Presenting Diversity Aware Recommendations:

Making Challenging News Acceptable

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ABSTRACT

Recommender systems find relevant content for us online, including the personalized news we increasingly receive on Twitter and Facebook. As a consequence of personalization, we increasingly see content that agrees with our views, we cease to be exposed to views contrary to our own. Both algorithms and the users themselves filter content, and this creates more polarized points of view, so called "filter bubbles" or "echo chambers". This paper presents a vision of a *diversity aware recommendation model*, for the selection and presentation of a diverse selection of news to users. This diversity aware recommendation model considers that: a) users have different requirements on diversity (e.g., challenge-averse or diversity seeking), and that b) items will satisfy these requirements to different extents (e.g., liberal or conservative news). By considering both item and user diversity this model aims to maximize the amount of diverse content that users are exposed to, without damaging system reputation.

CCS CONCEPTS

• Information systems → Decision support systems; • Human-centered computing → Human computer interaction (HCI);

KEYWORDS

diversity, explanations, user-centered design

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1 INTRODUCTION

Recommender systems find relevant content for us online, including the personalized news we increasingly receive on Twitter and Facebook [18, 28]. As a result of personalization, we increasingly see content that agrees with our views, we cease to be exposed to views contrary to our own. Both algorithms and the users themselves filter content, and this creates more polarized points of view, so called "echo chambers" [2, 6, 20]. Recommender systems have both the potential to increase the diversity of content and narrow it. Over time using recommender systems has been found to slightly decrease the diversity of content that users consume [19]. However, Flaxman et al. found evidence that recent technological changes both increase and decrease various aspects of the partisan divide. This suggests that there may be design choices for recommender systems that could decrease polarization.

In response to the issue of "echo chambers" and "filter bubbles", this paper therefore introduces a *diversity aware recommendation model* for selecting and presenting a diverse selection of news to people. The goal is to develop presentational strategies for recommendations that consider both item and user diversity, and maximize the diversity of recommendations given to a person, without losing trust, or polarizing their existing opinions. A complete solution to the problem needs to consider *both* the biases that algorithms and humans bring to the filtering process. If item selection and presentation is done in too simple a way, for example, by suggesting articles that the person strongly disagrees with, they simply might not return to the system, or become more extreme in their views [8, 11]. Building on advances in understanding both the influence of *user diversity* and *item diversity* on perceived recommendation quality and perceived diversity, it is now possible to address filter bubbles from a new angle. The proposed approach is to study people's *perceptions* of diversity using live experiments. Experimentation with people makes it possible to identify how *presentational strategies* can be used to manage the perceptions resulting from user and item diversity. These experimental findings will inform the new *diversity aware recommendation model*, which will allow us to expose people to a wider range of content, while maximizing their acceptance as much as possible for (for them) challenging content. By doing so, this research has the potential to decrease polarization of views.

2 RELATED WORK

Previous work focusing on mitigating filter bubbles can be divided into two approaches: better understanding of candidate items, and diversity aware recommendation algorithms. The first approach is reaching a point of maturity where it can start to support the second: helping users understand the candidate items through presentational strategies may mitigate the effects of challenging content presented to users through diversity aware algorithms.

Understanding the candidate items. The first approach is to help users to better understand the recommended items relative to a wider set of candidate items. Taking this approach, we have found that helping users control which people contributed to their information feed on Twitter increased their sense of transparency and control [14, 23]. However, we also found that users had a poor mental model for the degree of novel content discovered when presented with non-personalized tweets, and thus potentially more challenging, information. We also found that visualizing users' blind-spots, i.e., underexplored areas in the search space, encouraged them to explore these parts of the item space (under review). In this regard, the work of Nagulendra and Vassileva is also pertinent, finding

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that visualisation increased understandability of the filtering mechanism [17]. This approach of better understanding the candidate is also underpinned by studies on visualizations [27], explanations [25], and critiquing [15], in recommender systems.

