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Polarization in Social Media: A Virtual Worlds-based Approach

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Abstract: As social media becomes increasingly integrated within the fabric of our digital lives, it is clear that these platforms have a great impact on our mental well-being and interpersonal relationships. However, recent events and studies suggest that these changes are not always for the better as social media might contribute to social polarization. In this work, we leverage agent-based modelling (ABM) techniques to simulate the associated opinion dynamics of polarization in social media platforms. To accomplish this, we first develop a methodology for distinguishing between different types of polarization. This enables a more nuanced investigation into the interplay between behavior online and behavior offline. We next expand on the public-private split model by introducing a novel "virtual worlds" framework for representing an online social media platform. Agents from the neighbor-constrained "real world" can "log-in" to these virtual worlds with a certain probability and participate in a complete network; this reflects the unique socioeconomic and geographic anonymity provided through social media. Additionally, global homophilic influence is incorporated and its relationship with local virtual world structure is considered. We finally perform a sensitivity analysis over a set of model parameters, and find that the incorporation of virtual worlds can result in the simultaneous presence of different types of polarization in the real and virtual worlds. These findings align with studies on social media from the literature, and suggest that the online platform provided by social media poses unique challenges with regards to investigating the presence of polarization.

Keywords: Agent-Based-Model (ABM), Polarization Structure, Homophily, Polarization, Social Media Platforms

Introduction

1.1 Social media platforms such as Facebook and Twitter have come under scrutiny lately as the spread of conspiracy theories and misinformation becomes increasingly apparent. The potential danger inherent in these platforms is clear to their parent companies as well. For instance, an internal report at Facebook discovered that 64% of users in extremist groups arrived through recommendation algorithms, and social media corporations acknowledged that AI-driven algorithms played a role in the 2016 Myanmar genocide (Orlowski 2020; Hao 2021). While steps have been taken by corporate entities to address this emerging issue, such as the creation of the Responsible AI team by Facebook, these groups have been tasked with considering topics involving bias in AI instead of the potential polarization such software can bring (Hao 2021). Investigative work has suggested that such sentiments are partially intentional. In the 2020 Netflix documentary film The Social Dilemma, software engineers, ethics specialists, and critics were inquired as to their individual perspectives on social media and polarization; the majority agreed that associated corporations have found polarization to be profitable (Orlowski 2020). The investigation of what specific factors contribute the most to polarization is thus critical.

1.2 Unfortunately, a direct analysis of social media algorithms is difficult given they are the intellectual property of their respective corporations. Occasionally, relevant publications become available for public access. For

instance, Ahlgren et al. (2020) at Facebook recently documented the "WES" simulation platform. This software is designed to simulate interaction among AI-driven Facebook bots and determine potential pitfalls of the social media platform. However, because these types of sources are sanitized through the corporate approval process, pivotal details/social concerns pertinent to the study are likely to be absent. It is thus important to consider general modeling techniques which can provide an effective proxy for analyzing these problems independent of the actual commercial algorithm itself. An additional benefit of such a method is the opportunity it provides to investigate the time evolution of different types of polarization in a standardized manner. Indeed, a blend of computational opinion dynamics, agent-based modeling (ABM), and social analysis suggests a possible avenue.

1.3 Existing literature has considered several approaches to perform this kind of analysis. For instance, the social premise of homophily has been used in ABM studies to emulate the effect of social media algorithms (Mäs & Bischofberger 2015; Baumann et al. 2020; Keijzer & Mäs 2022). The computational implementation of this premise has varied: some interpretations use a probabilistic distribution which takes into account the relative similarity between participants, while others incorporate a fixed threshold (Ben-Naim et al. 2003; Mäs & Bischofberger 2015; Baumann et al. 2020; Keijzer & Mäs 2022). The structure and topology of social media networks has also been subject to study, with some works considering a disjoint set of online and offline agents (Dong et al. 2021) and others leveraging multi-layered/multiplexed models (Hristova et al. 2014; Peng & Porter 2022). Nevertheless, a systematic investigation into the types of polarization in social media through an agent-based representation of social media platform structure can be further explored.

1.4 To this end, we take a more sophisticated approach which is reflective of real-life social interaction. We first aim to distinguish among different types of polarization. Two important variants are *structural* and *un-structural* polarization: the former is characterized by the presence of relatively large/organized clusters of convictions, while the latter involves agents with varying convictions dispersed throughout the network (i.e., fragmentation). Note that in structural polarization the majority of individual agents will have fully concordant neighbors, leading to an "illusion of consensus" that is not present in un-structural polarization. This microscopic perspective allows for the development of mesoscopic congruence measures which can differentiate among the two types. We next introduce a novel virtual worlds framework to represent a social media platform from an ABM perspective. Agents "log-in" to virtual worlds with probability λ and can participate in a complete social network; this reflects the relative socioeconomic and geographic anonymity of social media (Suler 2004). After additionally integrating homophily as a social premise through a parameter h, we perform a sensitivity analysis with 4400 total independent simulation trials. We then investigate which model parameters are most relevant in the development of different types of polarization and outline a social commentary. Our results reveal that increasing the strength of homophily can lead to a fundamental asymmetry of polarization, where the real world demonstrates un-structural polarization while the virtual worlds feature structural polarization. These results agree with findings from previous studies, suggesting that this kind of superposition is a unique characteristic of social media platforms (Conover et al. 2011; Bakshy et al. 2015; Keijzer & Mäs 2022).

Social Media Characterizations

2.1 We consider a brief overview of social media platforms to motivate later discussions and modeling techniques. The basic principles underlying the technology were established under the Web 2.0 era, when increased computational power and new technologies enabled a philosophical transition of the internet towards "applied services" (van Dijck 2013, pg. 6). In the mid-2000s, Facebook and Twitter were released and began to take advantage of this medium for social communication (van Dijck 2013, pg. 7). These platforms have since achieved great success, with more than half the global human population currently users (Kemp 2022).

Social media algorithms, structure, and polarization

2.2 To help engage their userbase, social media platforms leverage a variety of algorithms and AI-driven technologies (van Dijck 2013; Vosoughi et al. 2018). For instance, Facebook uses proprietary EdgeRank and GraphRank algorithms to collect data and determine what each user should be shown on their News Feed (van Dijck 2013, pg. 49). Empirical research on the News Feed feature revealed the presence of homophilic tendencies and concluded that there exists a tangible susceptibility of these algorithms to polarization (Bakshy et al. 2015). However, this study suggested that individual action was more pivotal in maintaining such boundaries, a claim supported by the analysis of other platforms such as YouTube (Cho et al. 2020).

2.3 Another important aspect of social media platforms is subgroup structure. On one hand, these can emerge naturally through large-scale discussion on divisive issues. The presence of this in Twitter was empirically investigated through a cluster analysis (Conover et al. 2011; Gaisbauer et al. 2021). While "community structure" and political polarization were found in the retweet network, the mentions network was more unstructured. On the other hand, subgroups can be artificially delineated. For instance, on the popular site Reddit users are free to create their own communities (dubbed "subreddits") for different topics. The role of polarization in these settings is less clear.

The human impact of social media

2.4 Some of the observed human impacts of social media platforms can be summarized into the following two concepts. The first is the possibility for *addiction*. Turel et al. (2014) used magnetic resonance imaging (MRI) to reveal that platforms such as Facebook share "some neural features with substance and gambling addictions". Given that reward-based systems are key to the neurology underlying human impulsiveness, it becomes clear that social media platforms have the effect of disrupting the usual process underlying human motivation for rewards (Turel et al. 2014).

2.5 The second concept is *disinhibition*. Online environments are intrinsically different from those offline: for instance, users may use an anonymous pseudonym in several social media platforms (Tucker et al. 2018, pg. 11). As a result, some users may feel emboldened and cultivate a persona distinct from their offline personality. Suler (2004) coins this phenomenon as online disinhibition and defines it through a set of six distinct yet mutually interacting factors. An important theme throughout Suler's analysis is the understanding that the virtual setting of social media platforms fundamentally strips human interaction of socioeconomic behavioral cues (i.e., body language, wealth, authority, etc.) leading to a state where individuals can effectively ignore the limitations of their usual offline identity and interpersonal relationships (Suler 2004).

