

On the Inevitability of Online Echo Chambers

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While social media make it easy to connect with and access information from anyone, they also facilitate basic influence and unfriending mechanisms that may lead to segregated and polarized clusters known as “echo chambers.” Here we study the conditions in which such echo chambers emerge by introducing a simple model of information sharing in online social networks with the two ingredients of influence and unfriending. Users can change both opinions and social connections based on the information to which they are exposed through sharing. Model dynamics demonstrate that even with minimal amounts of influence and unfriending, the social network rapidly devolves into segregated, homogeneous communities. These predictions are consistent with empirical data from Twitter. Although our findings suggest that echo chambers are somewhat inevitable given the mechanisms at play in online social media, they also provide insights into possible mitigation strategies.

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I. INTRODUCTION

The rise of social media has led to unprecedented changes in the scale and speed at which people share information. Social media feeds are key tools for accessing high volumes of news, opinions, and public information. However, just by fostering such a proliferation of information to which people are exposed, social media may interfere with cognitive selection biases, amplifying undesirable phenomena such as extremism and misinformation spreading [34]. Further, they may introduce new biases in the way people consume information and form beliefs, which are not well understood yet.

Theories about group decision-making and problem-solving suggest that aggregating knowledge, insights, or expertise from a *diverse* group of people is an effective strategy to solve complex problems, a notion that goes under the name of *collective intelligence* [8, 49]. While the Web and social media have been often hailed as striking examples of this principle in action [6, 59], some of the assumptions upon which these systems are predicated may harm the very diversity that makes them precious sources of collective intelligence [52]. Social media mechanisms, in particular, tend to use popularity signals as proxies of quality or personal preference, despite evidence that rewarding engagement may come at the expense of viewpoint diversity and quality [15].

There is increasing empirical evidence of these phenomena: polarization is observed in social media conversations [9, 17, 18] and low diversity is found in online news consumption [5, 21, 26, 54]. These observations have in common two features: *network segregation* (the splitting of the social network in two or more disconnected or poorly connected groups) and *opinion polarization* (the high homogeneity of opinions within such groups). Fig. 1 shows what an information diffusion network with those two features looks like.

Human factors such as *homophily* [44] (the tendency to form ties with similar people) and *social influence* [28] (the tendency of becoming more similar to somebody as a result of social interaction) are often thought to drive the emergence of polarization and segregation. Del Vicario *et al.* [21, 22] observe that social media debates tend to polarize in exactly two opinion groups and study a class of models of social influence with confirmation bias (the tendency to pay attention only to information that aligns with prior beliefs) [46]. They model confirmation bias with the *bounded confidence* principle [20] and introduce an additional *repulsion* effect driving opinions outside the bounded confidence farther apart.

Some of the consequences of socio-cognitive biases have been explored in social dynamics models [10] and in the social psychology literature [34]. Yet, the interplay between these and additional

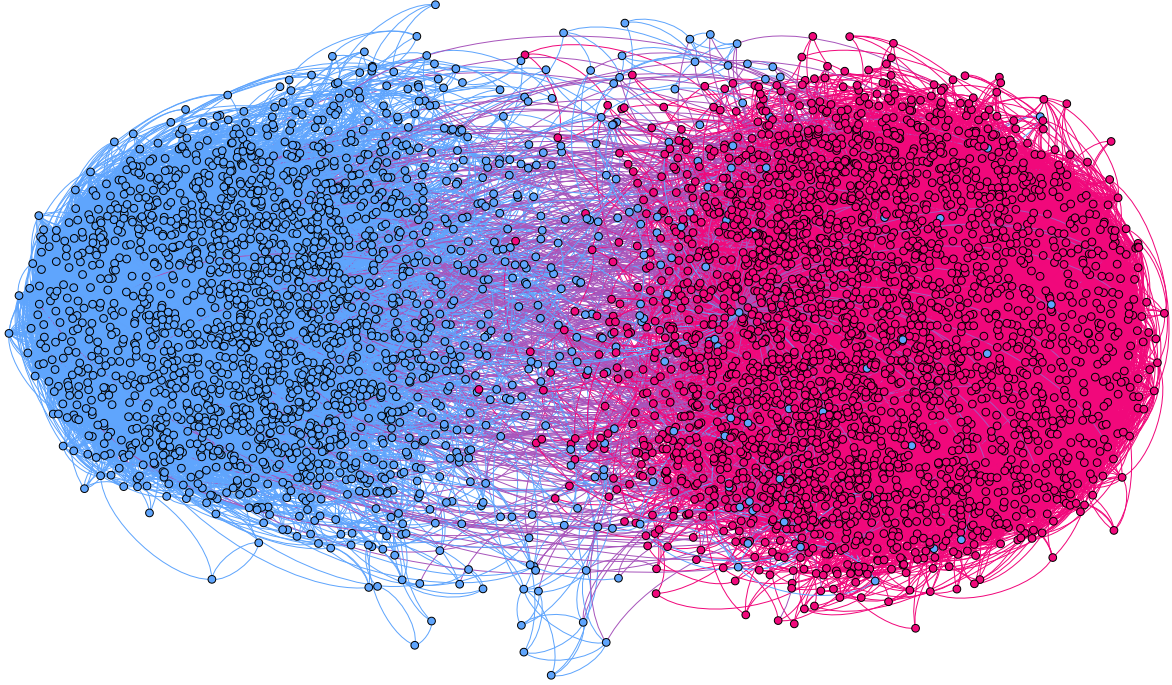


Figure 1. Example of a polarized and segregated network from Twitter. The network visualizes retweets of political hashtags from the 2010 US midterm elections. Nodes represent Twitter users and there is a directed edge from node i to node j if user j retweeted user i . Colors represent political preference: red for conservatives and blue for progressives [16]. For illustration purposes, only the nodes in the $k = 3$ core are visualized. See Methods for more details.

biases introduced by social media mechanisms is not clear. The algorithms at the heart of social media make a number of assumptions to deliver their recommendations. For example, news feed algorithms favor stories with which users are more likely to engage in the future, based on past engagement [2]. Friendship recommendation engines suggest new ties based on common interests, beliefs, and friends, often resulting in the closure of open triads [1, 3, 42, 63]. And finally, social media empower users to dissolve ties that, although not by design, often tend to be the ones connecting them with those with whom they disagree [56].

