

# How Elite Polarization Leads To Mass Polarization in US Through Twitter?

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## **Abstract**

This paper studies the impact of elites' polarization on mass polarization in social networks such as Twitter. We use an agent-based model to simulate information flows on a network. The model's parameters include bounded confidence (openness to different opinions), controversialness of a specific topic, and differential following probability between celebrities and ordinary people. The simulations show that the controversialness of the issue is crucial to determine if elites' polarization can make the public polarized. One counterintuitive finding is that the relationship between bounded confidence and opinion polarization is not linearly decreasing. Polarization is most likely to happen in societies where most citizens have moderate bounded confidence.

# 1 Introduction

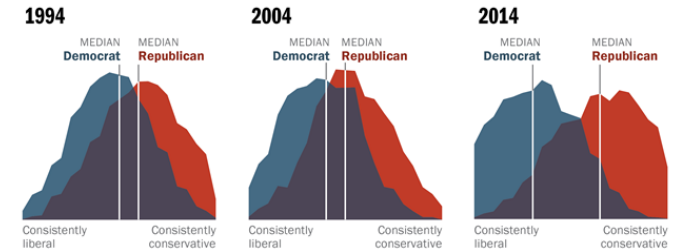
Political polarization has become a major focus of discussions in the U.S., both in academia and among the general public. Figure 1 shows that political polarization between Democrats and Republicans has become more severe than before. The polarization between political elites is especially severe. [McCarty et al. \(2016\)](#) argues that the elected representatives are more internally homogeneous but ideologically different from the opposite party. One noticeable difference in today’s U.S. politics and the past is the prevalence of social media, such as Twitter, making it easy to connect with and access information from celebrities and ordinary people. However, whether and how the division between elites induces polarization within the public is still unclear and controversial.

So, to solve this problem, this paper proposes an agent-based model to simulate the following/unfollowing mechanism and party polarization on Twitter. The model considers the influence of celebrities (following probability), the controversialness of the issue, and bounded confidence among citizens. Simulation shows that the crucial factor of mass polarization is the controversialness of the issue. One counterintuitive finding is that the relationship between bounded confidence and opinion polarization is not linearly decreasing.

This paper follows the definition of polarization from [Druckman et al. \(2013\)](#), “...high levels of ideological distance between parties and high levels of homogeneity within parties.” Figure 2 - 3 graphically explain the definition. Figure 2 shows the first requirement, high levels of distance between parties. Figure 3 shows the second requirement, homogeneity within parties and no connection between two opinion clusters. [Fiorina & Abrams \(2008\)](#) argues that “There is no conclusive evidence that the elite polarization has stimulated voters to polarize” by showing that there is no polarization on citizens’ position on public policy and no evidence on party sorting. In two experiments, [Robison & Mullinix \(2016\)](#) shows that whether ordinary people get polarized politically is greatly determined by how the news covers the polarization itself. They find that “elite polarization principally frames partisan divisions as rooted in the value of the parties.” [Druckman et al. \(2013\)](#) shows that the polarized environment could strengthen the party endorsement on the opinions and make more people accept those less substantively grounded opinions. All the above papers used regression analysis to analyze experimental data to study the impact of elite polarization on the mass public. The difference between this paper and the above papers is that this models opinion formation as a dynamic process. This paper thinks of polarization due to the interaction of different opinions in an evolving social network.

## Democrats and Republicans More Ideologically Divided than in the Past

*Distribution of Democrats and Republicans on a 10-item scale of political values*



Source: 2014 Political Polarization in the American Public

Notes: Ideological consistency based on a scale of 10 political values questions (see Appendix A). The blue area in this chart represents the ideological distribution of Democrats; the red area of Republicans. The overlap of these two distributions is shaded purple. Republicans include Republican-leaning independents; Democrats include Democratic-leaning independents (see Appendix B).

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Figure 1: Division Between Democrats and Republicans Over Time

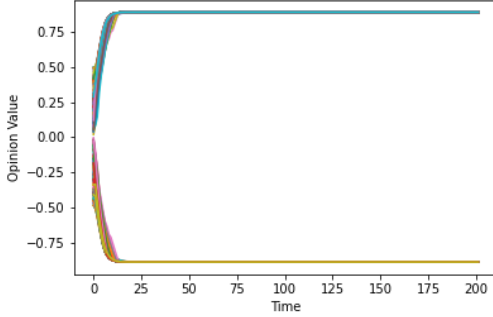


Figure 2: Opinion Evolution. The simulation time is 200.

