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Bursts of communication increase opinion diversity in the temporal Deffuant model

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Human interactions create social networks forming the backbone of societies. Individuals adjust their opinions by exchanging information through social interactions. Two recurrent questions are whether social structures promote opinion polarisation or consensus and whether polarisation can be avoided, particularly on social media. In this paper, we hypothesise that not only network structure but also the timings of social interactions regulate the emergence of opinion clusters. We devise a temporal version of the Deffuant opinion model where pairwise social interactions follow temporal patterns. Individuals may self-organise into a multi-partisan society due to network clustering promoting the reinforcement of local opinions. Burstiness has a similar effect and is alone sufficient to refrain the population from consensus and polarisation by also promoting the reinforcement of local opinions. The diversity of opinions in socially clustered networks thus increases with burstiness, particularly, and counter-intuitively, when individuals have low tolerance and prefer to adjust to similar peers. The emergent opinion landscape is well-balanced regarding groups' size, with relatively short differences between groups, and a small fraction of extremists. We argue that polarisation is more likely to emerge in social media than offline social networks because of the relatively low social clustering observed online, despite the observed online burstiness being sufficient to promote more diversity than would be expected offline. Increasing the variance of burst activation times, e.g. by being less active on social media, could be a venue to reduce polarisation. Furthermore, strengthening online social networks by increasing social redundancy, i.e. triangles, may also promote diversity.

Individual opinions are created by combining self-reflection and external inputs, such as mass media and information from social interactions. Social interactions play a significant role in opinion dynamics because individuals might be influenced by their peers (i.e. social contacts), and consequently, opinions diffuse through social networks^{1–4}. In the last decades, social media has become widespread by providing platforms for online social networks. In contrast to offline social networks, those networks are not bound by the physical space and thus increase people's exposure to information via long-range connections. The broader exposure facilitates the reinforcement of certain opinions with the formation of echo chambers, which eventually leads to polarisation and radicalisation of ideas^{4–11}. Such phenomena may be exacerbated by sharing emotional news stories, controversial opinions^{8,9,11}, or by controlling how information reaches social contacts^{12,13}.

There are different paradigms to model opinion dynamics^{14–17}. An important class of models is based on reinforcing opinions by social contacts^{18–20}. Such models assume that individuals are more likely to change their opinions if enough neighbours have a particular opinion. This complex contagion mechanism has been observed in experimental settings and social media and shown to depend on the underlying social network structure^{3,20,21}. The structural heterogeneity of complex social networks plays a pivotal role in regulating the spread of opinions via complex contagion. For example, clustering (e.g. network triangles) creates social redundancy and locally reinforces the prevalent opinion within the group (echo chambers)^{12,20}. On the other hand, socially poorly connected individuals will constantly be exposed to a single opinion and thus less to reinforcement. Another class of opinion dynamic models do not implicitly assume that reinforcement is needed, but single exposure may be sufficient^{22–24}. Some of these models make the realistic assumption that, despite individuals being embedded in social networks, interactions are most often one-to-one and thus, every social interaction has the potential to contribute to adjusting someone's opinion. The Deffuant model captures this mechanism, with individuals adjusting their opinions (defined by real values from 0 to 1) at each pairwise social interaction if the difference

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between their opinions is less than a given threshold²². One consequence of such assumption is that reinforcement is weakened because, at each interaction, a single individual influences only another individual, and thus some network structures become less relevant²⁵.

Another aspect of real-world opinion dynamics is the timings of interaction events between individuals. Temporal patterns of human communication follow some regularity, for example, circadian or weekly cycles²⁶, but are mostly highly heterogeneous²⁷. A common temporal heterogeneity is burstiness, i.e. bursts of interaction events followed by periods of inactivity^{28–31}. Burstiness is characterised by a right-skewed distribution of inter-event times between subsequent events and has been observed in various forms of social media and human communication^{27,28}. Researchers generally assume that the power-law is an appropriate model to describe the distribution of inter-event times due to its connection with critical phenomena, fitting the model to empirical data within short intervals of the distribution, i.e. not in the full range²⁷. Heterogeneous temporal activity affects dynamic processes, e.g. epidemic spread, opinion dynamics, and cooperation^{31–36}, and together with network structure, regulate the relaxation (mixing) time to stationarity³⁷. Heterogeneous interactions from online communication also contribute to emotional polarisation in co-evolving networks^{38–40}.

In this paper, we hypothesise that reinforcement can be obtained by repeated exposure to the same social contact and thus peer pressure (complex contagion) is not necessary to reinforce opinions. We thus design a variation of the Deffuant model (originally based on a single pairwise interaction per time step and therefore unable to create peer pressure) where the interactions follow burst activity patterns. Our model shows that burstiness not only slows down the dynamics towards stationarity but also increases the number of opinion clusters, i.e. promotes a multi-partisan society, independently of the network structure. Diversity increases the likelihood of extreme opinions but does not lead to the emergence of disproportionate large clusters. Furthermore, structurally clustered networks boost those effects by combining two forms of reinforcement, the first due to repeated exposure to the same social contact (temporal) and the second by the collective impact of peer pressure (structural).

Methods

Social networks

A social network comprises N nodes, each node i representing an individual i , and E links (i, j) representing social ties between nodes (individuals) i and j . The degree k_i is the number of the social relations to node i , whereas the average number of social ties in the network is given by the average degree $\langle k \rangle$. Nodes are clustered if they form triangles (social redundancy i.e. node A is connected to B and C , which are in turn connected as well), and the level of clustering can be measured by the clustering coefficient $cc_i = 2e_i / (k_i(k_i - 1))$, where e_i is the number of links between common neighbours of i . At the mesoscale, clustering can be quantified by the modularity Q , which measures the level of connectivity within groups of nodes (i.e. network communities) compared to what would be expected by chance. Higher modularity indicates a more robust community structure. These types of clustering will be referred to as structural clustering. Degree assortativity r is the tendency of nodes with similar degrees to be connected (homophily by degree)⁴¹.

Three network models are used to create social ties (links) between individuals. The Erdős-Rényi (ER) is the reference network model in which social ties are formed between pairs of nodes with a fixed probability p . This model generates a homogeneous random network where nodes have a characteristic degree⁴¹. The second model is the Watts-Strogatz (WS), which generates networks with local clustering (high clustering coefficient) yet short connections between any pair of nodes. The WS model is built by connecting the $k_{nn} = 6$ nearest neighbours of a node and then rewiring the social ties with probability q ⁴¹. The third model (fitness model) reproduces social networks more realistically by assuming that individuals tend to form social ties with others similar to them according to an attribute, e.g., age or gender (homophily by attribute)¹⁰. In the model, nodes are added to a network following a preferential attachment mechanism regulated by the level of similarity between the individuals. This is incorporated by using a fitness function $\phi_{I(i)}$ such that a newly added node J preferentially connects to a high-degree node taking into account its level of similarity to the existing nodes (eq. 1).

$$\phi_{I(i)} \propto k_i \exp(-\beta|\theta_j - \theta_i|), \quad (1)$$

where k_i and θ_i are respectively the degree and attribute of an existing node i , θ_j is the attribute of the newly added node J , and β is a coefficient controlling the fitness level regarding the attribute.