By curating the information to which users are exposed and by facilitating their management of social ties, social media platforms may enhance homophily and confirmation bias. This would have the net effect of leading social media users to connect preferentially with like-minded individuals, which would then result in *selective exposure* to only that information which conforms to their pre-existing beliefs, as opposed to more diverse points of view [55]. Ultimately, these dynamics would drive users of social media toward polarization and segregation [58], more so than users of

legacy media like TV, radio, or newspapers, where social sharing and link management mechanisms are not at play [30].

The risk that online communication networks could splinter into different ‘tribes’ was recognized since the dawn of cyberspace, and given the name of *cyber-balkanization* [38, 57] as an analogy to well-known phenomena of cultural, racial, and ethnic segregation [53]. With the rise of modern personalization technologies, there has been renewed interest in understanding whether algorithmic bias is accelerating the fragmentation of society. The terms *filter bubble* [50] and *echo chamber* [36] have been coined to refer to two different algorithmic pathways to opinion fragmentation, both related to the way algorithms filter and rank information. The first refers to search engines [27], the second to social media feeds [47, 48].

Analysis of online consumption of political news by Facebook users shows that exposure to cross-cutting ideological information is reduced for the most part by their social contacts and by their individual choice of what to click on [5]. Furthermore, opinion-reinforcing information promotes news story exposure [29]. Although those empirical observations suggest that the role of social media platforms in information exposure is relatively modest compared to individual preferences, they cannot explain why the network is so ideologically polarized and segregated. Empirical analyses of echo chambers in the literature are mainly based on observations of static network snapshots like the one shown in Fig. 1, therefore they too fail to account for how network segregation and opinion polarization emerge in the first place.

Here, we are interested in studying the emergence of joint polarization and network segregation in online social media, specifically focusing on the interplay between the mechanisms of influence and unfriending. Our approach is to model how these mechanisms are mediated by the basic activity of information diffusion in social media. Furthermore, we wish to explore how biases in recommendation algorithms may exacerbate the dynamics of echo chambers. Although our model is idealized, it captures some key feature of social media sharing — limited attention, social influence, and social tie curation. Through a series of simulations, we find conditions under which opinion polarization and network segregation coevolve, providing a generative mechanism for the formation of echo chambers in social media. We also illustrate how the predictions of the model are consistent with empirical data from Twitter.

II. MODEL

Let us introduce a model of opinion dynamics in an evolving social network. We incorporate various ingredients from models in the literature: information diffusion via social sharing [62], opinion influence based on bounded confidence [20], and selective unfriending [35].

The model begins with a random directed graph $G = (V, E)$ with $|V|$ nodes and $|E|$ directed edges, representing an online social network over which messages spread. Nodes represent social media users and edges represent follower ties, as in Twitter and Instagram. In the initial step, each user's *opinion* (o) is randomly assigned a value in the interval $[-1, +1]$. Each user has a *screen* that shows the most recent l messages posted (or reposted) by friends being followed. A message conveys the identity and opinion value m of the user who originated the post, together with the information about who reposted it. Users can see this information. A message's opinion m is *concordant* with an opinion o if they are within a *bounded confidence* distance ϵ ($|o - m| < \epsilon$). It is discordant otherwise. In addition, each user can unfollow a friend by rewiring the connection, thus following someone else in their place. These mechanisms allow us to capture two common ingredients of social media platforms: the possibility to share information with one's friends, and the possibility to form a new connections.

At every time step t , user i is selected at random, and sees messages on the screen that are posted or reposted by friends. The opinion of user i then changes based on the concordant messages on the screen:

$$o_i(t+1) = o_i(t) + \mu \frac{\sum_{j=1}^l I_\epsilon(o_i(t), m_j)(m_j - o_i(t))}{\sum_{j=1}^l I_\epsilon(o_i(t), m_j)}, \quad (1)$$

where μ is an influence strength parameter, the sum runs over the messages in i 's screen, and I_ϵ is an indicator function for concordant opinions based on the confidence bound ϵ :

$$I_\epsilon(o, m) = \begin{cases} 1 & \text{if } |o - m| < \epsilon \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

Equation 1 provides a simple mechanism for modeling social influence based on an individual's tendency to favor information that is similar to their pre-existing opinions ($o_i \pm \epsilon$), such as the confirmation bias and selective exposure mentioned earlier. This is referred to as *bounded social influence* and its breadth and strength are controlled by the parameters ϵ and μ . Larger ϵ indicates broader-minded users, and larger μ indicates stronger social influence.

Two more actions may be taken by user i at each time step t . First, with probability p , the user reposts a concordant message from the screen, if any is available; otherwise, with probability

$1 - p$, they post a new message reflecting their own opinion. Second, with probability q , the user selects a random discordant message from the screen, if one exists, and *unfollows* the friend who (re)posted the message, following a new friend in their place. We explore three different *rewiring strategies* for selecting the new friend:

- **random:** a user is selected at random among all nodes in the network that are not already friends of i 's;
- **repost:** a user is selected at random among the originators of reposts, if any are on i 's screen;
- **recommendation:** a user is selected at random among non-friends who recently posted concordant messages.

Note that the size, density, and out-degree sequence of the network stay the same throughout each simulation, while the in-degree distribution can change over time.

As we mentioned earlier, our model incorporates various elements that have been explored in the literature. Both opinion dynamics and rewiring of social ties (unfriending) are notably present in the model proposed by Holme and Newman [35], which first explored the roles of the two mechanisms. There are however a few key differences between the model presented here and previous ones. One is that in our model, opinions take continuous values and unfriending is based on bounded confidence. More importantly, when links are rewired, they do not necessarily select nodes with concordant opinion (this is only one of the three rewiring strategies we consider); rather, the targets of the selection are the links to be broken — those outside the opinion confidence bound. Finally, our model aims to capture the crucial features of information diffusion in social sharing platforms, where influence may take place indirectly. Consider for example the following scenario: user A posts a piece of information that reflects A's opinion; user B reshapes the message to their followers, which include user C. Now user C may be influenced by A's post, even though A and C are *not* directly connected, and irrespective of whether B's opinion was concordant with or influenced by A's opinion. This indirect influence mechanism is asymmetric: the opinion of the consumer of a post changes, while the opinion of the originator of the post does not. The average opinion is therefore not conserved, unlike in the model proposed by Deffuant [20].

