Extreme Ideas Emerging from Social Conformity and Homophily: An Adaptive Social Network Model

Hiroki Sayama[1,2]

[1] Center for Collective Dynamics of Complex Systems, Binghamton University, Binghamton, NY 13902-6000, USA
[2] Waseda Innovation Lab, Waseda University, Shinjuku, Tokyo 169-8050, Japan
sayama@binghamton.edu

Abstract

Extreme ideas and opinions are commonly seen growing in many aspects of today's society, ranging from political ideology to healthcare choices and from dietary preferences to technological innovation. Such a trend may be understood as an outcome of a spontaneous dynamical process driven by the recent advancement of information communication technology that allows people to preferentially select their information sources. Here we study, using an agent-based model of adaptive social network dynamics, how extreme ideas may arise in society in which individuals simply try to conform to social norm within their social neighborhood. Our model assumes that each node gradually assimilates its state to local social norm, i.e., the average of its in-neighbors' states, while also changing edge weights based on their states. Numerical simulations revealed that, when individuals tend to practice homophily by strengthening their ties selectively to neighbors with similar states, there tends to be many extreme ideas emerging in society while the network topology tends to become fragmented. Such outcomes are mitigated, however, when individuals also practice novelty-seeking behavior by increasing attention to neighbors whose ideas do not conform to the local social norm. These results paint a paradoxical picture of complex social processes — society produces difference when individuals seek sameness, or society reaches sameness when individuals seek difference.

Introduction

In today's highly interconnected world, we are constantly exposed to a wide variety of information in many different communication media. Often noticed is the increasing number of extreme ideas and opinions often expressed there. They are not limited to typical political ideologies (Conover et al., 2011; Prior, 2013; Morales et al., 2015) or religious extremism (Manrique et al., 2018; Badawy and Ferrara, 2018), but also include more casual topics related to our everyday life such as healthcare choices (Kata, 2012; Johnson et al., 2019) and dietary preferences (Cole and Morgan, 2011; Reilly, 2016), as well as more professional topics related to business, technologies, and innovation (Coccia, 2016; Naranjo-Valencia et al., 2017).

Such rise of extreme ideas could easily be attributed to specific causes or triggers. From a more complex systems oriented perspective, however, it may also be understood as an outcome of a spontaneous dynamical process driven by the recent advancement of information communication technology (Sayama, 2020), even if no one intentionally tries to go extreme (Sayama, 2016). In particular, mobile phones, social media, and other forms of modern information communication technology have allowed people to select their preferred information sources easily and freely. Such preferential selection of information sources has been argued to be a crucial factor inducing the polarization of our society, often forming "social bubbles" (Nikolov et al., 2015; Spohr, 2017).

To gain insight into social evolution and opinion dynamics driven by information exchange among social constituents, researchers have studied theoretical models of adaptive social networks, where the topologies of social ties between the constituents and their states co-evolve simultaneously (Gross and Sayama, 2009; Sayama et al., 2013). Most of them were mainly focused on phase transitions between connected and fragmented states of adaptive social networks (Holme and Newman, 2006; Zanette and Gil, 2006; Kozma and Barrat, 2008; Böhme and Gross, 2011; Sayama and Yamanoi, 2020), while others also studied global drift phenomena in social diffusion (Sayama and Sinatra, 2015). However, existing research is still quite limited in terms of how extreme ideas may spontaneously arise in society, particularly through interactions among well-meaning individuals who do not have intention to escalate things but simply try to conform to social norm within their neighborhood.

In this paper, we propose a computational agent-based model of adaptive social network dynamics and investigate the non-trivial social dynamics by which extreme ideas can arise through social conformity and homophily among such well-meaning individuals. We conduct systematic parameter-sweep numerical experiments and regression analyses to elucidate the effects of several individual behaviors (social conformity, homophily, and attention to novelty) on ideological dynamics on social networks.

