

# Network segregation in a model of misinformation and fact checking

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## Abstract

Misinformation under the form of rumor, hoaxes, and conspiracy theories spreads on social media at alarming rates. One hypothesis is that, since social media are shaped by homophily, belief in misinformation may be more likely to thrive on those social circles that are segregated from the rest of the network. One possible antidote is fact checking which, in some cases, is known to stop rumors from spreading further. However, fact checking may also backfire and reinforce the belief in a hoax. Here we take into account the combination of network segregation, finite memory and attention, and fact-checking efforts. We consider a compartmental model of two interacting epidemic processes over a network that is segregated between gullible and skeptic users. Extensive simulation and mean-field analysis show that a more segregated network facilitates the spread of a hoax only at low forgetting rates, but has no effect when agents forget at faster rates. This finding may inform the development of mitigation techniques and overall inform on the risks of uncontrolled misinformation online.

# 1 Introduction

Social media are rife with inaccurate information of all sorts. This is in part due to their egalitarian bottom-up approach to communication [6], by which users can choose to rebroadcast information to their social circles without any top-down form of quality control [16]. Examples of Internet misinformation range from rumors [12], hoaxes [20], up to elaborate — and surprisingly popular — conspiracy theories [3, 14].

A simple antidote to misinformation is *fact-checking*, or factual verification [9]. In particular cases (e.g. death hoaxes, crises) timely fact-checking efforts are enough to stop a rumor from spreading further [4]. However, fact checking may not always be as effective. This is especially the case when someone is exposed to misinformation that conforms with their preexisting beliefs and personal world-views [20]. Moreover, fact checking can *backfire*, meaning that providing accurate information to people who have been exposed to misinformation may cause them, on the long term, to forget the former and instead remember the latter [19].

One hypothesis is that, since social networks are shaped by homophily [17], misinformation may be more likely to thrive in those social circles that are *segregated* from the rest of the network. One example of such a scenario is given in Figure 1(a), where a hoax about a research project on information diffusion is shown to spread within the context of the retweet network of a highly segregated topic of conversation on the popular microblogging service Twitter. In this case, the overwhelming majority of those who broadcast the hoax fall within one cluster. The alternative hypothesis, i.e. that a segregated social network is not always required for the spread of misinformation, is exemplified by Figure 1(b), where another popular hoax — the alleged link between vaccines and autism — shows a more balanced spread.

Several models have been proposed in prior work to describe the propagation of rumor in a complex social network [10, 7, 18, 2]. Most are based on the epidemic compartmental models like the SIS (Susceptible–Infected–Susceptible) [21]. Another class of models uses branching processes on signed networks to take into account user polarization [11]. Neither type, however, takes into account the three aforementioned mechanisms — competition between hoax and fact-checking, forgetting mechanisms (i.e., backfiring), and segregation.

To consider all these features, here we introduce a simple agent-based model in which individuals are endowed with finite memory and a fixed

predisposition toward factual verification. In this model hoax and fact checks compete on a network formed by two groups, the *gullible* and the *skeptic*, marked by a different tendency to believe in the hoax. Varying the level of segregation in the network, as well as the relative credibility of the hoax among the two groups, we look at whether the hoax becomes endemic or instead is eradicated from the whole population.

