The dynamics of online polarization

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Abstract

Several studies pointed out that users seek the information they like the most, filter out dissenting information, and join groups of like-minded users around shared narratives. Feed algorithms may burst such a configuration toward polarization, thus influencing how information (and misinformation) spreads online. However, despite the extensive evidence and data about polarized opinion spaces and echo chambers, the interplay between human and algorithmic factors in shaping these phenomena remains unclear. In this work, we propose an opinion dynamic model mimicking human attitudes and algorithmic features. We quantitatively assess the adherence of the model’s prediction to empirical data and compare the model performances with other state-of-the-art models. We finally provide a synthetic description of social media platforms regarding the model’s parameters space that may be used to fine-tune feed algorithms to eventually smooth extreme polarization.

1 Introduction

The data-deluge [1] provided large amounts of data and digital traces of social activities that promised to improve the comprehension of large-scale social phenomena [2] through a quantitative background ranging from mobility patterns [3–5], to information spreading [6–8]. Along this path, several studies focused on polarization dynamics [9,10] especially about vaccines [11,12] or about the climate change debate [13,14].

Indeed, many human and environmental factors affect the spread and consumption of information online. On one side, human biases are the most relevant drivers for information selection, especially the confirmation bias [7,15], such that people tend to privilege information aligned with their system of beliefs [8,16] and filter-out dissenting information [17,18]. On the other side, most
of the online information circulates on social media platforms, whose business model aims to keep users as connected as possible; consequently, algorithmic choices may play a significant role in selecting which information is shown to the user [19, 20]. The combination of these factors shapes the social dynamics online. A particularly relevant effect is the formation of echo chambers [21–23], i.e. groups of people sharing aligned opinions (especially on controversial topics) against opposite views [24].

Across echo-chambers, individuals opinions result to be polarized and such polarization may act as a catalyst of misinformation [25], and a trigger for other problematic phenomena such as segregation [26, 27] and hate speech [28, 29], that may ultimately constitute a threat for democracies [30–32].

Currently, measures of polarization are performed on aggregated activity data extracted from social media platforms [23, 33]. A more difficult task is to find evidence of the dynamic that leads to a polarized network [34]. Nevertheless, the onset of polarization in a network can be investigated through computational opinion dynamics models [35, 36]. In these models [37, 38] agents are represented as nodes of a graph characterized by some properties usually representing opinions or attitudes. Connections among nodes may represent friendship relationships and allow users to interact with each other. Simulations consist of updating users’ opinions and/or network connections (rewiring) based on the opinion of neighbor users in the network. The opinion update scheme depends upon the specific model that may involve (i) the fundamental mechanism of homophily, by which individuals tend to interact and create connections with others sharing similar features [39, 40] (ii) social contagion [41, 42], i.e. the tendency of individuals to become similar each-other over time; (iii) algorithmic bias [43, 44]. A recent review of the main results in terms of opinion dynamics models is given in [45]. Interestingly, the authors conclude that the main limitation of the modeling approach is the missing empirical validation. In a research field exposed to high volatility of scientific results [46], referencing models to observed behaviors is of crucial importance to correctly identify the drivers of these phenomena. In this paper, we address this issue, providing a double contribution. First, we propose a flexible opinion dynamic model to investigate the interplay between the users’ attitudes and algorithmic influence; next, we perform a comparative analysis with other models [47, 48] by fitting with data from different social media platforms. This allows us to establish a link between an observed opinion distribution and the corresponding level of underlying algorithmic bias, providing a synthetic description of each social media in terms of model parameters that could be used as a reference for applying polarization-reduction policies.