When $\beta = 0$, the growth mechanism follows the classical preferential attachment, resulting in a Barabási-Albert network with degree distribution $P(k) \propto k^{-3.41}$. Attribute similarity is introduced with $\beta > 0$, which competes with the degree to attract new links. The distribution becomes closer to an exponential for larger β . This fitness function thus enables sweeping connections from high-degree nodes (reducing the rich-get-richer effect) to those with similar attribute values (balancing the network towards attribute homophily).

Dynamic social networks

A dynamic social network is defined by a sequence of links (i, j) active at certain times t . In other words, a link (i, j) can be active or inactive at time t , unlike static networks where links are persistently active, i.e. independently of the time. To generate dynamic networks following specific temporal patterns of inter-event times. We first define a fixed network structure and then activate links at random times t sampled from a normal distribution. The network then evolves via a sequence of random link activation. At each time a link (i, j) is active, the subsequent activation (or event) time t_{next} of the same link is set to $t_{\text{next}} = t + \Delta t$, where Δt is the inter-event time sampled from a distribution of inter-event times $P(\Delta t)$ and t is the time of the current link activation. Links are sorted to guarantee that the continuous activation times are chronologically ordered. The Markov process results in a transient period discarded before the network dynamics becomes stationary^{32,42}. This procedure guarantees

uncorrelation of structure and timings of link activation, where the dynamic network contains a pre-defined topology with asynchronous activation of links to the same node, also following a pre-defined activation pattern.

Different inter-event time distributions $P(\Delta t)$ can be used to simulate chosen patterns. The baseline model is the exponential distribution, $P(\Delta t) = be^{-b\Delta t}$, with $\langle \Delta t \rangle = 1/b$, defined as the average inter-event time, corresponding to a memoryless Poisson process. This model generates homogeneous activation times and is equivalent to activating a link uniformly at random at each time step t . Empirical evidence, however, suggests that human interactions have memory and are better described by heterogeneous right-skewed distributions. The power-law model is usually assumed to be an appropriate model for such distribution²⁷. Comparative rigorous statistical analysis⁴³ is, however, missing and thus competing models, such as the log-normal or Weibull, cannot be a priori rejected. A rigorous assessment of the best model fitting real data is beyond the scope of our study. We thus use a log-normal model to capture the burstiness of link activations (eq. 2). The log-normal has well-defined moments and allows us to study configurations with different shapes (Fig. 1). Furthermore, for large σ (see definition below), the log-normal and power-law are similar within the interval of interest⁴⁴.

$$P(\Delta t) = \frac{1}{\sqrt{2\pi}\sigma\Delta t} e^{-\frac{(\ln \Delta t - \nu)^2}{2\sigma^2}}, \quad (2)$$

where $\langle \Delta t \rangle = \exp(\nu + \sigma^2/2)$ (ν is a parameter) and the burstiness depends on the variance σ of the distribution^{29,37}. The log-normal distribution approaches a Dirac delta distribution as $\sigma \rightarrow 0$ and has nearly linear log density as $\sigma \gg 1$ (a power-law has linear log density). The log-normal distribution provides a convenient transition function between a random or low burstiness ($\sigma \ll 1$) regime and nearly power-law or high burstiness ($\sigma \gg 1$)³⁷.

Temporal Deffuant model

The Deffuant model of opinion dynamics assumes a population of N individuals, wherein individuals i and j are connected via a static social tie (i, j) ²². The collection of such social ties forms a social network. The opinions of the two individuals at time t are represented respectively by $x_i(t)$ and $x_j(t)$, with $x(t) \in [0, 1]$. Each individual i is assigned a random opinion $x_i(t)$ at time $t = 0$. At each time step t , a randomly chosen pair of connected individuals (i, j) interact pairwise. The interaction is successful if the difference between the individuals' opinions is smaller than a confidence level d (eq. 3), where d is constant and corresponds to the individuals' openness to adapt their opinion.

$$|x_i(t) - x_j(t)| < d \quad (3)$$

A successful interaction leads to both individuals updating their opinions based on the difference between their original opinions (eq. 4). The parameter $\mu \in [0, 1]$ defines the influenceability of an individual towards another, i.e. the extent that two opinions can adjust and converge.

$$\begin{aligned} x_i(t+1) &= x_i(t) + \mu(x_j(t) - x_i(t)) \\ x_j(t+1) &= x_j(t) + \mu(x_i(t) - x_j(t)) \end{aligned} \quad (4)$$

We design a variation of this model incorporating temporal dynamics to the original Deffuant model via dynamic social networks, meaning that a link (social tie) can now be active or inactive at different times. The opinions of both individuals $x_i(t)$ and $x_j(t)$ can thus only be updated if the link (i, j) is active at time t . The activation times follow independent (asynchronous) temporal activity patterns. The activation of links is independent of the opinion updates, but opinion exchanges can only occur via an active link. The dynamic network is initialised for a chosen inter-event time distribution $P(\Delta t)$. After the initial transient, the Deffuant opinion dynamics start. Each time a link (i, j) becomes active, the subsequent activation time of the same link (i, j) is defined as

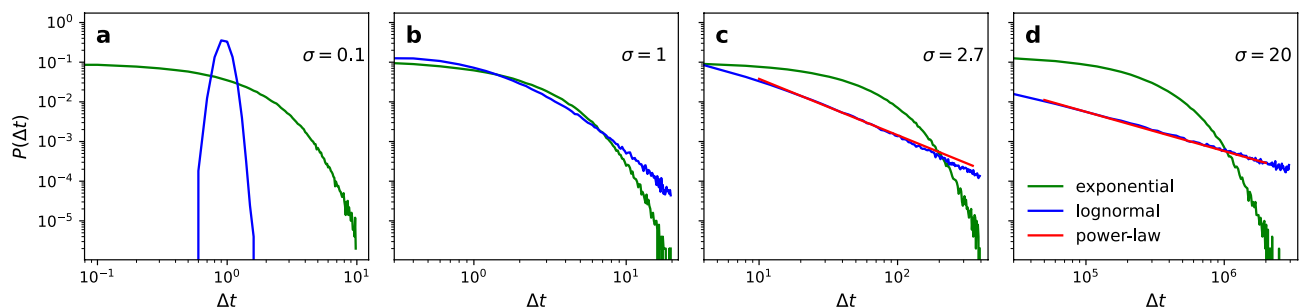


Figure 1. Exponential, log-normal, and power-law inter-event time distributions. The parameters of the log-normal are (a) $\sigma = 0.1$ ($\langle \Delta t \rangle = 1.0$), (b) $\sigma = 1$ ($\langle \Delta t \rangle = 1.65$), (c) $\sigma = 2.7$ ($\langle \Delta t \rangle = 37.9$), and (d) $\sigma = 20$ ($\langle \Delta t \rangle = 1.9 \times 10^4$). The parameters of the distributions are set such that the exponential (green curve) and the log-normal (blue curve) distributions have the same mean inter-event time. The parameter of the power-law (red curve) $P(\Delta t) \propto \Delta t^{-\gamma}$, drawn visually for reference, is (c) $\gamma = 1.42$ and (d) $\gamma = 0.99$. Both axes are in log scale.