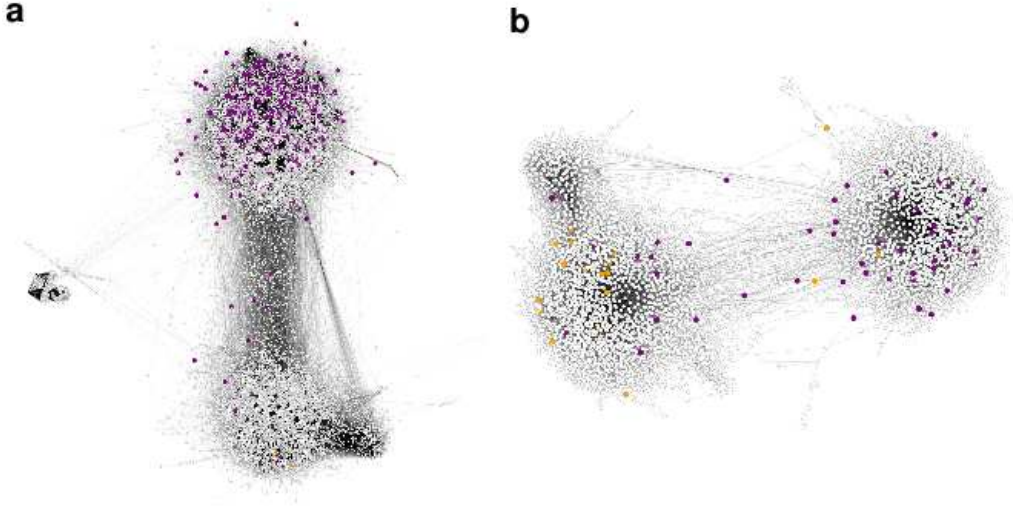


Figure 1: Network segregation and misinformation spread: **(a)** the misinformation campaign on the Truthy project ([truthy.indiana.edu](http://truthy.indiana.edu)) and, **(b)** the #CDCWhistleBlower hashtag. The plot shows two snapshots of the retweet networks of the hashtag #TCOT (acronym for “Top Conservatives On Twitter”), one of the most segregated topics of conversation on Twitter. We use these two groups as an example of high homophilistic information exchange network. Nodes represent Twitter user accounts; an edge connects two nodes if one of them has retweeted from the other a tweet with the #TCOT hashtag in it. The position of nodes was determined using a force-directed layout [15]. Purple nodes indicate users who tweeted the hoax. Yellow nodes indicate users who tweeted fact-checking contents.

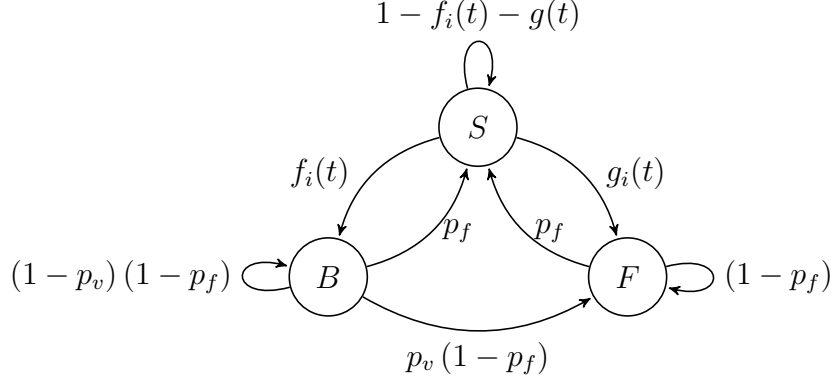


Figure 2: State transitions for the generic  $i$ -th agent of our hoax epidemic model. To simplify the model, here we set  $p_v = 1 - \alpha$ .

## 2 Model

Here we describe a model of the spread of the belief in a *hoax* and the related *fact checking* within a social network of agents with finite memory. An agent can be in any of the following three states: ‘Susceptible’ (denoted by  $S$ ), if they have not heard about neither the hoax nor the fact checking, or if they have forgotten about it; ‘Believer’ ( $B$ ), if they believe in the hoax and choose to spread it; and ‘Fact checker’ ( $F$ ) if they know the hoax is false — for example after having consulted an accurate news source — and choose to spread the fact checking.

Let us consider the  $i$ -th agent at time step  $t$  and let us denote with  $n_i^X(t)$  the number of its neighbors in state  $X \in \{S, B, F\}$ . We assume that an agent ‘decides’ to believe in either the hoax or the fact checking as a result of interaction over interpersonal ties. This could be due to social conformity [5] or because agents accept information from their neighbors [22]. Second, we assume that the hoax displays an intrinsic *credibility*  $\alpha \in [0, 1]$ , which, all else being equal, makes it more believable than the fact checking. Thus, the probability of transitioning from  $S$  to either  $B$  or  $F$  are given by functions

$f_i$ , and  $g_i$ , respectively:

$$f_i(t) = \beta \frac{n_i^B(1 + \alpha)}{n_i^B(1 + \alpha) + n_i^F(1 - \alpha)} \quad (1)$$

$$g_i(t) = \beta \frac{n_i^F(1 - \alpha)}{n_i^B(1 + \alpha) + n_i^F(1 - \alpha)} \quad (2)$$

where  $\beta \in [0, 1]$  is the overall spreading rate. Agents possess finite memory, which means that at each time step, any believer of fact checker can ‘forget’, with fixed probability  $p_f$ , about the hoax or the fact check and become susceptible again. Finally, any believer who has not forgotten the hoax yet can decide to check the news and stop believing in the hoax, becoming a fact checker. This happens with probability  $p_v$ . In any other case, an agent remains in its current state. The full model is shown in Fig. 2.

