

# Detecting New Phase Transition Points in Large-Scale Numerical Simulations of an Adaptive Social Network Model

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Understanding social fragmentation transition, i.e., transition of social states between many disconnected communities with distinct ideas and a well-connected single network with homogeneous ideas, is a timely research topic with high relevance to various current societal issues (Blex & Yasseri, 2020; Kozma & Barrat, 2008; Levin et al., 2021; Sasahara et al., 2021). We had previously studied this problem using numerical simulations of adaptive social network models (Sayama, 2020) and found that two individual behavioral traits, *homophily* (i.e., tendency to strengthen connections to similar agents and weaken those to dissimilar ones) and *attention to novelty* (i.e., tendency to strengthen connections to agents whose opinions stand out compared to others), among others, had the most significant impact on the outcomes of social network evolution. Specifically, when homophily was strong, the social network evolved into fragmented states of many disconnected clusters with diverse opinions, but when attention to novelty was strong, the social network evolved to well-connected yet informationally homogeneous states. However, the previous study was rather limited in terms of the range of parameter values examined, and possible interactions between multiple behavioral traits were largely ignored, especially about the other behavioral trait, *social conformity* (i.e., how strongly agents assimilate themselves to social neighbors).

In the present study, we have examined a broader spectrum of social network behaviors through a larger-scale numerical experiment with expanded parameter sweep ranges by an order of magnitude in each parameter dimension. Specifically, each of the five model parameters ( $c$  for conformity,  $h$  for homophily,  $a$  for attention to novelty, and two other threshold parameters; see (Sayama, 2020) for details) was varied over  $\{0.003, 0.01, 0.03, 0.1, 0.3, 1\}$  and each parameter value combination was simulated five times with independently generated random initial conditions. The whole set of simulations was conducted for three network sizes ( $n = 30, 100, 300$ ). This resulted in a total of 116,640 simulation runs, taking a substantial amount of computational time and resource. The simulations were conducted in Python.

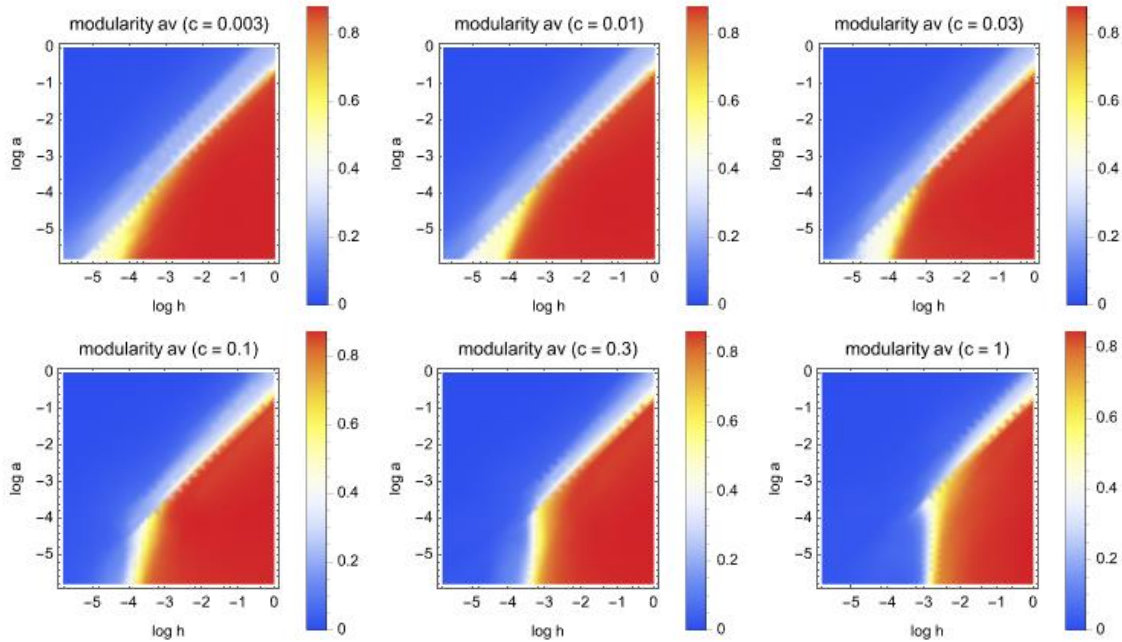
In order to capture nontrivial, nonlinear interactions among behavioral parameters, we have modeled and visualized the outcome dependence on parameters using neural networks

using Wolfram Research Mathematica 12's neural network predictor. The following five outcome measures were obtained and modeled from the final configuration of each simulation: average edge weight, number of communities, modularity, range of average community states, and standard deviation of average community states (Sayama, 2020). The first three outcome measures captured the network topology, while the last two did the opinion states of the social network.