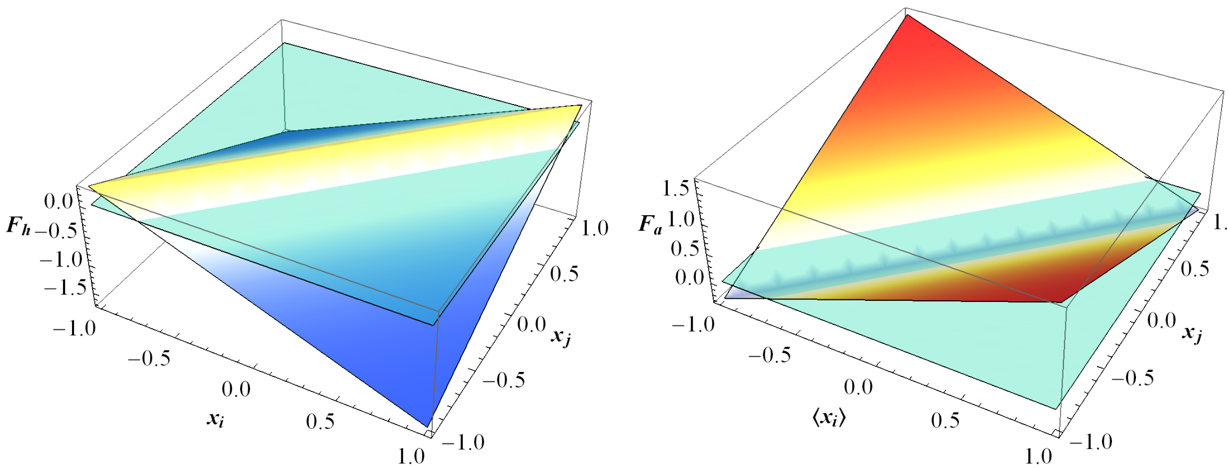

Figure 1: Typical functional shapes of F_h (left) and F_a (right), with $\theta_h = \theta_a = 0.3$ in these examples. Cyan planes are added at a zero level for reference.

Model

Our model describes distributed opinion dynamics on an adaptive social network made of n nodes. A node $i \in V$ represents an individual social constituent in the node set V, and it has its own idea state $x_i \in \mathbb{R}$. Each node receives information about its social neighbors' ideas through weighted directed edges. The weight of an edge that conveys information from node j to node i is denoted as $w_{ij} \in \mathbb{R}_{\geq 0}$.

The basic model assumption is that each node gradually assimilates its state to local social norm, i.e., the average of states of its in-neighbors (information sources), while also changes edge weights based on their states. Node and edge states x_i and w_{ij} co-evolve over time through the following four mechanisms: (1) social conformity, (2) homophily, (3) attention to novelty, and (4) random fluctuation. Their dynamics are mathematically described as follows:

$$\frac{dx_i}{dt} = c\left(\langle x \rangle_i - x_i\right) + \epsilon \tag{1}$$

$$\frac{dw_{ij}}{dt} = hF_h(x_i, x_j) + aF_a(\langle x \rangle_i, x_j) \tag{2}$$

$$\langle x \rangle_i = \frac{\sum_{j \in N_i} w_{ij} x_j}{\sum_{j \in N_i} w_{ij}} \tag{3}$$

Here N_i is the set of in-neighbors of node i; $\langle x \rangle_i$ is the local average idea, or social norm, perceived by node i; c, h, and a are parameters that determine the strength of social conformity, homophily, and attention to novelty, respectively; ϵ represents a stochastic fluctuation term for nodes' ideas; and F_h and F_a are behavioral functions that determine the rate of edge weight change based on idea distance, defined as follows:

$$F_h(x_i, x_j) = \theta_h - |x_i - x_j| \tag{4}$$

$$F_a(\langle x \rangle_i, x_j) = |\langle x \rangle_i - x_j| - \theta_a \tag{5}$$

Figure 1 illustrates typical shapes of these functions. They indicate that the edge from node j to node i becomes stronger if j's idea is close to i's (i.e., homophily, Fig. 1 left) but distant from the local average (i.e., attention to novelty, Fig. 1 right). Note that w_{ij} is bounded to be non-negative, i.e., any negative values would be rounded up to zero.