Agent-Based Modeling of Opinion Dynamics

3.1 In this section, we consider the basics of agent-based modeling (ABM) of opinion dynamics, a popular choice for simulating polarization. In this type of model, a graph represents a collection of "agents" and connections. Making a parallel to reality, agents represent individuals and connections represent acquaintances, while the graph represents a social network. Each agent can express an arbitrary set of opinions, although in several models these are limited to two options for simplicity. In general, agent opinions aim to mirror those of human individuals and can be expressed to various degrees of confidence, with the level of granularity implementation dependent; common options include nominal/discrete values or a continuous interval (Flache et al. 2017). Over time, the state of the model regularly updates during discrete events called time steps and the opinions of agents may change.

Modeling classes and premises

3.2 There are three major classes of agent-based models used for opinion dynamics. They are *assimilative* models, *similarity-biased* models, and *repulsive* models (Flache et al. 2017).

3.3 Assimilative models operate under the underlying assumption that interacting agents seek to reduce opinion differences. This is the orthodox perspective and is supported by empirical literature and cognitive consistency theories (Cartwright & Harary 1956; Festinger 1957; Heider 1967; Vinokur & Burnstein 1978; Friedkin & Johnsen 2011). Computationally, these models are characterized by the use of scaled weights between agents to capture mutual socioeconomic influence. The resultant system state often depends on the granularity of agent opinions. For instance, continuous models update through a process of social averaging and typically end with a final system state of consensus (DeGroot 1974). On the other hand, nominal interpretations (such as the voter model) have the potential for more sophisticated outcomes. General limitations of this modeling paradigm include the inability to track the development of opinion diversity (Axelrod 1997; Hegselmann & Krause 2002).

3.4 Similarity-biased models assume agents prefer interaction with like-minded neighbors. This paradigm is also supported by classic literature, such as social judgement theory and homophily (Lazarsfeld & Merton 1954; Sherif & Hovland 1961; McPherson et al. 2001). Computational implementations include *probabilistic homophily* and *bounded confidence*, the strength of which can be modified through the presence of tunable parameters.

The final outcome of the model depends on these parameter choices as well as on the opinion change function that the model implements. For instance, if bounded confidence is coupled with assimilation dynamics a narrow margin for agreement will lead to fragmentation, while larger confidence thresholds result in opinion clustering or global consensus (Deffuant et al. 2000; Hegselmann & Krause 2002; Flache et al. 2017). Despite its versatility, limitations of these models involve sensitivity to noise (Flache & Macy 2011; Flache et al. 2017). Averaging models are also not capable of producing extreme outcomes without further assumptions on the presence of stubborn "extremists" or more complex opinion structures (Deffuant et al. 2002; Mäs & Flache 2013; Tian & Wang 2017; Banisch & Olbrich 2021).

3.5 The final major category are repulsive models, which assume that it is possible for differentiation to occur. This is more of a revisionist perspective which reframes some of the social theories mentioned above to allow for negative influence (Jager & Amblard 2005; Baldassarri & Bearman 2007; Flache et al. 2017). Computationally, this is represented by allowing weights to be negative. Repulsive models demonstrate the widest variety of final system states, including fragmentation, extreme consensus, and structural polarization. Nevertheless, a fundamental limitation is high sensitivity to initial conditions (Flache et al. 2017). There is also limited contemporary empirical justification for the underlying social premises. For instance, Takács et al. (2016) observed that opinion difference and general dislike did not cause negative influence in a controlled online communication setting.

3.6 Alternative modeling classes also exist. One such approach involves argument-based models. These assume that the opinion of an agent is defined by a set of pro and con arguments which are exchanged in interaction (Mäs & Flache 2013; Banisch & Shamon 2021; Taillandier et al. 2021; Betz 2022). Another modeling class, which we dub the *public-private split* model, is unique in that it distinguishes between public expressions of and private convictions in opinions. In these models individuals express their opinion and react to approval and disapproval by their peers (Banisch & Olbrich 2019). Interactions between agents on the same side of the opinion spectrum lead to increased private confidence, while interactions between agents that express opposing opinions decrease it. A motivation for this approach is the sociological concept of *pluralistic ignorance*, which involves the dissonance between public expression and private opinions caused by social pressure (Asch 1955; Huang & Wen 2014; Mitsutsuji & Yamakage 2020). This, for instance, is relevant in the opinion dynamics of warmoods (Mitsutsuji & Yamakage 2020). Computational implementations of the approach differ. Martins (2008) leveraged a combination of Bayes rule and random walk theory to propose the CODA model, which can additionally be integrated with bounded confidence (Martins 2008; Zhan et al. 2022). Recently, Banisch & Olbrich (2019) proposed an implementation inspired by reinforcement learning/reward driven techniques and neurobiology studies (cf. Banisch et al. 2022). Note that despite not leveraging similarity-bias or negative influence, this model class is able to demonstrate a variety of outcomes such as polarization, consensus, and extreme convictions.

3.7 We decide to extend the *public-private split* model from Banisch & Olbrich (2019) for analysis due to its theoretical alignment with concepts from the *Social Media Characterizations* section. Specifically, the split between public and private expressions can be interpreted as an abstraction of the disinhibition effect, while the reward-driven neurological inspiration of the model parallels the underlying neural theory of social media platforms.

Representing social media computationally

3.8 In ABM, a common approach for representing social media has been through similarity-biased models and *homophily*. In general, homophily represents the social phenomenon in which individuals with similar opinions, personalities, or cultures are more likely to communicate with each other (McPherson et al. 2001). Within the context of ABM for opinion dynamics, homophilic interactions are often represented through a tunable numeric parameter which limits the extent to which agents can engage with discordant neighbors. The most common forms of computational implementation are *probabilistic homophily*, where interaction probabilities are weighted according to the relative similarity of a given neighbor, and *bounded confidence*, where neighbors beyond a specified upper bound for opinion difference are ignored (Carley 1991; Hegselmann & Krause 2002; Banisch et al. 2010; Mäs & Bischofberger 2015; Baumann et al. 2020; Keijzer & Mäs 2022).

3.9 We first outline *probabilistic homophily*, which often involves representing homophily as a continuous probabilistic distribution (Carley 1991; Axelrod 1997). For instance, in a popular variant by Axelrod (1997) different agents are assigned a "culture" with five traits. The probability distribution is then derived through a "similarity score," which is a discrete metric directly proportional to the number of matched traits (Axelrod 1997). Other variations have been designed specifically to model the effects of social media. Mäs & Bischofberger (2015) accounted for the presence of personalization in social media through a power law decay implementation of

probabilistic homophily, and Baumann et al. (2020) modeled social media algorithms using a similar approach; the latter was empirically verified through Twitter data.

3.10 The *bounded confidence* implementation differentiates itself by being more binary in nature (Hegselmann & Krause 2002). The concept was introduced by Hegselmann & Krause (2002), and involves a numerical threshold γ for a given agent. During the update step, all potential neighbors with an opinion difference greater than γ are ignored. The relative simplicity of this method has made it an object of analysis across several studies. For instance, Ben-Naim et al. (2003) observed that varying γ has a complex impact on the final system state. Others have developed extensions upon the basic premise to model social interactions online (Del Vicario et al. 2017; Sîrbu et al. 2019).

3.11 The structure of social media has been less accounted for in the literature; nevertheless, there are some relevant studies. For instance, Dong et al. (2021) characterizes social media interactions by considering a disjoint set of online and offline agents. Another approach includes using multi-layered/multiplexed models, which incorporate an ensemble of agent networks to represent alternative communication channels (Hristova et al. 2014; Peng & Porter 2022). In this study, we introduce a novel "virtual worlds" framework similar in concept to multi-layered models; this involves a set of online parallel agent networks which agents from the offline "real world" can "log in" to with probability λ. The virtual worlds are complete, which reflects the general absence of socioeconomic influence and the erosion of geographic limitations due to the disinhibition effect (Suler 2004). The virtual exploration rate parameter λ provides a variable abstraction of the addiction effect in social media; a higher λ represents a greater ability for the platform to distract users. We additionally incorporate homophily, and to account for the empirical results discussed in Bakshy et al. (2015) it is used as a general social premise at both the real world and virtual world levels. The implementation of probabilistic homophily from Mäs & Bischofberger (2015) is adopted due to its ease-of-use and reliability.