Since  $f_i(t) + g_i(t) = \beta$ , then  $\beta$  is equivalent to the infection rate of the SIS model. Indeed, if one considers the two states  $B$  and  $F$  as single ‘Infected’ state ( $I$ ), then our model is exactly an SIS model, with the only difference that the probability of recovery  $\mu$  is denoted by  $p_f$ .

Let us denote by  $s_i(t)$  the state of the  $i$ -th agent at time  $t$ , and let us define, for  $X \in \{B, F, S\}$ , the state indicator function  $s_i^X(t) = \delta(s_i(t), X)$ . The triple  $p_i(t) = [p_i^B(t), p_i^F(t), p_i^S(t)]$  describes the probability that a node  $i$  is in any of the three states at time  $t$ . The dynamics of the system at time  $t + 1$  will be then given by a random realization of  $p_i$  at  $t + 1$ . Thus,  $p_i(t + 1)$  can be described as:

$$p_i^B(t + 1) = f_i(t)s_i^S(t) + (1 - p_f)(1 - p_v)s_i^B(t) \quad (3)$$

$$p_i^F(t + 1) = g_i(t)s_i^S(t) + p_v(1 - p_f)s_i^B(t) + (1 - p_f)s_i^F(t) \quad (4)$$

$$p_i^S(t + 1) = p_f[s_i^B(t) + s_i^F(t)] + [1 - f_i(t) - g_i(t)]s_i^S(t) \quad (5)$$

In previous work [23] we analyzed the behavior of the model at equilibrium. Starting from a well-mixed topology of  $N$  agents, in which a few agents have been initially seeded as believers, we derived, in the infinite-time limit, expressions for the density of believers, fact checkers, and susceptible agents. Let us denote these by  $B_\infty$ ,  $F_\infty$ , and  $S_\infty$ , respectively. We found that  $S_\infty$  stabilizes around the same values in all simulations, independent of the network topology (Barabási-Albert and Erdős-Rényi), the value of  $p_v$ , and of  $\alpha$ . We confirmed such a result using both mean-field equations and simulation.

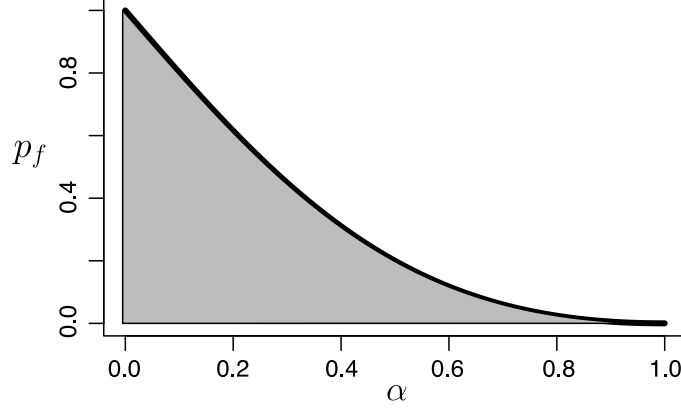


Figure 3: Epidemic threshold for the simplified version of the model given by Eq. 6. The grey area indicates the region of the parameter space where the hoax is completely removed from the network. The white part indicates the region of the parameter space where the hoax can become endemic.

At equilibrium, the relative ratio between believers and fact checkers is determined by  $\alpha$  and  $p_v$ : the higher  $\alpha$ , the more believers, and conversely for  $p_v$ . In particular, we showed that there always exists a critical value of  $p_v$  above which the hoax is completely eradicated from the network (i.e.,  $B_\infty = 0$ ). This value depends on  $\alpha$  and  $p_f$ , but not on the spreading rate  $\beta$ .

The model has several parameters, namely, spreading rate  $\beta$ , credibility of the hoax  $\alpha$ , probability of verification  $p_v$  and probability of forgetting  $p_f$ . To reduce this number, we set

$$p_v = 1 - \alpha \quad (6)$$

This simplification can be motivated by assuming that the more credible a piece of news, the lower the chances anybody will doubt its veracity. Re-computing mean-field equations such a case, we obtain a sufficient condition that guarantees the removal of the hoax which is given by

$$p_f \leq \frac{(1 - \alpha)^2}{1 + \alpha^2} \implies p^B(\infty) = 0 \quad (7)$$

The behaviour of  $p_f$  versus  $\alpha$  is shown in Fig. 3. For any combination of  $p_f$  and  $\alpha$  below the curve the hoax is completely removed from the network. For combinations above the curve, the infection is instead endemic.