We implemented the above adaptive social network model in Python 3.7 with NetworkX[1].

Experiments

Experimental Settings

Numerical simulations were conducted to systematically test all the combinations of the following parameter values:

- $n \in \{30, 100, 300, 1000\}$
- $c,\ h,\ a,\ \theta_h,\ \theta_a \in \{0.01, 0.03, 0.1, 0.3\}$

The total number of parameter settings was thus $4^6 = 4096$. Five independent simulation runs were conducted for each parameter value combination with $n = 30, 100, 300$, while only one run was conducted (so far) for cases with $n = 1000$ due to their high computational complexity. The total number of simulations was $(5 \times 3 + 1) \times 4^5 = 16384$.

The initial configuration of the network was such that every ordered pair of nodes were connected by a directed edge with a weight randomly sampled from the uniform distribution $[0, 1]$ and each node had a random node state sampled from the standard normal distribution $\mathcal{N}(0, 1^2)$. Each simulation run was conducted using a simple Euler forward method with time interval $\Delta t = 0.1$ for $t =$ 0–100. The stochastic effect of ϵ was simulated by adding to x_i a random number sampled from $\mathcal{N}(0, 0.1^2)$ at every interval Δt.

[1]The simulator code is available from the author upon request.

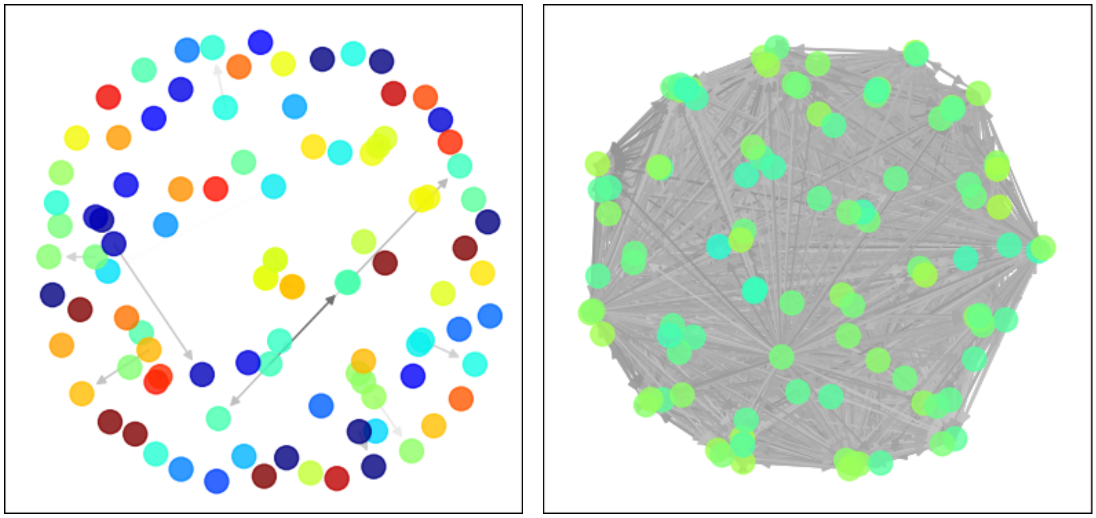

Figure 2: Illustrative examples of simulation outcomes with $n = 100$. Node colors represent their idea states. Left: Emergence of many isolated nodes/clusters with different ideas. $(c, h, a, \theta_h, \theta_a) = (0.01, 0.3, 0.01, 0.01, 0.03)$. Right: Homogenization of ideas in densely connected society. $(c, h, a, \theta_h, \theta_a) = (0.3, 0.01, 0.3, 0.3, 0.03)$.

