Exploring the Impact of Social Network Density and Agent Openness on Societal Polarization

Justin Mittereder, Robert S. W. Carroll, Brandon Frulla, Stephen Davies
University of Mary Washington
Department of Computer Science
Fredericksburg, Virginia
{jmittere,rcarrol2,bfrulla,stephen}@umw.edu

ABSTRACT

We present an agent-based model, inspired by the opinion dynamics (OD) literature, to explore the underlying behaviors that may induce societal polarization. Our agents interact on a social network, in which adjacent nodes can influence each other, and each agent holds an array of continuous opinion values (on a 0-1 scale) on a number of separate issues. We use two measures as a proxy for the virtual society's "polarization:" the average assortativity of the graph with respect to the agents' opinions, and the number of issues on which agents have persistent disagreement even after the model reaches an equilibrium.

We look at two model parameters that affect polarization. The first is the density of edges in the network: this corresponds to the average number of meaningful social connections that agents in a society have. Contrary to our early hypothesis, we find that lower edge density results in higher levels of assortativity. The second is the "openness" of agents to differing opinions; *i.e.*, how close a neighboring node's opinion on an issue must be to an agent's own before the agent will adjust its opinion on a different issue. We refer to this novel mechanism as cross-issue influence. Through this mechanism, we find that when agents in the model are less open to new opinions, there will be less consensus on any given issue for all agents in the model.

CCS CONCEPTS

• **Computing methodologies** → **Modeling and simulation**; **Agent / discrete models**;

KEYWORDS

opinion dynamics, echo-chambers, binary voter model, social networks, polarization

ACM Reference Format:
Justin Mittereder, Robert S. W. Carroll, Brandon Frulla, Stephen Davies. 2021. Exploring the Impact of Social Network Density and Agent Openness on Societal Polarization. In *Proceedings of CSSSA's Annual Conference on Computational Social Science (CSS'21).* ACM, New York, NY, USA, Article 4, 7 pages. https://doi.org/10.475/123_4

CSS'21, November 4–7, 2021, Santa Fe, NM, USA (virtual)

ACM ISBN 123-4567-24-567/08/06.
https://doi.org/10.475/123_4

1 INTRODUCTION

The recent events that transpired at the U.S. Capitol on January 6th were a vivid reminder of the deep divide within the nation. There are signs that the United States is experiencing political polarization now like it has never seen before. As individuals stormed the Capitol, Americans watched in horror. Although this singular event is now in the past, the underlying tension that preceded it still remains.

Polarization – reflected in echo chambers, entrenched views, and the vilification of those whose opinion differs – can be harmful to a democratic society. It can inhibit the reaching of consensus and compromise upon which a democracy is built, and can result in even greater amounts of damage than what ensued in the U.S. on January 6th if left unchecked. Further, polarization affects not only political actors, but also the interpersonal relationships among the rank and file citizens of a country which bolster and strengthen society.

In this paper, we look at two societal variables that we believe may significantly impact polarization in a society. The first is the density of social connections: in other words, the average number of social ties a member of that society has. The second is the degree of "openness" in the society: namely, how willing its members are to consider changing their views. We suspect that both of these factors play a role in determining the aggregate polarization of a society.

In order to explore these phenomena, we created an Agent-Based Model (ABM) of heterogeneous agents in the spirit of much of the Opinion Dynamics (OD) literature. These agents interact with each other on a random, static social network and change their opinions on issues over time based on the opinions of their network neighbors. One novel feature of our model, termed cross-issue influence, is the way agents influence one another: one agent will not allow another agent to influence its opinion on an issue unless the two agents already have sufficient agreement on another (randomly chosen) issue. The justification for this is related to the well-known observation of "homophily" in social psychology: people are prone to trust those who already agree with them on something, and hence are more likely to be persuaded by them on other matters.

The goal of our research is to determine what micro behaviors of individuals are sufficient to produce a change in the degree of political polarization in the society. As explained below, we choose to measure polarization in two different ways: the average similarity of an agent to its neighbors (called "assortativity" in social network terminology), and the likelihood that no consensus will be reached on an issue (called opinion "clustering" in the OD literature).

