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Fake News: "No Ban, No Spread—With Sequestration"

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Abstract: To curb the spread of fake news, I propose an alternative to the current trend of implementing coercive measures. This approach would preserve freedom of speech while neutralizing the social impact of fake news. The proposal relies on creating an environment to naturally sequestrate fake news within quite small networks of people. I illustrate the process using a stylized model of opinion dynamics. In particular, I explore the effect of a simultaneous activation of prejudice tie breaking and contrarian behavior, on the spread of fake news. The results show that indeed most pieces of fake news do not propagate beyond quite small groups of people and thus pose no global threat. However, some peculiar sets of parameters are found to boost fake news so that it "naturally" invades an entire community with no resistance, even if initially shared by only a handful of agents. These findings identify the modifications of the parameters required to reverse the boosting effect into a sequestration effect by an appropriate reshaping of the social geometry of the opinion dynamics landscape. Then, all fake news items become "naturally" trapped inside limited networks of people. No prohibition is required. The next significant challenge is implementing this groundbreaking scheme within social media.

Keywords: fake news; freedom of speech; sequestration; opinion dynamics; prejudices; contrarians; tipping points; attractors; sociophysics

1. Introduction

Fake news has emerged as a significant and critical component of today's information landscape. It plays a pivotal role in the shaping outcomes of critical debates surrounding social, political, and societal matters. Fake news exerts a substantial influence on the formation of public opinion via social media [1,2].

Frequently, fake news is crafted with malicious intent, disseminating false and deceptive information while employing emotional manipulation and exploring many prejudices deeply rooted in our social and political representations. Indeed, the motivation of individual spreaders has been investigated [3,4].

In addition, instances of foreign-originated fake news were observed during the 2016 US and 2022 French presidential elections, in which they interfered in favor of specific candidates. However, investigations have not established a quantifiable impact on the final electoral results, despite evidence pointing to a reinforcement of existing individual opinions [5].

Presently, fake news has evolved into a pervasive tool for distorting public discourse on crucial issues faced by modern societies. Consequently, its associated impact has become a pressing concern for democratic institutions. Policymakers are taking measures to implement various regulations aimed at curbing the spread of fake news.

A series of regulation measures are thus implemented to control and restrict the use of social media [6–8], which in practical terms are likely to end in limitations of individual freedom of speech. In addition, considerable resources and effort are being dedicated to establishing fact-checking platforms to assess the reliability of information disseminated online. Yet, fake news continues to thrive within social media platforms.

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Moreover, it is of importance to caution against the relevance of these coercive policies, because such regulatory bodies can be misused for partisan purposes, as proven in the past. Indeed, they could also turn counterproductive by preventing the revelation of real facts hidden by official institutions, providing a framework for dismissing state secrets revealed by whistleblowers as “fake news”. Famous examples include the “Watergate Scandal” [9], “Tuskegee Syphilis Study” [10], and “Iran-Contra Affair” [11].

At odd, Elon Musk has launched an opposite controversial governance of his social media X, advocating for freedom of speech [12,13], which in turn has produced a backslash from quite a number of people and institutions accusing him of promoting hate speech in the name of freedom of speech [14].

In this paper, I address the issue of curbing the spread of fake news by exploring another avenue I denote “No Ban, No Spread—with Sequestration”. The aim is to unveil a framework to sequestrate fake news posts within quite small networks of agents. My starting hypothesis is to consider that it may not be the content of fake news per se that matters, but rather the interaction of that content with the social and psychological geometry in which fake news emerges and propagates.

While this geometry is given independently of the specific content of a fake news item, it plays a crucial role in facilitating its spread. Given such a layout, my focus is to identify the related parameters capable of reversing the shape of the associated social and psychological geometry to make it block the spread of “fake news” instead of boosting it. Once done, fake news become “naturally” trapped and sequestrated in quite small networks of agents.

To test the soundness of my proposal, I consider a stylized social framework within sociophysics [15–18], to explore the features that control the propagation of fake news beyond its mere content. Sociophysics is a new active field of physics that tackles social and political phenomena adopting a physicist-like approach [19,20]. The challenge is not to substitute social sciences but to create a new hard science by itself [21–35].

Indeed, among the large spectrum of social and political issues covered by sociophysics [36–55], the study of the dynamics of opinion occupies a central place [56–64]. A good deal of papers consider binary variables [65–86] and fewer three or more discrete opinions [87–94]. Currently, the field of sociophysics is attracting growing interest with a rather large number of published papers [95–108].

Here, I extend the model of opinion dynamics I have been developing for a few decades (then, the Galam model) deployed in a multi-dimensional space of parameters, by exploring a novel combination of the heterogeneity of agents with contrarians embedded among floaters when tie-breaking prejudice is activated [109–115].

The study reveals that the combination of contrarians and tie-breaking prejudice is instrumental in shaping the geometrical landscape, which either blocks fake news items or on the contrary unlocks others fostering an overall spreading. It happens that the activation of a quite small proportion of contrarians associated with a favorable tie-breaking prejudice opens the path to a massive spread of fake news, even when it started being believed by only a handful of agents.

The findings could serve as a foundation to design non-restrictive regulations, which could prevent “naturally” any invasion of social media by fake news. The related lever is the setting of a geometrical sequestration of fake news within quite small networks of agents. Then, neither prohibition or restriction is required.

The rest of the paper is organized as follows. Section 2 reviews the Galam model of opinion dynamics, while Section 3 introduces a new combination of contrarians and prejudice tie breaking in local group updates of opinion. The mechanisms locking or unlocking the spread of fake news are unveiled in Section 4. Section 5 identifies new strategies to sequestrate fake news posts without prohibiting them. The Conclusions contains a summary of the main results.

2. The Galam Model of Opinion Dynamics

2.1. Floaters Dynamics and Local Majority

The bare Galam model considers two competing discrete opinions A and B within a homogeneous population of floaters. Floaters are agents holding an opinion. They advocate to promote it. However, floaters listen to opposite arguments in favor of the competing opinion and thus are susceptible to become convinced to shift opinion [111–113].

Given initial proportions p_0 and $(1-p_0)$ in favor of A and B, a dynamic is implemented by iterating a three-step procedure to update individual opinions. First, agents are distributed randomly in quite small groups of size r. Then, a local majority rule is applied separately to each group where all agents adopt the majority opinion. Third, agents are reshuffled. The update modifies the proportions p_0 and $(1-p_0)$ to new ones p_1 and $(1-p_1)$.

The scheme is then repeated n times with $p_0 \to p_1 \to p_2 \to \ldots \to p_n$. The associated update equation is given by

$$p_{r,1} = \left[\sum_{l=\bar{r}+1}^{r} \binom{r}{l} p_0^l (1-p_0)^{r-l} + \frac{1}{2}\delta\left(\bar{r} - \frac{r}{2}\right) \binom{r}{r/2} p_0^{r/2} (1-p_0)^{r/2} \right], \tag{1}$$

where $\bar{r} \equiv I[r/2]$, with $I[x]$ denoting the integer part of x and $\delta(x-a)$ is the Dirac delta function. Last term of Equation (1) means that for an even value of r at a tie, agents do not shift opinion.

The full landscape of the dynamics is obtained solving the fixed-point equation $p_{r,1} = p_0$. The equation yields one tipping point $p_t = 1/2$ and two attractors $p_A = 1$ and $p_B = 0$, which are all independent of the value of r. The associated dynamics are thus perfectly balanced with the opinion, which has gathered the majority of individual initial opinions, becoming larger and larger to reach eventually unanimity provided the number of updates n is sufficient.

The majority of agents have convinced individually via local discussing groups, agents holding initially the minority opinion to adopt the initial majority opinion. The dynamics are democratic with $p_0 < p_1 < p_2 < ... < p_n$ when $p_0 > 1/2$ and $p_0 > p_1 > p_2 > \cdots > p_n$ when $p_0 < 1/2$.

2.2. Floaters with Tie-Breaking Prejudice

However, the above ideal picture of democratic opinion dynamics breaks down when a tie breaking is included for evenly sized groups. In this case, at a tie, the group gets trapped into a collective doubt, with both opinions being equally acceptable. Since rationality cannot help to decide, everyone selects one of the two opinions at random, like tossing a coin. Individual choices are made by chance.

But contrary to the above rationale of random choices, the Galam model hypothesizes that indeed the "coin" is biased. For each agent, the state of doubting puts unconsciously some prejudice in control of the choice. The decision-making bias is monitored by the prejudice, which has been activated by the issue at stake. The decision is not made in the name of prejudice, but in the name of chance. To account for a distribution of different prejudices among agents, at a tie, opinion A is selected with probability k and opinion B with probability $(1-k)$.

Accordingly, for $r = 4$, Equation (1) reduces to

$$p_{4,k} = p_0^4 + 4p_0^3(1-p_0) + 6kp_0^2(1-p_0)^2, \tag{2}$$

which still has the two attractors $p_A = 1$ and $p_B = 0$. But now, the attractors are separated by a tipping point located at

$$p_{t,k} = \frac{(6k-1) - \sqrt{13 - 36k + 36k^2}}{6(2k-1)}, \tag{3}$$

instead of $p_t = 1/2$. For $k = 0, 1/2$, and 1, Equation (3) yields, respectively, $p_{t,0} = (1 + \sqrt{13})/6 \approx 0.77$, $p_{t,1/2} = 1/2$, and $p_{t,1} = (5 - \sqrt{13})/6 \approx 0.23$. Accordingly, $1/2 \leq p_{t,k} \leq 0.77$ when $0 \leq k \leq 1/2$ and $0.23 \leq p_{t,k} \leq 1/2$ when $1/2 \leq k \leq 1$. (Note some misprints in Equation (3) and the following paragraph in Ref. [115]).

With $p_t \approx 0.23$, instead of 0.50, the case $k = 1$ illustrates the phenomenon of minority spreading. With opinion A being favored by the group prejudice, it needs to gather at minimum initial minority support of only 0.23% to convince the initial majority of agents, who are sharing opinion B, to adopt instead opinion A via local and open-minded discussions.

