2024

TOWARDS A MODEL OF POLARIZATION REDUCTION WITH RECOMMENDER SYSTEMS

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Towards a Model of Polarization Reduction with Recommender Systems

Research in Progress

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Abstract. Polarization occurs within society's networks when highly connected groups form with weak intergroup links, leading to echo chambers and filter bubbles. These phenomena hinder exposure to diverse viewpoints, posing significant challenges to democracy and societal welfare. Despite extensive research on measuring and mitigating social network polarization, the effectiveness of existing metrics remains largely uncharted. This study reevaluates these metrics and recommender system-based reduction strategies, pinpointing inherent limitations. It highlights key factors influencing polarization and adopts a design science research approach to craft a recommender system-based model for reducing polarization in online networks, recognizing its complex nature.

Keywords: Polarization, Echo Chamber, Filter Bubble, Recommender System, Design Science

1 Introduction

In the dynamic landscape of modern society, social media serves as a powerful platform for exposing individuals to diverse viewpoints. However, increasing content filtering risks limiting access to challenging perspectives (Hargittai et al., 2008). These contentious issues often fuel radicalized attitudes and distort perceptions of events, a phenomenon known as polarization (Matakos et al., 2017). Polarization refers to the division of groups into opposing sub-groups with conflicting positions, leaving few individuals neutral or holding intermediate stances (Guerra et al., 2013). This phenomenon has given rise to concepts like "echo chambers", where users predominantly encounter information from like-minded individuals and are exposed to limited opposing views (Cossard et al., 2020; Garimella et al., 2017; Markgraf and Schoch, 2019; Matakos et al., 2017), and "filter bubbles", where algorithms amplify ideological segregation by presenting personalized content aligning with the user's attitudes (Flaxman et al., 2016; Matakos et al., 2017). The resulting network polarization divides individuals into factions and restricts their exposure to a variety of content, exerting a corrosive impact on communities, societies, and democracies (Matakos et al., 2017; Sunstein, 2001).

While polarization sparks public discourse, the unintentional formation of isolated echo chambers requires mitigation strategies (Garimella et al., 2018). In this context,

19th International Conference on Wirtschaftsinformatik,
September 2024, Würzburg, Germany

Recommender Systems (RS) have emerged as potential tools. Some studies suggest that RS, when combined with social network structures, can contribute to the formation of filter bubbles (Antikacioglu and Ravi, 2017; Koidl, 2018), while others propose that RS enhancements could mitigate polarization (Interian et al., 2023). Past literature frequently relies on one-dimensional measures even though recent surveys suggest that polarization can have multiple forms (Tölle and Trier, 2023), highlighting the need for reassessment. Similarly, RS-based methods designed to mitigate polarization often narrowly focus on singular aspects without thoroughly validating their effects on polarization as a complex phenomenon. Recognizing this urgency, evaluating the accuracy of polarization measures and corresponding reduction methods are crucial research tasks.

This study aims to align RS methods with polarization measures, emphasizing multidimensionality in both measurement and RS-based mitigation strategies. Our research involves evaluating polarization measures and RS techniques to construct a model aligning strategies with appropriate metrics. We start with related work, highlighting the drawbacks of current measures, reorganizing them, introducing important aspects in measuring polarization, and presenting RS strategies to reduce polarization in a concept matrix (Section 2). We then detail the Design Science Research Methodology (DSRM) for developing an RS-based polarization reduction model (Section 3).