2 RELATED WORK

2.1 Opinion Dynamics

Opinion Dynamics models seek to reproduce the phenomenon of individual agents forming opinions over time via mutual influence. They allow the researcher to explore the macro-level patterns that may arise in a society from a set of simple influence rules defined on the micro-level. For instance, the Binary Voter Model (BVM), the original and perhaps most influential OD model ([3, 16]), features a set of interacting agents, each of which holds a binary opinion. The single influence rule is that agents periodically change their opinion to match one of their influencers, chosen at random. Among other things, the model demonstrates that such a system will always eventually reach uniformity of opinion.

Many researchers (*e.g.*, [13, 24]) have expanded this idea to model continuous, rather than discrete, opinions: these are typically expressed as real numbers between 0 and 1. In addition to better capturing the nuance of real-life viewpoints (which are not usually completely black or white on any issue), continuous opinions lead naturally to incorporating a form of **homophily**[19] into the model: agents will only choose to be influenced by agents whose existing opinion is already close to their own. Termed "**bounded confidence**" (BC) by [15], this feature can result in non-convergence to uniformity depending on the value of the threshold agents use to gate influence.[7, 15, 23] The term "**clustering**" (or "opinion clustering") has been used to describe the resulting equilibrium reached by such models, in which subsets of the agents each converge on a different opinion value and are henceforth no longer persuadable by other agents.

A smaller number of studies have considered "**multidimensional opinions**," in which each agent maintains a separate opinion on each of several different "issues" rather than on just one.[1] The opinions in a multidimensional setting have been modeled as discrete ([7]) or even as boolean variables combined in arbitrary logic formulas ([1, 2]). Oddly, modeling multidimensional opinions as an array of continuous values is rarely seen. One purpose of using multidimensional opinions could be to see how an agent's opinions on different issues interact with one another. This is explored by the boolean expressions in [1] and [2]; in [7] the multidimensional opinion for each agent is instead used merely as an element in a vector space whose (Hamming) distance from other agents' multidimensional opinions can be computed and compared to a BC threshold.

With respect to these previous efforts, our model resembles the BVM but gives the agents continuous, multidimensional opinions. Our model also implements BC, but in a different way than models like [23] do: before accepting the influence of a fellow agent on an issue, an agent in our model must already be close in opinion to that agent on a *different* issue. This mechanism we refer to as cross-issue influence is meant to mimic a phenomenon of human behavior: if I learn that your viewpoint on issue A is close to my own, homophily suggests that I will trust you, and I will therefore be willing to consider your viewpoint on issue B. To our knowledge, this mechanism of agent influence has not been previously explored.

2.2 Polarization

Polarization can mean different things to different people; we therefore begin by briefly establishing a dictionary of terms that we will refer back to throughout this paper.

Arguably the most familiar manifestation of polarization – which we term "**diametricity**" – is when a group experiences opinions shifting away from common ground to polar sides, leaving nobody 'in the middle' on a specific issue. We do not study this flavor of polarization in this paper.

We use the graph theory term **assortativity** to represent a second type of polarization, which is rooted in the tendency that people have to form connections with people who have similar views. This idea is supported by [18] which focuses on physical proximity breeding connections, as well as [2] which states that we are more likely to form connections with those that we already are in agreement with on another issue. The well-known concept of homophily comes into play here, as studied in [5] and [22]. Assortativity is a way to quantify the presence of "echo chambers" in a society, in which people are exposed mostly (or solely) to opinions that confirm what they already believe.[4, 10]

Finally, a third form of polarization is one that can be measured as follows: how often do opinions on issues result in **clustering**? For example, if all individuals had the same belief, there would be one opinion cluster. However, in a polarized society, there are clusters of opinions for any given issue. In this way, higher clustering in a society represents when individuals are entrenched and no longer willing to change their opinion on a given issue. The mechanism that we use in this paper to calculate the number of opinion clusters will be explained later.

Regarding the role of a society's "openness," one question that arises is the psychological basis for this attribute. Which personality trait plays the biggest role in an individual's likelihood to change their opinions on a particular issue? The 'Big 5' personality trait group[17], well-researched since the 1980s, contains Openness-to-Experience (OE) as one of its five traits. OE can be defined as "cognitive flexibility"[8], or "[openness can be] associated with having a vivid imagination and [...] receptivity to one's own and other's emotions; a willingness to try new experiences"[12]. As the research shows, openness plays a crucial role in an individual's ability to relate to others, as well as to consider adopting outside ideas as their own. More than the Big 5's Agreeableness and Conscientiousness traits, OE seems to reflect well what our model is attempting to capture.