Diversity aware algorithms. The second approach is to develop diversity aware recommendation algorithms, or algorithms that address the risks of filter bubbles and polarization. To support discovery, news recommender systems need to strike a delicate balance between diversity and relevance: to find news articles that are diverse, and still highly relevant to a user. To increase relevance the computation of similarity (e.g., between items, users, or their ratings) has been the basis of recommendation algorithms. The challenge is thus to define similarity in a way that maintains relevance while sufficiently diversifying items in recommendation sets (c.f., [1, 30, 31]). Overall, item diversity has been successfully implemented before: diversified recommendations have been found to increase user satisfaction [31], helped users find target items faster [4], and increased the novelty of the items that are recommended [30]. Furthermore, while *perceived* novel content discovery contributes to the attractiveness of recommendations, diversification that is not mediated by perceived discovery has been found to *reduce* the attractiveness of recommendations [7]. More recent approaches (c.f., [13, 29]) have considered how re-ranking can be used to include diversity in an optimization function. However, these measures of diversity are still not well understood from a user-centered perspective, especially when dealing with*human perceptions of challenging news content.*

3 NEW RECOMMENDATION MODEL

The factors that are proposed for the diversity aware recommendation model are shown in Figure 1, and are described below in relation to: user diversity (e.g., personality), item diversity (e.g., re-ranking), and presentational strategies (e.g., item placement).

A combined study of both user- and item- diversity makes it possible to find solutions that address both user and algorithmic biases at once. By addressing the challenge of diversification from the angle of user perception, this diversity aware recommendation model builds on advances in the area of *presentational strategies* in recommender systems. An improved understanding of the factors that may influence the effectiveness of such a model make it possible to improve the positive impact of item diversification, and improve people's acceptance of diverse news articles.

3.1 User Diversity

Users naturally have different interests, one of they key motivators for personalization algorithms such as those used in recommender systems. Previous studies have found that users vary in terms of the degree of diversification that is optimal for them, and that this can be deduced from their previous rating behavior (see e.g., [13, 21]). Users also vary in terms of personality traits that are fixed, such as the Big Five [12]. Our, and others' work, has also found that recommendation algorithms may benefit from considering these traits [5, 16, 22]. One study investigated how people apply diversification for a sequence of book recommendations for a friend [22]. Others found that whether users were diversity-seeking or challenge-averse also influenced the perceptions of diversity in news [16], a user trait that may be more transient. Beam found that demographic factors such as gender, level of internet skill and education affected the extent to which users reported to think at depth about news [3].

3.2 Item Diversity

The items that are recommended to a user, or considered as candidate recommendations, can also be selected in a way that they are different from each other. Several approaches to item diversification are suggested in the literature. Ziegler et al. (2005) proposed a topic diversification approach based on taxonomy-based dissimilarity [31]. As may be anticipated, using simple dissimilarity also impacted accuracy negatively. An alternate set of approaches which re-rank a list of top items was found to improve diversity without a great loss in accuracy (c.f., [1, 13]). Zhang et al. found that diversification in recommendations increased novelty and decreased "unserendipity" (similarity between items in a user's history and new recommendations) [30].

These measures of diversity however suffer from a considerable limitation: they do not take into account whether they can be accepted or understood by a user. They also do not consider more subtle definitions of item diversity such as the the strength of sentiment, or preferences for certain styles of writing (stylometry). To understand which features influence users perceptions of item diversity, more exploratory studies, e.g., investigating users' perceptions of diversity in active consumption environments are required (c.f., [24]).

3.3 Presentational Strategies

The diversity aware recommendation model will consider design choices such item placement, primacy and recency effects, transitions, and interaction mechanisms:

Item placement. The position of surprising or risky items, influences the perceived diversity of a list [9, 16]. A number of design decisions can be made around how items are grouped (or if they are spread out), where they are placed (e.g., beginning, middle, or end of a list), and how pair-wise distances between specific items are considered (e.g., transitions).

Similarity grouping refers to whether articles that are different from the rest of a recommended list, such as top-N, are more easily grouped together (as predicted by Gestalt principles) than when similarity within a list is more homogeneous. For example, Ge et al. studied the placement of diverse items, finding an effect on perceived recommendation list diversity [10]. Placing items that differ from the others in the middle in the list, and as a block (rather than spread out) were found to *reduce* perceived diversity.

Primacy and recency effects. Primacy and recency effects refer to the first and last positions in a list of recommendations: given that the first and last article in a list are normally the easiest to remember in recall tasks, algorithms which affect the ranking of position of articles in these positions are likely to influences user perceptions of sets of recommendations. Previous studies have found some effects of item placement at the beginning or end of a list. Sorting agreeable content first appears to decrease satisfaction rather than increasing it [16]. In contrast, placing the diverse items at the bottom of the list can increase the perceived diversity [9].