2 Theoretical Background

2.1 Polarization Measures

We initiated our research on Google Scholar with terms like "polarization measures", "echo chamber", and "filter bubbles", leading us to a current and comprehensive review by Interian et al. (2023) on the Scopus database. Following methodological guidelines for conducting a systematic literature review in information systems (Schryen et al., 2020; vom Brocke et al., 2015), this review initially found 405 publications and narrowed them down to 78 through specific exclusion criteria. While they focused solely on five polarization measures, we recognized the imperative for a more comprehensive inventory. We initially skipped a forward search due to the recency of Interian et al.'s (2023) review but will include it in the extended manuscript. Conducting a backward search (Webster and Watson, 2002) from their dataset, we compiled an exhaustive list of measures (https://bit.ly/3IFKeWV) and categorized them into *network-based*, *content-based*, and *combined* measures, inspired by Emamgholizadeh et al. (2020), who identified these categories without specifying individual measures. Additionally, we discuss studies critiquing the efficacy of these measures in quantifying polarization, emphasizing the importance of considering additional aspects for accurate polarization assessment before selecting reduction methods. Our study expands upon Interian et al. (2023) by offering a broader array of measures and organizing them into distinct categories. It also differs from Emamgholizadeh et al. (2020), where the authors did not explore specific measures within these broad categories. Due to space constraints, we only briefly introduce main categories, discuss specific measures, and highlight their limitations, shaping our RS-based polarization reduction model.

The first category, **network-based measures**, captures the complexities of community interactions. Modularity, exemplified by Dal Maso et al. (2014) and Tien et al.

(2020), suggests communities should exhibit more internal connections than external ones (Dal Maso et al., 2014; Tien et al., 2020). However, modularity alone does not invariably indicate polarization; non-polarized networks can also have modular communities (Guerra et al., 2013). Using this metric, Garcia et al. (2015) underscored the significance of the *temporal dimension* in polarization measurement, noting that contradictions may vary in their persistence over time. This highlights the inefficiency of network-based measures in capturing the evolution of polarization over time (Garcia et al., 2015). Hence, considering the temporal aspect is crucial for understanding polarization dynamics comprehensively (Tsytsarau et al., 2011; Zhang et al., 2008).

Homophily, the inclination to associate with like-minded individuals, is also a network-based measure that fosters echo chambers and polarization (Samantray and Pin, 2019). However, Dandekar et al. (2013) argued that homophily alone fails to fully polarize society without *biased assimilation*, where individuals process new information based on pre-existing beliefs. Similarly, Interian and Ribeiro (2018) emphasized that relying solely on homophily is inadequate for quantifying polarization (Interian and Ribeiro, 2018). Surprisingly, Samantray and Pin (2019) found a negative correlation between homophily and polarization, underscoring the influence of information credibility, an underexplored aspect despite its significant impact on beliefs and polarization dynamics. Information lacking *source credibility* is less likely to influence individuals.

Random Walk, a notable network-based metric, assesses opposing opinions within conversation groups (Al-Ayyoub et al., 2018). Yet, the Random Walk Controversy score, while valuable, may falter on excessively small graphs (Garimella et al., 2018), necessitating additional factors like *content* for better polarization measurement (Garcia et al., 2015). While Interian et al. (2023) classified "content" as a polarization measure, we argue that content alone does not serve as a measure. Hence, we introduce ***content-based measures***, focusing on user-generated content, utilizing methods like hand-labeling, crowdsourcing, sentiment analysis, and natural language processing techniques (Chen et al., 2018; Emamgholizadeh et al., 2020; Garimella et al., 2018).

Previous research on controversial topics focused on specific network elements like boundary nodes (Guerra et al., 2013), structure (Garimella et al., 2018), or signed networks (Bonchi et al., 2019), overlooking valuable content and user profile information (Emamgholizadeh et al., 2020; Matakos et al., 2017). However, polarization extends beyond network states, cautioning that mere segregation does not equate to polarization (Dandekar et al., 2013; Matakos et al., 2017; Morales et al., 2015). Conversely, focusing solely on textual content poses challenges in interpreting natural language, particularly in short texts, and risks models becoming language- and topic-dependent. These approaches overlook network structure, potentially skewing polarization measurement accuracy and distorting polarization dynamics by neglecting group separation within the network. Thus, we advocate for ***combined methods*** that leverage synergies between network and content-based approaches for robust results (Al-Ayyoub et al., 2018; Chen et al., 2018; Emamgholizadeh et al., 2020). Hargittai et al. (2008) applied a combined measure, insularity alongside context, to analyze link patterns in political blogs and stressed the importance of incorporating link context analysis to better understand the dynamics of engaging with diverse viewpoints. Similarly, Cossard et al. (2020) highlighted context's significance in quantifying polarization, revealing limitations in domain-agnostic methods. Defining what is controversial or polarized varies based on *context*, emphasizing its vital role in polarization assessment (Garimella et al., 2018).