Outcome Measures

After each simulation run was completed, the final network configuration at $t = 100$ was first converted from directed to undirected by averaging weights of two directed edges between a pair of nodes into one undirected weight. The community structure was then detected using the Louvain modularity maximization method (Blondel et al., 2008), and the average node state was calculated within each community (called "average community state" hereafter). Using these, the following network metrics were calculated as outcome measures:

1. Average edge weight (= arithmetic average of all the edge weights in the network)
2. Number of communities
3. Modularity of communities
4. Range of average community states (= difference between largest and smallest average community states)
5. Standard deviation of average community states

Among these five outcome measures, the last two (range and standard deviation of average community states) were used to characterize how much extreme ideas were produced in the social network. These outcome measures were averaged over independent simulation runs for each combinations of parameter values described above, and their correlations with the model parameters were evaluated using linear regression analyses.

Results

Numerical simulations produced a wide range of outcomes. Two illustrative examples are presented in Fig. 2, showing complete fragmentation with a variety of different ideas (Fig. 2 left) and almost complete homogenization of ideas with dense social connection (Fig. 2 right).

Figures 3 and 4 present correlations between the five model parameters and the five outcome measures for $n = 100$ and $n = 1000$, respectively, which showed consistent trends despite different network sizes. Results for $n = 30$ and $n = 300$ also show very similar trends (results not shown), indicating that the observed correlations are robust against variations in network size.

It was clearly observed that parameter h (second column in Figs. 3 and 4), which determines the rate of homophilic edge weight change, promoted fragmentation of the network (captured in decrease of the average edge weight and increase of the number of communities and the modularity) and production of extreme ideas (captured in increase of the range and standard deviation of average community states). This is because homophily had an effect to weaken connections between nodes with distant idea states, turning the society into many isolated nodes/clusters (e.g., social bubbles), each of which would drift toward higher or lower idea states independently even if social conformity were in action.

Meanwhile, parameter a (third column in Figs. 3 and 4), which determines the rate of edge weight change by attention to novelty, had almost the complete opposite effects of h, alleviating social fragmentation and suppressing the rise of extreme ideas. This can be understood in that the attention to novelty, or information source that is different from the rest of the sources, tends to help create an informational