Methodology

4.1 In this section, we first outline the *public-private split* model by Banisch & Olbrich (2019), which serves as a computational basis for this work. Next, we introduce the virtual worlds framework and detail how it represents an abstraction of an online social media platform. We then describe relevant parameters in our analysis, such as α (learning rate) and ε (exploration rate) from the original model and h from the computational implementation of probabilistic homophily. We finally discuss metrics used to quantitatively analyze simulation runs and additionally conceptualize the notions of *structural* and *un-structural* polarization.

Theoretical framework

Public-private split model

4.2 The public-private split model is a novel ABM implementation which leverages reinforcement learning concepts in addition to the standard framework for opinion updates (Banisch & Olbrich 2019). In this model, each agent a_i expresses a publicly visible opinion $o_i \in \{-1, 1\}$ [1] and carries an associated private confidence for both opinions $Q_i(1), Q_i(-1) \in [-1, 1]$. The publicly visible opinion follows:

$$o_i = arg\,max\, Q_i(o), \text{where } o \in \{-1, 1\} \tag{1}$$

4.3 This means that the opinion with higher confidence is expressed in agent interactions. Occasionally however the agent may choose to express the opposite opinion with probability ε; this parameter is called the exploration rate. While the exploration rate is a fixed parameter in Banisch & Olbrich (2019), in this work we will incorporate a more adaptive variant in which ε becomes smaller as agents become more convinced in their opinions. This extension will be discussed more in detail in the *Public-private split parameters* section.

4.4 After specifying the values of relevant parameters, the simulation begins by creating a random graph of agents and then progresses for n time steps. At a given time step t, an agent a_i is randomly selected. Among potential candidates, an agent a_j is randomly matched and the pair play a "game." The public opinions o_i and o_j are compared: if the agents agree (i.e., $o_i = o_j$), then a_i had a "positive" experience and a_i's private confidence

increases. Otherwise, the opposite occurs (Banisch & Olbrich 2019). The update step can be defined according to the Q-learning update canonical form as:

$$\begin{bmatrix} Q_i(o_i) \\ Q_i(o_i') \end{bmatrix} \leftarrow \begin{cases} \begin{bmatrix} Q_i(o_i) + \alpha\left(o_i o_j - Q_i(o_i)\right) \\ Q_i(o_i') \end{bmatrix} & \text{w.p. } 1-\varepsilon \\ \begin{bmatrix} Q_i(o_i) \\ Q_i(o_i') + \alpha\left(o_i' o_j - Q_i(o_i')\right) \end{bmatrix} & \text{else} \end{cases} \tag{2}$$

4.5 Here, o_i is the public opinion of a_i (either 1 or -1) and o_i' is the other opinion; in general, agents favor agreement over disagreement. The parameters α and ε are the learning rate and exploration rate respectively and are discussed more in depth in the later *Public-private split parameters* section.

Spatial random graph

4.6 Agent-based models are typically initialized using scale-free graphs and small-worlds graphs (Flache & Macy 2011). The implementation from Banisch & Olbrich (2019) is unique in that it leverages a spatial random graph topology, which is a special case of the Erdos-Renyi random graph. A description is as follows: suppose we assign the 2D spatial coordinates $(x_i,\, y_i)$ to agent a_i. We define E as the set of all possible edges, and additionally define $C \subseteq E$ as the subset of edges which exist. Then, the probability of the edge $e_{ij} \in E$ which connects agent a_i and agent a_j existing is:

$$P\{e_{ij} \in C\} = \begin{cases} 1 & \text{if} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} < r \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

4.7 In other words, if the distance between two agents is less than a previously defined radius r, then the connecting edge will be created. The primary motivation for this topology over others is that it generates a spatial clustering which mimics the impact that sociodemographic factors have on spatial filtering and community formation. This is an appropriate model for the primary network/real world in our study as it captures the vast sociodemographic diversity present among potential social media platform users.

Virtual worlds

4.8 We introduce a novel virtual worlds infrastructure for representing online social media interaction. This is implemented through an additional set of m parallel agent networks, each of which is complete. We enforce this characteristic due to the relative socioeconomic and geographic anonymity provided by social media, which contrasts the primary network/real world described in the *Spatial random graph* section (Suler 2004).

4.9 A set of m virtual worlds begin empty and become populated as the simulation progresses (intuitively akin to subreddits on the social media site Reddit). At time step t, the chosen agent a_i decides to enter a virtual world with probability λ instead of immediately choosing a match as described in the *Public-private split model* section. The agent then evaluates the m parallel virtual worlds based on the ratio of publicly concordant members to publicly discordant members. For instance, consider the k^{th} virtual world v_k. Additionally, let $o_i \in \{-1, 1\}$ represent the public opinion for agent a_i and let o_i' be the other opinion. We define the number of members with opinion $o = o_i$ as f_{agree} and the number of members with opinion $o = o_i'$ as $f_{disagree}$. Then the evaluation χ_k of the k^{th} virtual world v_k is:

$$\chi_k = \frac{f_{agree} + 1}{f_{disagree} + 1} \tag{4}$$

4.10 Adding one to the numerator and denominator smooths the metric and prevents the possibility of a division by zero (i.e., this can occur if the virtual world is homogeneous in opinion or it is completely empty). This type of evaluation of the virtual worlds is inspired by social identity theory, which posits that individuals compare their ingroup and outgroup in relative rather than absolute terms (Brewer 1999; Tajfel & Turner 2004; Weisel & Böhm 2015).

4.11 The agent a_i then generates a probability p_k for the k^{th} virtual world v_k according to the softmax function:

$$p_k = \frac{e^{\chi_k}}{\sum_{i=1}^{m} e^{\chi_i}} \tag{5}$$

4.12 After randomly selecting a virtual world v_r according to the softmax probability distribution, the agent a_i "creates an account" if it has not visited v_r before by establishing links with every other agent in v_r; this link creation step enforces the complete nature of the virtual worlds. Otherwise, the agent a_i simply "logs-in" and does not create any additional links. The agent a_i then continues with the game described in the *Public-private split model* section, albeit limited to randomly matching with neighbors in v_r. In the edge case where v_r is empty (i.e., a_i is the first to join), a_i defaults to interacting with its usual set of neighbors from the real world.

Model summary

4.13 In this study, we simulate a set of N agents $\mathcal{A} = \{a_i : 1 \leq i \leq N\}$. Each agent a_i will follow the opinion model described in the *Public-private split model* section; specifically, every agent will have a private confidence and a public opinion, and opinion updates after matching will leverage Equation 2.

4.14 The topology of the simulation is described in Figure 1. We incorporate a primary network/real world according to the structure discussed in the *Spatial random graph* section and an additional m virtual worlds according to the form detailed in the *Virtual worlds* section. Note that the the set of agents $\mathcal{A}$ is constant throughout both the real world and virtual worlds; essentially, the purpose of the $m + 1$ total worlds is to dynamically adjust the matching process before two agents interact with each other.

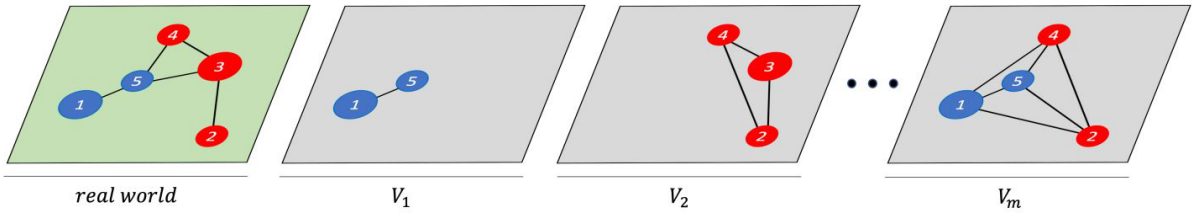


Figure 1: An illustration which demonstrates the topology associated with the simulation. In this example, there are overall $N = 5$ agents with real world neighbors determined by physical proximity. Agents are free to participate in any virtual world, although the composition of individual virtual worlds may differ. For instance, here we have that V_1 is a homogeneous "blue" network, V_2 is a homogeneous "red" network, and V_m is heterogeneous in opinion. Note that each virtual world is complete, allowing connections among agents which would not have been possible in the real world.