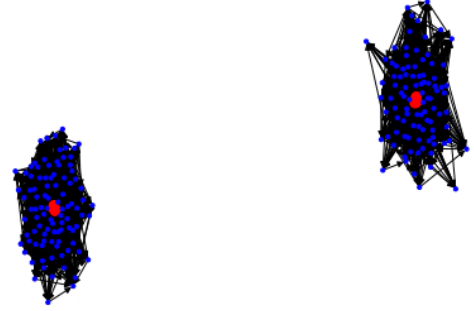


Figure 3: Final Network Structure. Red nodes represents influential nodes (i.e. celebrities) and blue nodes represent normal people. Edges between two nodes means one node follows another node.

Previous literature describes opinion polarization through the mechanism of bounded confidence and homophily. [Deffuant et al. \(2000\)](#) first defines bounded confidence, “...agents adjust continuous opinions as a result of random binary encounters whenever their difference in opinion is below a given threshold.” [Hegselmann et al. \(2002\)](#) also adopts this concept and studies the result of symmetric and asymmetric bounded confidence. [Axelrod \(1997\)](#), [McPherson et al. \(2001\)](#), [Bessi et al. \(2016\)](#) claim that people are more likely to interact with people who share similar opinion with them. This is defined as the homophily principle. “Homophily limits people’s social worlds in a way that has powerful implications for the information they receive, the attitudes they form, and the interactions they experience.” ([McPherson et al., 2001](#))

In terms of the agents-based model, [Sasahara et al. \(2019\)](#) studies the conditions in which polarization will emerge. Their model and simulation show that, as long as people only interact with people within their bounded confidence and establish/remove connections based on homophily principle, the social network will finally evolve into a segregation and homogeneous community. This model is inspired by [Sasahara et al. \(2019\)](#). But [Sasahara et al. \(2019\)](#) treats each node in the social network as homogeneous while this paper differentiates between ordinary and influential nodes. [Baumann et al. \(2020\)](#) also proposes a similar model and considers the influence of the controversialness of one topic. With the simulation, they prove that “a global consensus and emerging radicalized states is mostly governed by social influence and by the controversialness of the topic discussed.” Although [Baumann et al. \(2020\)](#) has similar conclusion with this paper. they take the social network structure as given, and nodes cannot establish and remove edges with other nodes. This model allows the social network to evolve. [Baumann et al. \(2021\)](#) uses the same model but with multidimensional opinion space.

## 2 Model and Hypothesis

### 2.1 Model

Below, we model information flows on social media via Twitter’s following/unfollowing mechanism.

1. At stage 0, nature forms the social network. Each node’s opinion is from a uniform distribution<sup>1</sup>  $[-0.5, 0.5]$ . Nature will select a certain amount of nodes as influential nodes.
2. After the formation of the network at stage 0, nodes establish directed edges with other nodes. If there is an edge from  $i$  to  $j$ , it means  $o_i(\text{opinion}_i)$  could affect  $o_j(\text{opinion}_j)$ . This means  $j$  follows  $i$ ’s Twitter, and  $j$  would change his opinion based on what  $i$  tweets. This initial establishment of edges follows the below rules,

- (a) Given node  $i$ , for each node  $j$  in this network ( $j \neq i$ ) and  $|o_i - o_j| \leq \lambda$ . If node  $j$  is an influential node, there is probability  $\mu$  that an directed edge from  $j$  to  $i$  will be established. If node  $j$  is a non-influential node, there is probability  $1 - \mu$  that an directed edge from  $j$  to  $i$  will be established.

$\lambda$  is the **bounded confidence**. It measures how people are tolerant of opinions different from their own. Opinion outside their bounded confidence (i.e.  $(o_i - \lambda, o_i + \lambda)$ ) would not influence the formation of  $i$ ’s opinion. Higher  $\lambda$  means that  $i$  is very open to a different opinion. Other opinions can very easily influence  $i$ ’s opinion.