$t_{\text{next}} = t + \Delta t$, where Δt is sampled from an inter-event time distribution. Opinions are updated following the temporal order of active links (See also Section “Methods” for more details on how links are activated).

The opinion dynamics evolves until the stabilisation of the opinions. This stabilisation time T_f is defined as the time after $\Delta t = N$ consecutive time steps without a successful exchange of opinions, i.e. either the nodes converged to the same opinion, or the opinions became so different that no more updates are possible. In this stationary state, individuals are clustered according to their opinions (hereafter called opinion clusters). This is done by sorting the (values of) opinions of the individuals. If two successive opinions differ less than $\epsilon = 10^{-4}$, the individuals are assigned to the same opinion cluster. Otherwise, a new opinion cluster is created. The number and sizes of opinion clusters are given by N_f and S_f , respectively. Some individuals may get stuck on a particular opinion and not converge to an opinion cluster. To distinguish those cases and individuals collectively forming opinion clusters, an opinion cluster must have at least 1% of the total population N .

The convergence parameter μ in the Deffuant model influences the relative speed of the dynamics but not the final state (i.e. the number of opinion clusters)²². Therefore, we set $\mu = 0.5$ in our experiments. We also set $N = 1,000$ and $\langle k \rangle = 20$. For each experiment, we generate 15 independent samples of a chosen random network model with the same set of parameters and repeat the simulations 20 times with random start conditions. Therefore, the average and standard deviations are calculated over $m = 300$ points.

Results

Evolution of the opinion dynamics

Figure 1 shows the log-normal distribution with different levels of burstiness, together with two reference models, the exponential distribution with the same average inter-event time, and the power-law. A low value of σ gives a distribution peaked around the mean (which results in nearly regular activation times). In contrast, increasingly right-skewed distributions (and thus increasingly burst activity) are obtained for increasing σ .

The evolution of the opinion dynamics with exponential inter-event times on a random network is equivalent to the standard Deffuant model on static networks²². Initially, opinions are homogeneously distributed among the individuals, but self-organisation leads to the emergence of opinion clusters in the stationary state. The number of opinion clusters and the stabilisation time depends on the confidence level d , with lower tolerance (i.e. lower values of d), leading to more opinion clusters (less consensus) (Fig. 2a–c). Burst activation patterns (log-normal distribution) also decrease consensus as d decreases. However, the system generally takes longer to reach the stationary state, and the number of emergent opinion clusters changes, for some configurations, compared to the reference exponential case using the same average inter-event times (Fig. 2d–f). Some individuals do not change opinions through social interactions due to poor connectivity. Consequently, their opinions do not converge to an opinion cluster. This effect decreases with burst activity. The stabilisation time T_f occurs sooner for the exponential case because of the absence of long inter-event times that slowdown the convergence to the stationary state.

Figure 3a–d shows the average number of final opinion clusters (N_f) for various levels of burstiness (log-normal with $\nu = 0$ and a given σ). A single opinion cluster always emerges for confidence levels $d \geq 0.3$, like the

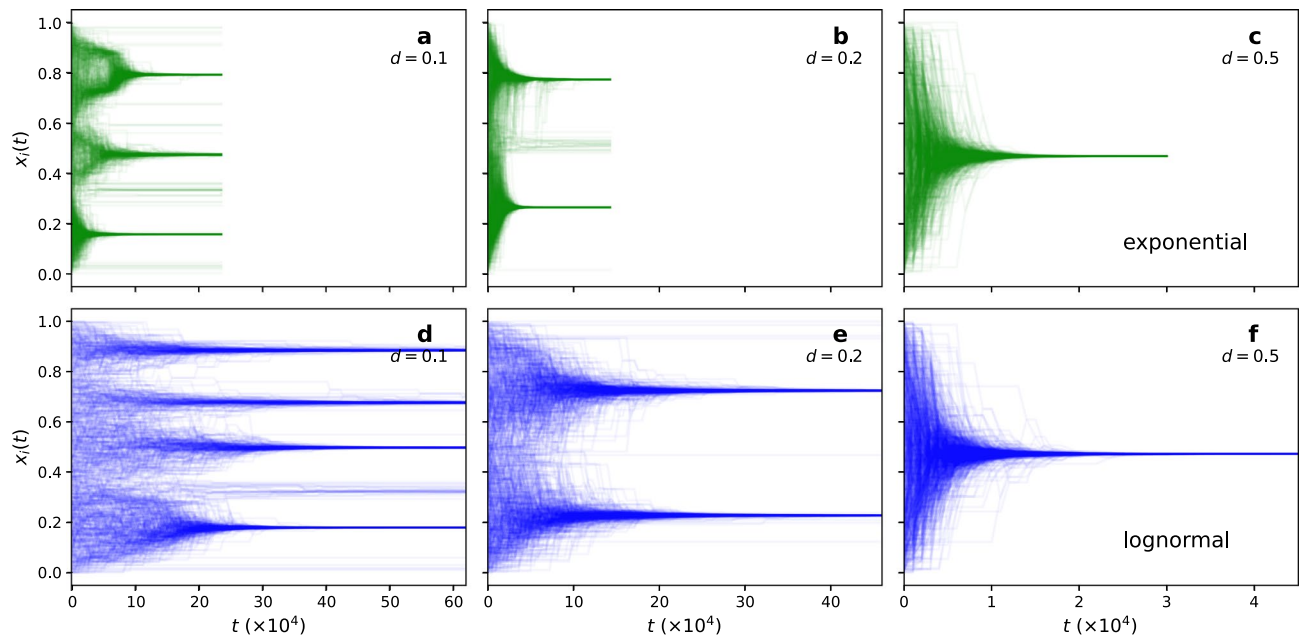


Figure 2. Temporal evolution of individual opinions. The tolerance level (a) $d = 0.1$, (b) $d = 0.2$, and (c) $d = 0.5$ for the exponential inter-event time distribution, and (d) $d = 0.1$, (e) $d = 0.2$, and (f) $d = 0.5$ for the log-normal ($\sigma = 2.7$) inter-event time distributions. All cases have the same $\langle \Delta t \rangle = 37.9$. The underlying network structure follows the Erdős-Rényi network model. The stabilisation time T_f occurs sooner for the exponential case and thus the simulation stops earlier as well. We plot all cases using the same time interval in the x-axis to highlight the slowdown to stationarity due to bursts.