Computational framework

Public-private split parameters

4.15 We briefly consider two important parameters in the public-private split model: the exploration rate ε and the learning rate α.

4.16 The exploration rate ε is a probability (restricted to $0 \leq \varepsilon \leq 1$) which dictates whether an agent a_i during an interaction expresses the opposite to their current public viewpoint o_i. The sociological objective of this parameter is to parallel the uncertainty individuals have in their own opinions, while the computational objective is to allow the confidence level associated with the opposing viewpoint to update periodically as per reinforcement learning theory. In the original public-private split model, the exploration rate is immutable (Banisch & Olbrich 2019). The exploration rate is modified in this work to be more adaptive by using a softmax-like function:

$$\varepsilon = \frac{e^{\beta \cdot Q(o_i')}}{e^{\beta \cdot Q(o_i')} + e^{\beta \cdot Q(o_i)}} \tag{6}$$

4.17 This implementation acknowledges that strongly convinced agents are less likely to change their opinions. A parameter β is introduced to dictate how soft or hard the max is.

4.18 The learning rate α is a positive scaling factor that controls the amount to which interactions among agents can adjust private confidence levels (Banisch & Olbrich 2019). For instance, a large learning rate corresponds to a situation in which disagreements among agents greatly impact confidence values, making opinion flipping more likely.

Probabilistic homophily parameter

4.19 As discussed in the *Representing social media computationally* section, our model incorporates *probabilistic homophily*. We adapt the variant from Mäs & Bischofberger (2015), where the probability $p_{j,t}$ that an agent a_i will contact an adjacent agent a_j at time step t follows:

$$sim_{ij,t-1} = 1 - \frac{|\Delta Q_{i,t-1} - \Delta Q_{j,t-1}|}{4} \tag{7}$$

$$p_{j,t} = \frac{(sim_{ij,t-1})^h}{\sum_{j=1,j\neq i}^{N} (sim_{ij,t-1})^h} \tag{8}$$

4.20 Here we define $\Delta Q_{i,t-1} = Q_{i,t-1}(1) - Q_{i,t-1}(-1)$ as the agent's conviction, with notation borrowed from the *Theoretical framework* section. $\Delta Q_{j,t-1}$ is defined analogously. An extra factor of $\frac{1}{2}$ is introduced in the similarity metric to account for the fact that $\Delta Q_{i,\,t-1}, \Delta Q_{j,t-1} \in [-2, 2]$. In general, the probability of a connection decreases as the difference in agent conviction increases.

4.21 The parameter h is of interest, as it directly impacts the extent to which concordant interactions are favored. Specifically, a greater value of h exponentially increases the weight of similar neighbors and vice versa. By tuning this, we can adjust underlying social assumptions about the innate propensity for individuals to seek out like-minded neighbors. Given the persistence of human-driven homophily in social media platforms (which is possibly enhanced by social media algorithms), we incorporate these effects in both the real world and virtual worlds (Bakshy et al. 2015; Mäs & Bischofberger 2015; Baumann et al. 2020). Note that from a computational perspective, this replaces the uniform probabilistic distribution assumed with the original public-private split model (Banisch & Olbrich 2019).

Virtual exploration rate parameter

4.22 The virtual exploration rate $\lambda \in [0, 1]$ is a parameter which represents the probability an agent a_i decides to explore virtual worlds. We leverage the modeling assumption that λ is probabilistically independent of each individual p_k generated, using notation from the *Virtual worlds* section. This reflects how the act of opening a social media application does not eventually impact the actual content consumed.

Code availability

4.23 Banisch & Olbrich (2019) have provided MATLAB code that implements the model from the *Public-private split model* section. We expand on this framework and write code to represent the virtual worlds data structure and probabilistic homophily implementation. The model code can be found at CoMSES through `https://www.comses.net/codebases/731b221c-438c-4ffa-b2c1-006a253a5999/releases/1.0.0/` or at GitHub via `https://github.com/djapp18/VirtualWorlds-ABM/tree/main`.

Simulation metrics

4.24 The model proposed in this paper may give rise to global consensus or opinion bi-polarization depending on the model parameters. In the context of the model, polarization means that agents develop and stabilize on strong convictions in opposing opinions. However, the model features two distinct types of bi-polarization which we refer to as structural and un-structural polarization. They differ with respect to how diverging opinions are distributed over the spatial random graph (see Figure 2). Therefore, in addition to standard measures that distinguish between a uni-modal consensus and a bi-modal polarized distribution (DiMaggio et al. 1996; Bramson et al. 2016), we implement a network-based measure to distinguish between these two different forms of polarization.

Consensus versus polarization

4.25 In order to differentiate consensus from bi-polarized opinion profiles we follow previous work (DiMaggio et al. 1996; Mäs & Flache 2013; Bramson et al. 2016; Banisch & Olbrich 2019) and consider the *dispersion* metric, which

is the variance over the distribution of convictions

$$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(\Delta Q_i - \Delta\bar{Q}\right)^2. \tag{9}$$

Our model gives rise to idealtypic opinion distributions and does not feature more complex, multi-modal distributions of "strong diversity" (Duggins 2017). For this reason, dispersion is sufficient to characterize the final state of the model and we do not need more complex measures such as those used in Lorenz et al. (2021). A small dispersion suggests that the agents are in consensus, while a high dispersion implies the presence of polarization. Nevertheless, to properly verify the presence of consensus, we additionally mark the fraction of runs across a set of trials which end in consensus.

4.26 Another characteristic that we track to characterize the emergent model distributions is the magnitude of average conviction (absolute value of the mean) which characterizes the shift of the distribution

$$|\Delta\bar{Q}| = \left|\frac{1}{N}\sum_{i=1}^{N}\Delta Q_i\right|. \tag{10}$$

A low value implies either polarization or neutral consensus, while a larger value implies extreme consensus. The former can be differentiated by considering the shift metric in conjunction with dispersion.

Structural versus un-structural polarization

4.27 While the distributions of convictions is sufficiently characterized by its mean and variance, a mesoscopic view on the system is needed to distinguish between structural and un-structural polarization. Here the question is how agents with opposing opinions are distributed over the network. The social feedback model by Banisch & Olbrich (2019) predicts polarization along structural holes between different network communities. As illustrated on the left of Figure 2, structural polarization is characterized by within-community alignment and across community alienation. On the other hand, models of homophily or bounded confidence (Deffuant et al. 2000; Hegselmann & Krause 2002) predict polarization even in completely connected graphs. On a network with communities, this leads to un-structural polarization in the sense that opinions of opposing sign co-exist within structural groups (i.e. network communities). This is illustrated on the right of Figure 2.

4.28 Notice that the spatial distribution of opinions over the network has a strong impact on how individuals perceive the current state of the system. Under structural polarization most neighbors share the same opinion creating an "illusion of consensus" for agents at both sides of the opinion spectrum. In the latter case of un-structural polarization instead, many agents have close neighbors with whom they disagree and thus agents have the impression of a polarized opinion landscape.

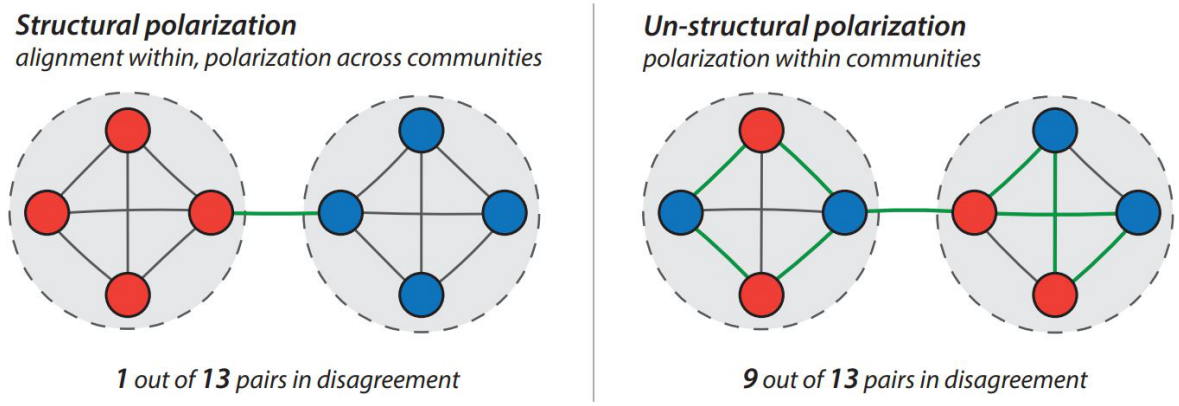


Figure 2: Different types of polarization that emerge from the model.