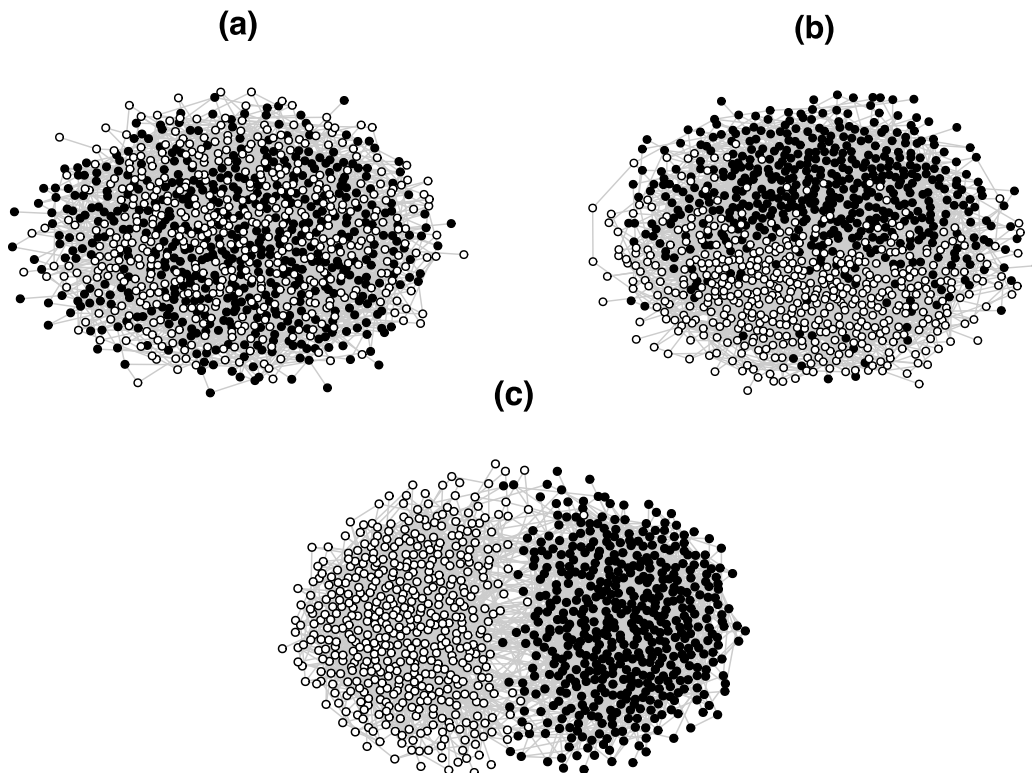


Figure 4: Network structure under different segregation regimes between two groups (in this case of equal size). In the figure, three different values of  $s$  were used. (a):  $s = 0.6$ , (b):  $s = 0.8$ , and (c):  $s = 0.95$ . Node layout was computed using a force-directed algorithm [13].

### 3 Results

To address our research question, we consider a simple generative model of a segregated network. Let us consider  $N$  agents divided into two groups, one comprised by  $t < N$  agents whose beliefs conform more to the hoax than the other one, which is comprised by the rest of the population. We call the former the *gullible* group, while the latter the *skeptic* group. To represent this in our framework, the value of  $\alpha$  of each agent is set to either  $\alpha_{\text{gu}}$  or  $\alpha_{\text{sk}}$ ,  $\alpha_{\text{gu}} > \alpha_{\text{sk}}$ , depending on the group they belong to.

To generate the network, we assign  $M$  edges at random. Let  $s \in [\frac{1}{2}, 1)$  denote the fraction of intra-group edges, regardless of the group. For each edge

we first decide, with probability  $s$ , whether two individuals from the same group (intra-group tie) or different groups (inter-group tie) should be connected. In the case of an intra-group tie, we select a group with probability proportional to the relative ratio of the total number of possible inter-group ties (of that group) to that of the whole network; then, we pick uniformly at random two agents from that group and connect them. In the second case, two agents are chosen at random, one per group, and connected. Fig. 4 shows three examples of network with different values of  $s$ .