$\mu$  is the **following probability**. This is the key difference between this model and Baumann et al. (2020), Sasahara et al. (2019). The models in both these two papers treat the connection probability between all nodes as homogeneous. For example, in their model, for all nodes  $j$  within the bounded confidence of node  $i$ , there is an equal probability that node  $i$  will establish edges (follow) with each  $j$ . But, this model assumes that node  $i$  will be more likely to follow influential nodes. So,  $\mu$  measures the probability that people choose to follow celebrities when celebrities and other normal nodes are in their bounded confidence. Higher  $\mu$  means that node  $i$  prefers to follow influential nodes more. But, this model assumes all the predecessors of node  $i$  can influence its opinion equally, regardless of their influential status. The next part will explain the opinion evolution equation in detail. So, each predecessor has the same weight on  $i$ ’s opinion formation. What matters is influential nodes are more likely to become the predecessor of other nodes.

Each node  $i$  will repeat the above procedures. Each node will try to establish edges with others nodes within its bounded confidence. As long as the edges have been established, node  $i$  will treat his predecessors’ node equally when forming an opinion.

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<sup>1</sup>Appendix shows the results with bimodal opinion distribution.

3. After the initial establishment of edges, each node will start updating his opinion. This opinion evolution equation follows [Baumann et al. \(2020\)](#). Suppose the stage is  $t$ , the update of opinion follows the below equations,

$$o_i(t+1) = \frac{o_i(t)r + \sum_{j=1}^l I_\lambda[o_i(t), o_j(t)] \tanh(\alpha \times o_j(t))}{N + r}, j \neq i \quad (1)$$

$$I_\lambda(t), o_j(t) = \begin{cases} 1 & \text{if } |o_i(t) - o_j(t)| < \lambda \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$\tanh(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^{2x} - 1}{e^{2x} + 1} \quad (3)$$

In equation 1,  $o_i(t)$  refers to the opinion of node  $i$  at stage  $t$ .  $r$  is the robustness of node  $i$ , measuring how hard it is to change  $i$ 's opinion. This is another key difference between this model and [Baumann et al. \(2020\)](#), [Sasahara et al. \(2019\)](#). In their model, the opinion formation rule is the same for each node. In this model, influential nodes will put more weight on their own opinion when forming an opinion. So, influential nodes are more likely to adhere to their own opinion. Higher  $r$  indicates more weight on his own opinion.  $l$  means the number of nodes in this network.  $N$  is the number of nodes that have a directed edge from  $j$  to  $i$ .

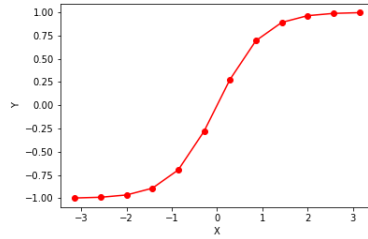


Figure 4: Tanh() Function

$\alpha$  is the controversial parameter, measuring how controversial this issue is among the public. Multiplying  $\alpha$  with  $o_j(t)$  means that the topic's controversialness itself will affect how  $j$ 's opinion influences  $i$ 's opinion. In the controversial issue, people's opinion will be automatically more extreme since there is no moderate standpoint.  $\tanh()$  is also called [hyperbolic tangent function](#). The definition is equation 3. Figure 4 graphically shows the function form. Its odd nonlinear shape guarantees that the social influence of extreme opinions is capped ([Jayles et al., 2017](#)).  $I_\lambda[o_i(t), o_j(t)]$  is a dummy variable.  $\lambda$  is the bounded confidence.

4. After the nodes finish the update of opinion at stage  $t$ , the network will start to update the edges at the same stage,

- (a) At time  $t$ , node  $i$  will randomly select a node  $j$  from his predecessors who are not in his bounded confidence ( $|o_i - o_j| \geq \lambda$ ). There is  $1 - \lambda$  probability that  $i$  will remove the edge between him and  $j$  if  $j$  is an influential node and  $\lambda$  probability if not. The removal of edge means  $i$  decides to not follow  $j$  on Twitter.
- (b) Once  $i$  removes his edge with  $j$ ,  $i$  will select a node  $k$  such that  $|o_i - o_k| < \lambda$  and establish a new edge with  $k$ .

To summarize, the network formation and evolve follows the below rules,

1. At stage 0, the nature forms the network and nodes establish edges with others.
2. At stage  $t$  ( $t = 1, 2, 3, \dots$ ), nodes first update opinions based on the edge formed at stage  $t - 1$  and update the edges based on the opinions formed at stage  $t$ .