2 Results

We consider a social network in which each node represents a user characterized by an opinion \(x_i\) and a firing rate \(\sigma_i\), and edges are weighted friendship relations (Figure 1). At each iteration the opinion of each user is updated according to
a filtered subset of its nearest neighbors. The filtering mechanism models the action of social media platforms algorithms that play a major role in shaping user online experience. Algorithmic bias effect is ruled by three parameters: radius $\alpha$, shift $\beta$ and discount $\gamma$. At every time step users undergo an opinion update, after interacting with their friends. We associate every time step to a session on a social media in which the platform algorithm proposes contents to users. We assume the perspective that platforms aims to maximize permanence of users, and tend to propose contents aligned with each users’ view [49]. To this aim, the radius $\alpha$ acts as a boundary for the opinion space accessible to a given user. It sets the maximum opinion distance reachable by a user, thus forcing the opinion to be updated according to like-minded connections. The shift $\beta$ instead, models the tendency to drive opinion towards extreme values, as it corresponds to a shift of the accessible opinion interval. The last parameter $\gamma$ models the tendency to consolidate explored connections and weaken links with nodes excluded from the opinion interaction interval. Moreover we consider two more parameters $a$ and $b$ ruling the initial opinion distribution (see Methods).

As illustrated in Figure 1 a user with opinion $x_i$ interacts with connected users whose opinion falls in the interval $[x_i - \alpha + \beta, x_i + \alpha + \beta]$. The connections with these users are reinforced by a factor $\gamma$, while relations with excluded users...
are weakened by the same factor (see Methods). The model idea roots in the Bounded Confidence Model [50] (BCM), with a paradigmatic shift from user-centric dynamic to an algorithmic-centric one. In fact, with respect to BCM we do not consider intrinsic limitation of user interactions with respect to opinion distance; we focus on the role of algorithmic bias that prevents interactions among users with distant opinion, with a tunable level of severity. Depending upon the parameters set $\sigma$, the model evolution produces different kind of opinion distributions on the network $\delta(\sigma)$, computed as the kernel-density estimate for the joint probability distribution of users and neighborhood opinions. In Figure 2(a-d) we report examples of characteristic distributions in the opinion space, namely pluralism in which all opinions are represented in the network and each user is surrounded by a multitude of opinions; consensus [38] is a condition in which all networks opinions collapse into a very narrow region. Conversely, fragmentation [51] is very similar to pluralism, apart from the fact that not all the opinion space is available. Eventually, polarization [7, 52, 53] is described as a fragmented and segregated opinion space: two main opinions are present, and users expressing each of them are connected with like-minded people.

To investigate the role of $(\alpha, \beta, \gamma)$, starting from a pluralism distribution, we computed the evolution for 900 different parameter combinations $S = \{\sigma_1, \ldots, \sigma_{900}\}$ (see Methods). Most of the produced opinion distributions can be classified in
the above-mentioned categories. Results are reported in Figure 2(e-g). As expected, a configuration in which users have the possibility to interact with many others while having low shift and discount leads to consensus. At low $\alpha$ values with moderate $\beta$ and $\gamma$ lead to fragmentation, mainly due to the narrow opinion space accessible by users. Conversely, $\gamma$, ruling the forget/reinforce mechanism, appears to be a pivotal driver to reach a polarized opinion space in which echo chambers arise.

Despite the large number of opinion dynamics models present in literature, a crucial missing point is a quantitative comparison with real opinion data from social media platforms. To address this point, we consider four examples of opinion distributions measured on four different social media platforms \( \mathcal{P} = \{ \pi_F, \pi_T, \pi_G, \pi_R \} \). Next, we quantitatively evaluate the difference of each distribution $\pi_p$ with all the opinion distributions computed via grid-search $\mathcal{D} = \{ \delta(\sigma_i), \sigma_i \in \mathcal{S} \}$, by computing the Jensen-Shannon divergence (JSD), a quantity suitable to compare distributions. For each platform $p$ the best parameters set $\sigma_p^*$ is identified as

$$
\sigma_p^* = \arg \min_{\sigma \in \mathcal{S}} \text{JSD} (\delta(\sigma), \pi_p),
$$

namely considering the minimum JSD. The best approximating distributions are shown in Figure 3 along with the optimal distribution obtained applying the same procedure to two recent opinion dynamics models, from Baumann et al. [47] and Arruda et al. [48]. The results are shown in Figure 3. Specifically, Facebook data relates to users interactions on discussions about vaccines; for Twitter, data involve discussions about abortion; Reddit and Gab datasets are instead referred to interactions of users with political or news contents [23].

All models show the flexibility required to well approximate various scenarios. Interestingly, no single model can well approximate all platform-related opinion distributions (see Discussion).