Code to simulate our model and reproduce our findings is available online at github.com/soramame0518/echo_chamber_model.

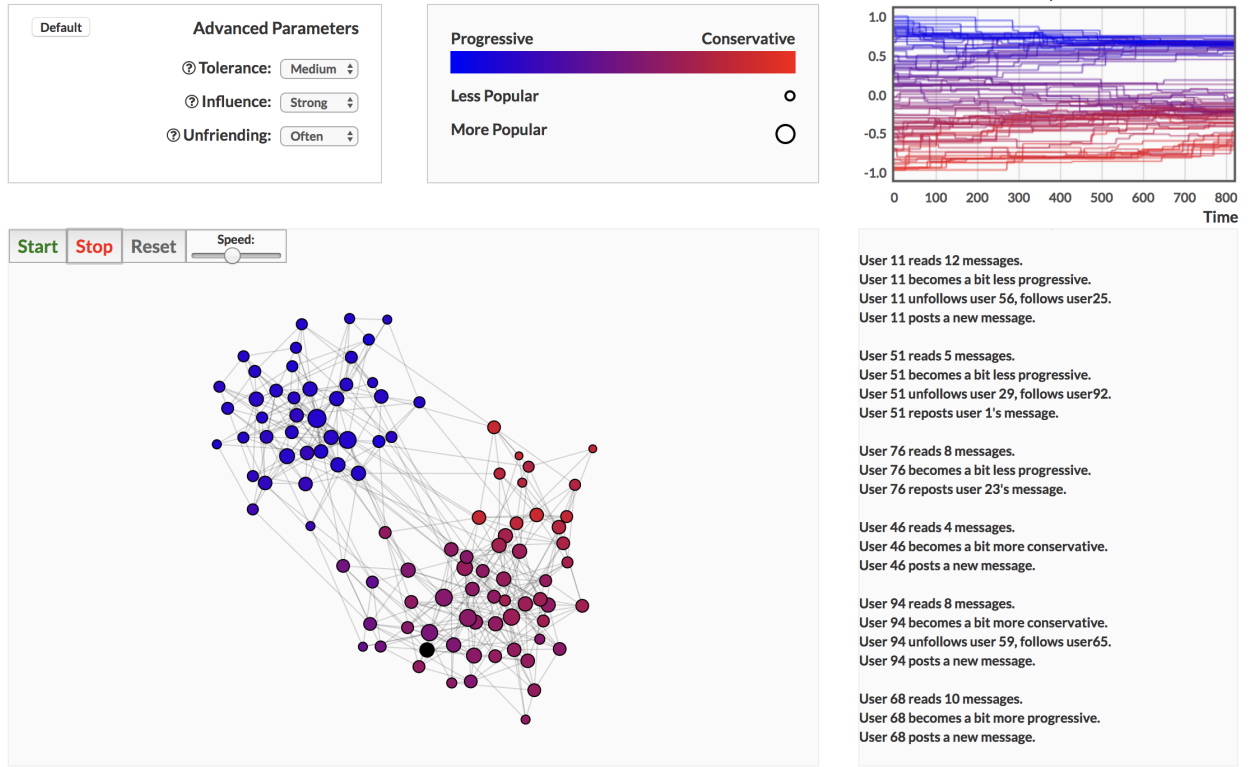


Figure 2. Screenshot of the echo-chamber model demo.

To facilitate the exploration of our model, we developed an interactive demo allowing one to run Web-based simulations with different realizations of the model parameters. The demo makes certain simplifications to be accessible to a broad audience: it is based on an undirected network, nodes can see all messages from their neighbors, and unfriending only occurs by random rewiring. Fig. 2 provides a screenshot of the demo, which is available online at osome.iuni.iu.edu/demos/echo/.

III. RESULTS

To illustrate the dynamics of the model, in Figure 3 we show one simulation run. Over time, due to social influence and unfriending, each user is increasingly exposed to similar messages endorsed by friends (Fig. 3A), and the system reaches a steady state characterized by two distinctive features often observed in reality: opinion polarization (Fig. 3B) and network segregation (Fig. 3C). Note that by “polarization” we mean a division of opinions into distinct homogeneous groups, which are not necessarily at the extremes of the opinion range.

We wish to examine the conditions under which opinion polarization and network segregation coevolve. Recall that our model has two mechanisms that appear to be relevant to this process:

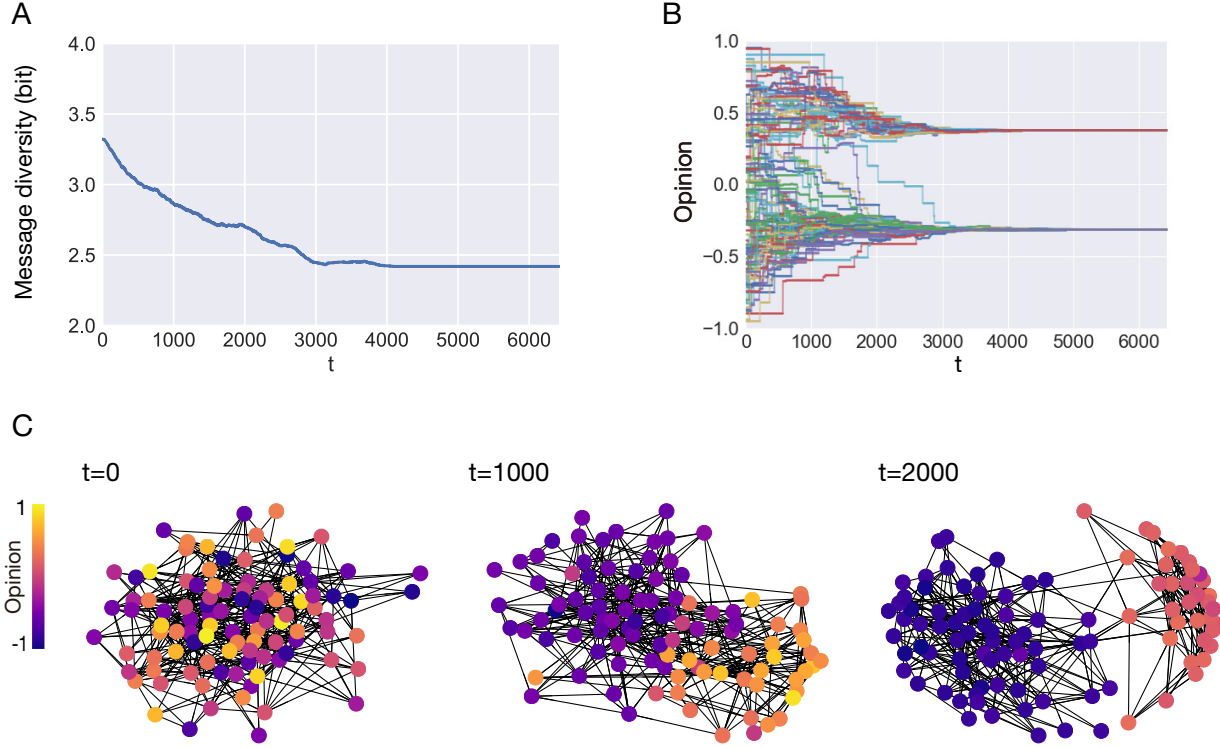


Figure 3. Coevolution of opinion polarization and network segregation. (A) Average diversity of messages on the screen, measured by Shannon entropy with the opinion range divided into 10 bins. (B) Temporal changes in population opinions. (C) Temporal changes in the social network structure. We use parameters $|V| = 100$, $|E| = 400$, $\epsilon = 0.4$, $\mu = 0.5$, $p = 0.5$, $q = 0.5$, and $l = 10$. The simulation is stopped after $t_{\max} = 10^5$ steps. A random rewiring strategy is applied, but similar dynamics are observed with different strategies.

social influence (regulated by parameters ϵ and μ) and rewiring (regulated by q). Let us first examine the role of the confidence bound parameter ϵ . This threshold affects the number of final opinion clusters and the diversity of surviving opinions, in a manner consistent with the original bounded confidence model [20] and some of its extensions [22]. As shown in Fig. 4(A,B), the smaller ϵ , the more opinion clusters with more heterogeneous opinions. If ϵ is large enough, the network converges to a single homogeneous opinion cluster.

Next, let us explore the joint effects of influence and rewiring. Here we limit our attention to the case $\epsilon = 0.4$, which yields, on average, two segregated opinion groups as illustrated in Fig. 3. In the presence of social influence alone without rewiring (Fig. 5A), the network structure is unaffected, but opinions may become polarized after a long time. In the presence of rewiring alone (Fig. 5B), no opinion change can happen but like-minded users cluster together and the network may become

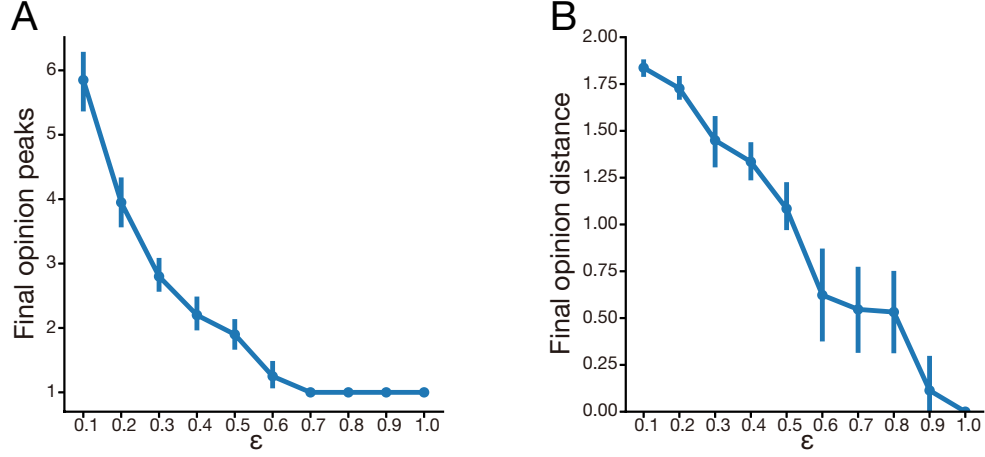


Figure 4. Dependence of stationary opinions on bounded confidence parameter ϵ : (A) number of opinion peaks and (B) maximum distance between opinions. The plots consider opinions at the steady state and show averages and standard deviations across 20 simulation runs with $|V| = 100$, $|E| = 400$, $\mu = 0.5$, $p = 0.5$, and $q = 0.5$.

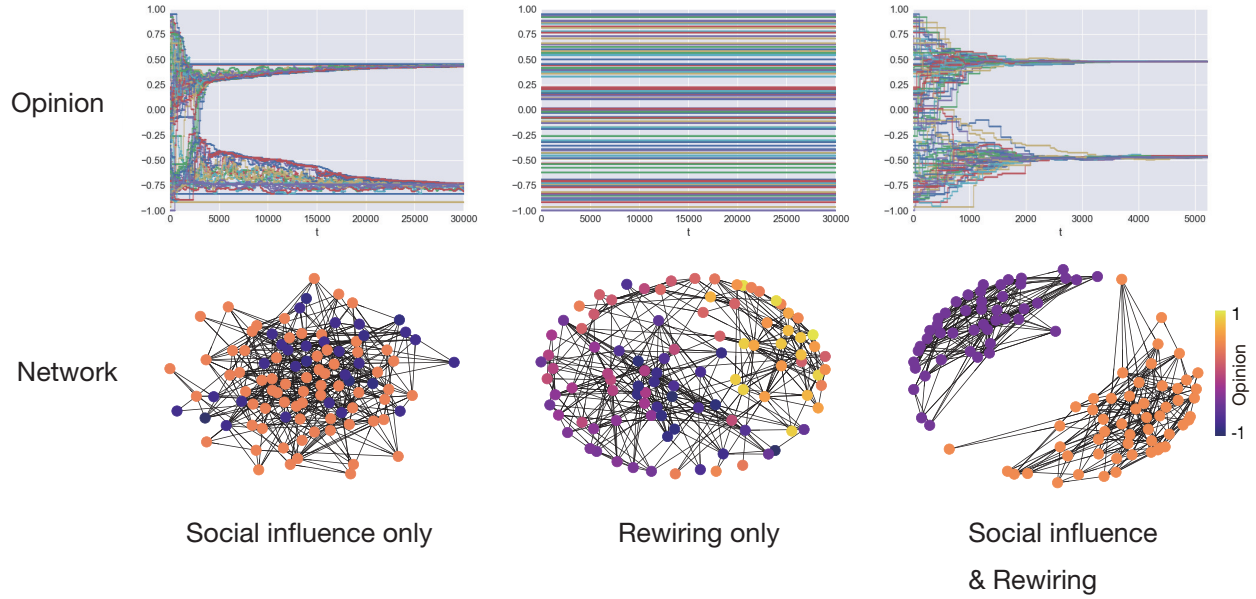


Figure 5. Conditions for the coevolution of opinion polarization (top) and network segregation (bottom). Left: $\mu = 0.1$ and $q = 0$. Center: $\mu = 0$ and $q = 0.1$. Right: $\mu = 0.1$ and $q = 0.1$.