The previous democratic character of the opinion dynamics has been broken naturally and unconsciously without notice in favor of the choice in tune with the prejudices of the group. No coercion has been used. However, the initial support of A must be larger than 0.23. Otherwise, the minority opinion does lose support.

2.3. Floaters and Contrarians

Like floaters, contrarians are agents having an opinion, arguing for it, and listening to opposite arguments. However, unlike floaters, instead of following the local majority in a discussing group (fake news is true, fake news is false), they automatically adopt the opposite opinion (fake news is false, fake news is true) whatever the majority is [114]. They do it also in case of initial unanimity.

On this basis, while local majority rule favors the strengthening of an initial majority between two competing opinions, contrarians on the other hand favor a minority stand, which in turn reduces the gap between the respective proportions of the two competing opinions.

As expected, contrarians prevent the disappearance of the minority opinion even when many successive updates have been implemented. For instance, for discussing groups of size 4, update Equation (2) becomes,

$$p_{1,x} = (1 - 2x)\left[p_0^4 + 4p_0^3(1 - p_0) + 3p_0^2(1 - p_0)^2\right] + x, \tag{4}$$

where $k = 1/2$ (no tie breaking), x is the proportion of contrarians, and $(1 - x)$ is the proportion of floaters.

The associated fixed-point equation $p_{1,x} = p_0$ yields $p_{t,x} = 1/2$ and

$$p_{A,x;B,x} = \frac{1 - 2x \pm \sqrt{1 - 8x + 12x^2}}{2(1 - 2x)}, \tag{5}$$

provided $0 \leq x \leq x_c$ with $x_c = 1/6 \approx 0.167$.

While the tie-prejudice effect preserves the floater attractors $p_A = 1$ and $p_B = 0$, shifting the tipping point away from $p_t = 1/2$, contrarians on the other hand preserve the tipping point $p_t = 1/2$ but shift both attractors, which in turn stabilize a coexistence of a large majority and a quite small minority with $p_{A,x} < 1$ and $p_{B,x} > 0$.

It is worth noticing that at $x = x_c = 1/6$, $p_A = p_B = 1/2$. Accordingly, for $x > x_c$, the dynamics is driven by a single attractor located at $1/2$. Any initial condition ends up at a perfectly balanced support for A and B. Here, I assume that $x \leq 1/2$, which is sound given the definition of a contrarian.

2.4. From Minority Opinion to Fake News

The Galam model deals with competing opinions A and B given some initial proportions p_0 and $(1 - p_0)$ of respective supports, making by definition one minority and the other one majority. Applying the model to fake news is performed naturally, noticing a restriction of the proportions. Denoting A fa piece of fake news implies by nature of the phenomenon to have A being ultra minority with $p_0 \ll 1/2$. The competing opinion B then denotes the dismissing of A for being false and always starts with overwhelming support.

In addition, it is worth stressing that each fake news post activates specific prejudices. Given the content, within a social and political context, a fake news item produces contrarians in different proportions.

3. Contrarians with Tie Prejudice Breaking

In Section 2, I reviewed some main results obtained from the Galam model of opinion dynamics. I now investigate for the first time the impact of having contrarians in a community of floaters with active tie prejudice breaking. I restrict the study to discussing groups of size 4. Combining Equations (2) and (4) leads to the update equation

$$p_{4,k,x} = (1-2x)\left[p_0^4 + 4p_0^3(1-p_0) + 6kp_0^2(1-p_0)^2\right] + x. \quad (6)$$

Despite of a simplicity of Equation (6), the related fixed-point equation $p_{4,k,x} = p_0$ cannot be solved analytically. A numerical treatment is required to determine the fixed points $p_{A,k,x}, p_{B,k,x}, p_{t,k,x}$, with their domains of existence within the full parameter space $0 \leq k \leq 1$ and $0 \leq x \leq 1$.

Before starting the investigation, it is worth reminding the effect on the opinion dynamics of having contrarians among a community of floaters without tie-breaking prejudice ($k = 1/2$) as shown in Figure 1 and discussed in Section 2.3. With contrarians opposing the local majorities, as expected, they prevent reaching unanimity, securing always a resilient proportion of agents sharing the minority opinion. The more contrarians, the larger the stable minority with both attractors moving towards the tipping point, which remains located at 50%.

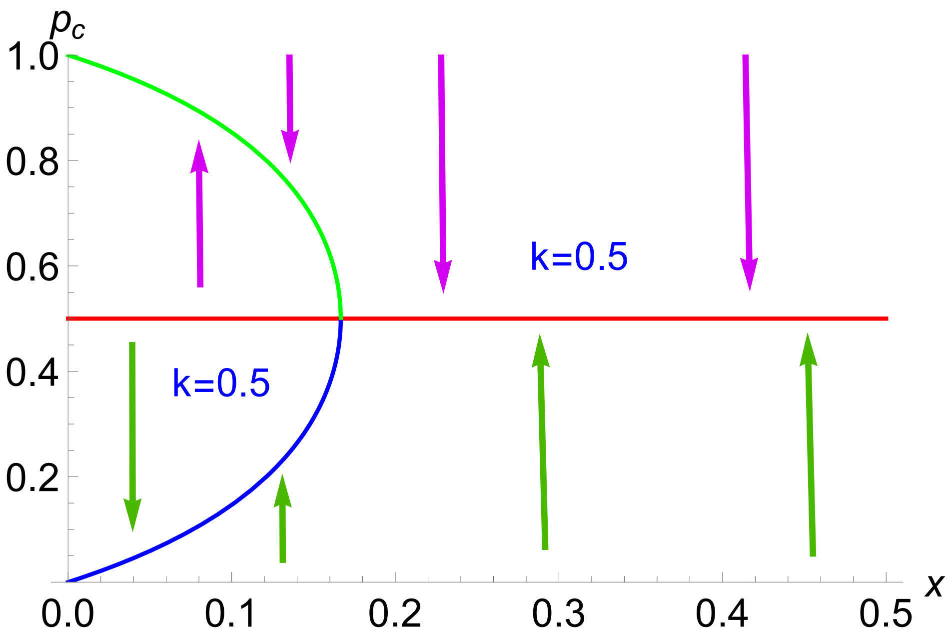

Figure 1. Evolution of attractors and tipping points as a function of the proportion x of contrarians for probability $k = 1/2$ (no tie breaking). The lower curve represents the attractor $p_{B,0.5,x}$ (in blue), the upper curve the attractor $p_{A,0.5,x}$ (in green), and the first part of middle line the tipping point $p_{t,0.5,x} = 0.5$ (in red). At $x_c = 0.167$, $p_{A,0.5,x_c} = p_{B,0.5,x_c} = p_{t,0.5,x_c} = 0.5$. For $x > x_c$, the unique attractor is located at precisely 1/2 (the second part of the red line). The violet and green arrows show the different directions of opinion dynamics. See text for more details.

Nevertheless, despite being smooth, the shift of attractors brings them to the tipping point for the small proportion of contrarians $x_c = \ \approx 0.167$. Then, for $x > x_c$, the dynamics are turned upside down, becoming a single 50% attractor dynamic. Beyond x_c, contrarians erase totally any initial difference in the proportions of support for A and B. The whole related dynamics is and stays symmetric ensuring a democratic balance.

However, as soon as $k \neq 0$, the symmetry between A and B is broken. To identify the consequences associated with the activation of contrarians, I choose arbitrarily to start from $k = 1$ to study the range $0 \leq k \leq 1$.

3.1. Fake News in Tune with Active Prejudices

Figure 2 exhibits the dynamics landscape of opinion as a function of x for $k = 1$. At the corner $(k = 1, x = 0)$, $p_{A,1,0} = 1$, $p_{B,1,0} = 0$ and $p_{t,1,0} \approx 0.23$. From there, slightly increasing the proportion x of contrarians shifts $p_{A,1,0}$, and $p_{B,1,0}$ to, respectively, lower and higher values $p_{A,1,x}$ and $p_{B,1,x}$, as one would expect and is shown in the Figure 2.

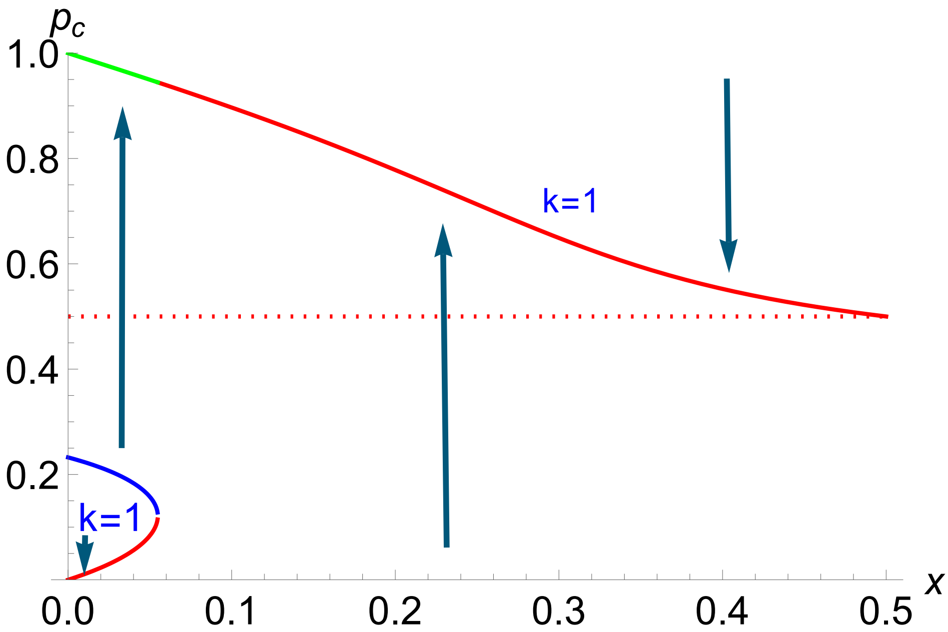

Figure 2. Evolution of attractors and tipping points as a function of the proportion x of contrarians for $k = 1$. The lower curve represents the attractor $p_{B,1,x}$ (in red), the upper curve the attractor $p_{A,1,x}$ (in green and red), and the middle curve the tipping point $p_{t,1,x}$ (in blue). At $x_c = 0.055$, $p_{A,1,x_c} = 0.944$ and $p_{A,1,0.20} = 0.778$, and $p_{A,1,0.30} = 0.649$. The red dotted line represents the majority threshold. The arrows show the different directions of opinion dynamics.