Importantly, we observe that all the three models have a sort of degeneracy with respect to the optimal solution for each platform. In fact, multiple configurations produce values of JSD very close each other, as shown in Supplementary Information. Thus, a more comprehensive description, in terms of model parameters, of each social networks, can be obtained looking at all the configurations whose corresponding JSD falls within the 5th percentile of the JSD distribution.

For our model, the results are reported in Figure 4. Each panel allows to asses the relevant values of each parameter in approximating the distribution from each social network, with respect to the entire grid-searched range. The best approximation for Facebook is obtained with relatively high values of $\alpha$, $\beta$ and $\gamma$, corresponding to a relevant presence of algorithmic filtering. On Twitter, the leading parameter is the small interaction radius $\alpha$, with a relevant dependency on the initial opinion distribution. Bias and reinforcement/discount of network connection play a less relevant role. This observation could highlight differences in the algorithmic filtering between the two platforms. On Reddit and Gab the opinion space related to news and politics discussions does not show
Figure 3: Evaluation of model outcomes adherence to real data. Left column: real opinion distributions measured in [23]. From second to last column: best approximation of the observed data provided by our and competing opinion dynamic models: Baumann [47] and Arruda [48].
polarization. The best fit of our model to these configurations corresponds to a mild algorithmic effect, expressed by the non-trivial combination of $\alpha$ and $\beta$; the most relevant role is instead exerted by $a$ and $b$, shaping the initial opinion distributions.

Figure 4: For each social media, we consider the top 5% approximating configurations, and display the corresponding parameter distribution in each panel, together with the full parameter range explored with the grid-search. This visualization allow to interpret the relevant range for each parameter and each social media.

The same analysis was conducted for the two other opinion dynamics models considered. Results are reported in Figure 5 and Figure 6. The model proposed by Baumann et al. [47] considers a dynamic network in which opinion dynamics is driven by interactions among agents, described by a system of coupled ordinary differential equations

$$
\dot{x}_i = -x_i + K \sum_{j=1}^{N} A_{ij} \tanh(\alpha x_j),
$$

where $x_i$ is the opinion of $i$-th user, $A$ is the adjacency matrix of the network, and $K$, $\alpha$ are free parameters of the model respectively representing the social
interaction strength among agents and the controversialness of the modeled topic. The social network underlying the opinion dynamics is updated at every iteration, with the probability of two users being connected proportional to

$$p_{ij} \sim |x_i - x_j|^{-\beta}.$$ 

The last free parameter is the reciprocity $r$, i.e. the probability that given a established link $i \rightarrow j$, it is reciprocated from $j \rightarrow i$. Despite the rather different working principle, this model displays good performances, except for not capturing the extremely polarized opinion distribution observed on Facebook. This results show that the main driver to approximate different opinion distributions is given by the power law exponent $\beta$, and the controversialness $\alpha$, with a less relevant role played by $K$ and $r$.

![Parameter distributions](image.png)

**Figure 5:** Fit of Baumann et al. [47]. For each social media, we consider the top 5% approximating configurations, and display the corresponding parameter distribution in each panel, together with the full parameter range explored with the grid-search. This visualization allow to interpret the relevant range for each parameter and each social media.

The model proposed by Arruda et al. [48] has a similar structure to the one proposed in this work, even though the mechanism for opinion updates
are rather different. In essence, the simulation is performed at the level of users producing information (posts) expressing a given opinion $\theta$, and reaching neighboring users. This interaction probabilistically leads to neighbors updating their opinion closer to or farther apart from the opinion expressed by the post. Different outcomes are obtained modifying the post transmission probability, the post distribution probability, the relative phase parameter and the possibility to rewire connections. The transmission probability distribution, which gives the probability for a user to post a piece of information, as a function of $d = |x_i - \theta|$, being $x_i$ the opinion of user $i$, and assumes three shapes:

\[ P^{uni}_t = 1 \quad P^{pol}_t = \cos^2\left(\frac{d \pi}{2}\right) \quad P^{sim}_t = \begin{cases} \cos^2\left(\frac{x \pi}{2}\right) & \text{if } x \leq 1 \\ 0 & \end{cases}. \]

A similar mechanism is considered for neighboring users that receive the information depending on their opinion distance from user $i$ (post distribution), according to two possible probability distributions.

\[ P_I(y) = \cos^2\left(\frac{y \pi}{2} + \phi\right) \quad P_{II}(y) = \cos^2\left(\frac{y \pi}{2} + \phi\right), \]

being $y = |x_j - x_i|$ and the phase $\phi$ a free parameter. The model investigates also the role of rewiring, which, if allowed, takes place with a probability proportional to $y$.