To understand the behavior of the model in this segregated network, we performed extensive numerical simulations. We set  $\alpha_{\text{sk}} = 0.4$  to a fixed value and we considered a wide range of values of  $\alpha_{\text{gu}}$ ,  $p_f$ ,  $s$ , and  $t$ . Fig. 5 reports the results of the first of these exercises, showing the overall number of believers  $B_\infty$  in the whole population at equilibrium.

Increasing either  $t$  or  $\alpha_{\text{gu}}$  we see an increase of  $B_\infty$ , all else being equal. However, when we changed the segregation  $s$  we observed two different situations: for small  $p_f$ , an increase of  $s$  resulted in an increase of  $B_\infty$ . Conversely — and perhaps a bit surprisingly — under high values of  $p_f$  increasing  $s$  does not change  $B_\infty$ .

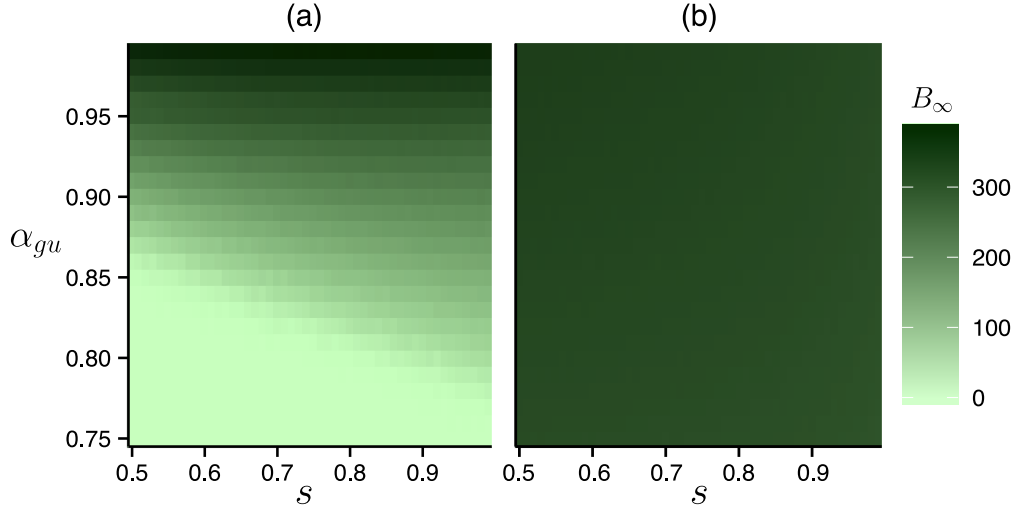


Figure 5: Believers at equilibrium in the phase space of  $s \times \alpha_{\text{gu}}$ . We considered two forgetting regimes: (a): low forgetting,  $p_f = 0.1$ , and (b): high forgetting,  $p_f = 0.8$ . Other parameters:  $\alpha_{\text{sk}} = 0.4$ . Each point was averaged over 50 simulations.