However, the value of the tipping point $p_{t,1,x}$ is seen to decrease, which is not expected. Indeed, being in a region where p is less than 0.23, a lower value for the tipping point means that A will keep increasing even when above 50%. That is not expected since contrarians are expected to decrease any majority as seen with the two attractors $p_{A,1,0} = 1$ and $p_{B,1,0} = 0$ being shifted to, respectively, lower and high values.

Moreover, contrary to the symmetric case where the three fixed points merge to result in one unique attractor located at 0.50, here, only the two fixed points $p_{B,1,x}$ and $p_{t,1,x}$ merge and disappear at a small value $x_c = 0.055$, leaving $p_{A,1,x}$ as the unique attractor driving the dynamics with $p_{A,1,x_c} = 0.944$. It is noticeable that when $x > x_c = 0.055$, $p_{A,1,x}$ is always located above 50%.

In addition to being counter-intuitive, the above results show a unexpected and alarming reality about the spread of fake news. Given a fake news item totally in tune $(k = 1)$ with the leading prejudice of a community, as soon as the proportion of active contrarians is larger than a few percent $(x > x_c = 0.055)$, a handful of agents sharing initially the fake news are sufficient to have it spread inexorably and invade large parts of this community, as seen with $p_{A,1,x_c} = 0.944$.

Although increasing the proportion of contrarians decreases the value $p_{A,1,x}$ towards equal probability as expected, the fake news can still reach more than the majority of the community, as seen with $p_{A,1,0.20} = 0.778$ and $p_{A,1,0.30} = 0.649$ in Figure 2.

In case the prejudices are heterogeneous with respect to the fake news post, the above phenomenon persists, requiring only a few more active contrarians. But the fake news post still requires only a handful of initial support agents to spread over and become the majority, for instance, with $k = 0.60$, $x_c = 0.114$, and $p_{A,0.60,x_c} = 0.843$, as seen in Figure 3.

For $x = 0.20$, $p_{A,0.60,0.20} = 0.648$, which indicates that a large minority $1 - p_{A,0.60,0.20} = 0.352$ remain dismissing the piece of fake news. For $x = 0.30$, $p_{A,0.60,0.30} = 0.537$, with the opposed minority reaching $1 - p_{A,0.60,0.30} = 0.463$.

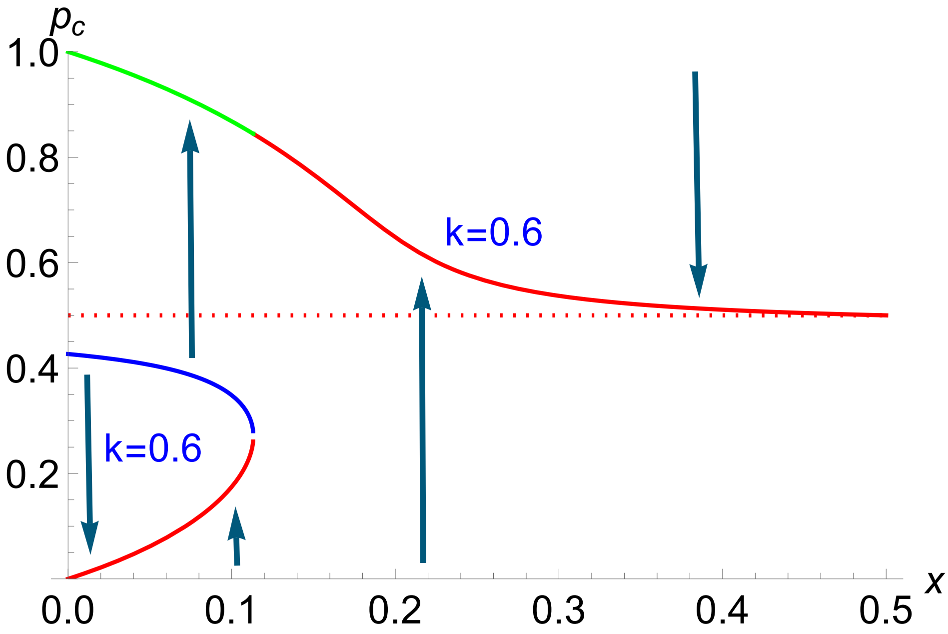

Figure 3. Evolution of attractors and tipping point as a function of the proportion x of contrarians for $k = 0.60$. The lower curve represents the attractor $p_{B,0.60,x}$ (in red), the upper curve the attractor $p_{A,0.60,x}$ (in green and red), and the middle curve the tipping point $p_{t,0.60,x}$ (in blue). At $x_c = 0.114$, $p_{A,0.60,x_c} = 0.843$, $p_{A,0.60,0.20} = 0.648$, and $p_{A,0.60,0.30} = 0.537$. The red dotted line represents the majority threshold. The arrows show the different directions of opinion dynamics.

Figure 4 exhibits both $k = 0.53$ and $k = 0.501$ cases, which show how the symmetrical case $k = 0.50$ is recovered (see Figure 2). Figure 2, left, has $x_c = 0.142$, $p_{A,0.53,x_c} = 0.753$, $p_{A,0.53,0.20} = 0.562$, and $p_{A,0.53,0.30} = 0.511$. Figure 2, right, has $x_c = 0.164$, $p_{A,0.501,x_c} = 0.589$, $p_{A,0.501,0.20} = 0.502$, and $p_{A,0.501,0.30} = 0.500$.

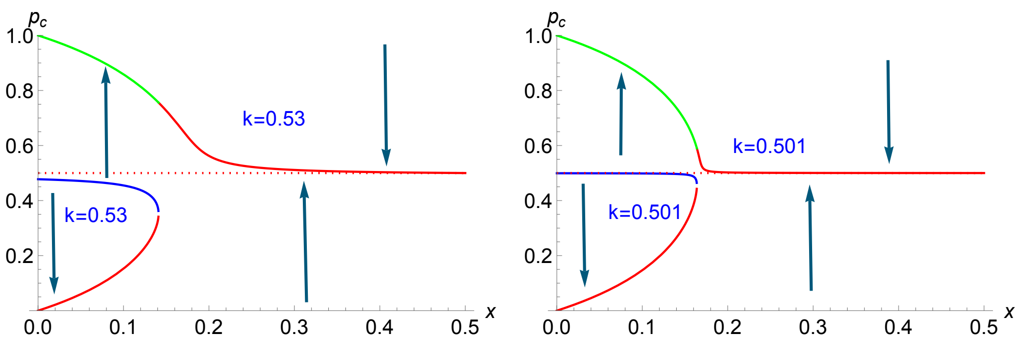

Figure 4. Evolution of attractors and tipping points as a function of the proportion x of contrarians for $k = 0.53$, $x_c = 0.142$, $p_{A,0.53,x_c} = 0.753$, $p_{A,0.53,0.20} = 0.562$, and $p_{A,0.53,0.30} = 0.511$ (**left**) and $k = 0.501$, $x_c = 0.164$, $p_{A,0.501,x_c} = 0.589$, $p_{A,0.501,0.20} = 0.502$, and $p_{A,0.501,0.30} = 0.500$ (**right**). The lower curves represent the attractor $p_{B,k,x}$ (in red), the upper curves the attractor $p_{A,k,x}$ (in green and red), and the middle curves the tipping point $p_{t,k,x}$ (in blue). The red dotted line represents the majority threshold. The arrows show the different directions of opinion dynamics.

3.2. Fake News at Odds with Active Prejudices

Let us look at the reverse situation with a fake news item at odds with the leading prejudices of the community. The extreme case $k = 0$ dynamics landscape is shown in

Figure 5. Comparing Figures 2 and 5 shows that the situation is anti-symmetrical from $k = 1$, where being in tune with the leading prejudices fosters drastically the spread of fake news even when initially shared by only a handful of agents.

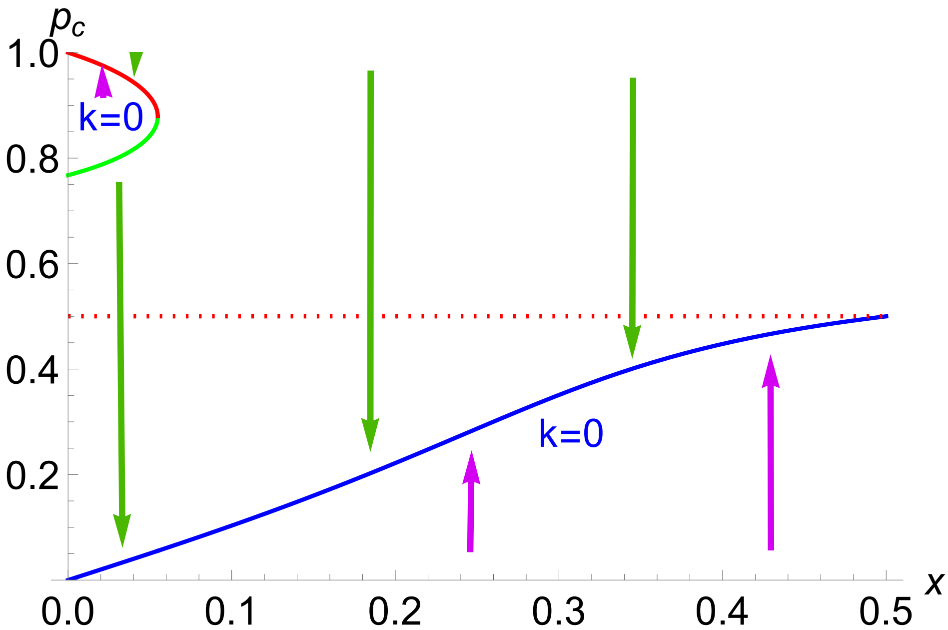

Figure 5. Evolution of attractors and tipping points as a function of the proportion x of contrarians for $k = 0$. The lower curve represents the attractor $p_{B,0,x}$ (in blue), the upper curve the attractor $p_{A,0,x}$ (in red), and the middle curve the tipping point $p_{t,0,x}$ (in green). At $x_c = 0.055$, $p_{B,0,x_c} = 0.056$, $p_{B,0,0.20} = 0.222$, and $p_{B,0,0.30} = 0.351$. The red dotted line represents the majority threshold. The violet and green arrows show the different directions of opinion dynamics.