The above model models the following/unfollowing mechanism based on information sharing via Twitter. It also models how people's opinion changes in Twitter's network. Bounded confidence ( $\lambda$ ) describes people's tolerance to a different opinion. For example, if one of the people you are following shares a tweet supporting Nazi, this is very unlikely to change your opinion regarding Nazi since it is a very extreme opinion, and it is out of your bounded confidence. However, if that tweet is very similar but slightly different from your current opinion, you may change your opinion since his opinion is in your bounded confidence. Following probability ( $\mu$ ) measures the probability that people will follow celebrities. Research shows that people conform readily to the wishes of authority figures even when those wishes are extreme (Burger, 2009). Robustness( $r$ ) measures how people adhere to their own opinion. Celebrities are supposed to be tougher and even more stubborn than normal people. The establishment and removal of edges based on similar information are also consistent with the homophily principle. "The homophily principle structures network ties of every type." (McPherson et al., 2001).

## 2.2 Hypothesis

The parameters we are interested in are bounded confidence ( $\lambda$ ), controversialness of one topic ( $\alpha$ ), and following probability ( $\mu$ ). Given the polarization of influential nodes in the network, we have below hypothesis:

1. Controversialness of the topic will be a more fundamental factor making the public get polarized. Garimella et al. (2018) shows that controversy is an essential factor driving the emergence of polarization. A controversial topic will naturally divide people into several opinion clusters, making it hard to form a social consensus.
2. With all else equal, the relation between bounded confidence and the degree of polarization is decreasing. The increase of bounded confidence indicates that people are more willing to tolerate and accept different opinions. So, people will communicate with each other more

frequently, making it less likely to form homogeneous opinion clusters without any connections between them.

### 3 Results and Discussion

In the below simulation, given the limitations of my computer’s processing capability, the number of nodes,  $N$ , is 200, and the number of influential nodes,  $N_{influ}$  is 10. Robustness ( $r$ ) is 1 for normal nodes and 20 for influential nodes <sup>2</sup> Figure 8 shows that all the opinions are drawn uniformly from range  $(-0.5, 0.5)$ <sup>3</sup>. To model, the polarization of political elites in the US, half of the influential nodes have opinion 0.4, and another half have -0.4. The number of stages is 200.

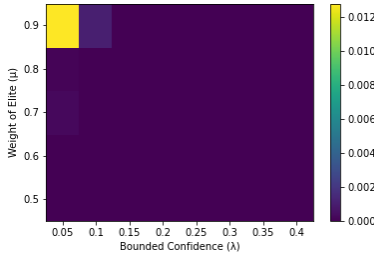


Figure 5: Controversialness = 0.2

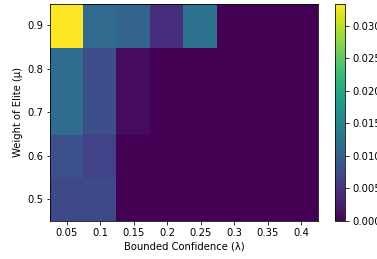


Figure 6: Controversialness = 1

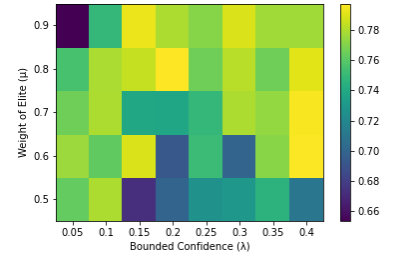


Figure 7: Controversialness = 1.6

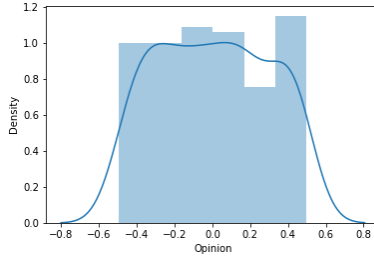


Figure 8: Uniform Distribution of Initial Opinion.