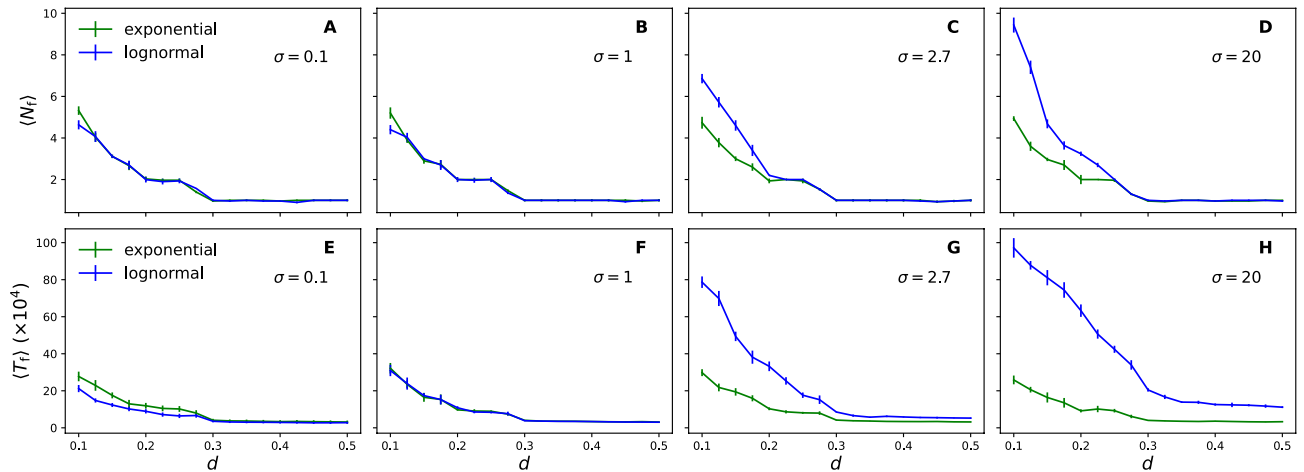


Figure 3. Opinion clusters and stabilisation times for burstiness. The average number of opinion clusters ($\langle N_f \rangle$) for different levels of burstiness (a) $\sigma = 0.1$, (b) $\sigma = 1.0$, and (c) $\sigma = 2.7$ and (d) $\sigma = 20$ as a function of the confidence level d . The average stabilisation time ($\langle T_f \rangle$) at the stationary state for different levels of burstiness (e) $\sigma = 0.1$, (f) $\sigma = 1.0$, and (g) $\sigma = 2.7$ and (h) $\sigma = 20$ as a function of the confidence level d . The averages are taken over $m = 300$ realisations. Vertical bars represent the standard errors.

homogeneous (exponential) and non-temporal cases (standard Deffuant model). This indicates that a sufficiently high tolerance for different opinions leads individuals to self-organise towards consensus. On the other hand, for $d < 0.3$, the population is split into multiple opinion clusters. Near regular ($\sigma = 0.1$) and exponential temporal patterns show similar results, but increasing heterogeneity (i.e. burstiness, with larger σ) leads to an increasing number of opinion clusters (more diversity). For example, $\sigma = 20$ creates two times more opinion clusters ($\langle N_f \rangle \sim 9$, for $d = 0.1$) than what would be created in the homogeneous case with the same (Δt) and d . If $\sigma = 1$, a significant difference in the number of opinion clusters happens only for $d = 0.1$ (low tolerance). A relatively small increase in burstiness ($\sigma = 2.7$) increases the tolerance level ($d = 0.2$) in which bursts disproportionately affect the number of emerging opinion clusters.

Figure 3e–h shows that the stabilisation times are also affected by burstiness; for both temporal patterns, decreasing d increases $\langle T_f \rangle$. Lower d means lower tolerance, which results in fewer interactions leading to opinion updates and thus requiring longer times before reaching stationarity. For $d < 0.3$, near regular ($\sigma = 0.1$) interactions lead to a small but significant speedup in the convergence to stationarity compared to the homogeneous case. On the other hand, increasing burstiness (larger σ) leads to a substantial slowdown (up to 5 times slower for $\sigma = 20$). In contrast to the number of opinion clusters, burstiness always affects the convergence times (compared to the homogeneous case); higher burstiness leads to a dynamic slowdown, despite both temporal patterns leading to global consensus for confidence levels $d > 0.3$.

Burstiness of social interactions means that pairs of individuals interact often during specific short periods of time, followed by extended periods of inactivity. Such fast and repeated interactions reinforce existing opinions, increasing the similarity of opinions locally and consequently creating spots or local clustering of opinions (local consensus). This local consensus makes the opinion clusters diverge more quickly early in the dynamics, followed by a slowdown in the convergence to stationarity due to the long periods of social tie inactivity (i.e. the large inter-event times).

Structure, burstiness and diversity

The complex network structure is included in the analysis via the fitness random model. The model generates networks with different structures by controlling the fitness parameter β (See Section “Methods”). The average degree $\langle k \rangle$ is fixed for all networks, but the average betweenness $\langle b \rangle$ and average clustering coefficient $\langle cc \rangle$ (i.e. triangles) are larger than expected in the configuration model (fixed degree sequence and rewired social ties⁴⁵) (Table 1). Figure 4 shows that lower β generates networks closer to those produced by the standard preferential attachment model (BA model), whereas larger β results in networks with fewer hubs, higher betweenness, and higher clustering coefficient. A modular structure emerges (measured by the modularity (Q)⁴⁶) for larger β , but the networks are not assortative by degree (measured by the assortativity index r^{41}), independently of the value of β . These results show that the fitness function (based on attribute preference) creates social clustering and, consequently, brokerage in the network.

Figure 5a shows that the clustered structure (increasing β) affects the opinion dynamics by creating more opinion clusters for $d < 0.3$, whereas it has no effect for $d \geq 0.3$ in the stationary state. Adding the heterogeneous temporal activity further affects the opinion dynamics by increasing the number of opinion clusters for all values of β (Fig. 5b,c). The results also indicate an overall slowdown of the opinion dynamics towards stationarity (Fig. 5d–f). In this case, the slowdown occurs for all values of d but is more pronounced for $d < 0.3$ (when opinion clusters emerge). The effect of burstiness is relatively more significant on the convergence time (T_f) compared to the formation (number) of opinion clusters (N_f). The triangles are sufficient to increase diversity

Model	β	$\langle k \rangle$	$\langle b \rangle$	$\langle cc \rangle$	$\langle Q \rangle$	$\langle r \rangle$
Fitness	0	5.98	0.0025	0.029	0	-0.08
Configuration	-	5.98	0.0025	0.025	0	-0.21
Fitness	20	5.98	0.0030	0.086	0.57	-0.09
Configuration	-	5.98	0.0026	0.021	0	-0.24
Fitness	100	5.98	0.0036	0.176	0.69	-0.06
Configuration	-	5.98	0.0027	0.014	0	-0.29
Watts-Strogatz	-	6	0.0036	0.177	0.50	-0.04
Configuration	-	6	0.0032	0.003	0	-0.01

Table 1. Summary of network statistics for the fitness random network model and the respective configuration model (swapping of one of the ends of two social ties chosen at random⁴⁵).