When the fake news item is at odds with the active prejudices, even if a large majority of agents have initially believed it is true, the repeated discussions between agents in quite small groups reduce drastically their proportion. Figure 5 exhibits the dynamics landscape as a function of x for $k = 0$. At the corner $(k = 0, x = 0)$, $p_{A,0,0} = 1, p_{B,0,0} = 0$ and $p_{t,0,0} \approx 0.77$. From there, slightly increasing the proportion of contrarians shifts $p_{A,0,0}$ and $p_{B,0,0}$ to, respectively, lower and higher values, as would be expected.

However, here, contrary to $p_{t,1,x}$, the value of the tipping point $p_{t,0,x}$ increases with x, which is expected since a higher value for the tipping point makes it more complicated for a majority to hold its status with contrarians reducing the gap between the majority and the minority. However, as just above, even when A turns into the minority, it keeps losing support.

Now, the two fixed points $p_{A,0,x}$ and $p_{t,0,x}$ instead of $p_{B,1,x}$ and $p_{t,1,x}$ merge and disappear, but still at the same small value $x_c = 0.055$, leaving $p_{B,0,x}$ to be the unique attractor driving the dynamics with $p_{B,0,x_c} = 0.056$.

While the results just above were alarming and unexpected, here, the results are reassuring with respect to the spontaneous curbing of fake news diffusion. Given a fake news item totally at odds $(k = 0)$ with the leading prejudice of a community, as soon as the proportion of active contrarians is larger than a few percent $(x > x_c = 0.055)$, even a particularly majority of agents sharing initially the fake news item will eventually shift opinion, making their proportion to shrink inexorably down to quite low values of believers as seen with $p_{B,0,x_c} = 0.056$.

Moreover, increasing the proportion of contrarians increases the value $p_{B,0,x_c}$ towards equal probability as expected but keeps it lower than 0.50. Indeed, when the fake news supporters are the majority, the dynamics turn them down to a minority, as seen with $p_{B,0,0.20} = 0.222$ and $p_{B,0,0.30} = 0.351$ in Figure 5.

In case the prejudices are heterogeneous with respect to the fake news item, the above phenomenon persists, requiring only a few more active contrarians. The fake news item still ends up in the minority. For instance with $k = 0.40$, $x_c = 0.114$, and $p_{B,0.40,x_c} = 0.157$, as seen in Figure 6. Nevertheless, Figure 6 shows that a large minority remains concerning the fake news item with $p_{B,0.40,0.20} = 0.352$ and $p_{B,0.40,0.30} = 0.463$ for, respectively, $x = 0.20$ and $x = 0.30$.

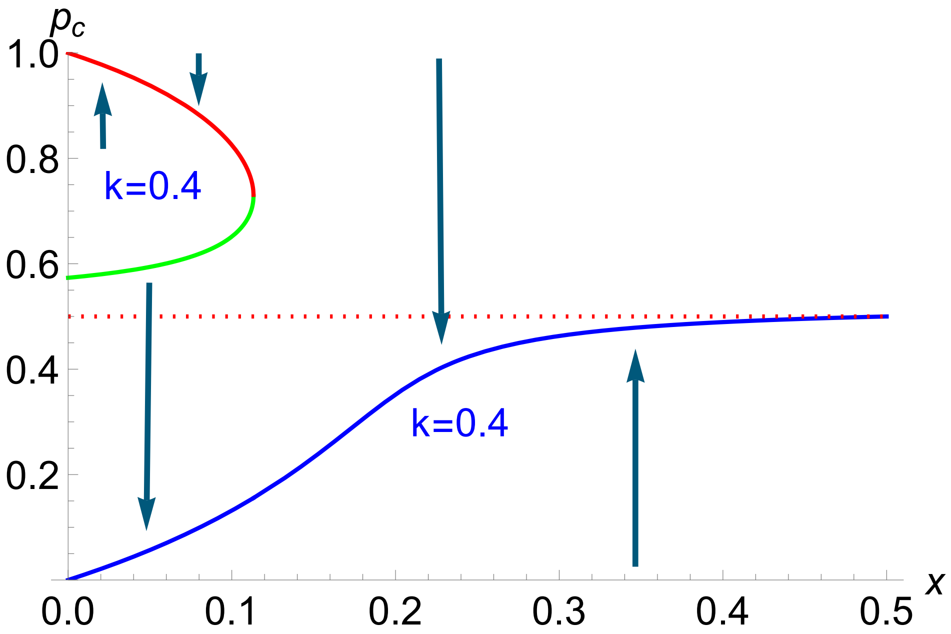

Figure 6. Evolution of attractors and tipping points as a function of the proportion x of contrarians for $k = 0.40$. The lower curve represents the attractor $p_{B,0.40,x}$ (in blue), the upper curve the attractor $p_{A,0.40,x}$ (in red), and the middle curve the tipping point $p_{t,0.40,x}$ (in green). At $x_c = 0.114$, $p_{B,0.40,x_c} = 0.157$, $p_{B,0.40,0.20} = 0.352$, and $p_{B,0.40,0.30} = 0.463$. The red dotted line represents the majority threshold. The arrows show the different directions of opinion dynamics.

Figure 7 exhibits both $k = 0.47$ and $k = 0.499$ cases, showing how the symmetrical case $k = 0.50$ is recovered from a lower value of k (see Figure 2). Figure 7, left, has $x_c = 0.142$ and $p_{B,0.47,x_c} = 0.247$. For, respectively, $x = 0.20$ and $x = 0.30$, $p_{B,0.47,0.20} = 0.438$ and $p_{B,0.47,0.30} = 0.489$. Figure 7, right, has $x_c = 0.164$ and $p_{B,0.499,x_c} = 0.411$ with $p_{B,0.499,0.20} = 0.498$ and $p_{B,0.499,0.30} = 0.500$.

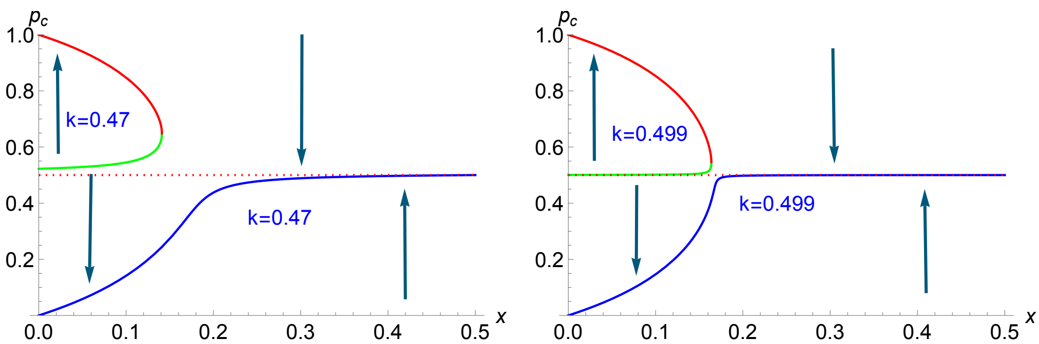

Figure 7. Evolution of attractors and tipping points as a function of the proportion x of contrarians for $k = 0.47$, $x_c = 0.142$, $p_{B,0.47,x_c} = 0.247$, $p_{B,0.47,0.20} = 0.438$, and $p_{B,0.47,0.30} = 0.489$ (**left**) and $k = 0.499$, $x_c = 0.164$, $p_{B,0.499,x_c} = 0.411$, $p_{B,0.499,0.20} = 0.498$, and $p_{B,0.499,0.30} = 0.500$ (**right**). The lower curves represent the attractor $p_{B,k,x}$ (in blue), the upper curves the attractor $p_{A,k,x}$ (in red), and the middle curves the tipping point $p_{t,k,x}$ (in green). The red dotted line represents the majority threshold. The arrows show the different directions of opinion dynamics.

4. Unlocking or Locking Fake News

The analyses in Section 3 have highlighted the critical impact of a few percent of contrarians on the dynamics of spreading fake news, once tie breaking by prejudice is activated. In addition, the direction of the contrarian impact is set by the overlap between the content of fake news and the leading prejudices prevailing in the social community.

It is useful to reemphasize that the selection of the prejudice being activated by the fake news is performed unconsciously when a discussing group gets trapped in a local doubt, determining the fake news validity. Either the fake news item benefits from the leading activated prejudices with $k > 1/2$ or it is impeded with $k < 1/2$. The respective effects on the dynamics of spreading are drastically different. But in both cases, only a few percent of contrarians are required to implement the drastic bias of the dynamics, as shown in Figure 8 and Table 1.

