Algorithmic recommendations

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How to break information cocoons

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Recommender systems are a predominant feature of online platforms and one of the most widespread applications of artificial intelligence. A new model captures information dynamics driven by algorithmic recommendations and offers ways to ensure that users are exposed to diverse content and information.

In their essence, recommender systems (RSs) suggest items that users are likely to find relevant. Items can be objects to purchase (in e-commerce), music to listen to (on audio streaming platforms), videos to watch (on video-sharing platforms), jobs to apply to (in human resources), news to read (in online newspapers) or even other users to connect with (on social networks). In a world where information is shared at unprecedent rates, RSs are an important tool to cope with information overload. RSs are advantageous to both content producers and users: the former can improve the outreach of items produced and ultimately add value to their business, while the latter can identify new products, discover interesting items and satisfy their needs more expeditiously. On the flip side, recommender systems have been associated with long-term negative effects. RSs can suffer from feedback loops, preferentially recommending already popular items[1]. Such systems can also fail to offer recommendations that reflect different viewpoints and fairly benefit all society groups[2,3]. Ultimately, RSs can contribute to reducing exposure to diverse contents[4]. On online social media platforms, recommender systems can lead to so-called information cocoons: that is, "communications universes in which we hear only what we choose and only what comforts and pleases us"[5]. A new paper in *Nature Machine Intelligence* by Piao et al.[6] proposes an important step to prevent such phenomena, by suggesting a new model to capture information dynamics driven by algorithmic recommendations, and by clarifying how RSs can reduce exposure to information diversity.

The advantages of offering users diverse algorithmic recommendations have been previously identified[7]. Optimizing RSs to offer such recommendations requires moving beyond evaluation metrics that only emphasize accuracy. Designing RSs to improve exposure to diverse contents is not an easy task. On the one hand, one might find important trade-offs between accuracy and diversity. On the other hand, fully understanding the effects of algorithmic recommendations on users' exposure to diverse contents calls for methods and data that capture temporal dynamics and long-term effects. Earlier works seeking to capture long-term effects of recommendation algorithms resort to simulation techniques[1,4,8–11]. However, it remains challenging to integrate simulation results and real data.

Piao et al. analyse real-world data and propose a new theoretical model to understand the phenomena of declining diversity in topics that users access. The datasets considered are remarkably large and cover a long period of time. The authors consider a dataset from one of the most heavily used video platforms in China, including more than 111,000 users, 9 million videos and 500 million interaction records between users and videos, over the course of a year. Additionally, the authors consider a news dataset comprising 90,000 users, 130,000 pieces of news and 36 million interaction records over 6 weeks. Each video belongs to one of 20 possible categories (topics), and each news piece belongs to one of 14 possible topics. The authors observe that,