4.29 We quantify this aspect by the relative number of neighbors that are in disagreement. Let us denote as $o_i = \text{sign}(\Delta Q_i)$ the opinion of agent i. If the total number of undirected edges in the network is $|E|$, the relative

number of linked agent pairs with different opinions is:

$$n_d = \frac{1}{|E|} \sum_{(i,j)\in E} \frac{1}{2}(1 - o_i o_j) \tag{11}$$

where the transformation $\frac{1}{2}(1-o_i o_j)$ assigns 1 if i and j disagree ($o_i \neq o_j$). Notice that this is very similar to the definition of the system's energy in Ising-like socio-physics models (Stauffer 2007; Krapivsky et al. 2010; Jdrzejewski et al. 2015). Additionally, note that n_d belongs to the general class of polarization measures proposed by Esteban & Ray (1994). By definition it directly adheres to the guiding principle to understand polarization in terms of the effective antagonism in the system, and we shall refer to n_d correspondingly as total effective antagonism or incongruent links percentage. Alternatively, for tracking purposes we can consider the inverse metric $1 - n_d$ which refers to agreement among neighbors instead of disagreement; we dub this the inverse total effective antagonism or congruent links percentage.

4.30 The two examples shown in Figure 2 illustrate how the total effective antagonism differentiates between structural and un-structural polarization. On the left, there is only one connection that links agents with opposing opinions (green). 12 out of 13 edges connect agents that agree to one another so that the total effective antagonism becomes very low ($n_d = 1/13$). On the right-hand side of Figure 2 instead 9 out of 13 agent pairs connected by the graph are at disagreement leading to $n_d = 9/13$. The measure is bound to the unit interval $n_d \in [0, 1]$ but extremal values of zero or one become possible in special cases. For instance, the measure is zero in the case of global consensus or if different opinions coexist in disconnected communities of the graph. On the other hand, it may reach one in low-dimensional lattices, for instance, on rings with an even number of nodes and opinions switching from node to node.

4.31 On a SRG with random assignment of opinions (initial condition) $n_d \approx 0.5$ meaning that around half of the edges are between unequal and the other half between equal opinions. Under the model dynamics the total effective antagonism does not reach higher values, but reduces to values close to zero if polarization becomes structural (see, e.g. Figures 4b and 6b). A low value of effective antagonism hence characterizes a high level of structural polarization.

Virtual worlds metrics

4.32 We also compute the following virtual world metrics at the end of each simulation run. Specifically, we introduce a metric designed to track polarization among a set of m virtual worlds called *virtual world dispersion*.

$$\sigma_V^2 = \frac{1}{m-1} \sum_{k=1}^{m} \left(\Delta\bar{Q}_{v_k} - \Delta\bar{Q}_v\right)^2 . \tag{12}$$

4.33 Each $\Delta\bar{Q}_{v_k}$ represents the average over the convictions in virtual world v_k, and is computed similarly to Equation 10 but without taking the absolute value.

4.34 Additionally,

$$\Delta\bar{Q}_v = \frac{1}{m} \sum_{k=1}^{m} \Delta\bar{Q}_{v_k} \tag{13}$$

is the overall average. Thus, this metric captures the extent to which the agent makeup of the virtual worlds are mutually different from each other. A high value implies that the virtual worlds are dissimilar in average agent conviction, and that there is *structural polarization* at the virtual worlds level. Note that there are computational edge cases to consider involving empty virtual worlds. Therefore, if some subset $W \subseteq V$ of all virtual worlds V has no members at the end of the simulation, we ignore W and calculate σ_V^2 as if there are only $m - |W|$ virtual worlds. In the scenario where $m - |W| \leq 1$, we define $\sigma_V^2 = 0$.

Social analysis framework

4.35 We will also determine the social theoretical implications of social media platforms by analyzing the data from our model. One manifestation of this method involves assigning social representations to key parameters within a computational model/algorithm and considering the impact of different tunings on final outcomes. Rieder (2012) leverages this kind of methodology while investigating Google's PageRank algorithm. He first

evaluates the algorithm within its broader historical context, and then actively adjusts a "damping factor" parameter to observe how the algorithm reacts (Rieder 2012). He concludes by remarking on the hypothetical state of the internet if different values were chosen for the damping factor. This serves as an important reference by demonstrating how to systematically interpret quantitative results based on different social assumptions of how users interact with software.

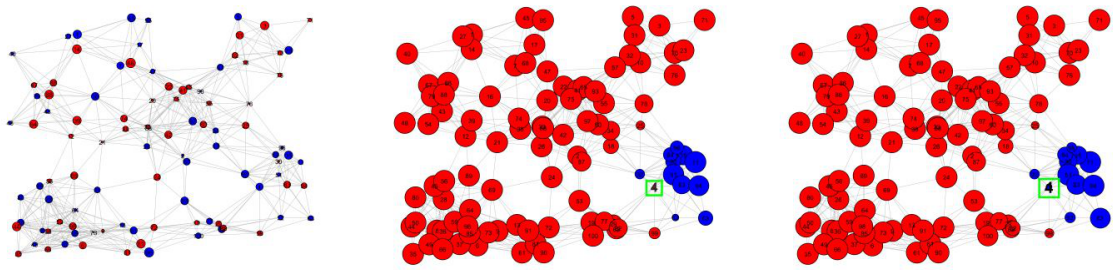
Results

Equivalency testing

5.1 As discussed in the *Public-private split parameters* section, we adjust the exploration rate parameter so that it now follows an adaptive softmax implementation instead of a constant value. To ensure that this adjustment preserves the social outcomes associated with the original model, in this section we check for consistency in the final system states of the two implementations. We perform this check to ensure that the modelling and social assumptions encoded within the original public-private split model are still valid for the adjusted model. Indeed, if final system states were vastly different, this would imply that the addition of the softmax implementation destructively interferes with the remainder of the original model; as a result, a more through investigation into the sociological cause for such a difference would be required.

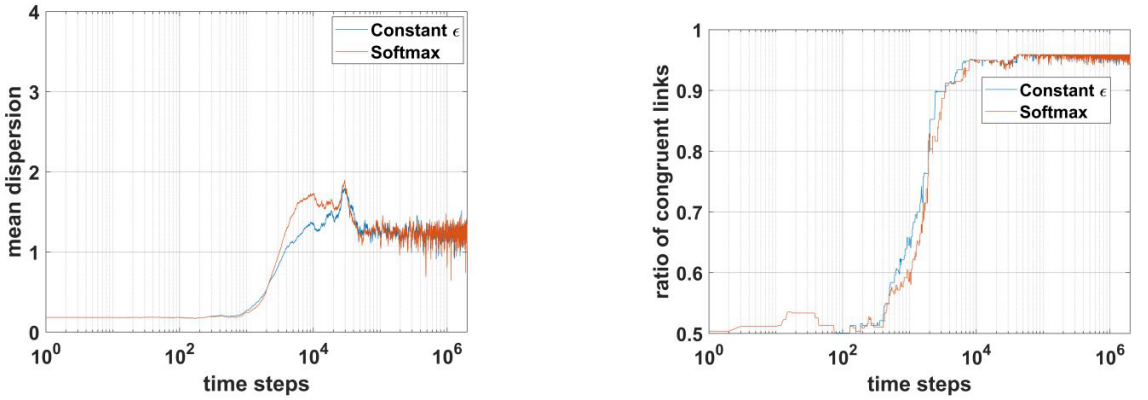
5.2 We leverage exemplary parameter settings of $\alpha = 0.1$, $N = 100$, and $r = 0.225$ for both implementations. Additionally, for this specific experiment we have $m = 0$ virtual worlds in order to maintain compatability with the original model (Banisch & Olbrich 2019). The simulations run for $n = 20000 \cdot N$ time steps. Despite the innate inability to draw a direct equivalency between the parameters ε and β, we set $\varepsilon = 0.1$ and $\beta = 1$; the choice of the latter ensures at maximum conviction the adaptive exploration rate reaches a minimum of $0.1192 \approx 0.1$. Additionally, while comparing simulations we ensure that both models encounter the same pseudo-random events. Intuitively, we expect to see some similarities between the final system states of both implementations. This is because as discussed previously, at maximum conviction the adaptive exploration rate approximates the constant implementation. When conviction is low, the adaptive exploration rate will be much higher than the constant implementation; however, at this point the associated agent is primed to flip its opinion regardless.