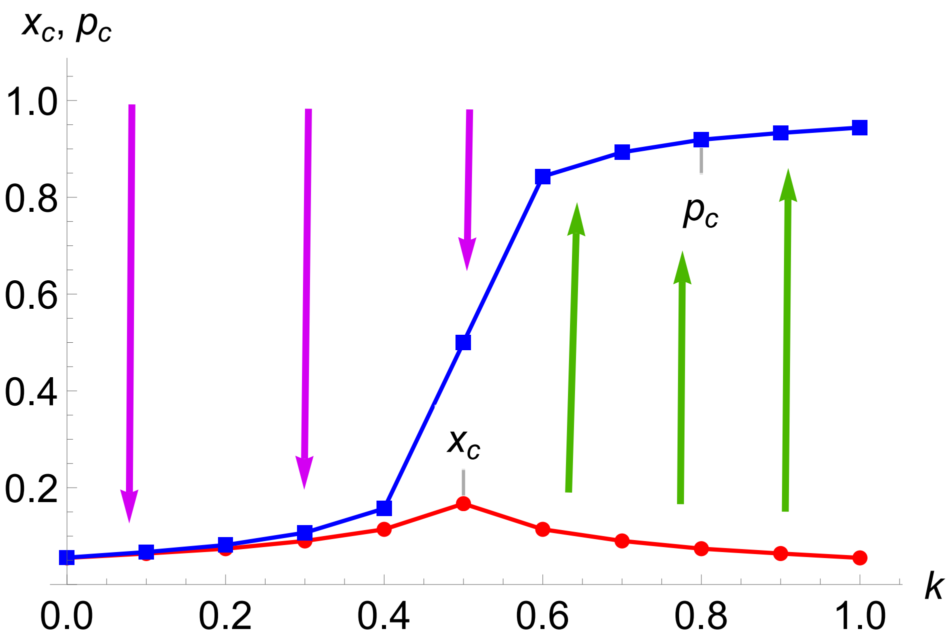

Figure 8. The values of x_c as a function of k. p_c denotes the values p_{B,k,x_c} for $0 \leq k \leq 0.5$ and p_{A,k,x_c} for $0.5 \leq k \leq 1$. The violet and green arrows show the different directions of opinion dynamics. See text for details.

Table 1. The values of x_c as a function of k with the values p_{B,k,x_c} for $0 \leq k \leq 0.5$ and p_{A,k,x_c} for $0.5 \leq k \leq 1$. See text for details.

k	0, 1	0.1, 0.9	0.2, 0.8	0.3, 0.7	0.4, 0.6	0.5
x_c	0.055	0.064	0.074	0.09	0.114	0.167
$p_{B,k\leq 0.5,x_c}$	0.056	0.067	0.0815	0.107	0.157	0.5
$p_{A,k\geq 0.5,x_c}$	0.944	0.933	0.919	0.893	0.843	0.5

Moreover, the values of x_c are identical for k and $(1-k)$ in the range $0 \leq k \leq 1/2$. The associated values of the unique attractor at x_c satisfy $p_{B,k\leq 0.5,x_c} + p_{A,k\geq 0.5,x_c} = 1$, as seen in Table 1. In addition, it is worth noticing that the values of the unique attractors at x_c stay either very low ($0 \leq k < 0.4$) or very high ($0.6 < k \leq 1$) beside in the range $0.4 < k < 0.6$ where the values, respectively, fall towards 0.5. Three very different regimes are thus obtained as a function of k:

Regime 1: $0 \leq k < 0.4$. When the activated prejudices are mainly detrimental to fake news, the unique attractor $p_{B,k,x}$ is always much lower than $1/2$, as seen in Table 1. This means that even if a fake news item is first believed to be true by an overwhelming majority of the agents, the subsequent informal discussions among quite small groups of agents will eventually turn most of them to reject the fake news item as being false.

Regime 2: $0.4 < k < 0.6$. When the activated prejudices are almost equally distributed with respect to fake news, whatever initial conditions, the fake news post ends up being shared by almost half of the agents. It is less than half when $0.4 < k < 0.5$ and more than half for $0.5 < k < 0.6$. In both cases, a substantial part of the community believes the fake news is true, while another substantial part believes it is false. The society is polarized with respect to the validity of the piece of fake news.

Regime 3: $0.6 < k \leq 1$. When the activated prejudices are mainly at the benefit of the fake news item, the unique attractor is $p_{A,k,x}$ is always much larger than $1/2$, as seen in Table 1 and Figure 8. It means that even if fake news is first believed by only a handful of agents, the informal discussions among them will inexorably increase the proportion of believers to end up with an overwhelming part of the community. Such case is most concerned with the fake news item reaching a stable status of being "true" within the related community.

To grasp the whole landscape of the various types of dynamics, I have aggregated the cases $k = 1, 0.6, 0.501$, and $k = 0.499, 0.4, 0$ shown in Figure 9, upper left and upper right, respectively. Figure 9, lower, includes both series.

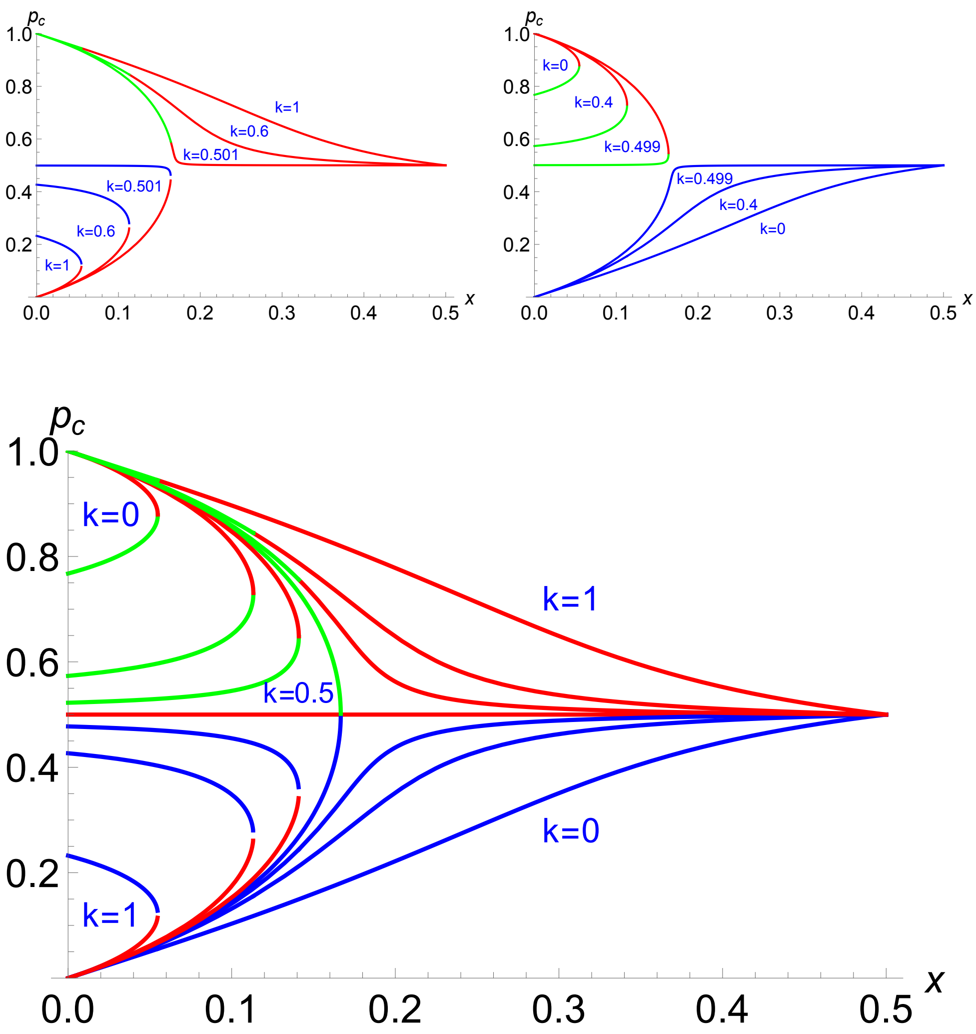

Figure 9. Attractors and tipping point as a function of x for $k = 1, 0.6, 0.501$ (**upper left**), $k = 0.499, 0.4, 0$ (**upper right**), and for both series (**lower**) for the attractors $p_{B,k,x}$ (in blue), $p_{A,k,x}$ (in red), and the tipping point $p_{t,k,x}$ (in green)—all denoted by p_c.

5. Strategies to Sequestrate Fake News without Prohibiting Them

The series of results obtained here highlight the critical roles played by contrarians and activated prejudices in shaping the fate of a given piece of fake news. It is worth stressing that their respective roles are implemented in parallel and without interaction between them. The findings set the frame to identify new avenues for designing strategies to curb the prominent spread of fake news and sequestrate it naturally into quite small networks of agents without the need for prohibition. The key findings are as follows.

(i) A few percent of contrarians are enough to modify drastically the full landscape of the associated dynamics of spreading or shrinking as exhibited in Figure 9. Contrarians have always the same impact, which is transforming the tipping-point dynamic into that of a single attractor. The consequence is that any initial support for any fake news ends up at this unique attractor whose value is independent of that of the initial support.

(ii) The location of the unique attractor of the dynamics is either above or below $1/2$ depending on the distribution of prejudices activated by the fake news item. It is also worth emphasizing that the single attractor is located mostly at either considerably low or considerably high values as a function of the distribution of activated prejudices.

(iii) The heterogeneities of the activated prejudices depend on the sociocultural composition of each community. Moreover, the prejudices that are activated spontaneously are selected by the content of the piece of fake news. As a result, some identical fake news may spread in some communities and shrink in others.

5.1. Most Fake News Do not Spread

While contrarians are instrumental to the drastic reshaping of the geometry of the dynamics landscape, I notice that they need to reach a proportion ranging between 6% and 20% to turn the tipping-point dynamics into a single attractor dynamics (see Table 1). More than 10% is a significant figure, which in turn indicates that it is unlikely that much fake news would generate such proportions of contrarians.

(i) When the contrarians are few in number, even in the case of beneficial (prejudices $k = 1$), fake news needs to start with a rather high proportion of individual believers and also rather hard to reach, as seen in Figure 9. For instance, with $x = 0$, the initial proportion must be higher than 23%. However, there are quite rare exceptions, such as the false claim that Israel bombed a hospital in Gaza in October 2023, which reached an impressive number of believers around the world in a matter of hours [116].

(ii) When the fake news item is at odds with the prejudices, the challenge becomes out of reach. In the case $k = 0$ and $x = 0$, the initial support must be higher than 77% (Figure 9). A particularly large figure is impossible to reach in most cases.