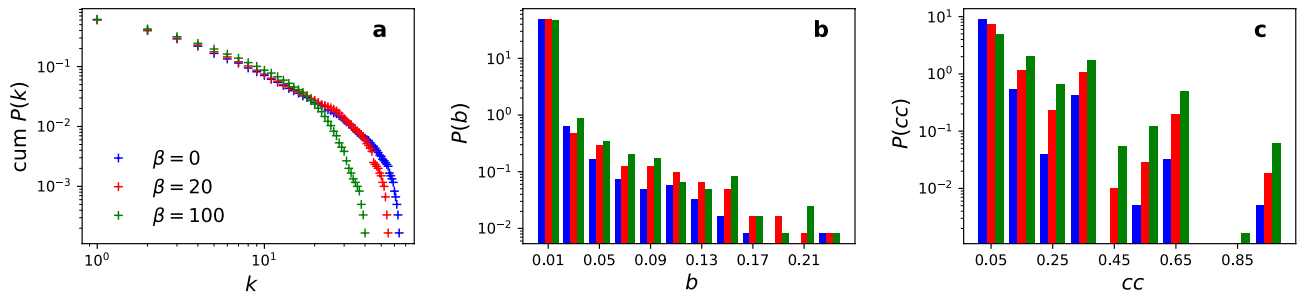


Figure 4. Structural characteristics of the fitness random network model. (a) cumulative degree distribution, (b) betweenness centrality distribution (bin size 0.02), and (c) clustering coefficient distribution (bin size 0.1) for different values of the fitness parameter β . The histograms (b) and (c) are normalised probability density functions, where each bin's height is scaled to maintain the total area under the histogram as 1.

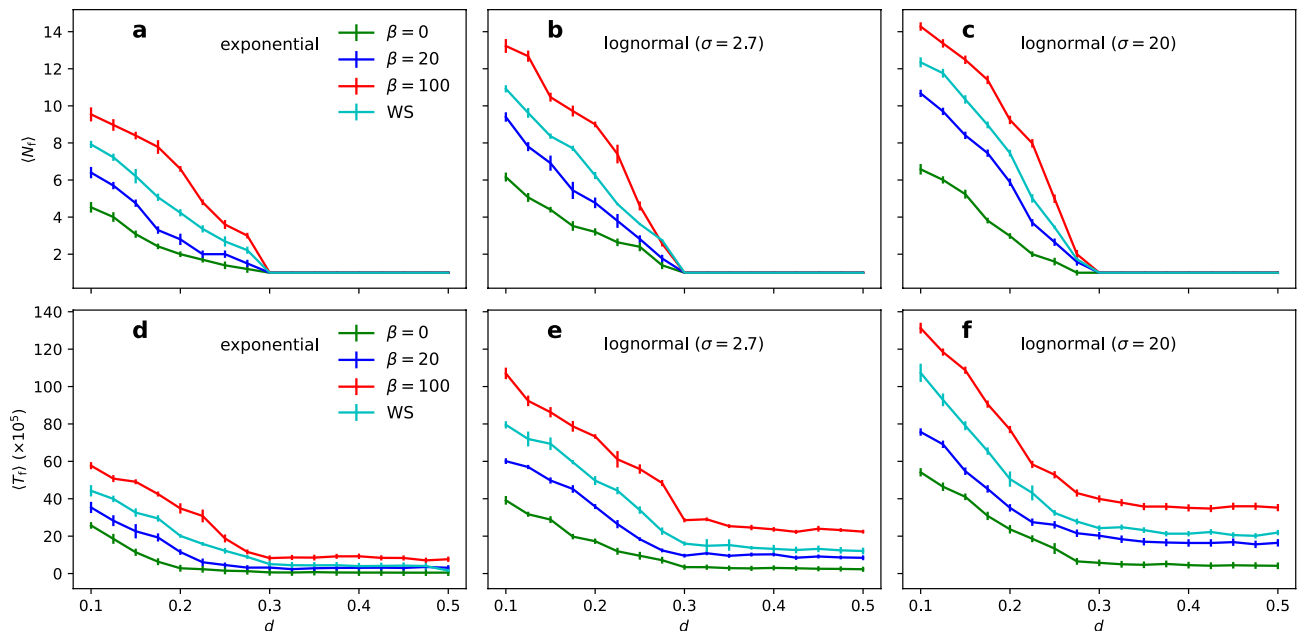


Figure 5. Opinion clusters and stabilisation times for burstiness and social clustering. The average number of opinion clusters (N_f) for the (a) exponential, (b) log-normal ($\sigma = 2.7$), and (c) log-normal ($\sigma = 20$) inter-event times as a function of the confidence level d . The average stabilisation time (T_f) for the (d) exponential, (e) log-normal ($\sigma = 2.7$), and (f) log-normal ($\sigma = 20$) inter-event times as a function of the confidence level d . The averages are taken over $m = 300$ realisations. Vertical bars represent standard errors.

(WS model), but the effect increases in the fitness model with the same average clustering coefficient but higher modularity (Table 1).

The results show that network clustering increases the emergence of opinion clusters while slowing down the creation process of those clusters. Network clustering, particularly triangles, creates local redundancies in communication and thus locally reinforces existing opinions. On the other hand, bridging nodes are exposed to opinions from different clusters and therefore take longer to converge to one or another opinion. The introduction of burstiness on clustered networks boosts the reinforcement mechanism because bursts on redundant social ties (e.g., in triangles) promote exchanges between social neighbours. This leads to local consensus and makes the small opinion clusters too different early in the dynamics. After a few interactions, individuals struggle to find neighbours sufficiently close in the opinion space to potentially adjust opinions. Furthermore, the long inter-event times slow the convergence to the stationary state because they counter-balance the fast local convergence with individuals having intermediate opinions.