In concluding this initial phase of our study, we contribute by identifying crucial aspects to consider when quantifying polarization in our RS-based polarization reduction model. These include *network structure* (Garimella et al., 2018), *temporal dimension* (Tsytsarau et al., 2011; Zhang et al., 2008), *biased assimilation* (Dandekar et al., 2013), *source credibility* (Cossard et al., 2020; Samantray and Pin, 2019), *content* (Morales et al., 2015), and *context* (Guerra et al., 2013; Hargittai et al., 2008).

2.2 Polarization Reduction with Recommender Systems

After quantifying polarization, it is crucial to develop means to counteract its detrimental effects on societies. Interian et al. (2023) reviewed studies focused on mitigating polarization's adverse effects. They highlighted RS as a relevant technological approach for reducing polarization by promoting diverse and balanced content. To conduct comprehensive research, we utilized Google Scholar's advanced search functionality, allowing for complex queries to be performed. Detailed explanations of keywords and exclusion criteria are provided in an online supplement (https://bit.ly/3Pp1fbE) due to page constraints. After exclusion, 16 articles remained. These studies aimed to expose online social media users to diverse content, with a focus on presenting varied information and identifying recipients for new information (Matakos et al., 2017). Then, we created a concept matrix (Webster and Watson, 2002) outlined in Table 1, featuring two primary dimensions, reduction methods and polarization metrics.

After crafting the concept matrix, we analyzed it to grasp the current state and research prospects for polarization reduction with RS. Our analysis revealed four key insights. First, there was a notable focus on network-based measures and edge modification reduction approaches. Second, only one study utilized content-based measures and corresponding modification strategies to reduce polarization. Third, none of these studies employed combined methods for polarization measurement. We advocate for their adoption to enable effective strategy selection based on RS, crucial for addressing the multidimensional aspects of polarization. Lastly, all studies relied on conventional RS, despite the availability of powerful techniques like deep learning-based or graph neural network-based RS. In our next phase, we employ a DSRM to develop a model for polarization reduction with RS, focusing on the multidimensionality of polarization and respective approaches for reduction.

3 Design Science Research Methodology

The above overview demonstrates that RS offer a promising approach to counter polarization's societal harm. Understanding key aspects in measuring polarization and implementing preventive strategies is crucial to mitigate its impact. To develop a conceptual model for RS-based polarization mitigation, prioritizing critical aspects to understand polarization's complexity and select effective mitigation strategies, we adopt the DSRM process proposed by Peffers et al. (2007). This process model encompasses six primary activities, enabling us to develop an artifact that can be evaluated and implemented to accomplish our research objective. The initial two activities, which involve identifying a problem and motivation, as well as establishing objectives for a solution, have been discussed in the previous sections of this paper. In this subsection, we look into the intricacies of designing and developing our proposed model.

Table 1. Conceptual analysis of polarization reduction with recommender systems

	Reduction Methods			**Polarization Metrics**			
RS Categories	Node Modification	Edge Modification	Content Modification	Network-based	Content-based	Combined	Reference
Content-Based Filtering			X		X		(Badami et al., 2017)
		X		X			(Grossetti et al., 2019)
		-		X			(Treuillier et al., 2023)
	X	X		X			(Giakatos et al., 2023)
Collaborative Filtering		X			-		(Sacharidis, 2019)
		X		X			(Ramaciotti Morales and Cointet, 2021)
		X		X			(Ramaciotti Morales and Cointet, 2021)
		X		X			(Haddadan et al., 2021)
		X		X			(Grossetti et al., 2021)
		X		X			(Donkers and Ziegler, 2021)
	X			X			(Warton et al., 2022)
		X		X			(Haddadan et al., 2022)
		X					(Cinus et al., 2023)
		X		X			(El-Moutaouakkil et al., 2023)
Hybrid Systems		X		X			(Fabbri et al., 2022)
		X		X			(Sánchez et al., 2023)