Results are shown in Figure 1 for modularity and range of average community states. The competition between homophily ( $h$ ) and attention to novelty ( $a$ ) is still observed as the primary determinant of social fragmentation in a low-conformity ( $c$ ) regime (top rows in Fig. 1a and 1b), seen as the diagonal phase transition line in the plots. However, another vertical transition line emerges at an intermediate homophily level in a high-conformity regime (bottom rows in Fig. 1a and 1b), which was not previously known. This new result shows that, when agent's social conformity is sufficiently strong, social homogenization can occur even without attention to novelty. This also implies a previously unrecognized competition between social conformity ( $c$ ) and homophily ( $h$ ) in low- $a$  regions (near the bottom edge of each plot in Fig. 1). Namely, when  $c$  is low, social fragmentation dominates, but when  $c$  is high, social homogenization emerges for sufficiently small values of  $h$ .

This study has detected new phase transition points in the adaptive social network model and demonstrated nontrivial, nonlinear interactions among the multiple behavioral mechanisms. In particular, the competition between social conformity and homophily (observed in the absence of attention to novelty) is intriguing because both behaviors have very similar effects at an individual agent level (i.e., they both make ego and alter similar to each other) and their differences are often vague and undetectable in empirical social network studies (Shalizi & Thomas, 2011). Meanwhile, those two behaviors are mathematically distinct since social conformity is about node dynamics while homophily is about edge dynamics. The finding that their competition may lead to very different societal outcomes down the road, offers a lot of implications for how we should rethink/redesign our social interactions in this highly interconnected world.

(a) Modularity of network



(b) Range of average community states

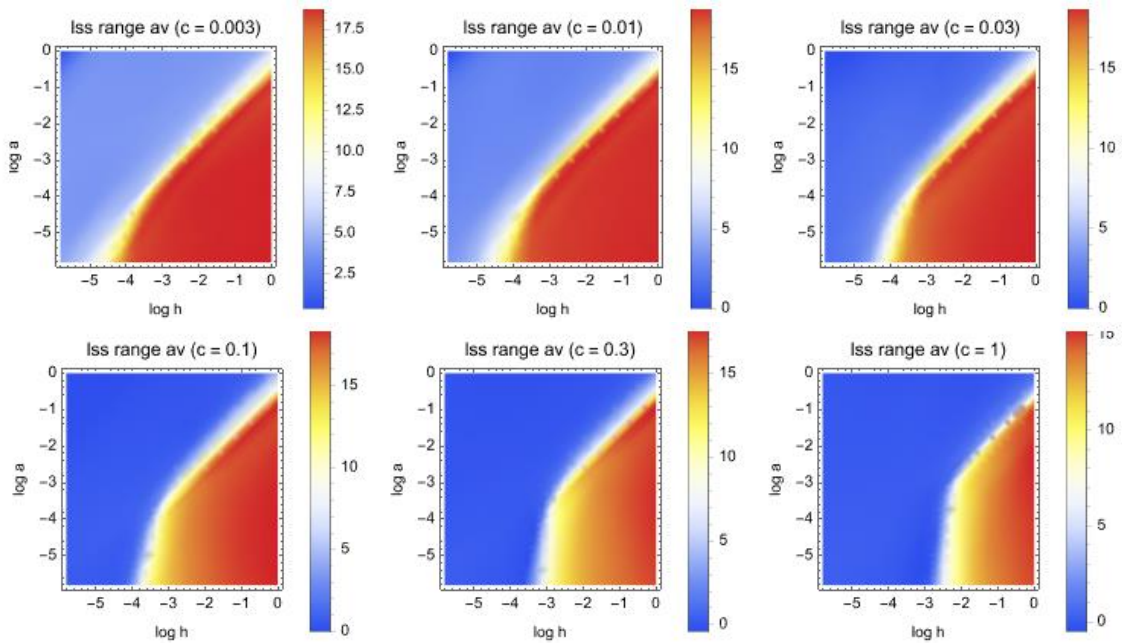


Figure 1: Phase diagrams of adaptive social network evolution. Results of large-scale parameter-sweep numerical simulations were modeled and visualized using neural networks. Each plot shows outcome dependence on homophily ( $h$ , horizontal axis), attention to novelty ( $a$ , vertical axis) and conformity ( $c$ , varied from top-left to bottom-right). (a) How final network topology (modularity) depends on  $h$ ,  $a$  and  $c$ . (b) How final opinion diversity (range of average community states) depends on  $h$ ,  $a$  and  $c$ . Red and blue regions correspond to fragmented and homogenized network states, respectively. Number of nodes  $n = 300$ . Similar patterns were observed for other outcome measures and network sizes.

## Acknowledgments

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