(iii) In cases where the fake news item does generate proportions of contrarians about 10%, substantial proportions of initial believers are still necessary for both $k < 1/2$ and $k > 1/2$, as seen in Figure 9,

All these observations indicate that most fake news does not spread and thus does not pose a threat to democratic unbiased public debates.

5.2. Some Rare Fake News Turn Spontaneously Invasive

When the fake news item is able to simultaneously generate more than 15% of contrarians and be in tune with most activated prejudices, only a handful of initial believers is sufficient to launch an invasive dynamics of opinion. Then, the proportion of supporters grows unseen till reaching eventually a majority of agents despite being initially dismissed as false by the majority of the community as shown in Figure 9,

It may also happen, although quite rarely, that a fake news post is believed at once as true by almost everyone [116]. When that happens, if the fake news item is in tune with the activated prejudices, it stays widely believed through local discussions and settled as "true" within the population.

5.3. Novel Strategies to Curb Invasive Fake News

Indeed, the above findings and results indicate that to prevent malicious fake news from thwarting the outcomes of balanced democratic public debates about central societal and political issues. The focus could be not on banning the making of fake news but on either preventing their spread or driving their downsizing.

As long as a fake news item stays confined to a quite small group of agents it does not pose a threat. Therefore, instead of limiting the freedom of speech with heavy control of social media, it may be more efficient to address the geometry of the landscape of opinion, which drives the propagation of fake news. The subsequent goal becomes to identify the features that keep most fake news confined and then apply them to the ones that do spread over. Accordingly, I advocate setting the conditions for sequestrating invasive fake news within quite small networks of agents. In the rare cases where the initial proportion of believers is quite high, the aim is to reduce the initial support to quite small values and to keep it there.

Within the extended Galam model of opinion dynamics, two parameters can fulfill this goal of ”No ban, No spread—with Sequestration”. The first one is k, the spectrum of prejudices activated spontaneously when groups of discussing agents become trapped at a tie, with the two choices, true and fake, being equally acceptable. The second one is x, the proportion of contrarian agents, which is produced by both the content of the fake news item and the social environment of the agents.

The values of these two parameters determine the geometry of the landscape in which the fake news dynamics are deployed. When the geometry boosted a fake news propagation, its reshaping requests to modify these values to set them at quite low values to activate the sequestration of fake news with no possibility of spreading out. More specifically, the proportion of contrarians must be reduced, which implies individual changes of attitude. In addition, tie-breaking cases must be tuned against the fake news item, which requires modifying the associated prejudices. In the case of an initial high proportion of believers, turning k from quite high to quite low values triggers a shrinking dynamic.

Once this avenue is selected, the follow-up instrumental question is how to implement such a reshaping scheme within the real world. That requires elaborating appropriate novel tools to modify k and x in order to reshape the social geometry of the landscape of the dynamics of fake news.

However, defining the appropriate corresponding tools is beyond my skills and expertise. At this stage, I have shown that the scheme of “No Ban, No Spread—with Sequestration” is feasible within a stylized model of opinion dynamics. To transpose the related findings to the real world requires an interdisciplinary collaboration with scientists from computer, psychological, cognitive, and behavioral sciences. I hope this paper will stimulate in these communities an interest along this point of view.

6. Conclusions

In this paper, I addressed the issue of how to curb the spread of fake news by exploring a new avenue denoted “No Ban, No Spread—with Sequestration”, which aims both to preserve full freedom of speech and neutralize the impact of fake news.

To illustrate my proposal, I used the sociophysics Galam model of opinion dynamics focusing on the impact of having simultaneously contrarians when prejudice tie breaking is activated. These two parameters are independent of each other. Solving the update equations has revealed the existence of a critical value for the proportion of contrarians, above which the dynamics landscape is turned upside down. There, the dynamics shift abruptly from tipping-point dynamics to single attractor dynamics. Remarkably, the related contrarian critical value is small with values between 6% and 20%.

In parallel, the associated single attractor is found to be located at either relatively high or quite low proportions of fake news believers. The selection depends on the fake news item being in tune or at odds with the main activated prejudices. A high value means the fake news item does eventually invade the social space, whatever its initial support, even with only a handful of agents. On the contrary, a quite low value means the fake ends up sequestrated into a quite small proportion of believers, even if it starts from an initial high support.

These results are instrumental in determining the fate of fake news. Unveiling the social geometry of the opinion landscape has shown that most pieces of fake news never reach significant proportions of believers and stay confined to quite small numbers of agents. Therefore, they pose no threat.

There is, however, a subgroup of fake news that simultaneously generates sufficient contrarians and is in tune with most activated prejudices. Those items of fake news do spread and invade large parts of a social community, even when initially shared by only a handful of agents. The phenomenon is counter-intuitive and unexpected, highlighting an alternative understanding of the "natural" spread of fake news.

At this point, it is worth noticing that while my study is performed using groups of size 4, the main results are still valid when accounting for a combination of group sizes, including larger sizes (weaker tie-breaking effect) and pairs of people (stronger tie-breaking effect) [109]. Moreover, although social media groups may be quite large when considering a given thread of discussion, most contributors are likely to read only a few earlier comments, keeping quite small the effective size of the group. For future work, investigating the effect of networks and the influence of external factors like competence could be of interest.

The above findings allow envisioning new targeted paths to tackle only those threatening pieces of invasive fake news by sequestrating them via a modification of the underlying social geometry to prevent their otherwise propagation towards a majority of believers. Neither ban nor control of the net is required, allowing both full freedom of speech and the guarantee of getting the threatening fake news items naturally sequestrated into limited social networks involving only quite small numbers of agents. However, it is of importance to stress that allowing the existence of fake news per se does not mean allowing speech of hate, which is forbidden by law and thus must be prosecuted and condemned.

To conclude, I would like to stress that I am aware that there is a significant gap between my findings in the context of a stylized model and the implementation of these findings in the real world of social media. My purpose is to open up a new hypothetical direction for curbing the spread of fake news, hoping that experts working on the ground could use the proposal to eventually design new appropriate protocols. In particular, a discussion within the sociophysics community to tackle the challenge of possible real-life implementation would be particularly useful.

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References

1. Pennycook, G.; Rand, D.G. The implied truth effect: Attaching warnings to a subset of fake news stories increases perceived accuracy of stories without warnings. *Manag. Sci.* **2018**, *67*, 4944–4957.
2. Lewandowsky, S.; Ecker, U.K.H.; Cook, J. Beyond misinformation: Understanding and coping with the post-truth era. *J. Appl. Res. Mem. Cogn.* **2017**, *6*, 353–369. [CrossRef]
3. Petersen, M.B.; Osmundsen, M.; Arceneaux, K. The "Need for Chaos" and motivations to share hostile political rumors. *Am. Political Sci. Rev.* **2023**, *117*, 1486–1505. [CrossRef]
4. Arceneaux, K.; Gravelle, T.B.; Osmundsen, M.; Petersen, M.B.; Reifler, J.; Scotto, T.J. Some people just want to watch the world burn: The prevalence, psychology and politics of the "Need for Chaos". *Philos. Trans. R. Soc. B* **2021**, *376*, 20200147. [CrossRef] [PubMed]
5. Grinberg, N.; Joseph, K.; Friedland, L.; Swire-Thompson, B.; Lazer, D. Fake news on twitter during the 2016 U.S. presidential election. *Science* **2019**, *363*, 374–378. [CrossRef] [PubMed]