---

[1] This is to be carefully distinguished from "**opinion vectors**," which represent an agent's degree of support for each of several alternatives on the *same* issue. (See, *e.g.*, [21].) Unlike multidimensional opinions, these opinion vectors are often restricted to be members of a probability simplex.

To be concrete about the difference, an agent in a model with multidimensional opinions might have a value of .8 for the "pro-gun control" issue, .9 for the "raise the minimum wage" issue, and .4 for the "restrict fracking" issue. By contrast, an agent in a model with opinion vectors might have a value of .2 for the "raise taxes to fund infrastructure" alternative, .7 for the "cut military spending to fund infrastructure" alternative, and .1 for the "increase IRS audits to fund infrastructure" alternative, all possible solutions to the single "how to fund infrastructure" issue. In the latter case, the options are considered mutually exclusive and must sum to 1 for any agent.

(Of course, the specific real-world examples here are only for illustration; OD models represent "issues" and the "opinions" about them completely abstractly.)

3 VARIABLES

In this section we define the two important independent variables whose effect on the model's behavior we seek to discover, and the two dependent variables we measure at simulation's end.

3.1 Independent variables

3.1.1 Openness. As mentioned earlier, research shows that **openness** plays a crucial role in an individual's ability to relate to others, as well how easily they adopt outside ideas as their own. To quantify this as a model parameter, we incorporate openness as a threshold on a continuum from 0 to 1; this threshold is used to compare agent opinions during their pairwise interactions. Low levels of openness produce models in which agents only very rarely change their opinions (namely, only when encountering neighboring agents whose opinion on another issue is very close to their own). High levels produce models in which agents eagerly incorporate the opinions of others on almost every interaction.

3.1.2 Edge probability. The other parameter represented in our model is the *density* of social connections. To implement the concept of different degrees of social connection, we used the Erdös-Rényi graph generation algorithm to generate a random graph of connected nodes. With the Erdös-Rényi graph generation algorithm, we can specify the **edge probability** which represents the probability that there will be an edge between any two given nodes. Using the edge probability, we can control the density of the resulting graph. As a result, edge probability directly corresponds to the density of social connections in our model.

3.2 Dependent variables

3.2.1 Graph assortativity. One way we measure the simulated society's polarization is through the resulting network's "assortative mixing," or simply graph **assortativity**. This represents the degree to which an agent's opinions will have similar values to those of its network neighbors, on average.

The assortativity of a network has a value between −1 and 1, where 1 indicates "perfect assortative mixing" – *i.e.*, a situation where every agent's opinions are identical to each of its graph neighbors'. An assortativity of 0 indicates that the agents' social connections have no correlation at all with their opinion values: having a social tie with another agent does not mean an agent is any more (or less) likely to have opinions similar to that agent. This will be approximately true when the model is initialized and before the iterative process begins. (Negative assortativity values correspond to networks in which an agent is *less* likely to agree with its network neighbors than with agents in general.)

Assortativity is thus a way to measure the extent to which agents become surrounded by (only) like-minded agents, and are therefore no longer exposed to alternative points of view. Since we need to obtain the graph's assortativity with respect to *multiple* attributes (*i.e.*, the opinions an agent has on all of the issues), we simply compute the network's assortativity for each issue separately (as defined in [20], p.5) and average it over all the issues.

3.2.2 Opinion clustering. The second dependent variable of our model is opinion **clustering**. This measures how often the opinions that agents have on a given issue fail to converge to a uniform value, instead remaining bifurcated among two or more values in perpetuity. Each group of agents who, at simulation's end, have the same opinion on an issue (within some small tolerance ϵ) are termed an "opinion cluster" (a term used by [11]) on that issue.

For clarity, we refer to any issue on which all agent opinions eventually converge to the same value as a "**uniform issue**," and any issue that instead produces opinion clusters as a "**clustered issue**."

One challenge is defining what qualifies as an clustered issue, given that agent opinions are represented as real numbers that may asymptotically converge to, but never actually reach, the same value. We use the following mechanism. To calculate the number of clusters for an issue, we add agents to a cluster after every step of the model. If the absolute value of the difference between an agent's opinion and the average opinion of a pre-existing cluster is within a threshold (0.05), the agent is added to that cluster. If this is not the case, the agent is added to a new cluster in which it is the first occupant.