The confidence level d , as well as, structural and temporal patterns affect the number of opinion clusters (Fig. 5a–c). We measure the relative size of these opinion clusters (Ω), i.e. the number of individuals per cluster divided by N . Figure 6 shows that opinion clusters are symmetric around the centre of the opinion space and $\langle \Omega \rangle$ decreases with the increasing number of opinion clusters N_f . This means that the individuals are redistributed to different opinion clusters when more clusters emerge in the opinion dynamics. In configurations where individuals self-organise into several opinion clusters (e.g., for smaller d), cluster size heterogeneity exists. Still, the emergence of (large or small) disproportionate clusters is not observed. Opinion clusters are usually equally spaced but not always of the same size in the (structure and activity) homogeneous case (Fig. 6a). Adding temporal heterogeneity brings a better balance on the size of clusters in both homogeneous (ER)(Fig. 6b) and heterogeneous (fitness)(Fig. 6d) network structures. Furthermore, extreme opinions are more likely when multiple clusters emerge, i.e. in case of higher diversity, but they are generally observed within a relatively small fraction of the population.

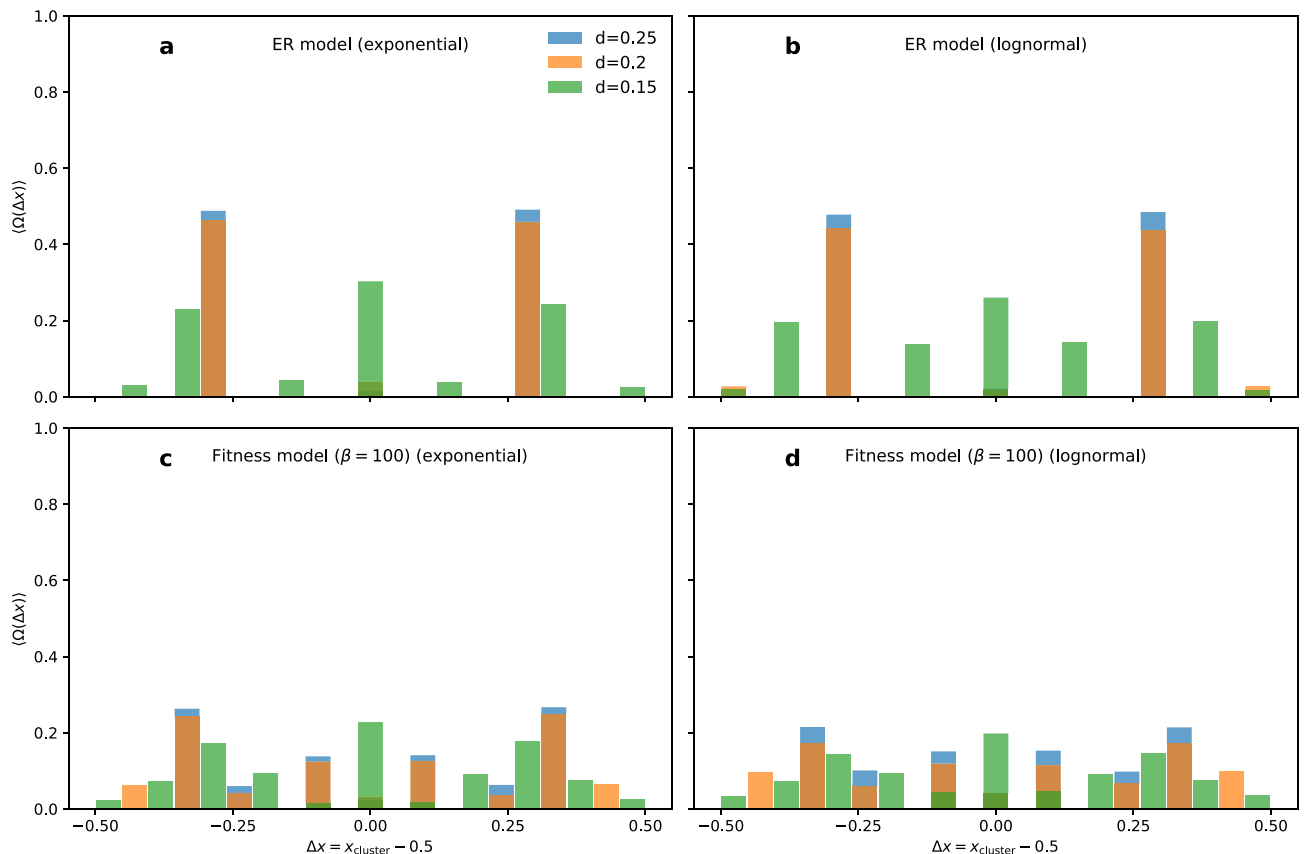


Figure 6. Size of opinion clusters. The relative average size of an opinion cluster ($\Omega(\Delta x)$) as a function of the distance ($\Delta x = x_{\text{cluster}} - 0.5$) of the cluster from the central opinion ($x = 0.5$) for various confidence levels d . (a) ER model and exponential inter-event times, (b) ER model and log-normal ($\sigma = 2.7$) inter-event times, (c) fitness model and exponential inter-event times, and (d) fitness model and log-normal inter-event times ($\beta = 100$). Simulations are repeated for $m = 300$ starting conditions with the same set of parameters.

Discussion

Individuals attempt to adjust their opinions via social interactions and communication. One-to-one exchanges occur when individuals are similar, but those with disparate opinions may hardly reach consensus⁴⁷. The cost to reduce large gaps in the opinions of different individuals is too large, and potential incremental gains to close this gap may be relatively insignificant and unable to homogenise opinions. Attempting to mitigate large gaps may be more damaging because lacking common ground may encourage individuals to push back if facing opposite views⁴⁸. In this paper, we approached the problem from a different perspective. We studied fundamental mechanisms to encourage interactions between relatively similar individuals and analysed the potential for departing from consensus and polarisation towards a more diversified opinion landscape. We designed a temporal version of the Deffuant opinion dynamics model to include the social network structure and temporal patterns of pairwise interactions. We first studied the impact of burstiness on the formation of opinion clusters (local consensus), then analysed the effect of the same temporal pattern in combination with social network clustering on opinion dynamics.

A fundamental mechanism to advance opinions towards others is reinforcement, the act of repeatedly exposing someone to a given opinion so that the individual might eventually accept it. Reinforcement may be implemented by social influence of peers (i.e. social contacts)¹⁶, nudging⁴⁹, algorithmic reinforcement^{12,50} or, as we demonstrated in this paper, by bursts of interactions. We found that burstiness promotes local consensus due to frequent pairwise opinion adjustments during short periods, followed by longer periods of no interaction, slowing down the process of opinion cluster stabilisation. The emergence of various spots of local consensus impedes individuals to self-organise into larger groups sharing the same opinion. Homogeneous (Poisson) temporal activity often leads to consensus or the emergence of two or four opinion clusters, typical signs of polarisation. Burstiness, on the other hand, leads to a multi-partisan population with up to ten opinion clusters in completely random social structures. This effect is more substantial for lower tolerance to adjust opinions; if individuals only accept interacting with those very similar to them, chances are higher that multiple opinion clusters emerge. As mentioned above, local structural clustering (i.e. social triangles) also promotes reinforcement. The higher the social clustering, the higher the number of opinion clusters. According to our computational experiments, the combination of burstiness and clustering substantially reduces polarisation with the emergence of at least ten opinion clusters for relatively high tolerance values ($d \leq 0.2$). Furthermore, these temporal structures refrain the emergence of disproportionately large groups dominating the population, independently of the number of opinion clusters. Furthermore, burstiness promotes a more balanced opinion landscape, where opinion clusters are less far apart. Moderate opinions generally prevail, but diversity led to higher chances of extreme opinions, albeit those clusters with extreme opinions are relatively smaller than moderates.