5.3 After running simulations for both implementations, we found that they often demonstrated similar quantitative and qualitative results. Figure 3 shows a case in which the results were similar and end in structural polarization. In both models the final system state is qualitatively the same, except for a few agents (i.e., agent 4 is opinion "red" in the constant exploration rate model, but is opinion "blue" in the softmax model). Quantitative agreement among the two implementations is also clear when inspecting the polarization metrics in Figure 4. For instance, dispersion in both models peaks at 30000 time steps with a value of 1.87, then declines and stabilizes around 1.25 (see Figure 4a). Congruent links percentage in both models demonstrates a sharp increase, followed by stabilization at 40000 time steps around a value of 96% (see Figure 4b). Note that final dispersion is high, and final congruent links percentage is high (but not 100%) as expected for structural polarization. In general, the softmax implementation seems to fluctuate more, possibly because of its adaptive nature.



(a) Initial state (b) Final state, constant ϵ (c) Final state, softmax

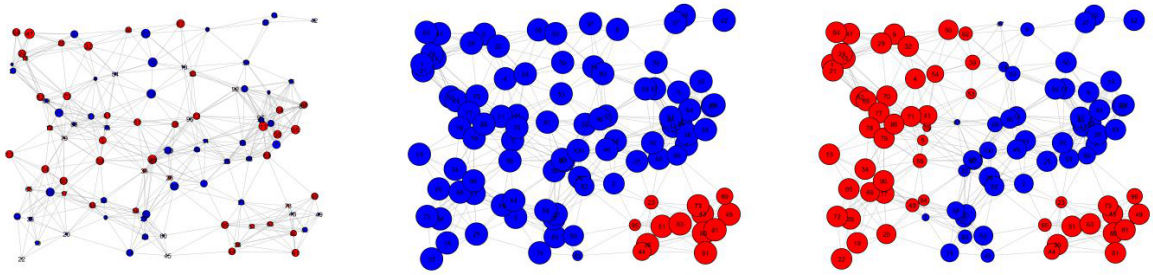
Figure 3: System state tracked over time in a sample run where both models demonstrated similar results; only agent 4 was different, and is highlighted in the figures. Agent node size is proportional to the magnitude of their convictions.



(a) Dispersion for both models (b) Congruent links percentage for both models

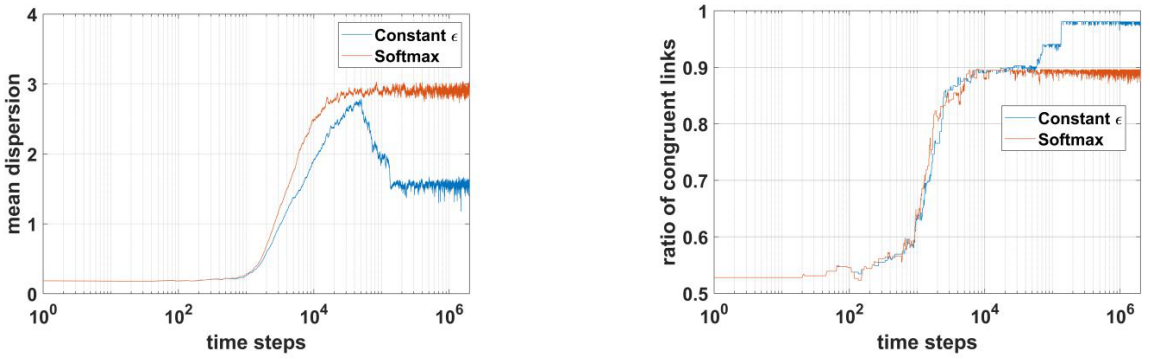
Figure 4: Time evolution of selected metrics for both models; note that in this sample run, the temporal trajectories are very similar.

5.4 On the other hand, occasionally the two implementations demonstrated different results. Figure 5 shows such a case in which both models lead to structural polarization, although the final structures are different. Qualitatively, the constant exploration rate model features a large opinion "blue" cluster with a small opinion "red" cluster, while the softmax model features a medium opinion "blue" cluster and two disconnected opinion "red" clusters. Additionally, a comparison of the polarization measures in Figures 6a and 6b reveals quantitative disagreement among the two implementations. For instance, dispersion stabilizes around 1.6 for the constant exploration rate model but stabilizes around 2.9 for the softmax model. For congruent links percentage, stabilization occurs around 98% for the constant exploration rate model but 89% for the softmax model. Note that despite visual differences in final system state, there is still internal consistency among the qualitative and quantitative metrics for both models. Final dispersion is low and final congruent links percentage is high (but not 100%) for the constant exploration rate model, which agrees with the qualitative observation of a final system state close to consensus. Additionally, final dispersion is high and final congruent links percentage is low for the softmax model, which aligns with the qualitative observation of a final system state in structural polarization with disconnected groups. Unlike the previous example, fluctuations occur in the polarization metrics for both models.



(a) Initial state (b) Final state, constant ε (c) Final state, softmax

Figure 5: System state tracked over time in a sample run where the models demonstrated different results. Agent node size is proportional to the magnitude of their convictions.



(a) Dispersion for both models (b) Congruent links percentage for both models

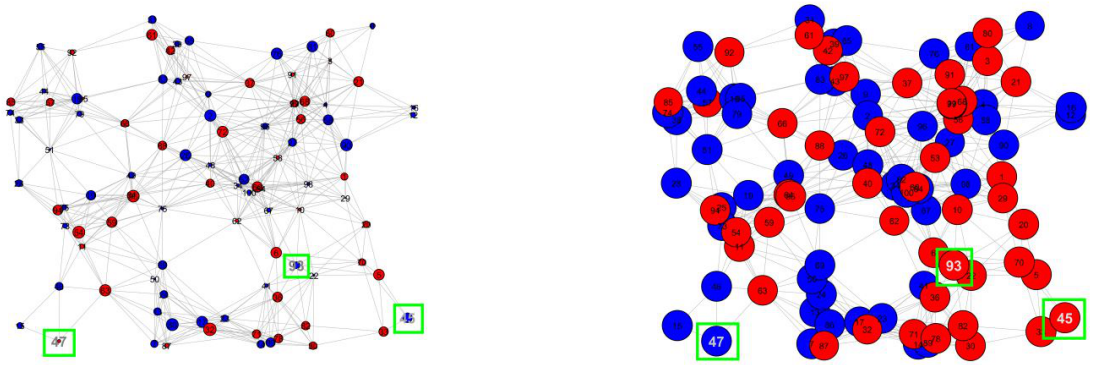
Figure 6: Time evolution of selected metrics for both models; note that in this sample run, the temporal trajectories are very different.

5.5 To determine which of the cases above is more common, we systematically checked for general quantitative and qualitative agreement across several trials. Specifically, we applied a simple heuristic which considered the two models to be equivalent if at least 95% of agents demonstrated the same public opinion. This cutoff was chosen as it enabled some leniency for opinion flips on boundaries, but prevented the possibility for major structural differences in the final system states. After running 100 simulations, it was found that 63% of cases ended with the two models in agreement. Given that the same common parameter settings are used in subsequent analysis, we consider the two models to be equivalent for the purposes of this work. A more rigorous statistical investigation is not within the scope of this paper.