From Figure 6 we observe that, for the social where this model performs best, namely Reddit and Twitter, the kind of post distribution function play a less relevant role; the phase distributions $\phi$ in the top 5% of configurations instead show much more localized values, suggesting a relevant role of this parameter. With respect to post transmission and rewiring, in Reddit we observe a prevalence of the $pol$ type, and a balanced representation of $uni$ and $pol$. Lastly, the possibility to rewire connection is key to well approximate the opinion distributions.

3 Discussion

Understanding the social and algorithmic mechanisms that leads to online polarization is a great challenge with profound implications in a number of fields including psychology, social sciences and policy. Polarization is a complex phenomenon, interpretable both as a state and as a process [34], arising from the interplay between the distribution of opinions and the structural peculiarities of a network.

Polarization can be measured aggregating interaction data from social networks [23, 33]. These post-hoc polarization measurements can be used as a reference to develop models capable to reproduce them. This allows to map opinion distributions stemming from peculiar network interactions onto a specific parameter set of a given model. Once assessed a good quantitative agreement between models prediction and empirical data, the model itself could be used as a starting point for scenario analysis.
Figure 6: Fit of Arruda et al. [48]. For each social media, we consider the top 5% approximating configurations, and display the corresponding parameter distribution in each panel, together with the full parameter range explored with the grid-search. This visualization allow to interpret the relevant range for each parameter and each social media.
In this work, going beyond a qualitative comparison of synthetic and real opinion distributions, we consider a quantitative metric, namely the Jensen-Shannon divergence. Moreover, by comparing the performances of our model with others, we demonstrate that a silver-bullet in terms of opinion dynamics models, doesn’t exist (yet) in capturing the full spectrum of real-world opinion distributions. Notably, however, the models do perform well regardless of the level at which the data are collected: with respect to Gab and Reddit we are observing opinion distributions sampled at the community level, while for Twitter and Facebook the data are specifically related to a given topic (abortion and vaccination, respectively). Including more complex mechanisms ruling the opinion dynamics may lead to better numerical results at the cost of preventing a simple interpretation of the results.

4 Conclusions

In this work we propose a novel, flexible opinion dynamics model explicitly considering the algorithmic dimension of online information exchange among users; second, we “close the loop” by quantitatively measure the adherence of model outcomes to empirical data, and obtain a description of social media platforms in terms of model parameters. This aspect is particularly relevant in presence of extreme polarization, a phenomenon associated to segregation of users in echo chambers, that in turn could foster problematic phenomena (e.g. misinformation spreading). We found that, according to our model, the parameter $\gamma$, ruling the algorithmic reinforcement and weakening of relative influence of neighbors plays a major role, and maybe used as a control knob to reduce polarization.

5 Methods

5.1 Opinion dynamics model

We consider a social network, sketched in Figure 1(a), with $N$ nodes, each representing a user. Each node $i$ has an activation (or firing) rate, randomly sampled from a uniform distribution $\sigma_i \sim U(0, 1)$ and opinion $x_i \sim P(x)$. Edges are randomly weighted, such that $w_{ij} \sim U(0, 1)$ represents the strength of social relationships between user $i$ and $j$. This random initialization corresponds to the leaning distribution shown in Figure 1(b), in which no opinion segregation nor polarization is present.