These results suggest that homogeneity (i.e. a lack of social clustering and absence of burstiness) promotes polarisation. Burstiness and structural clustering (triangles and community structure), on the other hand, increase opinion diversity. A maximum variety of opinions is, of course, observed if each individual has their own opinion. However, in real settings, groups often converge to a consensus by sharing similar views. Fitting our model to real data is challenging because data on the temporal patterns of daily offline social interactions are unavailable. However, previous research suggested that the distribution of inter-event times of communication via letters fits a power-law $P(\Delta t) \propto \Delta t^{-1.551}$ (which is approximately our log-normal model with $\sigma = 2.7$) whereas online communication follows $P(\Delta t) \propto \Delta t^{-1.28}$ (which is approximately our log-normal model with $\sigma = 20$). In these cases, our experiments suggest that online communication should create less polarisation than expected in offline communication. We argue that this phenomenon is not observed in real-life (i.e. less polarisation online) because structural clustering is substantially lower in online social media ($cc_{\text{median}} \sim 0.04$) compared to offline social networks ($cc_{\text{median}} \sim 0.37$)⁵². We stress that the relatively low social clustering observed in social media is thus sufficient to promote polarisation. The reported difference in social clustering is independent of the network size⁵², but the studied offline social networks are relatively small, with a few hundred individuals. Individuals are constrained and organised into strong (network) communities (e.g., within schools, work, clubs, cities). The potential fragmentation of offline social networks would further promote diversification and thus a multi-partisan society, as suggested by our model. This rationale implies that the low cost of creating online friends, leading to almost unrestricted opportunities for social interactions, creates the sufficient conditions for polarisation, independently of any other social mechanisms.

Our study also showed that the convergence towards stationarity is extended in the presence of heterogeneity, with both network clustering and burstiness contributing to the slowdown of the dynamics. This is a consequence of the coexistence of several small clusters of different opinions. Bridging individuals (i.e. brokers, with high betweenness and more often observed in highly clustered networks) require more time to position themselves in a particular opinion cluster because they are exposed to different social groups. Similarly, the longer periods of absence of activity (due to the tail of the distribution of inter-event times) increases the time needed for pairs of individuals to converge to one or another opinion^{33,34,37}. Similar dynamics have been observed in the spread of simulated infectious diseases, with bursts initially accelerating the spread but eventually slowing down the diffusion because the long periods of inactivity reduce the chances of finding susceptible nodes to infect^{30–32,53}.

Our study starts with the assumption that individuals adjust their opinions via pairwise interactions with similar peers. Therefore, both social network structure and the timings of social interaction are shown to be responsible for regulating the emergence of groups of individuals sharing the same opinion. This is reasonable in both offline and online environments. However, in real-life settings, individuals are also exposed to mass media (e.g., radio, TV, newspapers) and group activism that may contribute to shaping opinions. Future models could include broadcasting and synchronous group interactions to accommodate that mechanism²³. Information personalisation also plays a role. In offline social interactions, power relations, norms, or contextual conversations may prevent individuals from sharing certain opinions socially. On the other hand, automated algorithmic

personalisation is the norm in online settings and biases the information exposed to individuals based on their previous activity, creating the so-called filter bubbles¹². Other social structures and temporal patterns may also play a role. We assumed populations with a fixed size, fixed density of social contacts, and a log-normal distribution of inter-event times. Other models may be more appropriate, including higher density networks and the power-law model of inter-event times, which is often adopted due to scale invariance properties. Future studies should fit real structural and temporal data to our opinion model to further validate our results in different contexts. Although all those mechanisms contribute to opinion dynamics and can be actively exploited to manipulate opinions, our study suggests that more attention must be given to reshaping the underlying structure of online social networks to promote a multi-partisan society. Burstiness in social media communication may induce opinion diversity by creating local spots of consensus. Such diversity may be boosted by increasing social redundancy via social triangles strengthening online social relations.

Data availability

All data generated or analysed during this study are included in this published article.