4 MODEL

The model is presented using an abbreviated version of the ODD protocol[14].

4.1 Purpose

The model simulates interactions on a random social network of agents, each with an array of continuous, numeric **opinion** attributes. Its purpose is to investigate the way in which two factors contribute to the emergence of polarization in the network: the **edge_probability**, a value reflecting the density of social connections in the network; and the **openness**, a value representing how closely one of an agent's opinions must be to that of a potential influencer in order to accept influence. (See Section 4.3, below.)

Using the model, we hope to gain general insight on the emergence of this polarization within social networks and how different parameters affect this.

4.2 Entities, State Variables and Scales

The entities within the model are Agents, having the following attributes:

- **ID** A unique ID for the agent.
- **Opinions** An array of numbers, representing opinions on issues, each having a value between 0 and 1. This represents the degree to which the agent "agrees" or "disagrees" with an issue, with 0.5 being neutral.
- **Neighbors** A subset of the other agents in the model, to whom this Agent has a social connection. The entire set of Agents and their social connections form an undirected graph (*i.e.*, all social connections are bidirectional) and the graph is fixed throughout the simulation.

4.3 Process Overview and Scheduling

After the model has been initialized, the following sequence is executed for each of a fixed number of steps in the simulation:

(1) An agent X is chosen at random.
(2) A neighbor of X (call it Y) is chosen at random.
(3) An issue I_1 is chosen at random.

(4) The absolute difference between X's opinion on I_1 and Y's opinion on I_1 is measured.
(5) Another opinion I_2 ($\neq I_1$) is chosen at random.
(6) If the difference between X's and Y's opinion on issue I_1 is less than or equal to the model's **openness** parameter, set X's opinion on I_2 to be the average of X's and Y's current I_2 opinions.

4.4 Initialization

The simulation is initialized with 50 agents, each having 5 opinions set to independent uniform random values between 0 and 1. The agents are then connected to each other using a random undirected Erdös-Rényi graph[9] with parameters $N = 50, p =$ **edge_probability**. (If the graph is not connected, a new random graph is generated until a connected one is obtained.)

The model's step limit is usually set to 150, as most change in the agent's opinions after 150 steps is negligible.

5 HYPOTHESIS

We form the following hypotheses about the model's behavior.

Hypothesis 1a: (H_{1a}). Mean assortativity will increase with the edge probability of an Erdös-Rényi graph.

Hypothesis 1b: (H_{1b}). Mean assortativity will increase when the openness parameter of agents in the model is lower.

Hypothesis 2a: (H_{2a}). The number of clustered issues will be negatively correlated with the edge probability of an Erdös-Rényi graph.

Hypothesis 2b: (H_{2b}). The number of clustered issues will increase when the openness parameter is lower for all agents in the model.

For H_{1a}, we hypothesize that increasing the connectivity of an Erdös-Rényi graph by raising the edge probability will result in higher assortativity. This hypothesis is based mainly on real-world observations: the number of social connections available to those with Internet access has increased in the past few decades (due to social media[6]), and the degree of homophily exhibited in members of a social circle has also (at least anecdotally) increased. Since both the density of connections and the homophily of those joined by such connections has increased in the real world, we presume the same effect will follow in our model.

For H_{1b}, we hypothesize that when agents in the model are less open to new opinions, there will be a higher average assortativity and therefore polarization. When all agents have a lower level of openness, they will only be interacting with agents that have opinions similar to their own; therefore, we expect to see higher levels of assortativity.

For H_{2a}, we assume that raising the connectivity of an Erdös-Rényi graph by increasing the edge probability will result in fewer clustered issues. As a graph becomes more densely connected, agents will have a wider variety of neighbors to receive influence from. As a result, agents should merge to the consensus opinion for any given issue more often in a more densely connected graph.

For H_{2b}, we believe that lowering the openness parameter of agents in the model will result in more clustered issues across the model. When agents are less open to distant opinions, there will be more variety of opinion for any given issue.