Figure 5 - 7 examines how final opinion variance evolves with  $\lambda$  (bounded confidence),  $\mu$  (following probability) and  $\alpha$  (controversialness). The x-axis represents the  $\lambda$ , and the y-axis represents  $\mu$ . Higher  $\lambda$  means people are more tolerant of different opinions. Higher  $\mu$  means there is a higher chance that people will follow celebrities and get influenced by their opinion. When  $\mu$  is 0.5, it indicates a 50% chance that people will follow influential nodes and a 50% chance that people will follow ordinary people. So, if  $\mu = 0.5$ , there is no difference between influential nodes and ordinary nodes regarding the following probability.

<sup>2</sup>In the appendix, we report results with different  $r = 5$  and  $r = 10$  for influential nodes.

<sup>3</sup>In the appendix, we report results with bimodal distribution.

In each figure of Figure 5 - 7, given the value of  $\alpha$ , I run the simulations with different values of  $\lambda$  and  $\mu$ . Each square cell in the figure represents a combination of  $\lambda$  and  $\mu$ . The darkness of each cell indicates the final opinion variance. Darker means less opinion variance, indicating lower opinion polarization and higher social consensus.

### 3.1 Controversialness and Polarization

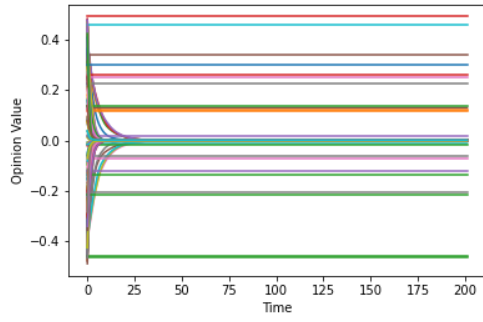
We first test the relationship between controversialness and public opinion polarization. Figure 5 shows that when the topic is very uncontroversial, it is unlikely for the final opinion to be polarized. Even when bounded confidence is 0.05 and the following probability is 0.9 - the situation where polarized opinion is very likely - the final opinion variance is only 0.012. Figure 9 shows that there are not any opinion clusters in the final network. Edges and opinion distribution are very dense. The value of all the other cells in Figure 5 are deep dark, indicating that the divergence of final opinion is very low.

Figure 6 describes the situation most similar to our life. Controversialness is 1, meaning that the topic itself will not change people's opinion endogenously. Other people's opinions will influence one's opinion without any fluctuation. The result in Figure 6 is almost the same with the result in Figure 5. The highest opinion polarization (i.e., the cell with the largest variance) happens when bounded confidence is 0.05 and the following probability is 0.9. Figure 10 also shows that there is no opinion clusters. Figure 6 also shows that, given the following probability fixed, the possibility of reaching social consensus is increasing with the bounded confidence. For example, the top row of cells in Figure 6 shows that the final variance of opinion is decreasing with the increase of bounded confidence (the color of the cell gradually becomes darker from left to right). We can also see this pattern when the following probability is 0.8 or 0.7.

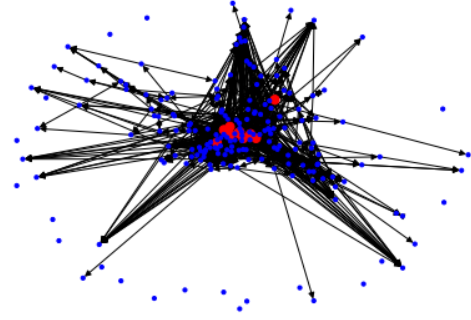
Also, if the following probability is low, even if bounded confidence is also low, the society could still achieve consensus. For example, when bounded confidence is 0.05 in Figure 6, final opinion variance is decreasing with the following probability.

Figure 7 describes the situation of a very controversial topic.  $\alpha$  is 1.6, meaning that there is no moderate standpoint in this issue. People can only choose either far right or far left. For example, it could be abortion in the US. Figure 7 shows that it is impossible to achieve social consensus. The value of each cell in Figure 7 is much higher than Figures 5 and 6. Even when people are very open to different views (bounded confidence is 0.4) and influential nodes cannot influence other people so much (the following probability is 0.5), the final opinion variance is still 0.64. The cell with the highest variance is  $\lambda = 0.4, \mu = 0.6$ . Figure 11 describes this situation, showing that there is an obvious opinion difference between the two groups and no connection between the two groups.