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References

- Brown, J., Broderick, A. J. & Lee, N. Word of mouth communication within online communities: conceptualizing the online social network. *J. Interact. Mark.* **21**, 2–20 (2007).
- Muchnik, L., Aral, S. & Taylor, S. J. Social influence bias: a randomized experiment. *Science* **341**, 647–651 (2013).
- State, B. & Adamic, L. The diffusion of support in an online social movement: evidence from the adoption of equal-sign profile pictures. In *CSCW 2015, March 14–18, 2015* (2015).
- Del Vicario, M. *et al.* The spreading of misinformation online. *Proc. Natl. Acad. Sci.* **113**, 554–559 (2016).
- Del Vicario, M. & *et al.* Echo chambers: Emotional contagion and group polarization on Facebook. *Sci. Rep.* **6**, 37825 (2016).
- Mason, L. *Uncivil Agreement: How Politics Became Our Identity* (University of Chicago Press, 2018).
- Jääskeläinen, P. & Huhtinen, A. M. Online polarization, radicalization, and conspiracy. In *ECCWS 2020 19th European Conference on Cyber Warfare and Security*, 151 (Academic Conferences and Publishing Limited, 2020).
- Conover, M. & *et al.* Political polarization on twitter. In *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 5, 89–96 (2011).
- Mocanu, D., Rossi, L., Zhang, Q., Karsai, M. & Quattrociocchi, W. Collective attention in the age of (mis) information. *Comput. Hum. Behav.* **51**, 1198–1204 (2015).
- Gargiulo, F. & Gandica, Y. The role of homophily in the emergence of opinion controversies. *J. Artif. Soc. Soc. Simul.* **20** (2017).
- Quattrociocchi, W., Scala, A. & Sunstein, C. R. Echo chambers on facebook. *Soc. Sci. Res. Netw.* (2016).
- Perra, N. & Rocha, L. E. C. Modelling opinion dynamics in the age of algorithmic personalisation. *Sci. Rep.* **9**, 1–11 (2019).
- Woolley, S. C. & Howard, P. N. Computational propaganda worldwide: Executive summary. Working Paper 2017.11, Oxford, UK (2017).
- Castellano, C., Fortunato, S. & Loreto, V. Statistical physics of social dynamics. *Rev. Mod. Phys.* **81**, 591 (2009).
- Xia, H., Wang, H. & Xuan, Z. Opinion dynamics: A multidisciplinary review and perspective on future research. *Int. J. Knowl. Syst. Sci.* **2**, 72–91 (2011).
- Guilbeault, D., Becker, J. & Centola, D. Complex contagions: A decade in review. In Lehmann, S. & Ahn, Y. Y. (eds.) *Complex Spreading Phenomena in Social Systems*, 3–25 (Springer, Cham, 2018).
- Cencetti, G., Contreras, D. A., Mancastroppa, M. & Barrat, A. Distinguishing simple and complex contagion processes on networks. *Phys. Rev. Lett.* **130**, 247401 (2023).
- Sznajd-Weron, K. & Sznajd, J. Opinion evolution in closed community. *Int. J. Mod. Phys. C* **11**, 1157–1166 (2000).
- Galam, S. Heterogeneous beliefs, segregation, and extremism in the making of public opinions. *Phys. Rev. E* **71**, 046123 (2005).
- Centola, D. The spread of behavior in an online social network experiment. *Science* **329** (2010).
- Lerman, K. & Ghosh, R. Information contagion: An empirical study of the spread of news on Digg and Twitter social networks. *Int. Conf. Weblogs Soc. Med.* **10**, 90–97 (2010).
- Deffuant, G., Neau, D., Amblard, F. & Weisbuch, G. Mixing beliefs among interacting agents. *Adv. Complex Syst.* **3**, 87–98 (2000).
- Hegselmann, R. & Krause, U. Opinion dynamics and bounded confidence model, analysis, and simulation. *J. Artif. Soc. Soc. Simul.* **5** (2002).
- Redner, S. Reality-inspired voter models: A mini-review. *C R Phys.* **20**, 275–292 (2019).
- Fortunato, S. Universality of the threshold for complete consensus for the opinion dynamics of Deffuant. *Int. J. Mod. Phys. C* **16**, 259–270 (2005).
- Gandica, Y., Lambiotte, R., Carletti, T., dos Aidos, F. S. & Carvalho, J. Circadian patterns on wikipedia edits. In *Studies in Computational Intelligence*, 293–300 (Springer International Publishing, 2016).
- Karsai, M., Jo, H. H. & Kaski, K. *Bursty human dynamics* (Cham, Springer International, 2018).
- Barabási, A. L. The origin of bursts and heavy tails in human dynamics. *Nature* **435**, 207–211 (2005).
- Goh, K. I. & Barabási, A. L. Burstiness and memory in complex systems. *Europhys. Lett.* **81**, 48002 (2008).
- Rocha, L. E. C., Liljeros, F. & Holme, P. Simulated epidemics in an empirical spatiotemporal network of 50,185 sexual contacts. *PLoS Comput. Biol.* **7**, e1001109 (2011).
- Karsai, M. & *et al.* Small but slow world: How network topology and burstiness slow down spreading. *Phys. Rev. E* **83** (2011).
- Rocha, L. E. C. & Blondel, V. D. Bursts of vertex activation and epidemics in evolving networks. *PLoS Comput. Biol.* **9**, e1002974 (2013).
- Jo, H. H. & Masuda, N. Finite-size effects on the convergence time in continuous-opinion dynamics. *Phys. Rev. E* **104** (2021).
- Li, G. J. & Porter, M. A. A bounded-confidence model of opinion dynamics with heterogeneous node-activity levels. *arXiv Preprint: 2206.09490* (2023).
- Su, Q., McAvoy, A. & Plotkin, J. B. Strategy evolution on dynamic networks. *Nat. Comput. Sci.* **3**, 763–776 (2023).
- Li, A. *et al.* Evolution of cooperation on temporal networks. *Nat. Commun.* **11**, 2259 (2020).
- Delvenne, J. C., Lambiotte, R. & Rocha, L. E. C. Diffusion on networked systems is a question of time or structure. *Nat. Commun.* **6**, 7366 (2015).
- Šuvakov, M., Mitrović, M., Gligorijević, V. & Tadić, B. How the online social networks are used: Dialogues-based structure of MySpace. *J. R. Soc. Interface* **10**, 20120819 (2013).
- Tadić, B., Gligorijević, V., Mitrović, M. & Šuvakov, M. Co-evolutionary mechanisms of emotional bursts in online social dynamics and networks. *Entropy* **15**, 5084–5120 (2013).

40. Dankulov, M., Melnik, R., Roderick & Tadić, B. The dynamics of meaningful social interactions and the emergence of collective knowledge. *Sci. Rep.* **5**, 12197 (2015).
41. Newman, M. *Networks* (Oxford University Press, 2018).
42. Masuda, N. & Rocha, L. E. C. A gillespie algorithm for non-markovian stochastic processes. *SIAM Rev.* **60**, 95–115 (2018).
43. Clauset, A., Shalizi, C. R. & Newman, M. E. J. Power-law distributions in empirical data. *SIAM Rev.* **51**, 661–703 (2009).
44. Mitzenmacher, M. A brief history of generative models for power law and lognormal distributions. *Internet Math.* **1**, 226 (2003).
45. Fosdick, B. K., Larremore, D. B., Nishimura, J. & Ugander, J. Configuring random graph models with fixed degree sequences. *SIAM Rev.* **60**, 315–355 (2018).
46. Newman, M. Modularity and community structure in networks. *Proc. Natl. Acad. Sci.* **103**, 8577–8582 (2006).
47. Baronchelli, A. The emergence of consensus: A primer. *R. Soc. Open Sci.* **5**, 172189 (2018).
48. Bail, C. A. & et al. Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences* **115**, 9216–9221 (2018).
49. Thaler, R. H. & Sunstein, C. R. *Nudge: Improving Decisions about Health, Wealth and Happiness* (Yale University Press, 2008).
50. Botte, N., Ryckenbusch, J. & Rocha, L. E. C. Clustering and stubbornness regulate the formation of echo chambers in personalised opinion dynamics. *Phys. A* **599**, 127423 (2022).
51. Oliveira, J. & Barabási, A. L. Darwin and Einstein correspondence patterns. *Nature* **437** (2005).
52. Rocha, L. E. C., Ryckenbusch, J., Schoors, K. & Smith, M. The scaling of social interactions across animal species. *Sci. Rep.* **11** (2021).
53. Stehlé, J. & et al. Simulation of an SEIR infectious disease model on the dynamic contact network of conference attendees. *BioMed Central Med.* **9**, 1–15 (2011).

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Author contributions

L.E.C.R. and Y.G. conceived the experiments; F.Z. conducted the experiments; all authors analysed the results; F.Z. wrote the initial draft; L.E.C.R. wrote the final manuscript; all authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

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