3.1 Towards a Conceptual Model for RS-based Polarization Reduction

In this subsection, we introduce a model as the artifact of the DSRM (Peffers et al., 2007). The proposed model, depicted in Figure 1, comprises three main components. Recognizing the multidimensional nature of polarization, we rigorously reassess quantification methods and identify critical aspects, ensuring the validity of reduction strategies in addressing polarization. Consequently, we introduce the first component of our model, which harnesses data extracted from social networks. This component considers factors like *network structure*, *temporal dimension*, *source credibility*, *biased assimilation*, *content*, and *context* to quantify polarization. We assert that a robust polarization measure should incorporate a combination of these determinants, as neglecting any may compromise the reliability of the results. Following this, we systematically explore potential solutions by examining various polarization measures and reduction methods to effectively tackle different dimensions of polarization. Subsequently, we introduce the second component, which includes the main categories of polarization measures. We advocate for a combined approach that integrates both network structure and content. Focusing solely on one type of measure may overlook valuable insights.

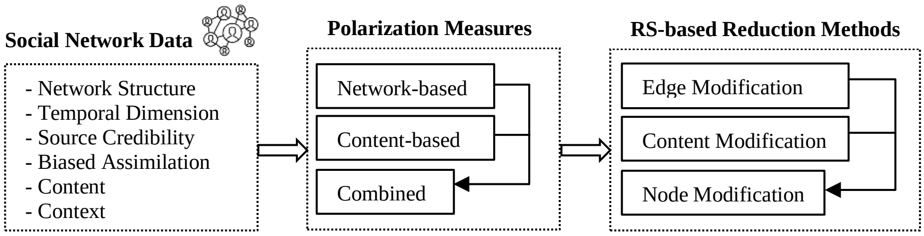

Figure 1. A conceptual model for RS-based polarization reduction

The third component involves RS-based reduction approaches, including edge modification based on network-based measures and content modification based on content-based measures. We argue that prioritizing one aspect over the other may lead to inaccurate polarization detection and ineffective mitigation strategies. We emphasize node modification as a potentially effective approach, altering both network structure and content by introducing nodes such as bots to reduce polarization. Hence, we believe employing combined measures may enhance the effectiveness of this strategy, though further empirical evidence or references are needed to substantiate this claim.

Additionally, it is important to recognize that the description in this section provides a broad overview of our approach. While we outline the general methodology, specific RS methods, design decisions like edge modifications, architectural details, and other nuanced aspects are not extensively explained here. These details are essential for a comprehensive understanding of our work and will be expanded upon in future work.

3.2 Demonstration and Evaluation

Due to space constraints and a publication that presents research-in-progress, we focus on problematization and the early steps of the DSRM process while only briefly explaining the demonstration and evaluation steps in the revised version. Using a Twitter dataset containing social network data and user-generated content, our model employs content-based, network-based, and combined measures to accurately quantify polarization. Gephi will be utilized to visualize polarized networks in the second phase. Following the identification of a polarized network, our focus shifts to reduction techniques, particularly node modification involving the introduction of new nodes such as bots, due to practical constraints favoring bots over normal users. Using Gephi, we simulate and demonstrate the long-term impact of these interventions.

For evaluation, we systematically assess network polarization across stages: establishing a baseline by measuring polarization without intervention, implementing and evaluating content modification techniques, and then edge modification techniques. Finally, we introduce bots for node modification and evaluate the resulting changes using specific polarization measures. Comparing these results aims to identify the most effective strategy and guide necessary adjustments.

In conclusion, this research introduces a DSRM-based model for quantifying and mitigating social network polarization based on RS. Integrating network-based and content-based measures, and emphasizing bot-driven node modification, our study demonstrates potential effective strategies for reducing polarization while highlighting the importance of ongoing refinement and validation in future research.

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