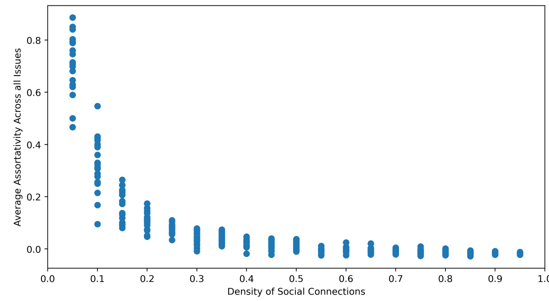

Figure 1: Average Assortativity across all Issues and Edge Probability

6 RESULTS

6.1 H_{1a} and H_{1b}

To test H_{1a}, we first establish a model with 50 agents, 5 issues, and an openness parameter of 0.40. In order to measure the impact of varying edge probability on average assortativity across all issues, we run each combination of parameters 20 times starting with an edge probability of 0.05 and ending with an edge probability of 0.95, in increments of .05. The results of this model run are shown in Figure 1.

We see that as the edge probability (or density of social connections) increases, the average assortativity across all issues decreases. This is the exact opposite of our hypothesis. One possible explanation for this result is that when connections are more dense, there is a higher chance that agents will be exposed to a more diverse set of opinions. There is thus a higher chance that agents will be pulled to the 'average' opinion for a given issue, which would produce lower assortativity. From this finding, we may be able to infer that societies where individuals are more densely connected may experience less polarization than more sparsely-connected societies do.

In addition to the negative correlation between density of social connections and polarization, we also see that the relationship between these two variables appears negative-exponential in nature. The variance was too high, however, for us to draw a solid conclusion on whether the relationship truly conforms to a negative-exponential, a power-law, or any other standard distribution.

To test H_{1b}, we first establish a model with 50 agents, 5 issues, and an edge probability of 0.50. In order to measure the impact of varying the openness parameter on average assortativity across all issues, we ran each combination of inputs 20 times with an openness parameter ranging from 0.05 to 0.95 in increments of .05. The results of this model run are shown in Figure 2. As is depicted, there is no obvious relationship at all between the openness parameter and the average assortativity across all issues.

This is an interesting result. Agents in the model are influenced when they are close in opinion (within our openness parameter) to another agent on the same issue. Therefore, we believed that openness would play a role in determining the assortativity of a society. It should be noted that we tested this hypothesis with multiple different values of the edge probability (0.15, 0.40, and

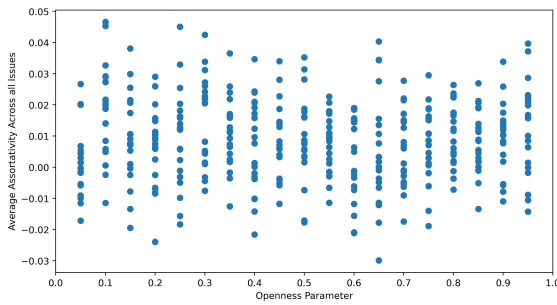

Figure 2: Average Assortativity across all Issues and Openness Parameter

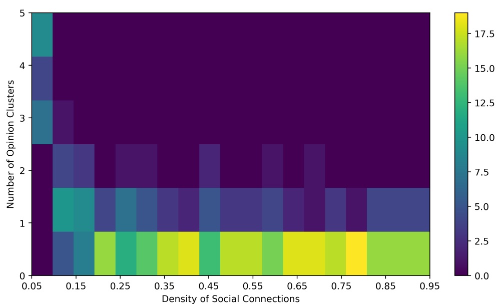

Figure 3: Number of Opinion Clusters and Edge Probability (0.05 - 0.95)

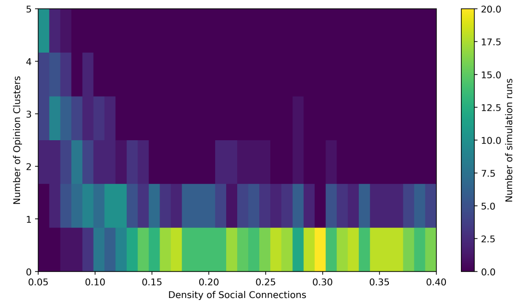

Figure 4: Number of Opinion Clusters and Edge Probability (0.05 - 0.40)