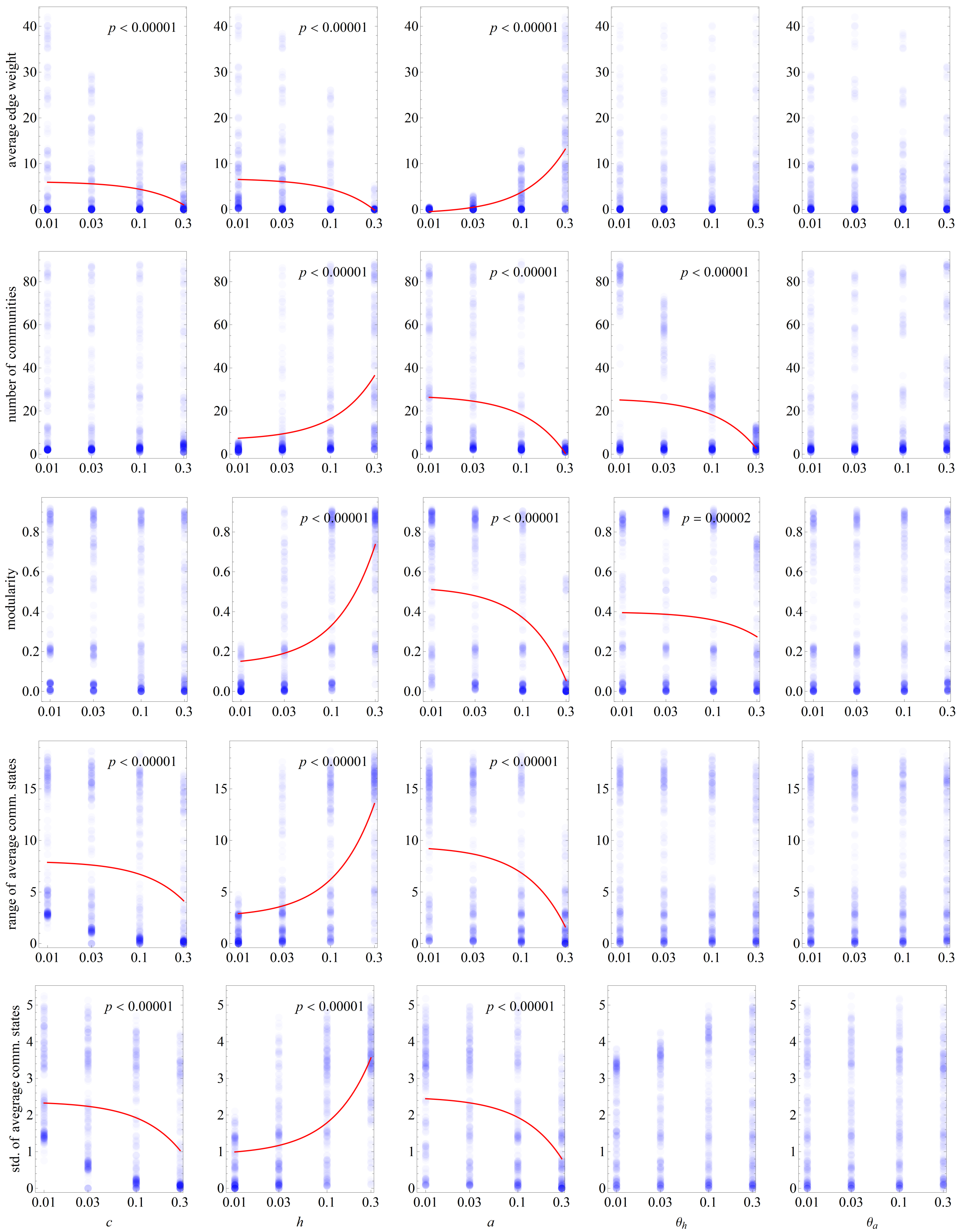

Figure 3: Distributions of outcome measures plotted over parameters for networks of $n = 100$. Each dot represents an average of 5 identical simulation runs. Statistically significant correlations with $p < 10^{-4}$ are shown with trend lines obtained by linear regression. Horizontal axes are in log scale to aid visibility (hence the red curves shown in these plots are actually linear trend lines).