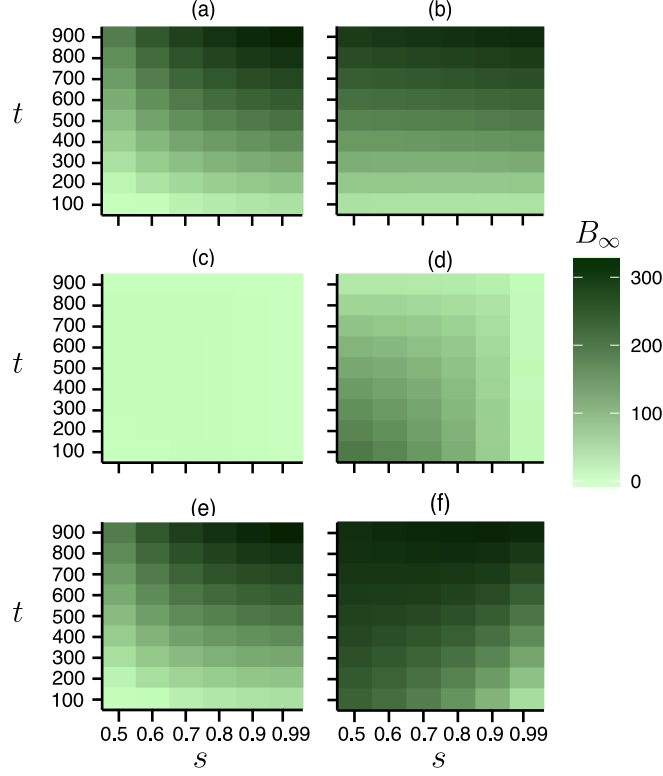


Figure 6: Believers at equilibrium under low ( $p_f = 0.1$ ) and high forgetting ( $p_f = 0.8$ ) rate. The number of believers at equilibrium is broken down as  $B_\infty = B_\infty^{\text{gu}} + B_\infty^{\text{sk}}$ . Phase diagrams in the space  $s \times t$  for (a)  $B_\infty^{\text{gu}}$ , low forgetting, (b)  $B_\infty^{\text{gu}}$ , high forgetting, (c)  $B_\infty^{\text{sk}}$  low forgetting, (d)  $B_\infty^{\text{sk}}$  high forgetting, (e)  $B_\infty$  low forgetting, and (f)  $B_\infty$  high forgetting. We fixed  $\alpha_{\text{gu}} = 0.9$  and  $\alpha_{\text{sk}} = 0.05$ .

Trying to better understand the role of  $p_f$ , we further explored the behavior of the model varying the size of the gullible group  $t$ . In Fig. 6 we report the phase diagrams breaking down the number of believers at equilibrium in each group, i.e.,  $B_\infty = B_\infty^{\text{gu}} + B_\infty^{\text{sk}}$ . If  $p_f$  is low (Fig 6, left column), the overall number of believers depends heavily on  $B_\infty^{\text{gu}}$  [see Fig. 6(a)] while  $B_\infty^{\text{sk}} \approx 0$ , and the segregation is unimportant [see Fig. 6(c)].

Instead, with an high rate of forgetting (right column),  $B_\infty$  mainly depends on  $B_\infty^{\text{sk}}$  [Fig. 6(d)], that decreases if  $s$  increases. In the gullible group [Fig. 6(b)] is less important to the overall  $B_\infty$  and  $s$  has fewer influence.

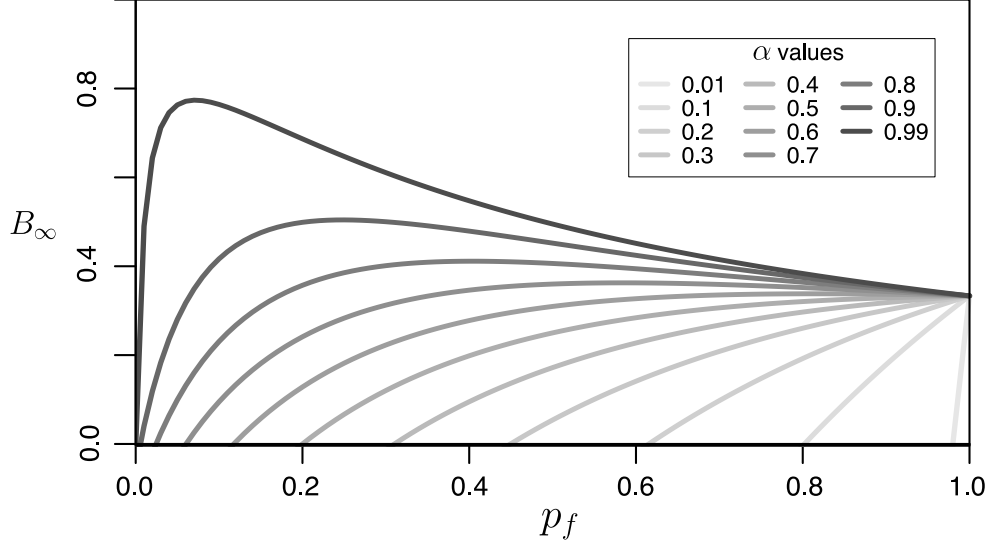


Figure 7: Behaviour of the solutions of the mean-field equations for different values of  $\alpha$ .