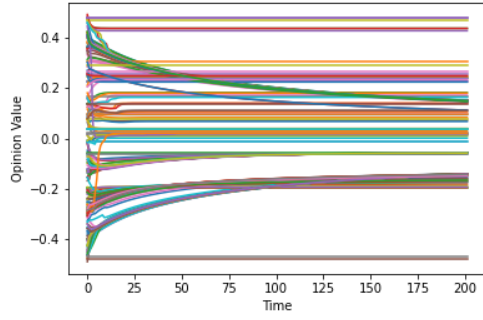


(a) Opinion Evolution

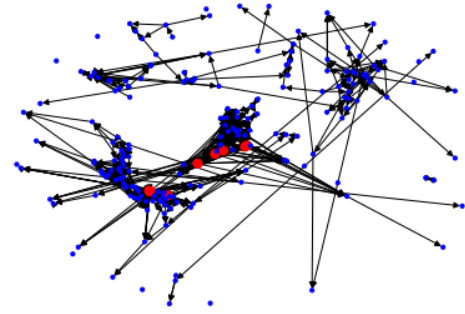


(b) Final Network

Figure 9: Bounded Confidence = 0.05, following probability = 0.9, Controversialness = 0.2

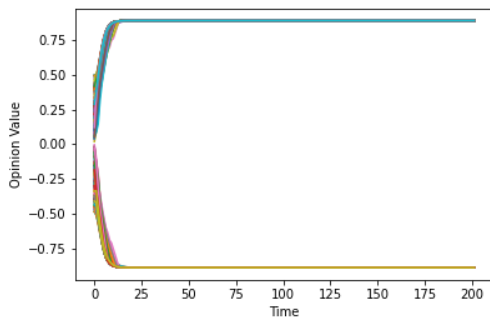


(a) Opinion Evolution

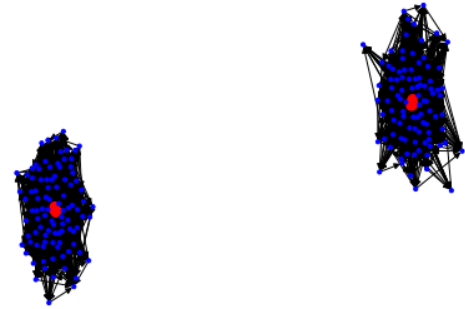


(b) Final Network Structure

Figure 10: Bounded Confidence = 0.05, following probability = 0.9, Controversialness = 1



(a) Opinion Evolution



(b) Final Network Structure

Figure 11: Bounded Confidence = 0.4, following probability = 0.6, Controversialness = 1.6

The above discussions show that controversialness will greatly determine public opinion polarization. This result is robust with different initial opinions' difference between the two parties. The x-axis of Figures 13 and 14 represents different initial opinion difference ( $\delta$ ) between two group of influential nodes. For example, if  $\delta = 0.1$ , half of the influential nodes have opinion 0.05, and another half have opinion -0.05. Since all the nodes in the network are uniformly distributed, asymmetric distribution will have the same result as the symmetric situation discussed here.

Figure 13 shows that, when the topic is very controversial ( $\alpha = 1.6$ ), it is very likely to make opinion distribution polarized. Even if the initial opinion difference between two parties is in the range (0.2, 0.3), the final achieved variance is high. Instead, Figure 14 shows that if the topic is less controversial, regardless of the difference of opinion between two parties, the final opinion variance does not vary a lot. Figure 12 also indicates that opinion variance is strictly increasing with the controversialness when it is above a certain threshold value.

The results in this section is robust with different distribution of initial opinion and values of robustness. In appendix A, Figures 18 - 21 shows that when the initial distribution is bimodal, the opinion variance of extreme controversial topic (Figure 20) is still greatly higher than the variance of two less controversial topics (Figures 18 and 19). In appendix B, Figures 22 and 23 shows that such pattern does not change if robustness of influential nodes are 5 and 10, respectively.