segregated after a very long time. The joint effect of social influence and rewiring accelerates the joint emergence of both polarization and segregation (Fig. 5C).

To further explore how influence and rewiring jointly affect the speed of emergence of echo chambers, we plot in Fig. 6 the time until two conditions are both satisfied: (i) the network

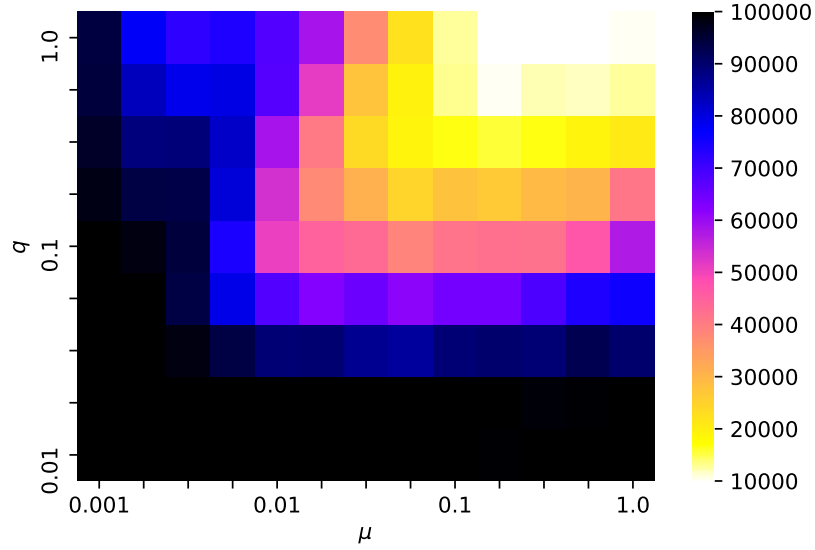


Figure 6. Time until emergence of echo chambers as a function of influence strength μ and rewiring rate q . We use a logarithmic scale to explore small values of the parameters. For each (μ, q) parameter configuration we ran 200 simulations with $|V| = 100$, $|E| = 400$, $\epsilon = 0.5$, and $p = 0.5$. A few simulations were excluded (see text), so that the median number of runs is 197. Colors represent averages across these simulation runs. The simulations were stopped after $t_{\max} = 10^5$ steps in cases when segregation and convergence have not both occurred yet.

clusters are segregated and (ii) opinions are homogeneous, i.e., any two nodes within the same cluster have opinions that differ by less than the bounded confidence ϵ . In some cases, a cluster may form that is smaller than the out-degree of one or more of its nodes, so that links from these nodes cannot be rewired to their own cluster; these cases are excluded because segregation can never occur. Focusing instead on the common cases in which segregation can take place, even relatively small amounts of influence and rewiring greatly accelerate the emergence of segregated and polarized echo chambers. When both the rewiring rate q and the influence strength μ are above 0.1, echo chambers appear in a fraction of the time. We therefore observe a synergistic effect in which influence and unfollowing reinforce each other in leading to the formation of echo chambers.

All three rewiring strategies used in the model (random, repost, recommendation) produce comparable stable states in terms of the number and diversity of stationary opinion clusters. In other words, what leads to an echo chamber state is selective unfollowing and not the specific mechanism by which one selects a new friend to follow. However, the emergence of echo chambers

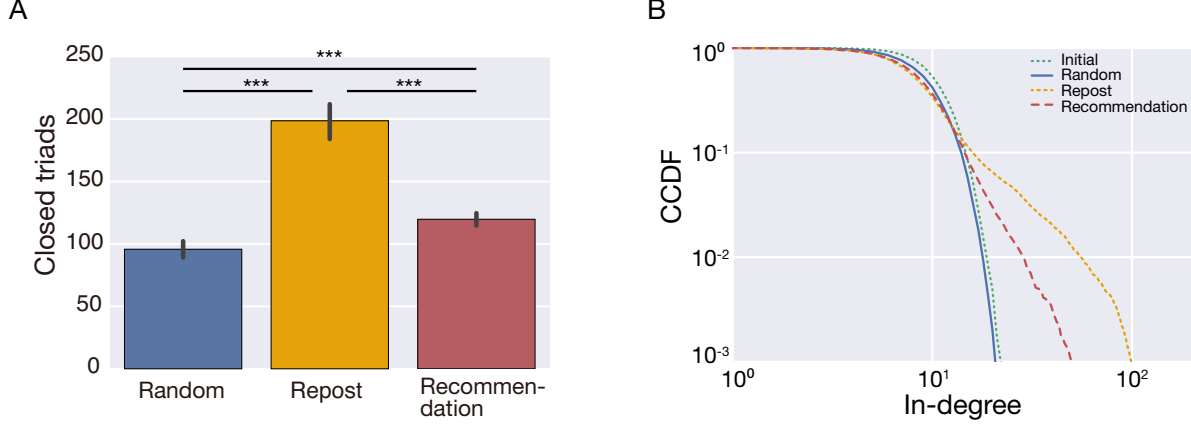


Figure 7. Effects of different rewiring strategies on evolved social networks. (A) The number of closed triads is averaged across 20 simulations with $|V| = 100$ and $|E| = 400$; all differences are statistically significant ($P < 0.01$). (B) Cumulative in-degree distributions with $|V| = 10^4$ and $|E| = 10^5$.

is greatly accelerated by the rewiring strategy based on recommendations of users with concordant opinions. The speed of convergence to the steady state is more than doubled compared to the other rewiring strategies.