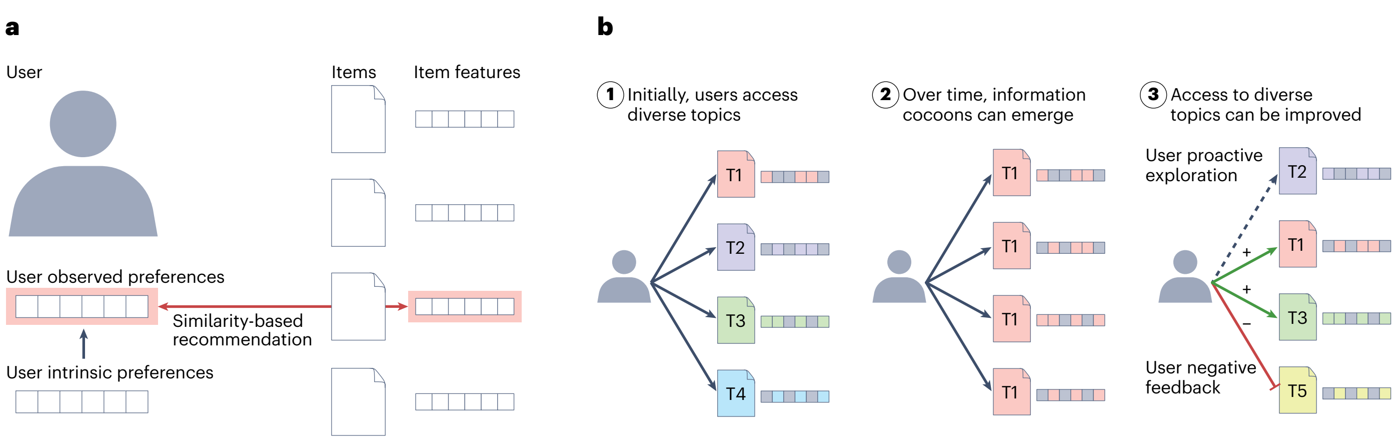

Fig. 1 | Emerging information cocoons and ways to break them. a, In the proposed model, users have observed and intrinsic preferences. Items are recommended based on similarity between the items' characteristics and the users' observed preferences. Users provide positive or negative feedback based on similarity between the items recommended and their intrinsic preferences. **b**, Each item belongs to a topic. By analysing empirical data, Piao et al. show that users become exposed to fewer topics over time as information 'cocoons' emerge, and hence they propose a model that can capture these dynamics. Two suggestions to counter the lack of topic diversity are advanced: (i) balance similarity-based recommendations with incentives for users' proactive exploration of contents (above right) and (ii) use negative feedback to update users' observed preferences (below right).

over time, a large fraction of users' access videos and news pieces belonging to less diverse topics.

To illuminate why diversity declines over time, and test potential interventions to mitigate this, the authors formalize a theoretical model that can be initialized based on empirical data. This model assumes that users are characterized by (i) intrinsic preferences, which are fixed, and (ii) observed preferences, which change over time (Fig. 1). Both preferences can be understood as numerical vectors defining the characteristics of items that a user is interested in. Importantly, algorithmic recommendations rely only on observed preferences. Although intrinsic and observed preferences can be correlated, a mismatch between the two can lead users to provide negative feedback about a recommendation. If a recommendation is aligned with users' intrinsic preferences, they provide positive feedback. Such feedback is then used by recommender systems to update future recommendations. To understand the long-term dynamics resulting from this feedback loop, the authors resort to tools typically applied in dynamical systems theory and statistical mechanics.

The model defined in Piao et al.[6] allows to test how the emergence of information cocoons depend on RSs design principles such as (i) the level of similarity between the users' preferences and item characteristics when automatically selecting recommendations and (ii) the weight placed on the positive and negative feedback provided by users when inferring their preferences; finally, the model makes it possible to test (iii) the level of users' self-exploration, that is, their willingness to explore items regardless those recommended by RSs. By comprehensively exploring this model, the authors identify the scenarios in which information cocoons are more likely to emerge. This happens when algorithmic recommendations depend excessively on similarity-based matching or when RSs strongly depend on positive feedback to infer users' preferences.

New research directions can be identified from the work by Piao et al.[6]. First, the proposed model assumes that users' intrinsic preferences are static and that only preferences observed by RSs (that is, inferred) change over time. A more complex human decision-making model could account for the role of recommendations in influencing the users' intrinsic preferences, thereby clarifying the contexts in which algorithmic recommendations are more likely to directly affect people's attitudes and behaviours[12]. Second, the results emphasize that users might be exposed to low diversity within each platform. People can use multiple platforms, suggesting that the intra-platform decrease in accessing diverse topics can be overcome by an increase in diversity across platforms (that is, users might end up using different platforms to access different viewpoints). Third, Piao et al.[6] underline the role of AI-based recommendations. It remains, however, relevant to compare how the decline in diversity observed would differ relatively to human recommendations[8]. Future studies can use the proposed model with parameters that are likely to characterize various editorial decisions by humans[8]. Finally, the model can be used to study the interplay between diversity and fairness in recommendations. As users are exposed to a narrower set of topics, producers of specific contents might receive less attention[2] and the visibility of some society groups can be reduced[3]. The proposed model could be extended to test interventions that aim at improving users' access to diverse topics and a fair representation of different communities.

The paper by Piao et al.[6] is noteworthy for several reasons. It considers data spanning a long period of time, providing evidence that a significant fraction of users are nudged to access less diverse topics on online platforms. Furthermore, Piao et al.[6] define an innovative model that can be directly tuned with parameters inferred from empirical data, providing a promising bridge between real-world observations and theoretical modelling. Finally, this study offers actionable guidelines on how to prevent the emergence of information cocoons on online platforms (Fig. 1b): (i) offering recommendations based on user-item similarity should be counterbalanced with the opportunity for users to self-explore and exercise autonomy over algorithmic recommendations; (ii) negative feedback provided by users should have a more prominent role in determining future recommendations, as opposed to the traditional emphasis on positive feedback. These suggestions are timely given the general interest in understanding diversity in recommender systems, and the effects that diversity in algorithmic recommendations can have on users' satisfaction[7] and the health of democracies[8].

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Competing interests

The author declares no competing interests.