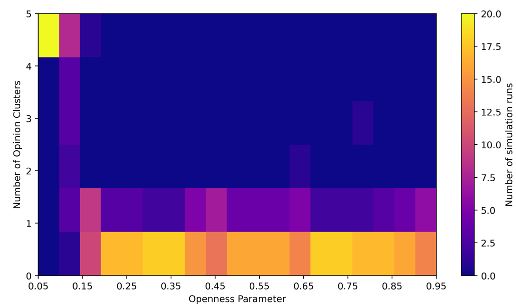

Figure 5: Number of Opinion Clusters and the Openness Parameter (0.05 - 0.95)

0.50), to ensure that the edge probability was not having an impact on our results. Even still, we hope to investigate this hypothesis further in future research.

6.2 H_{2a} and H_{2b}

To test H_{2a}, we establish a model with 50 agents, 5 issues, and an openness parameter of 0.30. First, we ran a parameter sweep varying the edge probability from 0.05 to 0.95 to measure the impact of this parameter on the number of opinion clusters. The results of this parameter sweep are shown in Figure 3.

We noticed that as with H_{2a}, there appears to be a tipping point with the number of opinion clusters and the edge probability. To further explore this hypothesis, we ran another parameter sweep, this time varying the edge probability from 0.05 to 0.40 incrementing by 0.01 for each suite of 20 model runs. The results of this parameter sweep are depicted in Figure 4.

Our results confirm H_{2a}; the number of opinion clusters and edge probability have a negative relationship. We believe this may be explained by the implications of a high density for a graph of nodes. For example, when a graph of 50 nodes has a density of 0.05, the average number of social connections will be 2.5. We are able to calculate the average number of social connections by multiplying the chance there will be an edge between any two nodes (edge probability) and the number of nodes. When the edge probability, or density of the graph, increases slightly to 0.2, the average number of social connections will rise to 10 connections. As a result, the geodesic distance between two nodes decreases rapidly because each node is proportionately connected to more nodes in the graph. This may reveal why we saw that only a certain level of density is required for the number of opinion clusters to drop sharply. Undeniably, a tipping point exists with the number of opinon clusters when increasing the density of an Erdös-Rényi graph in our model.

To test H_{2b}, we establish a model with 50 agents, 5 issues, and an edge probability of 0.50. First, we ran a parameter sweep varying the openness parameter from 0.05 to 0.95 to measure the impact of varying the openness parameter on the number of opinion clusters. The results of this parameter sweep are shown in Figure 5.

We noticed that there was little to no difference between an openness parameter of 0.5 and 0.7. However, we observed that the openness parameter had more impact on the number of opinion clusters when the parameter was closer to 0.10. To further explore this result, we ran another parameter sweep with 50 agents, 5 issues, an edge probability of 0.50, and a suite size of 20. This time, we varied the openness parameter from 0.05 to 0.40. Our results are depicted in Figure 6.

This graph indicates that there is a tipping point for the openness parameter. When the openness for agents in the model is very low, the agents did not agree on many issues. However, as Figure 6

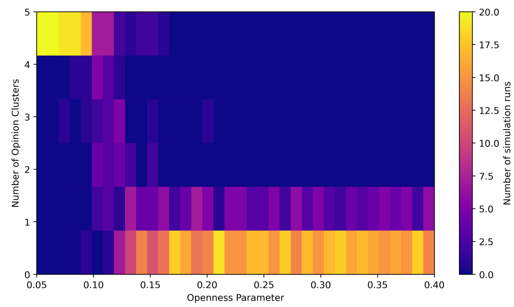

Figure 6: Number of Opinion Clusters and Openness (0.05 - 0.40)

indicates, when we increase the openness parameter slightly, the number of opinion clusters across the model quickly drops. As a result, we can infer that low levels of openness in a society may induce more polarized societies. When agents in the model are less open to distant opinions, there are more opinion clusters for any given issue. However, the tipping point leads us to believe that slightly higher levels of openness are sufficient to reach uniformity on a given issue for all agents in the model. To conclude, when using the cross-issue influence mechanism, marginally higher levels of openness led to to less polarization in the model.