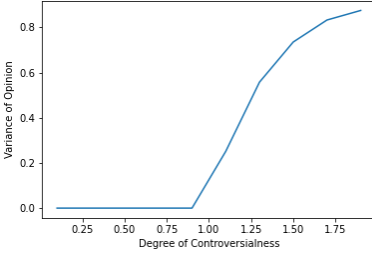


Figure 12: Opinion Variance and Controversialness

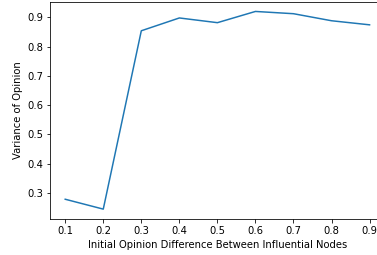


Figure 13: Controversialness = 1.6

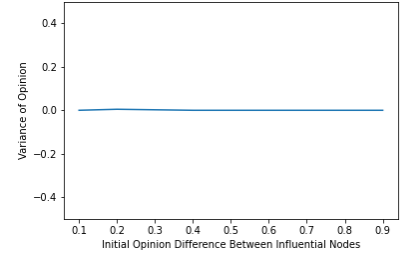


Figure 14: Controversialness = 0.2

### 3.2 Bounded Confidence and Polarization

Section 3.1 shows that the controversialness ( $\alpha$ ) will greatly determine the final opinion polarization among public. This section tests the relationship between bounded confidence ( $\lambda$ ) and polarization. Figures 15 - 17 describes the situation when controversialness is 1 and the opinion of influential nodes are 0.4 and -0.4.

Figure 15 shows that, when bounded confidence is very low ( $\lambda = 0.1$ ), people will only interact with a small circle of people who share identical opinion with themselves. The following probability in Figure 15 is 0.9. But, since the final opinion between each clusters are very small in Figure 15, it can not be regarded as polarization. When bounded confidence is 0.4, Figure 16 clearly shows that the distance between two opinion clusters are huge and there is no connection between them.

So, there is opinion polarization in Figure 17. When bounded confidence is 0.6, which is extremely high, social consensus finally achieved. Compared with Figures 16 and 17, a diversified opinion distribution like Figure 15 is better for democracy political system to function well. Figures 15 - 17 shows that the relation between bounded confidence and network polarization is not linearly decreasing. The polarization happens when  $\lambda = 0.4$ . There is no polarization when  $\lambda = 0.1$  and  $\lambda = 0.6$ .

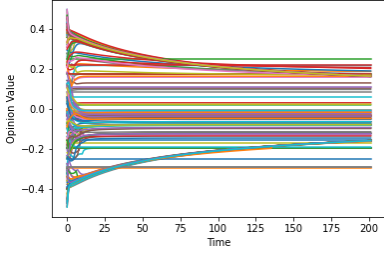


Figure 15: Bounded Confidence = 0.1

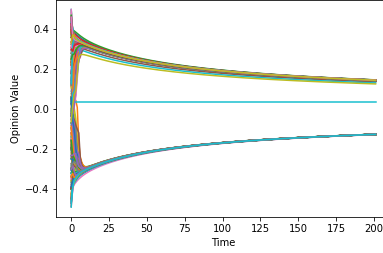


Figure 16: Bounded Confidence = 0.3

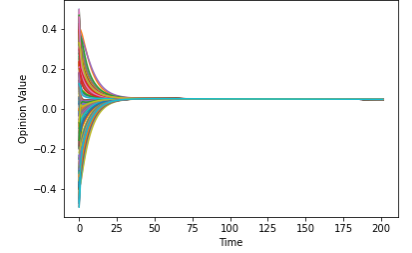


Figure 17: Bounded Confidence = 0.6

### 3.3 Discussion

This model follows the rich tradition of the agent-based model studying polarization and social consensus. The model adopts the two common features from the literature, bounded confidence and homophily<sup>4</sup>. Instead of treating each node as homogeneous, this model differentiates influential nodes and normal nodes by following probability and robustness.

There are two main findings from the simulations. First, the controversialness of one topic will determine if elites' polarization could lead to public polarization. The results suggest that, given the following/unfollowing mechanism on Twitter, as long as the controversialness of one topic is above a certain threshold, public polarization is highly possible even if the opinion difference between two parties is not so high. Figure 13 shows that, when initial opinion difference is only 0.3, the final opinion variance is 0.9. This result is different from Sasahara et al. (2019). They claim that as long as Twitter users only prefer information within their narrow bounded confidence and decide to follow or unfollow someone based on whether their opinion is similar (Homophily), public polarization is very likely. But, the results of this paper show that little bounded confidence and Homophily are not necessary for public polarization. Figure 14 shows that if the topic is not controversial enough, polarization is very unlikely. This result is similar with what Baumann et al. (2020) argues, "The transition between a global consensus and emerging radicalized states is mostly governed by social influence and by the controversialness of the topic discussed. "

Second, the relation between bounded confidence and polarization is not linearly decreasing. It is true that very high bounded confidence leads to social consensus (Figure 17). But, Figures

<sup>4</sup>Homophily refers to the tendency for people to have ties with people who are similar to themselves.