Virtual worlds testing

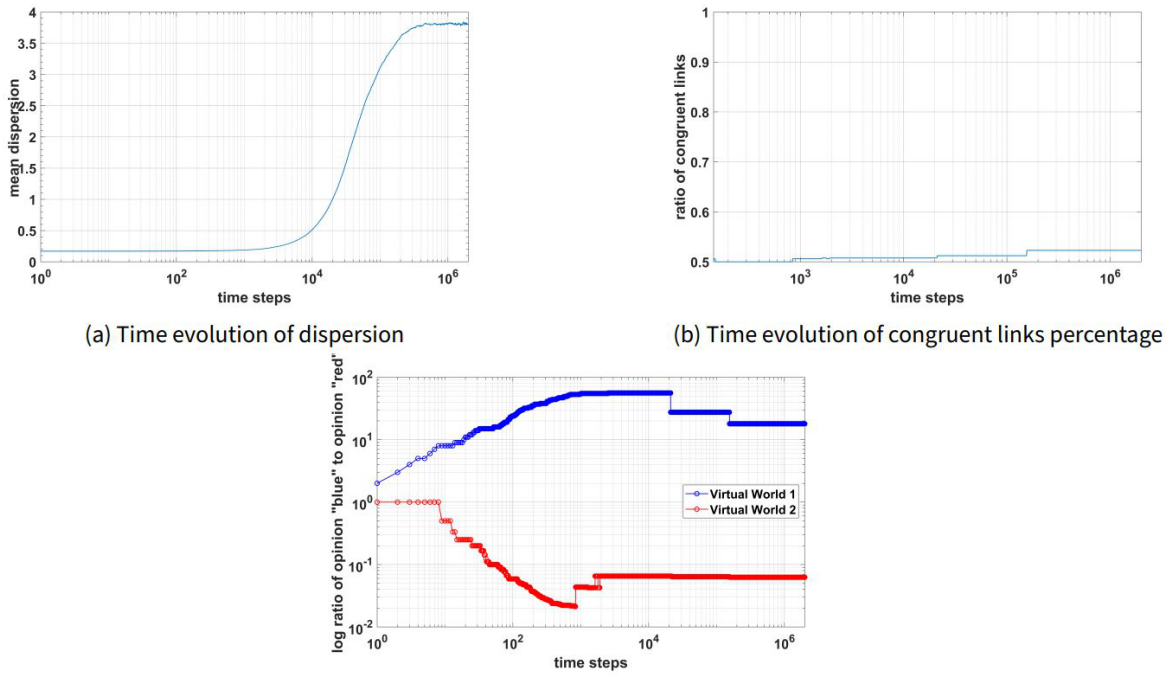
5.6 We now demonstrate an illustrative run of the virtual worlds framework, with $m = 2$ virtual worlds. We set $\alpha = 0.01$, $\beta = 1$, $N = 100$, and $r = 0.225$. Additionally, we set $h = 4$ and $\lambda = 0.4$. The simulation runs for $n = 20000 \cdot N$ time steps.

5.7 Figure 7 shows the initial and final states of the model and Figure 8 shows relevant time-series data. Note that the final system state does not seem to have large clusters, suggesting the presence of un-structural polarization in the real world; this is supported quantitatively by a high final dispersion around 3.8 and a low final congruent links percentage around 52%. Simultaneously, there is structural polarization in the virtual worlds; this is clear as the virtual world evaluation ratio χ_1 stabilizes around 1.25 while χ_2 ends around -1.20. Interestingly, the congruent links percentage and the virtual world ratios are constant from 160000 time steps onward. This aligns with the qualitative observation that only three agents ultimately flip their public opinion by the final system state (agents 45, 47, 93).



(a) Initial state (b) Final state

Figure 7: Initial and final system states for a simulation run where $m = 2$ virtual worlds are enabled. Edges correspond to those specified by the spatial random graph structure from the primary network/real world. Note that while the majority of agents maintain their public opinions, they become more extreme in their convictions; agents 45, 47, and 93 are the only agents to flip their opinions and are highlighted in the figures. Agent node size is proportional to the magnitude of their convictions.



(a) Time evolution of dispersion

(b) Time evolution of congruent links percentage

(c) Time evolution of virtual world ratios

Figure 8: The value of selected metrics over time for a simulation run where virtual worlds are enabled. High dispersion yet low congruent link percentage suggests un-structural polarization in the real world; additionally, the clear delineation between the two virtual world ratios χ_1 and χ_2 implies structural polarization in the virtual worlds.

5.8 The sample run outlined here reveals the possibility for structural polarization to form at the virtual world level despite the underlying peer influence level demonstrating un-structural polarization. It suggests that agents can engage in a broader society with a tangible number of discordant contacts (i.e., this corresponds to the relatively low final congruent links percentage) and yet simultaneously participate in a social media platform which is clearly bipolarized. Additionally, the observation that few agents flip their public opinion by the end implies that the dynamics of this type of polarization is “in situ”: the presence of homophily and a social media platform has the combined effect of making initial convictions more extreme.

$h - \lambda$ grid search

5.9 We now perform a $h-\lambda$ grid search to determine the impact of these parameters on polarization and gain further insight into our model. We continue to let $m = 2$, $\alpha = 0.01$, $\beta = 1$, $N = 100$, $r = 0.225$ and run simulations for $n = 20000 \cdot N$ time steps. Within the grid we vary $h \in \{0, 2, 4, 6\}$ and $\lambda \in \{c \cdot 0.05 : 0 \leq c \leq 10, c \in Z\}$, with 100 trials for each point.

5.10 Figure 9 shows the results of this computational experiment. We note that in general an increase in h leads to higher dispersion and reduced chance of consensus (see Figures 9a, 9b, and 9c). Interestingly, λ seems to impact the metrics differently depending on the value of h. For instance, when $h \leq 2$, increasing λ leads to less dispersion until the inflection point of $\lambda = 0.4$; this is possibly due to the complete nature of the virtual worlds overcoming weak homophily and leading to consensus (i.e., in general a complete network tends towards consensus as demonstrated in Banisch & Olbrich 2019). On the other hand, when $h \geq 4$, increasing λ consistently leads to greater dispersion; it is likely that in this regime the homophily is strong enough to overcome the complete nature of the virtual worlds.

5.11 The metrics also reveal important information about the types of polarization occurring during the simulations. In the real world, increasing λ has the general effect of reducing the congruent links percentage and making polarization more un-structural (see Figure 9d). For instance, when $h \leq 2$ there is a pivot in final system state from extreme consensus to un-structural polarization at the inflection point $\lambda = 0.4$. When $h \geq 4$, a transition from structural polarization to un-structural polarization is prominent around $\lambda = 0.2$ to $\lambda = 0.3$. In the virtual worlds, increasing λ makes the virtual world dispersion greater and introduces structural polarization; this effect is most pronounced when homophily is also high (see Figure 9e). Indeed, congruent links percentage being low and virtual world dispersion being high when λ and h are both high gives further validation for the single run analysis performed in the *Virtual worlds testing* section.