7 DISCUSSION AND FUTURE WORK

Multiple results in this research surprised us. Firstly, the results from testing H_{1a} did not reflect our anecdotal experiences. When increasing the density of a society's connection, we instead saw *lower* assortativity. We believe this may be due to the static nature of the model's social network. In the real world, homophily not only causes existing friends to become more like each other, but also causes people to select (or reject) friends based on their similarity. In future work, we intend to add this feature to the model, producing a dynamic graph, and discover whether this addition is sufficient to produce a positive density/assortativity relationship.

The lack of a relationship for H_{1b} was another surprising result. We extensively tested this hypothesis, but the results did not indicate any statistically significant relationship. This result remains unexplained.

The tipping points observed when testing hypotheses H_{2a} and H_{2b} were compelling results. When even slightly increasing the density of a graph, the number of clustered issues can drop quickly. This would seem to indicate that the degree to which a society forms consensus can be quite sensitive to the average number of social connections people maintain, at least within a certain range. Too, the openness of a society's members – however that might be quantified in a real population – produced an even steeper tipping point. One interpretation would be that even small changes in the tolerance people have for dissenting views can produce great gains in reducing polarization. We also plan to investigate the behavior of models with agents that are heterogeneous with respect to openness, since OE and other traits are obviously not uniform across a real population.

Another mechanism we hope to explore more in future research is cross-issue influence. This concept is an extension of Hegselmann and Krause's bounded-confidence mechanism. In this research we explore cross-issue influence with only attracting forces. However, we hope to investigate the results that would be produced when a repelling force is implemented into the cross-issue influence mechanism. Rather than only having agents move closer to one another on issue X, we could also have them be pushed away from each other on issue X if they disagree above a certain threshold on a separate issue Y.

REFERENCES

[1] Enzo Battistella and Laurence Cholvy. 2019. Modelling and Simulating Extreme Opinion Diffusion. In *Agents and Artificial Intelligence*, Jaap van den Herik and Ana Paula Rocha (Eds.). Vol. 11352. Springer International Publishing, Cham, 79–104. https://doi.org/10.1007/978-3-030-05453-3_5 Series Title: Lecture Notes in Computer Science.

[2] Laurence Cholvy. 2016. Diffusion of Opinion and Influence. In *Scalable Uncertainty Management (Lecture Notes in Computer Science)*, Steven Schockaert and Pierre Senellart (Eds.). Springer International Publishing, Cham, 112–125. https://doi.org/10.1007/978-3-319-45856-4_8

[3] Peter Clifford and Aidan Sudbury. 1973. A Model for Spatial Conflict. *Biometrika* 60, 3 (1973), 581–588. https://doi.org/10.2307/2335008 Publisher: [Oxford University Press, Biometrika Trust].

[4] Pranav Dandekar, Ashish Goel, and David T. Lee. 2013. Biased assimilation, homophily, and the dynamics of polarization. *Proceedings of the National Academy of Sciences* 110, 15 (2013), 5791–5796. Publisher: National Acad Sciences.

[5] Stephen Davies. 2017. The twin impact of homophily and accessibility on ideological polarization. In *Proceedings of the 2017 International Conference of The Computational Social Science Society of the Americas.* 1–8.

[6] Brian Dean. 2021. How Many People Use Social Media in 2021? (65+ Statistics). (2021). https://backlinko.com/social-media-users

[7] Guillaume Deffuant, David Neau, Frederic Amblard, and Gerard Weisbuch. 2000. Mixing beliefs among interacting agents. *Advances in Complex Systems* 3, 01n04 (2000), 87–98. http://www.worldscientific.com/doi/abs/10.1142/S0219525900000078

[8] Colin G. DeYoung, Jordan B. Peterson, and Daniel M. Higgins. 2005. Sources of Openness/Intellect: Cognitive and Neuropsychological Correlates of the Fifth Factor of Personality. *Journal of Personality* 73, 4 (Aug. 2005), 825–858. https://doi.org/10.1111/j.1467-6494.2005.00330.x

[9] Paul Erdös and Alfréd Rényi. 1959. On random graphs, I. *Publicationes Mathematicae (Debrecen)* 6 (1959), 290–297. http://www.citeulike.org/group/3509/article/4012374

[10] Seth Flaxman, Sharad Goel, and Justin M. Rao. 2016. Filter bubbles, echo chambers, and online news consumption. *Public opinion quarterly* 80, S1 (2016), 298–320. Publisher: Oxford University Press.

