommendation and Decision-Making

Herbert Simon's concept of *bounded rationality* [18] explains human limitations in decision-making amidst vast choices. RSs, in return, can bypass these limi-

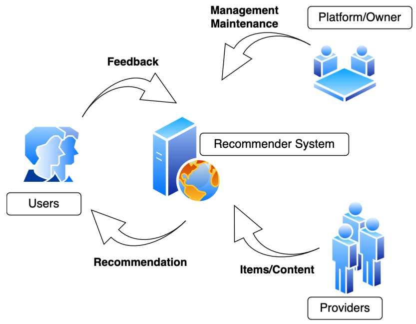

Fig. 1: Simplified structure of the recommendation process.

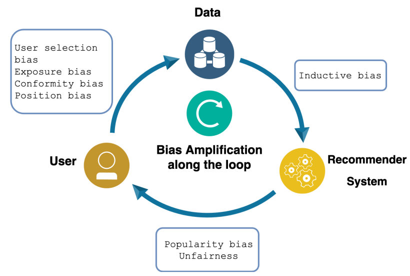

Fig. 2: Bias types and its propagation through the recommendation feedback loop [2].

tations with the access to all the information and available choices at the same time. Yet, by doing so, RSs can at the same time influence (often negatively) the user choices through framing [4], nudging [19] and anchoring [20]. RSs can affect *preference construction* [11] by reshaping decision contexts, potentially steering decisions for external benefits rather than user autonomy. Participatory design, which involves users in RS development, may enhance transparency and trust while guiding preference construction and user autonomy.

3 Privacy and User Control Over Data

RSs rely heavily on user data, raising concerns about profiling, sensitive attribute inference, third-party data sharing, and limited user control over their own personal data [3]. Despite GDPR[1] and similar regulations, transparency in data handling remains a challenge. Users are often unaware of how their data is being stored or used, or the mechanisms to opt out from data collection or adjust the privacy settings are not available. Empowering users with privacy controls and offering clear explanations of data use can lead to significant improvements of trust [6] and increase engagement and satisfaction. As a result, enhanced user participation has a chance of improving recommendation quality while safeguarding user autonomy at the same time [12].

4 Biases

In 1970s, cognitive biases [10] were defined as *"bias ... that occurs when humans are processing and interpreting information"*. Nowadays, the information provided to users for processing can already be influenced by biases within RSs. This results in a complex, multi-layered interaction of biases originating from both humans and algorithms. Biases in RSs can be introduced, propagated and

[1] https://gdpr-info.eu/

even reinforced at different stages of the recommendation process (see Fig.2). First, sampling errors or unrepresentative datasets skew recommendations, amplifying disparities among user demographics, which can be categorized as *data bias*. Second, RSs often excessively promote popular content (popularity bias), create "filter bubbles" and "echo chambers" that polarize opinions and reinforce stereotypes - all of these phenomena are mostly attributed to *algorithmic bias*. Last but not least, the way the information is presented to the user is of great importance, as *presentation bias* can manifest at this stage. Design elements, like list positions, disproportionately influence user engagement, reducing content diversity. These biases are amplified in the feedback loop, where user interactions reinforce existing patterns. Solutions to these issues should include fairness-aware algorithms, diverse datasets, and inclusive evaluation frameworks.

5 Fairness in Recommender Systems

When considering fairness in recommendation, it is crucial to acknowledge the goals and priorities of all the actors in this complicated system. The concept of*multistakeholder fairness* [1] has been introduced to emphasize equity across these diverse groups:

- User Fairness: Recommendations should be unbiased and inclusive across demographics. For instance, RSs in job markets must avoid systematically disadvantaging specific groups.
- Provider Fairness: Small-scale content creators or businesses should compete equitably with established entities. RSs can help by balancing exposure opportunities.
- Community Fairness: Addressing polarization and misinformation is vital to maintaining open public discourse. RSs should mitigate filter bubbles to promote diverse viewpoints.
- Regulatory and Ethical Fairness: RSs must comply with legal frameworks like GDPR and adhere to ethical principles like transparency and accountability. Incorporating multistakeholder perspectives fosters trust and ensures long-term societal benefits.

6 Conclusion

RSs significantly enhance convenience of day-to-day decision making, however, they can also pose risks to user autonomy, privacy, and equity. Addressing biases, transparency, and fairness is crucial to maximizing societal benefits while minimizing harm. Ethical and participatory approaches, alongside strong regulations, can ensure RSs serve users' best interests.

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