The rewiring strategy also affects the development of closed social triads. A closed social triad is a network motif with three nodes A, B, C and links $A \rightarrow B, A \rightarrow C, C \rightarrow B$. It can be thought as the smallest unit of an echo chamber network [37], since it enables the same information to be transmitted from a source A to a recipient B through different paths, directly and via an intermediary C . As shown in Fig. 7A, rewiring strategies based on recommendations of users with concordant opinions and on exposure via reposts — both common mechanisms in social media — result in significantly more closed triads than following users at random. Repost-based rewiring, in particular, leads to doubling the number of directed closed triads, making it much more likely that users are exposed to the same opinions from multiple sources. The number of users posting/reposting a message can affect its ranking and be displayed to the user through platform-dependent interface elements, boosting user attention and exposure.

Finally, the rewiring strategy affects the in-degree distribution of the network in the stable state. Compared to random rewiring, the other two methods yield more skewed in-degree distributions, indicating the spontaneous emergence of popular users with many followers, whose message have potentially broader reach (Fig. 7B). Again, the effect on hubs is stronger in the case of repost-based rewiring. This is consistent with the *copy model* for network growth, which approximates preferential attachment [40]. However, unlike the copy model, the number of nodes and links is

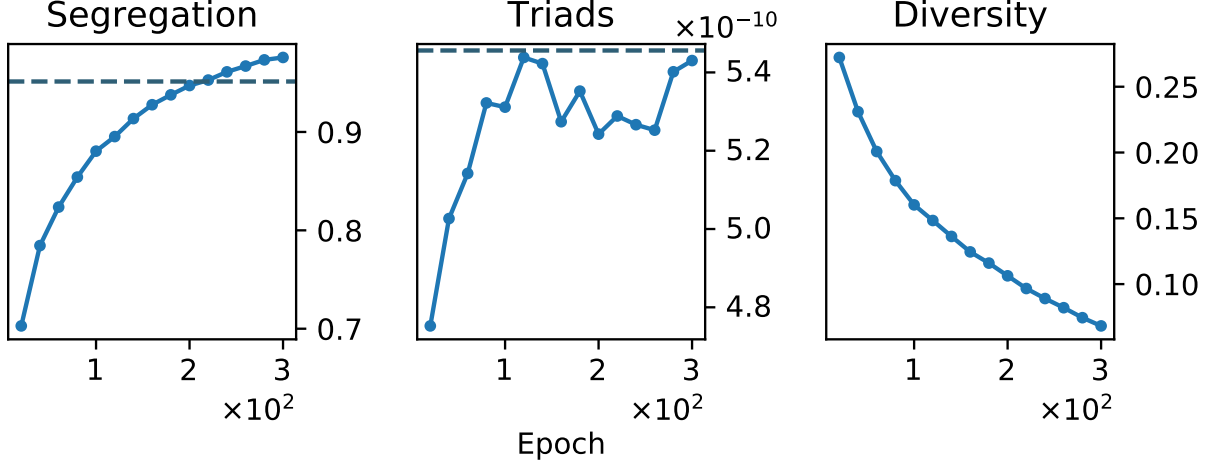


Figure 8. Comparison between model and empirical retweet networks. The solid blue lines represent the evolution of three metrics as a function of simulated time (epochs). The dashed line represents the empirical value for the segregation index (left) and fraction of closed directed triads (center), defined in Methods § V D and V E respectively. Diversity (right) is the average distance between neighbor opinions.

fixed in our model; only the patterns of connection change. Thus, the skewed in-degree distribution arises due to the spread of information. Since recipients can see who originally posted each message, the originators of popular messages have the best chance of receiving new followers and becoming hubs.

It is tempting to use our model to reproduce a few stylized facts about empirical echo chambers. To this end, let us consider data about an empirical retweet network of US political conversations (see Methods, § V A). To fit the model against this data, we plug in values of known parameters estimated in prior work, and then perform a sweep of the remaining parameters (§ V B). We simulate the resulting calibrated model to see if the synthetic network snapshot generated at the end of the simulation is in agreement with the observed snapshot of the empirical network (§ V C). As a stopping criterion for the simulations, we check that the simulated network has reached the same level of segregation as the empirical one (§ V D).

Fig. 8 shows the results. We compute two metrics to draw a comparison between the empirical data and our simulations. The first is the fraction of *closed triads* in the network. To compute the number of triads, we record each time a user reposts something in our model as a ‘retweet,’ and build a simulated retweet network. We then count all instances of closed directed triangles in both networks (§ V E). The central panel in Fig 8 shows that the fraction of triads in the synthetic network is consistent with that observed in the empirical data.

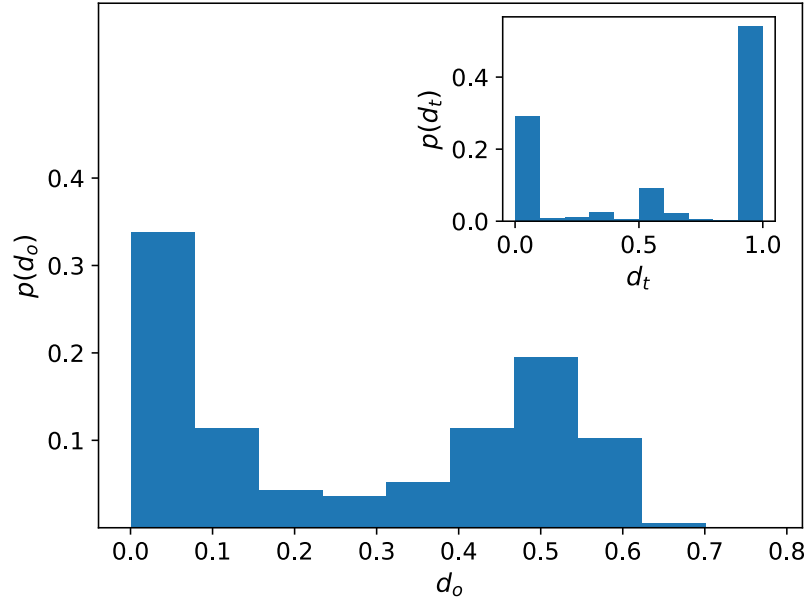


Figure 9. Distribution of pairwise opinion distances. The calibrated model was simulated until the segregation of the synthetic retweet network matched the observed one (see § V D and Fig. 8). The main plot shows the distribution of opinion distances d_o across pairs of users in the simulated network. The inset shows the distribution of opinion distances d_t among Twitter users from the empirical data.