At each discrete time-step, sequentially, each node randomly undergoes an interaction, with probability $\sigma_i$, represented as node size in Figure 1. If user $i$ is active, then its opinion gets updated according to the opinion of its first neighbors $\mathcal{N}(i)$ and the effect of platform filtering, similarly to other bounded confidence implementations. In absence of algorithmic bias, the opinion of the selected user $x_i$ is updated
as

\[ x_{i}^{t+1} = x_{i}^{t} + \delta, \]

with

\[ \delta = \mu \left( x_{N(i)}^{t} - x_{i}^{t} \right), \]

being \( x_{N(i)}^{t} \) the average weighted neighborhood opinion

\[ x_{N(i)}^{t} = \frac{\sum_{j \in N(i)} x_{j}^{t} w_{ij}}{\sum_{j \in N(i)} w_{ij}}. \]

where \( \mu \) is a convergence factor, set to \( \mu = 0.3 \).

Algorithmic bias is introduced in the model as a filter on the neighborhood \( N(i) \) of each user, that depends on three parameters: interaction radius \( \alpha \), opinion shift \( \beta \) and discount \( \gamma \). With reference to Figure 1 (c-f), the algorithm selects neighbors whose opinion lies in the interval \([x_i - \alpha + \beta, x_i + \alpha + \beta]\). The opinion shift \( \beta \) sign is given by

\[ \text{sign}(\beta) = \text{sign}(x_i - 0.5), \]

These parameters govern the actual interaction of user in shaping the opinion dynamics. Only neighbors falling within the interval effectively contribute to the update of user opinion, such that

\[ x_{N(i)}^{t} = x_{N(i,\alpha,\beta)}^{t}. \]

After the update of user opinion, links within the filtered neighborhood are reinforced, while those outside are discounted, depending on the value of \( \gamma \):

\[ w_{ij}^{t+1} = \begin{cases} w_{ij}^{t}(1 + \gamma) & \text{if } j \in N(i, \alpha, \beta) \\ w_{ij}^{t}(1 - \gamma) & \text{if } j \notin N(i, \alpha, \beta) \end{cases} \]

Opinion and weight values are forced to the \([0, 1]\) interval through clipping. The network dynamics generally converges to a stable state after 50-100 time steps (see Supporting Information). The evolution of users opinion and networks connections determine the final opinion distribution.

### 5.2 Fit procedure

Beyond the three parameters \((\alpha, \beta, \gamma)\) representing the effect of algorithmic bias, the model evolution depends upon the initial opinion distribution \(P(x)\) from which users opinions are sampled. We consider the beta distribution,

\[ P(x; a, b) \propto x^{a-1}(1 - x)^{b-1}, \]

ruled by \( a > 0 \) and \( b > 0 \) with support in the \([0, 1]\) range. Thus, the free parameters set of the model is \( \sigma = \{\alpha, \beta, \gamma, a, b\} \). The size and average degree of
the underlying social network were fixed respectively to \( N = 5000 \) and \( \langle d \rangle = 6 \), while the number of iterations is fixed to \( T = 500 \).

To characterize the model outcomes and compare them with data measured on social media, we performed a grid search of 900 different parameter configurations. For each parameter the variation range is expressed in Table 1.

| Parameter | Values (start, stop, step) |
|-----------|-----------------------------|
| \( \alpha \) | (0.1, 1, 0.1) |
| \( \beta \) | (0, 1, 0.1) |
| \( \gamma \) | \( 10^\wedge (-3, -1, 1) \) |
| \( a \) | (1,3,1) |
| \( b \) | (1,3,1) |

Table 1: Parameter variability range

For each final opinion configuration we computed the kernel-density estimate for the joint probability distribution of users and neighborhood opinions. This allows us to directly compare model outcomes with measured data [23].

The agreement between a model realization and data is quantitatively evaluated by the Jensen–Shannon (JS) divergence, that is the symmetric version of the Kullback-Leibler divergence between two distributions \( P \) and \( Q \)

\[
D(P \parallel Q) = \int_{-\infty}^{+\infty} P(x) \log \left( \frac{P(x)}{Q(x)} \right),
\]

where \( p \) and \( q \) are probability densities. From this definition the JS divergence is defined as

\[
JSD(P \parallel Q) = \frac{1}{2} D(P \parallel M) + \frac{1}{2} D(Q \parallel M),
\]

with \( M = \frac{1}{2}(P + Q) \).

The same procedure is applied for the alternative models considered.

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