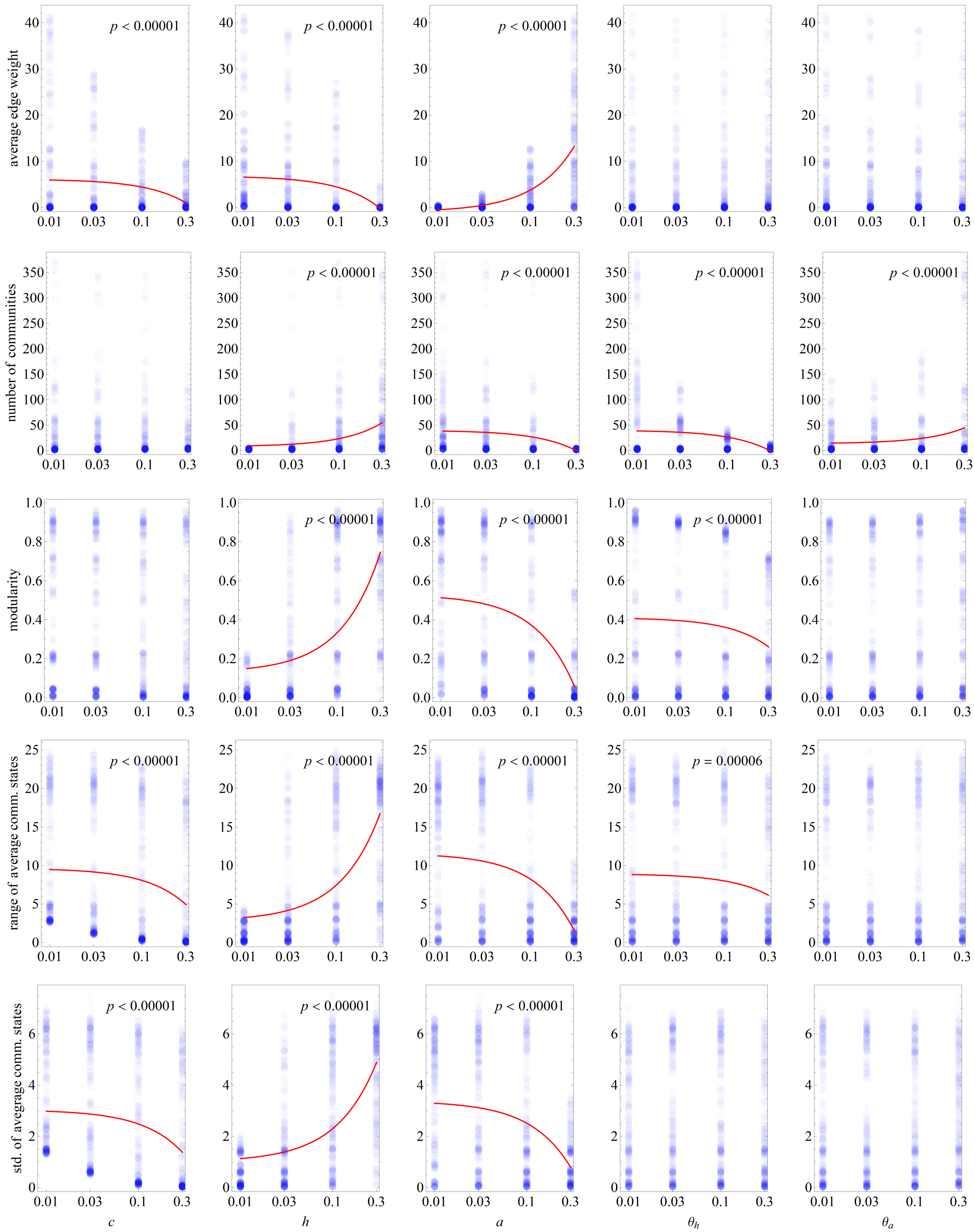

Figure 4: Distributions of outcome measures plotted over parameters for networks of $n = 1000$. Each dot represents one simulation run. Statistically significant correlations with $p < 10^{-4}$ are shown with trend lines obtained by linear regression. Horizontal axes are in log scale to aid visibility (hence the red curves shown in these plots are actually linear trend lines).

Table 1: Results of multiple linear regression of each outcome measure (top header) on model parameters (middle) and their interactions (bottom). Data obtained with networks of size $n = 100$ were used in this table. Statistically significant coefficients are indicated with asterisks (***: $p < 10^{-4}$; **: $p < 10^{-3}$; *: $p < 10^{-2}$). Coefficients of model parameters with the largest and second largest effect sizes are indicated in bold (red: positive, blue: negative), which confirms the observation that h and a are the two important parameters that have the largest effects on social network evolution.

Outcome measure	average edge weight	number of communities	modularity	range of average comm. states	std. of average comm. states
const.	-0.336133	17.9348	0.306332	6.36077	1.92395
c	-6.32563^{***}	-19.9322	-0.311658^{***}	-14.0533^{***}	-4.52717^{***}
h	**-11.8516^{***}**	**196.224^{***}**	**2.52259^{***}**	**48.7035^{***}**	**9.21682^{***}**
a	**100.97^{***}**	**-90.2584^{***}**	**-1.44367^{***}**	**-23.1149^{***}**	**-5.0213^{***}**
θ_h	0.139315	-66.0141^{***}	-0.161914^{***}	-2.06788^{***}	0.98742
θ_a	-1.68908^{***}	26.8527^{***}	0.206154^{***}	0.440309^{*}	-0.482658^{*}
ch	96.777^{***}	-2.40873	0.496937	1.44904	3.96937
ca	-196.254^{***}	62.63	1.21425^{*}	32.9133^{***}	4.85103
$c\theta_h$	0.938596	23.7479	-1.42933^{*}	-31.1381^{**}	-11.4987^{***}
$c\theta_a$	1.65429	22.5155	0.415723	7.85521	3.23167
ha	-234.986^{***}	-421.495^{***}	-3.68595^{***}	-88.4928^{***}	-11.1493^{***}
$h\theta_h$	4.31408	-498.796^{***}	-1.75052^{***}	-29.9663^{**}	2.28346
$h\theta_a$	32.3537^{***}	47.8377	0.356691	8.55397	1.59301
$a\theta_h$	18.5702	447.439^{***}	1.27031^{*}	20.2363	-3.5686
$a\theta_a$	-77.7543^{***}	-79.4616	0.0335362	8.32262	4.16891
$\theta_h\theta_a$	-6.09341	-72.9776	-0.39431	-1.1345	0.91514