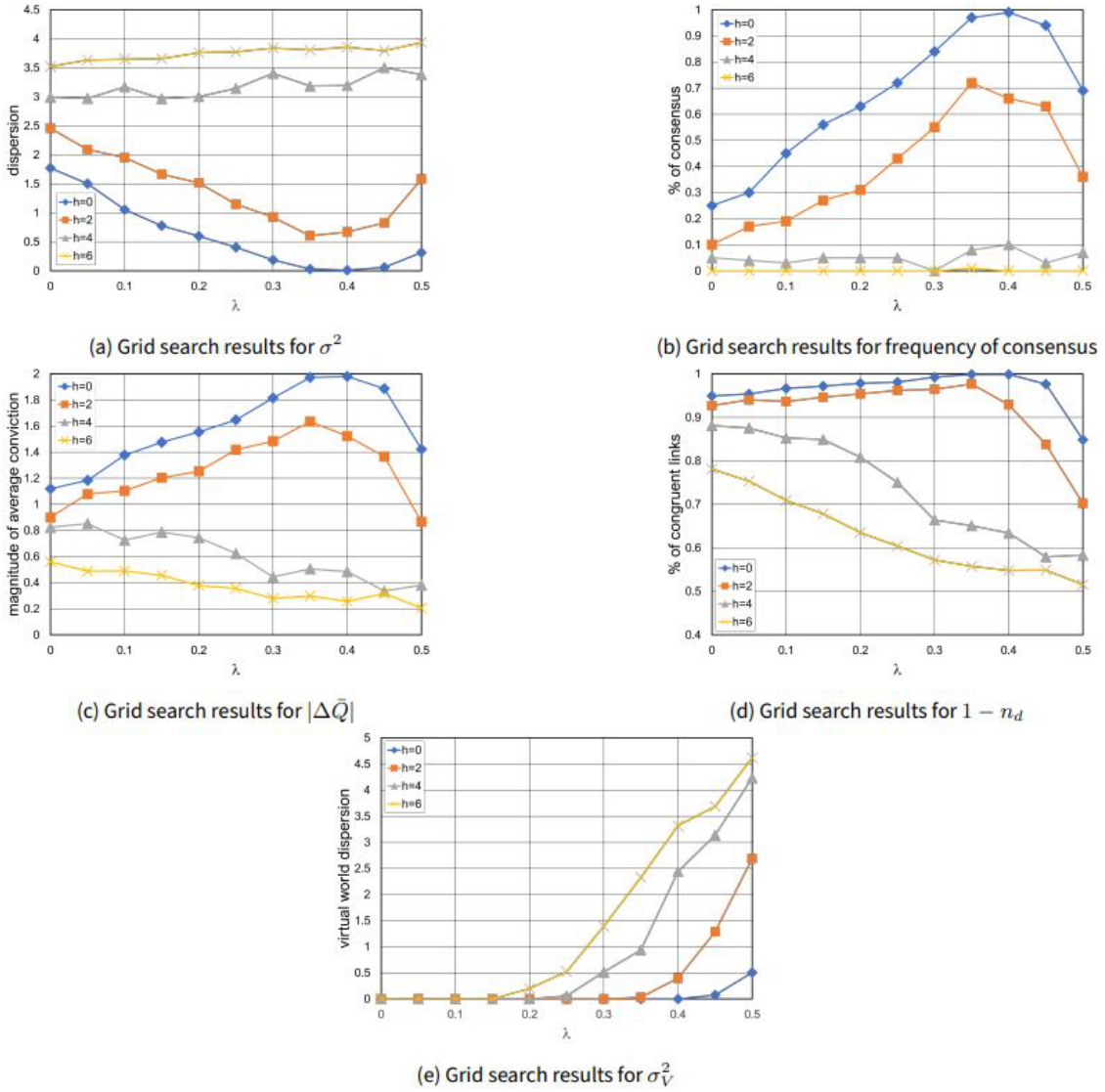


Figure 9: Results of parameter analysis. Increasing λ leads to higher virtual world dispersion regardless of amount of homophily; this represents structural polarization in the virtual worlds. Simultaneously, it leads to lower congruent links percentage; this represents un-structural polarization in the real world.

Discussions

6.1 By analyzing the impact of virtual exploration λ and homophily h on polarization metrics from the previous section, we can leverage the methodology described in Rieder (2012) and perform a social commentary. We reference the discussions from the *Representing social media computationally* section and consider λ to represent the extent to which a social media platform is addictive and h to represent the propensity of individuals to prefer concordant perspectives.

6.2 When homophily is not present, increasing λ results in no polarization at the virtual world level and increases the chance of consensus at the peer influence level. Thus, under the social assumption that agents do not demonstrate preferences for their interactions, this implies that the more addictive a particular social media platform is the more likely agents arrive at consensus. Indeed, under such an assumption the presence of a social media platform simply provides agents the capability to interact with a larger body of neighbors beyond the restrictive space defined by r; coupled with the social assimilative features encoded within the original *public-private split* model, the trend in consensus aligns with expectation.

6.3 Different trends are observed when homophily is present. As λ increases, structural polarization begins to appear at the virtual world level and un-structural polarization becomes more common at the peer influence level.

Thus, a relatively addictive social media platform coupled with homophilic preferences has the combined effect of leading to a situation in which agents may be individually exposed to discordant perspectives but nevertheless contribute to structural polarization at the virtual worlds level. A possible intuition is that when a social media platform is addictive, agents are less likely to connect with possibly discordant real world neighbors and instead will log-in to social media. Here, high homophily augments initial convictions and leads to a positive feedback mechanism in which agents begin to prefer the virtual world with the higher evaluation ratio χ. This leads to structural polarization at the virtual worlds level. Simultaneously, agents become strongly convinced in their initial opinions leading to un-structural polarization at the peer influence level. In summary, agents become more distant from their real world neighbors due to the "illusion" of consensus in the virtual worlds. Note that the presence of the inflection point around $\lambda = 0.4$ for $h \leq 2$ implies that this behavior takes precedence over the model's natural drive towards consensus. There is thus an imbalance between the influence of λ and h on the model, with λ having a greater impact. Essentially, the presence of virtual worlds causes the social assimilative features of the original *public-private split* model to be swapped for repulsion and xenophobia.

6.4 Thus, our model suggests that it is possible for agents in a social network to participate in cross-cutting ties while still contributing to structural polarization. The value of our modeling framework becomes more apparent when considering connections to previous studies. For instance, Conover et al. (2011) showed that the social network associated with Twitter is structurally polarized; this result is consistent with our findings within the specific computational regime of $h \geq 4$ and $\lambda \geq 0.3$ (i.e., a combination of high homophily and high addictiveness respectively). On the other hand, Bakshy et al. (2015) claimed that the presence of cross-cutting ties among users on Facebook supported the theory that social media platforms are not responsible for polarization (Keijzer & Mäs 2022). The fundamental disconnect between the empirical studies outlined here is that they consider social media platforms from two different frames of reference. The former performs an analysis from a global view, while the latter focuses on the role of individuals and not the platform itself. While resolving this debate will certainly require additional empirical investigation, the results from our computational experiment imply that the innate structure of social media platforms is uniquely conducive to the co-existence of multiple forms of polarization.

6.5 Indeed, one important practical implication of our analysis is that un-structural polarization implies the possibility for a society to feature cross-cutting ties (i.e., interaction among those with discordant perspectives) despite the overall presence of bi-polarization. On the other hand, as discussed in *Structural versus un-structural polarization*, structural polarization means that at the microscopic level most individual agents will experience an "illusion of consensus." For future work it might not be enough to simply consider the immediate topology; certain types of polarization may only be evident when investigating the relationships among agents from different perspectives (i.e., global vs. group-level vs. individual scale).

Conclusions

7.1 In this paper, we expanded on the recently proposed *public-private split* model by Banisch & Olbrich (2019) through a novel virtual worlds framework in order to investigate polarization in social media platforms. After performing a sensitivity analysis, we discovered that an increase in the addictiveness of a platform can cause structural polarization at the virtual world level with un-structural polarization at the peer influence level. While previous studies disagree on the presence of polarization in social media, our results show that the innate structure of these platforms mandates analysis of resultant opinion dynamics from different perspectives (Conover et al. 2011; Bakshy et al. 2015; Keijzer & Mäs 2022). Indeed, the possibility for different types of polarization to co-exist implies that fixation on any particular frame of reference will ignore key observations.

7.2 In general, we note that these results demonstrate the possibility for social media platforms to generate unique forms of polarization. There is thus a need for more ethically designed platforms which are conscious of their innate design. Possible approaches involve associated corporations organizing specialized committees dedicated to analyzing the impact of platforms from a social lens or investigating methods to proactively limit the extent of polarization.

7.3 The computational methodology in this study also offers several promising avenues for future work. First, the properties of structural virtual world polarization with un-structural peer influence polarization can be studied further from a theoretical perspective. One approach is to model agent interactions using random processes and perform a sensitivity analysis similar to that in Banisch & Olbrich (2019). Next, we note that the virtual worlds framework was incorporated as an extension to the original *public-private split* model with little difficulty. One takeaway from this is that the general robustness of the *public-private split* model in our experimentation has established it as a plausible canonical model. This signals the importance of pivoting to more

localized interpretations of social networks in future agent-based models. Another takeaway is that the modular nature of the virtual worlds framework could enable it to be used with other base models to test alternative social assumptions and theories. Finally, an interesting direction to consider is the possibility of online "lurkers" who read but do not participate. In real life several social media platforms do not require users to have an account in order to read content; it will be interesting to simulate scenarios in which these users become polarized without directly engaging with rest of the social network.

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Notes

[1]In all figures, $o_i = 1$ is represented by opinion "blue" and $o_i = -1$ is represented by opinion "red"

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