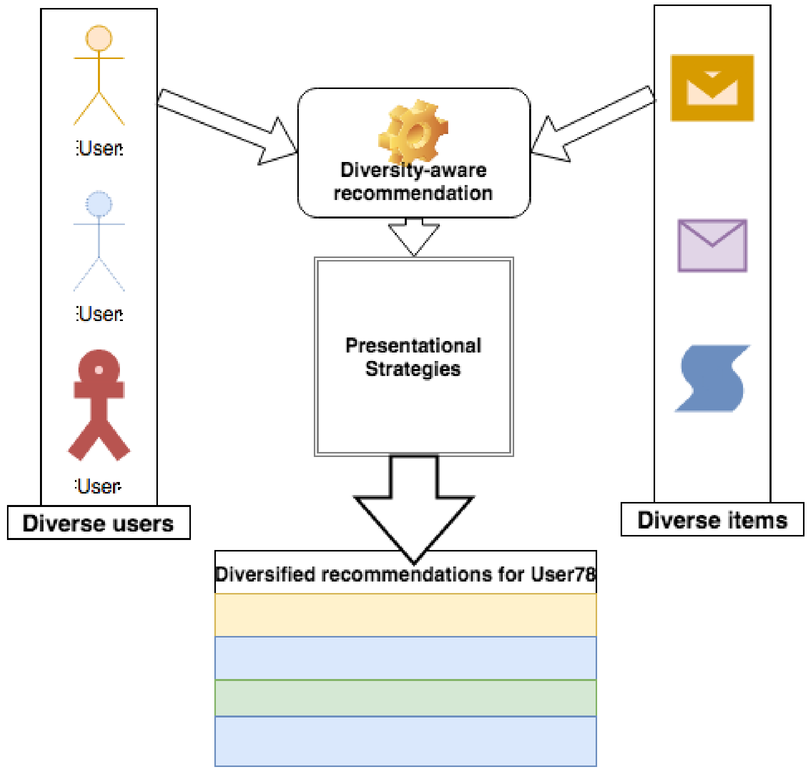

Figure 1: The proposed diversity aware recommendation model considers that both users and items are diverse. The resulting recommendation list consequently contains articles on a range of topics. The last item is on a highly relevant item represented in blue, but there are also yellow and green items in the list. These yellow and green items are relevant to User78 but are not necessarily the *most* similar to the user's preferences.

Transitions. Transitions consider the size and types of gaps between pairs of items. Due to anchoring and other similar effects, the order of presentation matter. Intuitively, there are orderings that would be unsuitable for most users, like moving directly from a very sad news story to a very happy one, even if both stories are relevant to a given user.

Interaction Mechanisms. System designers can chose to introduce interaction mechanisms that help users manage diverse content. For example, explicit explanation mechanisms, such as textual explanations for surprising items, may help users understand the choice of specific item. Systems can also include implicit interaction mechanisms, such as linking the recommendation list to a visual interface to support exploration (c.f., [26]). The interaction can also be designed to help users both discover and explore their blindspots.

4 CONCLUSION AND OUTLOOK

Building on previous research in information presentation, this paper suggests approaching diversification from a more user-centered approach than has been previously considered. To address filter bubbles, we consider the problem from *both* a computational *and* user-centered point of view. This is the first attempt to create a diversity-aware recommendation framework that considers how presentational strategies can help aid the diversification of content. This work allows us to better understand how to maximally increase the diversity of content a user is exposed to, while maintaining user satisfaction.

By considering both user and item diversity this approach is a unique and valuable contribution toward addressing the issue of over tailoring, leading to more balanced news consumption. By doing so, this *diversity aware recommendation model* enables us to address the challenges of both user and algorithmic biases, which often conspire to the creation of filter bubbles.

In line with this vision, first steps have been taken to study how different presentational strategies influence perceptions of diversity, a.o., studying the effects of different kinds of transitions between diverse items (under preparation), and users' expectations, and perceptions, of diversity in playlists [24]. We will also continue to build on our previous work on explanation interfaces that used weak ties to support content discovery [14, 23], to study the role of item positions in relation to perceptions of diversity. By defining diversity in a way that is understandable and acceptable to users, it becomes possible to move research on explanation-aware recommendation to the next level: how we present diverse items in recommender systems can help users not only to understand the recommendations, but also themselves and their own biases. In doing so, it may be possible to maximize the amount of diverse content that users are exposed to, without damaging system reputation.

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