6. Carter-Ruck. Insights Hub. Fake News, Authentic Views. 2019. Carter-Ruck: London, UK, 2019. Available online: https://www.carter-ruck.com/insight/fakes-news-authentic-views/ (accessed on 11 May 2024).
7. Edwards, L. How to Regulate Misinformation. *The Royal Society. Blog*, 25 January 2022. Available online: https://royalsociety.org/blog/2022/01/how-to-regulate-misinformation/ (accessed on 11 May 2024).
8. Tan, C. Regulating disinformation on Twitter and Facebook. *Griffith Law Rev.* **2022**, *31*, 513–536. [CrossRef]
9. Woodward, B.; Bernstein, C. *All the President's Men*; Simon and Schuster: New York, NY, USA, 1974. Available online: https://archive.org/details/allpresidentsmen0000bern (accessed on 11 May 2024).
10. Jones, J.H. *Bad Blood: The Tuskegee Syphilis Experiment*; The Free Press/Macmillan Publishing Co, Inc.: New York, NY, USA, 1981. Available online: https://archive.org/details/badbloodtuskegee00jone (accessed on 11 May 2024).
11. Tower, J.; Muskie, E.; Scowcroft, B. *The Tower Commission Report: The Full Text of the President's Special Review Board*; Bantham Books, Inc.; Times Books, Inc.: New York, NY, 1987. Available online: https://archive.org/details/towercommission00unit/ (accessed on 11 May 2024).
12. Sullivan, M. Elon Musk's hypocrisy about free speech hits a new low. *The Guardian*, 7 September 2023. Available online: https://www.theguardian.com/commentisfree/2023/sep/07/elon-musks-hypocrisy-about-free-speech-hits-a-new-low (accessed on 11 May 2024).
13. Nover, S. Elon Musk is finally fighting a genuine free speech battle. *Quartz*, 13 September 2023. Available online: https://qz.com/elon-musk-is-finally-fighting-a-genuine-free-speech-bat-1850833829 (accessed on 11 May 2024).
14. Milmo, D. Anti-hate speech group accuses Elon Musk's X Corp of intimidation over legal threat. *The Guardian*, 31 July 2023. Available online: https://www.theguardian.com/technology/2023/jul/31/anti-hate-speech-group-accuses-elon-musk-x-corp-intimidation (accessed on 11 May 2024).
15. Brazil, R. The physics of public opinion. *Phys. World* **2020**, 33, 24–28. [CrossRef]
16. Schweitzer, F. Sociophysics. *Phys. Today* **2018**, *71*, 40–47. [CrossRef]
17. Galam, S. *Sociophysics: A Physicist's Modeling of Psycho-Political Phenomena*. Springer Science + Business Media, LLC: New York, NY, USA, 2012. [CrossRef]
18. Chakrabarti, B.K.; Chakraborti, A.; Chatterjee, A. (Eds.) *Econophysics and Sociophysics: Trends and Perspectives*; Wiley-VCH Verlag GmbH & Co. KGaA: Weinheim, Germany, 2006.
19. Galam, S. Physicists, non physical topics, and interdisciplinarity. *Front. Phys.* **2022**, *10*, 986782. [CrossRef]
20. da Luz, M.G.E.; Anteneodo, C.; Crokidakis, N.; Perc, M. Sociophysics: Social collective behavior from the physics point of view. *Chaos Solitons Fractals* **2023**, *170*, 113379. [CrossRef]
21. Mobilia, M. Polarization and consensus in a voter model under time-fluctuating influences. *Physics* **2023**, *5*, 517–536. [CrossRef]
22. Zheng, S.; Jiang, N.; Li, X.; Xiao, M.; Chen, Q. Faculty hiring network reveals possible decision-making mechanism. *Physics* **2023**, *5*, 851–861. [CrossRef]
23. Filho, E.A.; Lima, F.W.; Alves, T.F.A.; Alves, G.d.; Plascak, J.A. Opinion dynamics systems via Biswas–Chatterjee–Sen model on Solomon networks. *Physics* **2023**, *5*, 873–882. [CrossRef]
24. Oestereich, A.L.; Pires, M.A.; Queirós, S.M.D.; Crokidakis, N. Phase transition in the Galam's majority-rule model with information-mediated independence. *Physics* **2023**, *5*, 911–922. [CrossRef]
25. Ellero, A.; Fasano, G.; Favaretto, D. Mathematical programming for the dynamics of opinion diffusion. *Physics* **2023**, *5*, 936–951 [CrossRef]
26. Malarz, K.; Masłyk, T. Phase diagram for social impact theory in initially fully differentiated society. *Physics* **2023**, *5*, 1031–1047 [CrossRef]
27. Li, S.; Zehmakan, A.N. Graph-based generalization of Galam model: Convergence time and influential nodes. *Physics* **2023**, *5*, 1094–1108. [CrossRef]
28. Ghosh, A.; Chakrabarti, B.K. Do successful researchers reach the self-organized critical point? *Physics* **2024**, *6*, 46–59. [CrossRef]
29. Mori, S.; Nakamura, S.; Nakayama, K.; Hisakado, M. Phase transition in ant colony optimization. *Physics* **2024**, *6*, 123–137. [CrossRef]
30. Kaufman, M.; Kaufman, S.; Diep, H.T. Social depolarization: Blume–Capel model. *Physics* **2024**, *6*, 138–147. [CrossRef]
31. Ausloos, M.; Rotundo, G.; Cerqueti, R. A Theory of best choice selection through objective arguments grounded in linear response theory concepts. *Physics* **2024**, *6*, 468–482. [CrossRef]
32. Llabrès, J.; Oliver-Bonafoux, S.; Anteneodo, C.; Toral, R. Aging in some opinion formation models: A comparative study. *Physics* **2024**, *6*, 515–528. [CrossRef]
33. Caticha, N.; Calsaverini, R.S.; Vicente, R. Statistical mechanics of social hierarchies: A mathematical model for the evolution of human societal structures. *Physics* **2024**, *6*, 629–644. [CrossRef]
34. Merlone, U.; Forno, A.D. The influence of lobbies: Analyzing group consensus from a physics approach. *Physics* **2024**, *6*, 659–673. [CrossRef]
35. Deffuant, G. Complex transitions of the bounded confidence model from an odd number of clusters to the next. *Physics* **2024**, *6*, 742–759. [CrossRef]
36. Demming, A. The laws of division. *Phys. World* **2024**, *37*, 37–41. [CrossRef]
37. Vilone, D.; Polizzi, E. Modeling opinion misperception and the emergence of silence in online social system. *PLoS ONE* **2024**, *19*, e0296075. [CrossRef]

38. Cui, P.-B. Exploring the foundation of social diversity and coherence with a novel attraction-repulsion model framework. *Physica A* **2023**, *618*, 128714. [CrossRef]
39. Liu, W.; Wang, J.; Wang, F.; Qi, K.; Di, Z. The precursor of the critical transitions in majority vote model with the noise feedback from the vote layer. *arXiv* **2023**, arXiv:2307.11398. [CrossRef]
40. Banisch, S.; Shamon, H. Validating argument-based opinion dynamics with survey experiments. *J. Artif. Soc. Soc. Simul. (JASSS)* **2024**, *27*, 17. [CrossRef]
41. Pal, R.; Kumar, A.; Santhanam, M.S. Depolarization of opinions on social networks through random nudges. *Phys. Rev. E* **2023**, *108*, 034307. [CrossRef] [PubMed]
42. Bagarello, F. Phase transitions, KMS condition and decision making: An introductory model. *Philos. Trans. R. Soc. A Math. Phys. Engin. Sci.* **2023**, *381*, 20220377. [CrossRef] [PubMed]
43. Galam, S.; Mauger, A. On reducing terrorism power: A hint from physics. *Phys. A Stat. Mech. Appl.* **2003**, *323*, 695–704. [CrossRef]
44. Crokidakis, N. Radicalization phenomena: Phase transitions, extinction processes and control of violent activities. *Int. J. Mod. Phys. C* **2023**, *34*, 2350100. [CrossRef]
45. Coquidé, C.; Lages, J.; Shepelyansky, L.D. Prospects of BRICS currency dominance in international trade. *Appl. Netw. Sci.* **2023**, *8*, 65. [CrossRef]
46. Mulyaa, D.A.; Muslim, R. Phase transition and universality of the majority-rule model on complex networks. *Int. J. Mod. Phys. C* **2024**, *in print*. [CrossRef]
47. Neirotti, J.; Caticha, N. Rebellions and impeachments in a neural network society. *arXiv* **2023**, arXiv:2309.11188. [CrossRef]
48. Shen, C.; Guo, H.; Hu, S.; Shi, L.; Wang, Z.; Tanimoto, J. How committed individuals shape social dynamics: A survey on coordination games and social dilemma games. *Eur. Phys. Lett. (EPL)* **2023**, *144*, 11002. [CrossRef]
49. Grabisch, M.; Li, F. Anti-conformism in the threshold model of collective behavior. *Dyn. Games Appl.* **2020**, *10*, 444–477. [CrossRef]
50. Forgerini, F.L.; Crokidakis, N.; Carvalho, M.A.V. Directed propaganda in the majority-rule model. *Int. J. Mod. Phys. C* **2024**, *in print*. [CrossRef]
51. Crokidakis, N. Recent violent political extremist events in Brazil and epidemic modeling: The role of a SIS-like model on the understanding of spreading and control of radicalism. *Int. J. Mod. Phys. C* **2024**, *35*, 2450015. [CrossRef]
52. Huang, C.; Bian, H.; Han, W. Breaking the symmetry neutralizes the extremization under the repulsion and higher order interactions. *Chaos Solitons Fractals* **2024**, *180*, 114544. [CrossRef]
53. Azhari, A.; Muslim, R.; Mulya, D.A.; Indrayani, H.; Wicaksana, C.A.; Rizky, A. Independence role in the generalized Sznajd model. *arXiv* **2023**, arXiv:2309.13309. [CrossRef]
54. Naumisa, G.G.; Samaniego-Steta, F.; del Castillo-Mussot, M.; Vázquez, G.J. Three-body interactions in sociophysics and their role in coalition forming. *Phys. A* **2007**, *379*, 226–234. [CrossRef]
55. Galam, S. The invisible hand and the rational agent are behind bubbles and crashes. *Chaos Solitons Fractals* **2016**, *88*, 209–217. [CrossRef]
56. Hamann, H. Opinion dynamics with mobile agents: Contrarian effects by spatial correlations. *Front. Robot. AI* **2018**, *5*, 63. [CrossRef] [PubMed]
57. Guo, L.; Cheng, Y.; Luo, Z. Opinion dynamics with the contrarian deterministic effect and human mobility on lattice. *Complexity* **2015**, *20*, 43–49. [CrossRef]
58. Tiwari, M.; Yang, X.; Sen, S. Modeling the nonlinear effects of opinion kinematics in elections: A simple Ising model with random field based study. *Phys. A* **2021**, *582*, 126287. [CrossRef]
59. Chacoma, A.; Zanette, D.H. Critical phenomena in the spreading of opinion consensus and disagreement. *Pap. Phys.* **2014**, *6*, 060003. [CrossRef]
60. Cheon, T.; Morimoto, J. Balancer effects in opinion dynamics. *Phys. Lett. A* **2016**, *380*, 429–434. [CrossRef]
61. Landry, N.W.; Restrepo, J.G. Opinion disparity in hypergraphs with community structure. *Phys. Rev. E* **2023**, *108*, 034311. [CrossRef]
62. Mulyaa, D.A.; Muslim, R. Destructive social noise effects on homogeneous and heterogeneous networks: Induced-phases in the majority-rule model. *Int. J. Mod. Phys. C* **2024**, *in print*. [CrossRef]
63. Mihara, A.; Ferreira, A.A.; Martins, A.C.R.; Ferreira, F.F. Critical exponents of master-node network model. *Phys. Rev. E* **2023**, *108*, 054303. [CrossRef] [PubMed]
64. Gärtner, B.; Zehmakan, A.N. Threshold behavior of democratic opinion dynamics. *J. Stat. Phys.* **2020**, *178*, 1442–1466. [CrossRef]
65. Toth, G.; Galam, S. Deviations from the majority: A local flip model. *Chaos Solitons Fractals* **2022**, *159*, 112130. [CrossRef]
66. Kowalska-Styczeń, A.; Malarz, K. Noise induced unanimity and disorder in opinion formation. *PLoS ONE* **2020**, *15*, e0235313. [CrossRef] [PubMed]
67. N. Crokidakis, Nonequilibrium phase transitions and absorbing states in a model for the dynamics of religious affiliation. *Phys. A Stat. Mech. Appl.* **2024**, 643, 129820. [CrossRef]
68. Redner, S. Reality-inspired voter models: A mini-review. *C. R. Phys.* **2019**, *20*, 275–292. [CrossRef]
69. Galam, S.; Moscovici, S. Towards a theory of collective phenomena. III: Conflicts and forms of power. *Eur. J. Soc. Psychol.* **1995**, *25*, 217–229. [CrossRef]
70. Jedrzejewski, A.; Marcjasz, G.; Nail, P.R. Sznajd-Weron, K. Think then act or act then think? *PLoS ONE* **2018**, *13*, e0206166. [CrossRef]