To give an analytical support to our findings, we obtained the mean-field equations for the model. However, when  $s \approx 1$  the problem approximates to the case of two separate disconnected networks with different values of  $\alpha$  (see Appendix). In this limit case, the solutions of mean-field equations for the gullible and the skeptic groups are given by:

$$B_{\infty}^{\gamma} = \frac{1}{2} \cdot \frac{\beta [p_f (1 + \alpha_{\gamma}^2) - (1 - \alpha_{\gamma})^2]}{\alpha_{\gamma} (\beta + p_f) (1 - \alpha_{\gamma} + \alpha_{\gamma} p_f)}, \quad \gamma \in \{\text{sk}, \text{gu}\} \quad (8)$$

Fig. 7 shows the behaviour of the above solutions for different values of  $\alpha$ . If we consider now a completely segregated network,  $B_{\infty}^{\text{sk}}$  and  $B_{\infty}^{\text{gu}}$  are represented by two of these lines: we can observe that for high forgetting probability (on the right) there is a significant number of believers also in the skeptic group (low values of  $\alpha$ ), while with a low  $p_f$  the number of believers is significant only in the gullible group (high values of  $\alpha$ ), because in the skeptic there are no believers at equilibrium.

It should be noted that any ‘network effect’ present in our model will only appear in the infection phase, that is for transitions  $S \rightarrow B$  and  $S \rightarrow F$ .

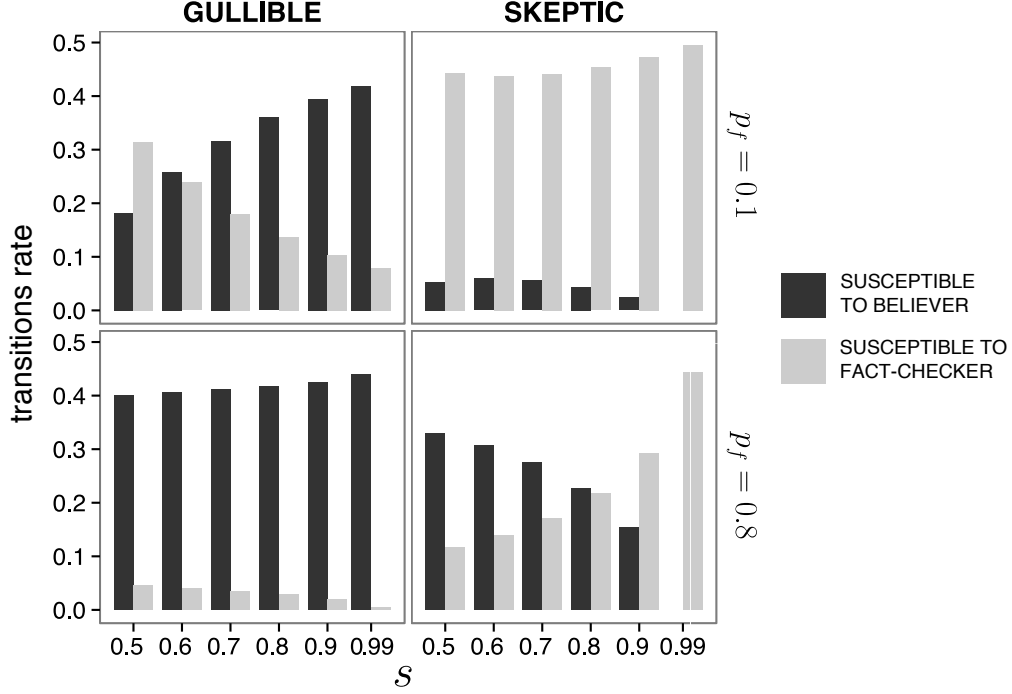


Figure 8: Rate of transitions of type  $S \rightarrow B$  and  $S \rightarrow F$  at equilibrium. We run the simulation until the system has reached the steady state and then compute the average number of transitions per susceptible. The plot shows averages over 50 simulations.

To better understand what happens in both groups, we computed the rate at which these transitions happen, that is, the conditional probability of, being susceptible, becoming either believer or fact checker. Let us consider a susceptible agent in the gullible group:

- At low forgetting rates, in the gullible group more intra-group ties (i.e. an higher  $s$ ) increase the chances of becoming a believer and reduce those of becoming fact checker; see Fig. 8 (top left). In the skeptic group, the segregation effect is almost negligible (top right). This happens because inter-group ties expose the susceptible agents, among the gullible, to more members of the skeptic group, who are largely fact checkers.
- At high forgetting rates, instead, we observe the opposite behavior:

more inter-group ties translate into more exposure, for susceptible users in the skeptic group, to gullible agents who are, by and large, believers. In the gullible group (bottom left of Fig. 8), segregation is not very important while, in the skeptic group, more connections with the gullible mean more believers (bottom right of Fig. 8).