[11] Dimitris Fotakis, Dimitris Palyvos-Giannas, and Stratis Skoulakis. 2016. Opinion Dynamics with Local Interactions. *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence (IJCAI-16)* (2016), 7.

[12] Adrian Furnham and Helen Cheng. 2016. Childhood intelligence predicts adult trait openness: Psychological and demographic indicators. *Journal of Individual Differences* 37, 2 (2016), 105–111. https://doi.org/10.1027/1614-0001/a000194 Publisher: Hogrefe Publishing.

[13] Javad Ghaderi and R. Srikant. 2012. Opinion Dynamics in Social Networks: A Local Interaction Game with Stubborn Agents. *arXiv:1208.5076 [cs]* (2012). http://arxiv.org/abs/1208.5076 arXiv: 1208.5076.

[14] Volker Grimm, Uta Berger, Finn Bastiansen, Sigrunn Eliassen, Vincent Ginot, Jarl Giske, John Goss-Custard, Tamara Grand, Simone K. Heinz, Geir Huse, Andreas Huth, Jane U. Jepsen, Christian Jørgensen, Wolf M. Mooij, Birgit Müller, Guy Pe'er, Cyril Piou, Steven F. Railsback, Andrew M. Robbins, Martha M. Robbins, Eva Rossmanith, Nadja Rüger, Espen Strand, Sami Souissi, Richard A. Stillman, Rune Vabø, Ute Visser, and Donald L. DeAngelis. 2006. A standard protocol for describing individual-based and agent-based models. *Ecological Modelling* 198, 1–2 (2006), 115–126. https://doi.org/10.1016/j.ecolmodel.2006.04.023

[15] Rainer Hegselmann and Ulrich Krause. 2002. Opinion dynamics and bounded confidence models, analysis, and simulation. *Journal of Artificial Societies and Social Simulation* 5, 3 (2002). http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.454.3597&rep=rep1&type=pdf

[16] Richard A. Holley and Thomas M. Liggett. 1975. Ergodic Theorems for Weakly Interacting Infinite Systems and the Voter Model. *The Annals of Probability* 3, 4 (1975), 643–663. https://doi.org/10.1214/aop/1176996306 Publisher: Institute of Mathematical Statistics.

[17] Oliver P. John and Sanjay Srivastava. 1999. *The Big-Five trait taxonomy: History, measurement, and theoretical perspectives*. Vol. 2. University of California Berkeley.

[18] Philip A. Klinkner and Ann Hapanowicz. 2005. Red and Blue Déjà Vu: Measuring Political Polarization in the 2004 Election. *The forum : a journal of applied research in contemporary politics* 3, 2 (2005). https://doi.org/10.2202/1540-8884.1079 Publisher: Walter de Gruyter GmbH & CoKG.

[19] M. McPherson, L. Smith-Lovin, and J. M. Cook. 2001. Birds of a feather: Homophily in social networks. *Annual review of sociology* (2001), 415–444. http://www.jstor.org/stable/10.2307/2678628

[20] Mark EJ Newman. 2003. Mixing patterns in networks. *Physical review E* 67, 2 (2003), 026126. Publisher: APS.

[21] Alina Sîrbu, Vittorio Loreto, Vito Servedio, and Francesca Tria. 2013. Opinion Dynamics with Disagreement and Modulated Information. *Journal of Statistical Physics* 151, 1/2 (April 2013), 218–237. https://doi.org/10.1007/s10955-013-0724-x

[22] Cameron E. Taylor, Alexander V. Mantzaris, and Ivan Garibay. 2018. Exploring how homophily and accessibility can facilitate polarization in social networks. *Information* 9, 12 (2018), 325. Publisher: Multidisciplinary Digital Publishing Institute.

[23] Alan Tsang and Kate Larson. 2014. Opinion dynamics of skeptical agents. In *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*. International Foundation for Autonomous Agents and Multiagent Systems, 277–284. http://dl.acm.org/citation.cfm?id=2615778

[24] Gerard Weisbuch, Guillaume Deffuant, Frederic Amblard, and Jean Pierre Nadal. 2001. Interacting Agents and Continuous Opinions Dynamics. *arXiv:cond-mat/0111494* (2001). http://arxiv.org/abs/cond-mat/0111494 arXiv: cond-mat/0111494.