The second metric is the distribution of *opinion distances*. We infer the latent opinions of the Twitter users in our data from their hashtag usage (§ V F), and define a distance d_t in hashtag binary vector space. In the model, we simply consider the distance $d_o(o_i, o_j) = |o_i - o_j|$ between two users in opinion space. Fig. 9 shows that both distance distributions have peaks around low values of distance for users in the same cluster and around high values for users in different clusters. While the ways in which the distances are measured and consequently the distributions are necessarily different, the qualitatively similar binomial behaviors suggest that the calibrated model attains an analogous level of opinion polarization in correspondence of the level of network segregation observed in the empirical data.

IV. DISCUSSION

In studying an idealized social media platform using an agent-based model, we followed the rich tradition of several models of opinion dynamics under social influence [10], in which agents adjust their opinions based on those of the ones with whom they are connected (social influence), and rewire their ties with peers based on their shared opinions (social selection). Other models have

explored the essential tension between social influence and social selection [19, 23, 35, 60, 65]. The model presented here seeks to capture two key components of social media on which prior models have not focused: (i) indirect interactions enabled by information diffusion, and (ii) disagreement-driven dissolution of ties via unfollowing/unfriending. Our model combines social influence and selection with the competition for limited attention, which has been shown to explain the empirical scale-free distribution of content popularity in social media [32, 62].

The results presented here suggest that the proliferation of online echo chambers may be an inevitable outcome of basic cognitive and social processes facilitated by social media: namely, the human tendency to be influenced by information and opinions to which one is exposed, and that of disliking disagreeable social ties. Social influence and rewiring appear to provide synergistic conditions for the rapid formation of completely segregated and polarized echo chambers; this phenomenon is accelerated by an order of magnitude in the presence of both relatively strong influence and relatively common unfollowing, compared to cases when either mechanism is weak.

A social network that is both segregated and polarized can be also generated with a variant of the Schelling model [53] on networks, proposed by Henry *et al.* [33]. This model is based on aversion-driven rewiring, but starts from a bimodal distribution of opinions. Our approach shows how both polarization and segregation emerge without assuming that opinions are already polarized. The literature has explored other factors and mechanisms that foster the emergence of isolated cultural or political subnetworks as well as polarization of opinions: one-to-many communication and network transitivity [39] are also incorporated in our model; pressures toward stronger opinions [25] or more radical opinions [21] are not. Finally, echo chambers can emerge from cognitive mechanisms, such as confirmation bias, when information propagates through centralized channels reaching a large portion of the population [31].

Focusing on the rewiring of social ties, we tested three different selection mechanisms: two inspired by triadic closure and social recommendation — intended to model the ways in which social media work in practice — and one based on purely random choice. All variations yield qualitatively similar steady states, suggesting that disagreement-driven unfollowing is a sufficient rewiring condition for echo chamber emergence. However, the more realistic selection mechanisms help explain two additional features of online social networks. First, the presence of users with many followers. These hub nodes affect the dissemination of the same messages in many cases, but not always [4]. Second, the large number of closed triads [63]. Triadic closure connects individuals to friends of their friends, facilitating repeated exposure to the same opinion. Such “echoes” are a powerful reinforcing mechanism for the adoption of beliefs and behaviors [11].

Although our model does not account for the adoption of false information, it has been speculated that echo chambers may make social media users more vulnerable to this kind of manipulation [41, 43]. There are multiple ways in which echo-chamber structure may contribute to the spread of misinformation. First, because people are repeatedly exposed to homogeneous information inside an echo chamber, the selection of belief-consistent information and the avoidance of believe-inconsistent information are facilitated, reinforcing confidence in minority opinions, such as conspiracy theories and fabricated news, even in the presence of preponderant contrary evidence [34]. Second, echo chambers foster herding, which may lead to quick and premature convergence to suboptimal solutions of complex problems and simplistic interpretations of complex issues [15, 34]. Finally, the threshold for perceiving a piece of content as novel may be lower within echo chambers by virtue of the reduced diversity of viewpoints to which people are exposed. The crafting of false news with perceived novelty may thus be promoted, leading to faster and broader consumption of misinformation [61] and triggering the production of more information about similar topics [14]. More work is certainly needed to validate such hypotheses.

Our results suggest possible mitigation strategies against the emergence of echo chambers on social media. Often-recommended solutions involve exposure to content that increases a user’s social distance from their preferences. However, such strategies must be consistent with current understanding of cognitive biases [34]. For example, it does not help to promote content that will be disregarded [43]. A more neutral possibility suggested by our findings is to discourage triadic closure when recommending the formation of new social ties. Moreover, the complete dissolution of ties with those users with whom one disagrees should be discouraged, for example by providing alternative mechanisms, like snooze buttons — a solution that some social media platforms are already experimenting with [45] — or the possibility to block only certain types of information, but not others. Another approach is to alert users who are about to unfollow their only conduits to certain types or sources of information.

As we better understand the unintended consequences of social media mechanisms, ethical and transparent user studies are needed to carefully evaluate countermeasures before they are deployed by platforms. We must not only ensure that new mechanisms mitigate undesired outcomes, but also that they do not create new vulnerabilities.

V. METHODS

A. Data

To evaluate the model’s prediction, we use empirical data from Conover *et al.* [17], who studied the political polarization of Twitter users. The data comprises a sample of public tweets about US politics, collected during the 6 weeks prior to the 2010 US midterm elections. The tweets were obtained from a 10% random sample of all public tweets. The dataset is available online at `carl.cs.indiana.edu/data/#icswm2011_2`.

Tweets with hashtags about US politics were included in the dataset. The hashtags were drawn from a list, which was obtained by expanding a manually curated seed set of then-popular political hashtags, such as #TCOT (‘Top conservatives on Twitter’) and #P2 (‘Progressives 2.0’). This initial set was recursively expanded with co-occurring hashtags above a minimum frequency, until no additional hashtag could be found. Finally, the list was manually checked and any hashtag that was not about US politics was expunged. The final list included 6,372 hashtags about US politics.