Summarizing, the role of segregation, being related to the abundance of inter-group tie, can have both a positive and negative role in stopping the spread of misinformation: for low forgetting rates, these links can help the spread of the debunking in the gullible group, while for high forgetting rates, they have the opposite effect, helping the hoax spread in the skeptic group.

## 4 Discussion

By means of extensive simulation, we have analyzed the role of the underlying structure of the network on which the diffusion of a piece of misinformation takes place. In particular we consider a network formed by two groups — gullible and skeptic — characterized by different values of the credibility parameter  $\alpha$ . In order to study how the social structure shapes information exposure, we introduce a parameter  $s$  that regulates the abundance of ties between these two groups. We observe that  $s$  has an important role in the diffusion of misinformation. If the probability of forgetting  $p_f$  is small then the fraction of the population affected by the hoax will be large or small depending on whether the network is respectively segregated or not. However, if the rate of forgetting is large, segregation has no effect on the spread of the hoax.

The probability of forgetting could be also interpreted as a measure of how much a given topic is discussed. A low value of  $p_f$  could perhaps fit well with the scenario of a persistent belief in misinformation, for example conspiracy theories, while a high value with short-lived beliefs that are either easy to debunk or are no more interesting than mere gossip. Hoaxes about the alleged death of celebrities, for instance, could fall within this category.

On the basis of the promising findings presented in this paper, further research will be dedicated on the role of segregation in the misinformation spread processes: for conspiracy theories, it could be useful to analyze what happens if the communication among different groups increases.

In conclusion, understanding the production and consumption of misinformation is a critical issue [8]. As several episodes are showing, there

are obvious consequences connected to the uncontrolled production and consumption of inaccurate information [1]. A more thorough understanding of rumor propagation and the structural properties of the information exchange networks on which this happens may help mitigate these risks.

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## A Appendix

### Mean-Field computations

In previous work we showed MF analysis for our model on a homogeneous network [23]. Similarly, we develop here MF analysis for our model on a network segregated in two groups, skeptic and gullible: for each group we have three equations (see Eq. 5) representing the spreading process. In these equations we can substitute  $s_i(t)$  with  $p_i(t)$  and when  $t \rightarrow \infty$  we can assume  $p_i(t) = p_i(t+1) = p_i(\infty)$  for all  $i \in N$ , and hereafter we will simplify the notation using  $p_g^B(\infty) = p_g^B$  (and analogously for the other cases). Now let us consider the spreading functions: in the hypothesis that all vertices have the same number of neighbors  $\langle k \rangle$  and these neighbors are chosen randomly, we can write  $n_i^B = [s \cdot p_g^B + (1-s) \cdot p_{sk}^B] \cdot \langle k \rangle$  and  $n_i^F = [s \cdot p_g^F + (1-s) \cdot p_{sk}^F] \cdot \langle k \rangle$ , so they are not dependent on  $i$  and we can simplify  $f_{i_g}, f_{i_{sk}}, g_{i_g}, g_{i_{sk}}$  with  $f_g, f_{sk}, g_g, g_{sk}$ . We have:

$$\begin{aligned}
p_g^S &= (1-\beta)p_g^S + p_f(p_g^F + p_g^B) \\
p_g^B &= f_g \cdot p_g^S + \alpha_g(1-p_f)p_g^B \\
p_g^F &= g_g \cdot p_g^S + (1-\alpha_g)(1-p_f)p_g^B + (1-p_f)p_g^F \\
p_{sk}^S &= (1-\beta)p_{sk}^S + p_f(p_{sk}^F + p_{sk}^B) \\
p_{sk}^B &= f_{sk} \cdot p_{sk}^S + \alpha_{sk}(1-p_f)p_{sk}^B \\
p_{sk}^F &= g_{sk} \cdot p_{sk}^S + (1-\alpha_{sk})(1-p_f)p_{sk}^B + (1-p_f)p_{sk}^F.
\end{aligned} \tag{9}$$

Now, if we consider  $s \approx 1$ , we have that  $n_i^B \approx p_g^B \cdot \langle k \rangle$  and  $n_i^F \approx p_g^F \cdot \langle k \rangle$ , then we have exactly two independent systems for which we can compute the solutions of the MF equation as we did in [23].

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