71. Singh, P.; Sreenivasan, S.; Szymanski, B.K.; Korniss, G. Competing effects of social balance and influence. *Phys. Rev. E* **2016**, *93*, 042306. [CrossRef] [PubMed]
72. Bagnoli, F.; Rechtman, R. Bifurcations in models of a society of reasonable contrarians and conformists. *Phys. Rev. E* **2015**, *92*, 042913. [CrossRef] [PubMed]
73. Carbone, G.; Giannoccaro, I. Model of human collective decision-making in complex environments. *Eur. Phys. J. B* **2015**, *88*, 339. [CrossRef]
74. Sznajd-Weron, K.; Szwabiński, J.; Weron, R. Is the Person-situation debate important for agent-based modeling and vice-versa? *PLoS ONE* **2014**, *9*, e112203. [CrossRef] [PubMed]
75. Florian, R.; Galam, S. Optimizing conflicts in the formation of strategic alliances. *Eur. Phys. J. B* **2000**, *16*, 189–194. [CrossRef]
76. Javarone, M.A. Networks strategies in election campaigns. *J. Stat. Mech.* **2014**, *2014*, P08013. [CrossRef]
77. Javarone, M.A.; Singh, S.P. Strategy revision phase with payoff threshold in the public goods game. *J. Stat. Mech.* **2024**, *2024*, 023404. [CrossRef]
78. Goncalves, S.; Laguna, M.F.; Iglesias, J.R. Why, when, and how fast innovations are adopted. *Eur. Phys. J. B* **2012**, *85*, 192. [CrossRef]
79. Ellero, A.; Fasano, G.; Sorato, A. A modified Galam's model for word-of-mouth information exchange. *Phys. A Stat. Mech. Appl.* **2009**, *388*, 3901–3910. [CrossRef]
80. Gimenez, M.C.; Reinaudi, L.; Vazquez, F. Contrarian voter model under the influence of an oscillating propaganda: Consensus, bimodal behavior and stochastic resonance. *Entropy* **2022**, *24*, 1140. [CrossRef]
81. Iacominia, E.; Vellucci, P. Contrarian effect in opinion forming: Insights from Greta Thunberg phenomenon. *J. Math. Sociol.* **2023**, *47*, 123–169. [CrossRef]
82. Brugnoli, E.; Delmastro, M. Dynamics of (mis)information flow and engaging power of narratives. *arXiv* **2022**, arXiv:2207.12264. [CrossRef]
83. Sobkowicz, P.; Now, W. Opinion modelers? *Front. Phys.* **2020**, *8*, 587009 . [CrossRef]
84. Weron, T.; Nyczka, P.; Szwabiński, J. Composition of the influence group in the *q*-voter model and its impact on the dynamics of opinions. *Entropy* **2024**, *26*, 132. [CrossRef]
85. Gsänger, M.; Hösel, V.; Mohamad-Klotzbach, C.; Müller, J. Opinion models, data, and politics. *Entropy* **2024**, *26*, 212. [CrossRef] [PubMed]
86. Shang, Y. Hybrid consensus for averager-copier-voter networks with non-rational agents. *Chaos Solitons Fractals* **2018**, *110*, 244–251. [CrossRef]
87. Mobilia, M.; Fixation and polarization in a three-species opinion dynamics model. *Eur. Phys. Lett.* **2011**, *95*, 50002. [CrossRef]
88. Calvaő, A.M.; Ramos, M.; Anteneodo, C.; Role of the plurality rule in multiple choices. *J. Stat. Mech.* **2016**, *2016*, 023405. [CrossRef]
89. Maciel, M.V.; Martins, A.C.R.; Ideologically motivated biases in a multiple issues opinion model. *Phys. A Stat. Mech. Appl.* **2020**, *553*, 124293. [CrossRef]
90. Dworak, M.; Malarz, K. Vanishing opinions in Latané model of opinion formation. *Entropy* **2023**, *25*, 58. [CrossRef]
91. Galam, S.The drastic outcomes from voting alliances in three-party democratic voting (1990–2013). *J. Stat. Phys.* **2013**, *151*, 46–68. [CrossRef]
92. Ferri, I.; Gaya-Ávila, A.; Guilera, A.D. Three-state opinion model with mobile agents. *Chaos* **2023**, *33*, 093121. [CrossRef] [PubMed]
93. Tsintsaris, D.; Tsompanoglou, M.; Ioannidis, E. Dynamics of social influence and knowledge in networks: Sociophysics models and applications in social trading, behavioral finance and business. *Mathematics*, 2024, *12*, 1141. [CrossRef]
94. Coquidé, C.; Lages, J.; Shepelyansky, D.L. Opinion formation in the world trade network. *Entropy* **2024**, *26*, 141. [CrossRef] [PubMed]
95. Oliveira, I.V.G.; Wang, C.; Dong, G.; Du, R.; Fiore, C.E.; Vilela, A.L.M.; Stanley, H.E. Entropy production on cooperative opinion dynamics. *Chaos Solitons Fractals* **2024**, *181*, 114694. [CrossRef]
96. Segovia-Martin, J.; Rivero, R. Cross-border political competition. *PLoS ONE*, **2024**, *19*, e0297731 [CrossRef] [PubMed]
97. Zimmaro, F.; Galam, S.; Javarone, M.A. Asymmetric games on networks: Mapping to Ising models and bounded rationality. *Chaos Solitons Fractals*, **2024**, *181*, 114666. [CrossRef]
98. Macias, R.C.; Vera; Vera, J.M.R. Dynamics of opinion polarization in a population. *Math. Soc. Sci.* **2024**, *128*, 31–40. [CrossRef]
99. Battiston F.; Cairoli A.; Nicosia V.; Baule, A.; Latora V. Interplay between consensus and coherence in a model of interacting opinions. *Phys. D Nonlinear Phenom.* **2016**, *323–324*, 12–19. [CrossRef]
100. Ghosh, S.; Bhattacharya, S.; Mukherjee, S.; Chakravarty, S. Promote to protect: Data-driven computational model of peer influence for vaccine perception. *Sci. Rep.* **2024**, *14*, 306. [CrossRef]
101. Götz, T.; Krüger, T.; Niedzielewski, K.; Pestow, R.; Schäfer, M.; Schneider, J. Chaos in opinion-driven disease dynamics. *Entropy* **2024**, *26*, 298. [CrossRef] [PubMed]
102. Soares, J.P.M.; Fontanari, J.F. *N*-player game formulation of the majority-vote model of opinion dynamics. *Phys. A Stat. Mech. Appl.* **2024**, *643*, 129829. [CrossRef]
103. Zhang, H.-B.; Tang, D.-P. Effects of group size and noise on cooperation in population evolution of dynamic groups. *arXiv* **2024**, arXiv:2402.16317. [CrossRef]
104. Kononovicius, A.; Astrauskas, R.; Radavičius, M.; Ivanauskas, F. Delayed interactions in the noisy voter model through the periodic polling mechanism. *arXiv* **2024**, arXiv:2403.10277. [CrossRef]

105. Cao, W.; Zhang, H.; Kou, G.; Zhang, B. Discrete opinion dynamics in social networks with stubborn agents and limited information. *Inf. Fusion* **2024**, *109*, 102410. [CrossRef]
106. Maksymov, I.S.; Pogrebna, G. Quantum-mechanical modelling of asymmetric opinion polarisation in social networks. *Information* **2024**, *15*, 170. [CrossRef]
107. Behrens, F.; Hudcová, B.; Zdeborová, L. Dynamical phase transitions in graph cellular automata. *Phys. Rev. E* 2024, 109, 044312. [CrossRef] [PubMed]
108. Martins, A.C.R. Discrete opinion dynamics with *M* choices. *Eur. Phys. J. B* **2020**, *93*, 1. [CrossRef]
109. Galam, S.; Cheon, T. Tipping points in opinion dynamics: A universal formula in five dimensions. *Front. Phys.* **2020**, *8*, 446. [CrossRef]
110. Galam, S. Majority rule, hierarchical structures, and democratic totalitarianism: A statistical approach. *J. Math. Psychol.* **1986**, *30*, 426–434. [CrossRef]
111. Galam, S.; Chopard, B.; Masselot, A.; Droz, M. Competing species dynamics: Qualitative advantage versus geography. *Eur. Phys. J. B* **1998**, *4*, 529–531. [CrossRef]
112. Galam, S. Minority opinion spreading in random geometry. *Eur. Phys. J. B* **2002**, *25*, 403–406. . [CrossRef]
113. Galam, S. Heterogeneous beliefs, segregation, and extremism in the making of public opinions. *Phys. Rev. E* **2005**, *71*, 046123. [CrossRef] [PubMed]
114. Galam, S. Contrarian deterministic effects on opinion dynamics: "The hung elections scenario". *Phys. A Stat. Mech. Appl.* **2004**, *333*, 453–460. [CrossRef]
115. Galam, S. Unanimity, coexistence, and rigidity: Three sides of polarization. *Entropy* **2023**, 25, 622. [CrossRef]
116. Greenblatt, J.A. ADL: Media helped spread blood libel against Israel, jews in Gaza hospital news coverage. *USA Today Opinion*, 22 October 2023. Available online: https://eu.usatoday.com/story/opinion/2023/10/22/gaza-hospital-explosion-hamas-israel-war-misinformation/71246499007/ (accessed on 11 May 2024).