Three networks are provided in the dataset: retweets, mentions, and retweets plus mentions combined. We used the largest strongly connected component of the retweet network ($|V| = 18,470$ and $|E| = 48,365$), which is known to be polarized in two groups, roughly corresponding to the two main US political factions — conservatives and progressives. The network is the same shown in Fig. 1.

B. Parameter Fitting

Our model includes several parameters that need to be estimated. The rate of reposting was set to $p = 0.25$ based on empirical results from Twitter [51].

The number of nodes in the simulations was taken to be the same as the number of Twitter users in the empirical retweet network. Edges were drawn at random between any two nodes with probability chosen so that the density of the follower graph is $d = 1.8 \times 10^{-4}$. This value is within the range observed in the literature [7, 12].

We performed a parameter scan for the rest of the parameters, finding the following values: screen length $l = 10$, rewiring rate $q = 0.3$, influence strength $\mu = 0.015$, and tolerance $\epsilon = 0.65$. Note that the tolerance value to reproduce the two opinion clusters in the US-based online political conversations is larger than the value $\epsilon = 0.4$ found for smaller networks (Fig. 4). Finally, for simplicity, we use the random rewiring rule.

C. Model Evaluation

Our goal is to compare model predictions about the emergence of echo chambers with empirical data from social media. Unfortunately, lacking a probability distribution over the data, our model does not allow us to compute the likelihood of a given network or distribution of opinions. Thus we need to devise a method to evaluate our approach. This has become a common challenge, especially with the rise of agent-based modeling in the social sciences [24]. There is a vast literature devoted to developing rigorous methods to test simulation models on empirical data of social phenomena [13, 64]. Although no single universal recipe exists, we adopt the common approach of generating synthetic data from our agent-based model and comparing them to the empirical data under appropriate distance measures.

Our main hypothesis is that both social influence and rewiring are required to reproduce patterns consistent with the empirical data. Under those conditions, the system will always reach a state in which there will be no ties connecting users with discordant opinions (see Fig. 5). In reality, the empirical network is never completely disconnected in two communities. Therefore, we simulate our model until the system reaches the same level of segregation observed in the empirical data, and compare the two networks.

The empirical and model networks are however different. The former is a network of retweets, while the latter is a network of ‘follower’ ties. Therefore we cannot compare these two networks directly, but instead we generate a synthetic retweet network from the simulated data. Every time a user performs a ‘repost’ action in our simulations, we count it as a retweet, and add the corresponding edge in the simulated retweet network.

The plots in Figs. 8 and 9 are based on snapshots of this synthetic retweet network, taken at evenly spaced time intervals of 10 epochs each. Each epoch consists of $|V|$ steps of the model, so that each user performs one post and/or rewiring action per epoch on average. At the end of each tenth epoch we consider the latest $|E|$ distinct retweet edges, so that each simulated network snapshot is guaranteed to have the same number of edges as the empirical one. We then consider the largest strongly connected component of each simulated network snapshot. Therefore, the two networks do not generally match in the number of nodes.

D. Segregation

To measure the segregation in both the simulated and empirical networks, we group users into two clusters (C_-, C_+). In the simulated network, C_- is defined as the set of users having opinion $o < 0$ and C_+ as the set with $o \geq 0$. In the empirical network, the two clusters correspond to the labels obtained via label propagation [16]. Let E_b denote the set of edges connecting nodes in different clusters. We define the *segregation index* as:

$$s = 1 - \frac{|E_b|}{2d|C_+||C_-|}. \quad (3)$$

The segregation index compares the actual number of edges across the two clusters with the number we would observe in a random network with the same density d . When the network is completely segregated, $s = 1$.

E. Closed Triads

Let us denote by $i \rightarrow j$ a directed edge from node i to node j . A *closed directed triangle* or *closed triad* is any node triplet $i, j, k \in V$ such that $\{i \rightarrow j, j \rightarrow k, i \rightarrow k\} \subseteq E$. An *open directed triangle* or *open triad* is any node triplet for whom only a proper subset of those edges exists in E . Let us denote by T the set of closed triads and by T_u the set of open triads. We compute the frequency of closed triads as the ratio

$$f_T = \frac{|T|}{|T \cup T_u|} = \frac{|T|}{N!/(N-3)!},$$

where $N = \binom{V}{3}$ is the number of all node triplets.

F. Latent Opinion Inference

Our model generates opinions in the $[-1, +1]$ range, while the empirical network has binary labels (‘liberal’ or ‘conservative’) inferred from a training set and propagation through the network [16]. Comparing the opinions predicted by the model to these labels would not be meaningful, since the labels are trivially correlated with the network structure, by construction.

A more meaningful comparison is between pairwise opinion distances, which we can generate for the Twitter users using a criterion that is not induced by the network’s community structure. Since hashtag usage is also polarized [17], we infer opinions distances from adopted hashtags. We say that a hashtag is adopted by a user if it is found either in tweets retweeted by the user (incoming

edges), or in tweets by the user that were retweeted by someone else (outgoing edges). Let us consider the i -th user and the k -th hashtag. We define an *empirical opinion vector* $\hat{o}_i \in \{0, 1\}^D$ where $\hat{o}_{ik} = 1$ if user i adopted hashtag k , and 0 otherwise. We define the *empirical opinion distance* between two opinion vectors based on shared tags:

$$d_t(\hat{o}_i, \hat{o}_j) = 1 - \frac{\hat{o}_i \cdot \hat{o}_j}{\min\{\|\hat{o}_i\|, \|\hat{o}_j\|\}}, \quad (4)$$

where $\|\cdot\|$ is the \mathcal{L}_1 norm, or number of shared tags. To mitigate the effects of sparsity and noise, we use only the $D = 20$ most popular hashtags to define the vectors. The selected hashtags were adopted by 93% of the users. We restrict the retweet network to the subgraph spanned by those users, but the overall results do not change significantly if we select enough hashtags to cover 100% of the users.

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Author Contributions

K.S., G.L.C., A.F., and F.M. designed the research. K.S. and W.C. performed simulations, W.C. and F.M. analyzed the data. H.P. developed the online demo. K.S., G.L.C., F.M., and A.F. drafted the manuscript. All authors reviewed and approved the manuscript.

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