bridge between ideologically different parts of the network, bringing back otherwise fragmenting society and mixing the ideas circulating inside it.

Compared to h and a, the threshold parameters (θ_h and θ_a) did not have as much effects on social outcomes, probably because their values were not as significant once the ideas were diversified within the network. This observation may change if a much wider range of parameter values are tested for θ_h and θ_a.

To quantify the relative effect size caused by each model parameter, we further conducted multiple linear regression of the outcome measures on the model parameters and their interactions. Table 1 shows the results (for networks of size $n = 100$), which confirmed that parameters h and a played major roles, in completely opposite directions, for social network evolution. There were also significant interactions among the parameters, suggesting that their effects on the outcome measures are nonlinear.

Conclusions

In this paper, we proposed an agent-based adaptive network model of opinion dynamics to demonstrate how extreme ideas and opinions might arise in society made of individuals that had no intention to go extreme but only wanted social conformity with like-minded others. We examined the effects of model parameters on the evolution of social networks and their states through a set of systematic numerical simulation experiments and regression analyses. The results showed that, when individuals tend to practice homophily by strengthening their ties selectively to neighbors with similar ideas, the network tends to evolve into a fragmented topology with many extreme ideas. However, when individuals also practice novelty-seeking behavior by increasing attention to non-conforming neighbors whose ideas are different from the local social norm, the network tends to remain well connected with homogeneous idea states.

These results paint a paradoxical picture of complex social processes that exhibit phenomenological contradiction between individual intentions and global outcomes. On the one hand, when social constituents seek sameness via social conformity and homophily, the macroscopic state of society tends to end up with little connectivity yet great diversity of different ideas. On the other hand, when the constituents seek difference and novelty, the macroscopic state of society tends to achieve global sameness with little diversity of ideas yet high connectivity. This counter-intuitive observation may provide useful, practical insight into how we should shape our individual behaviors in order to achieve a goal at a societal level. For example, what should we do as individuals if we want to achieve a global consensus, or if we want to nurture radically innovative ideas?

Our model and experiments are still preliminary with many limitations. For simplicity, we tested only linear behavioral functions, F_h and F_a, which can be easily made non-linear to increase realism of human behavior. These behavioral functions and their parameter values were assumed to be identical across all the individuals, but real society is behaviorally quite heterogeneous and such heterogeneity could produce nontrivial outcomes (Sayama and Yamanoi, 2020). The values of model parameters swept in the experiments were also limited only to four discrete values in the $[0.01, 0.3]$ range, but they should be expanded to a wider range to test if the observed trends would generalize further (possibly including negative values as well). These limitations were largely due to the enormous computational costs in running numerical simulations of our current model, which requires updating dynamical states of both nodes and edges of a *fully connected* dynamical network all the time. This would quickly become expensive when the network size increases[2]. Re-implementing the model in different environment to speed up numerical experiments is our next immediate goal. This should allow more thorough exploration of model behaviors, revealing more detailed pictures of their effects on global outcomes as well as non-trivial interplays among parameters and assumptions.

Acknowledgments

This work was supported in part by JSPS KAKENHI Grant Number 19K21571 and the Visitors Program of the Max Planck Institute for the Physics of Complex Systems in Dresden, Germany.

References

Badawy, A. and Ferrara, E. (2018). The rise of jihadist propaganda on social networks. *Journal of Computational Social Science*, 1(2):453–470.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., and Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10):P10008.

Böhme, G. A. and Gross, T. (2011). Analytical calculation of fragmentation transitions in adaptive networks. *Physical Review E*, 83(3):035101.

Coccia, M. (2016). Radical innovations as drivers of breakthroughs: characteristics and properties of the management of technology leading to superior organisational performance in the discovery process of R&D labs. *Technology Analysis & Strategic Management*, 28(4):381–395.

Cole, M. and Morgan, K. (2011). Vegaphobia: derogatory discourses of veganism and the reproduction of speciesism in UK national newspapers. *The British Journal of Sociology*, 62(1):134–153.

Conover, M. D., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., and Flammini, A. (2011). Political polarization on Twitter. In *Fifth International AAAI Conference on Weblogs and Social Media*.

[2]Our current implementation of the model with Python and NetworkX takes about four hours to complete a single simulation run with $n = 1000$.

Gross, T. and Sayama, H. (2009). *Adaptive Networks*. Springer.

Holme, P. and Newman, M. E. (2006). Nonequilibrium phase transition in the coevolution of networks and opinions. *Physical Review E*, 74(5):056108.

Johnson, N., Velasquez, N., Restrepo, N. J., Leahy, R., Gabriel, N., Wuchty, S., and Broniatowski, D. (2019). Health wars and beyond: The rapidly expanding and efficient network insurgency interlinking local and global online crowds of distrust. *arXiv preprint arXiv:1910.02103*.

Kata, A. (2012). Anti-vaccine activists, Web 2.0, and the postmodern paradigm–an overview of tactics and tropes used online by the anti-vaccination movement. *Vaccine*, 30(25):3778–3789.

Kozma, B. and Barrat, A. (2008). Consensus formation on adaptive networks. *Physical Review E*, 77(1):016102.

Manrique, P. D., Zheng, M., Cao, Z., Restrepo, E. M., and Johnson, N. F. (2018). Generalized gelation theory describes onset of online extremist support. *Physical Review Letters*, 121(4):048301.

Morales, A., Borondo, J., Losada, J. C., and Benito, R. M. (2015). Measuring political polarization: Twitter shows the two sides of Venezuela. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 25(3):033114.

Naranjo-Valencia, J. C., Jimenez-Jimenez, D., and Sanz-Valle, R. (2017). Organizational culture and radical innovation: Does innovative behavior mediate this relationship? *Creativity and Innovation Management*, 26(4):407–417.

Nikolov, D., Oliveira, D. F., Flammini, A., and Menczer, F. (2015). Measuring online social bubbles. *PeerJ Computer Science*, 1:e38.

Prior, M. (2013). Media and political polarization. *Annual Review of Political Science*, 16:101–127.

Reilly, N. R. (2016). The gluten-free diet: recognizing fact, fiction, and fad. *The Journal of pediatrics*, 175:206–210.

Sayama, H. (2016). Going extreme without leaders. https://medium.com/@hsayama/going-extreme-without-leaders-e2f1ea0ba520. Accessed: 2020-01-06.

Sayama, H. (2020). Enhanced ability of information gathering may intensify disagreement among groups. *arXiv preprint arXiv:2002.01049*.

Sayama, H., Pestov, I., Schmidt, J., Bush, B. J., Wong, C., Yamanoi, J., and Gross, T. (2013). Modeling complex systems with adaptive networks. *Computers & Mathematics with Applications*, 65(10):1645–1664.

Sayama, H. and Sinatra, R. (2015). Social diffusion and global drift on networks. *Physical Review E*, 91(3):032809.

Sayama, H. and Yamanoi, J. (2020). Beyond social fragmentation: Coexistence of cultural diversity and structural connectivity is possible with social constituent diversity. In *Proceedings of NetSci-X 2020: Sixth International Winter School and Conference on Network Science*, pages 171–181. Springer.

Spohr, D. (2017). Fake news and ideological polarization: Filter bubbles and selective exposure on social media. *Business Information Review*, 34(3):150–160.

Zanette, D. H. and Gil, S. (2006). Opinion spreading and agent segregation on evolving networks. *Physica D: Nonlinear Phenomena*, 224(1-2):156–165.