15 - 17 show that the polarization only emerge when bounded confidence is moderate. Minimal bounded confidence results in many small-sized opinion clusters but without huge opinion differences between them (Figure 15). High bounded confidence makes people extremely willing to accept different opinions, and thus social consensus easily achieves (Figure 17). This counterintuitive finding indicates that polarization is most likely to happen in a society with many citizens with moderate bounded confidence when political elites have already been polarized. (Figure 16).

## 4 Conclusion

This paper studies the situation where political elites' polarization would induce public polarization. Given the polarization of elites, we find that the controversialness of one topic is the fundamental factor determining if the public also gets polarized. It is more important than bounded confidence, following probability and initial opinion difference between two parties. One counterintuitive finding is that the relationship between bounded confidence and opinion polarization is not linearly decreasing. Polarization is less likely to happen if bounded confidence is too great or too small. If political elites have already been polarized, polarization is most likely to occur in a society where many citizens have moderate bounded confidence.

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## A Simulation with Bimodal Distribution

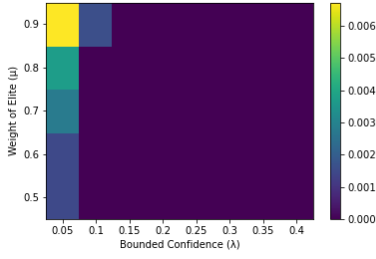


Figure 18: Controversialness = 0.2

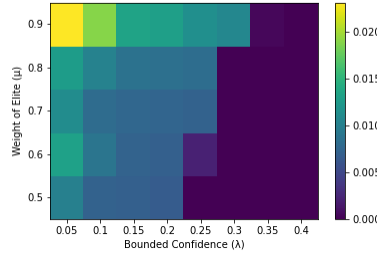


Figure 19: Controversialness = 1

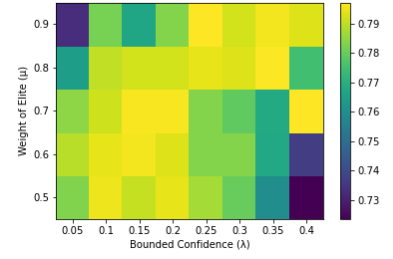


Figure 20: Controversialness = 1.6

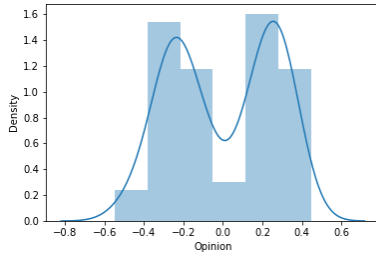
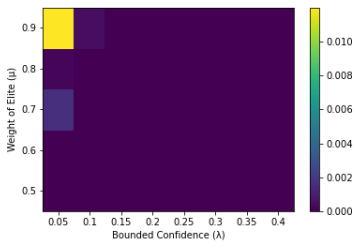
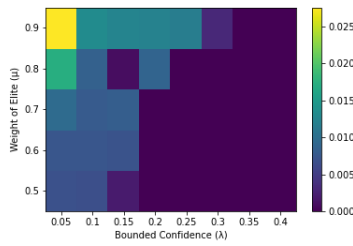


Figure 21: Bimodal Distribution of Initial Opinion. The two modes are 0.2 and -0.2.

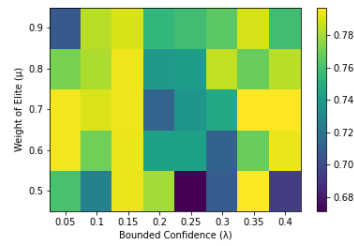
## B Simulation with Different Values of Robustness ( $r$ )



(a) Controversialness=0.2



(b) Controversialness=1



(c) Controversialness=1.6

Figure 22: Bounded Confidence = 0.05, Controversialness = 1, robustness (influential nodes) = 5

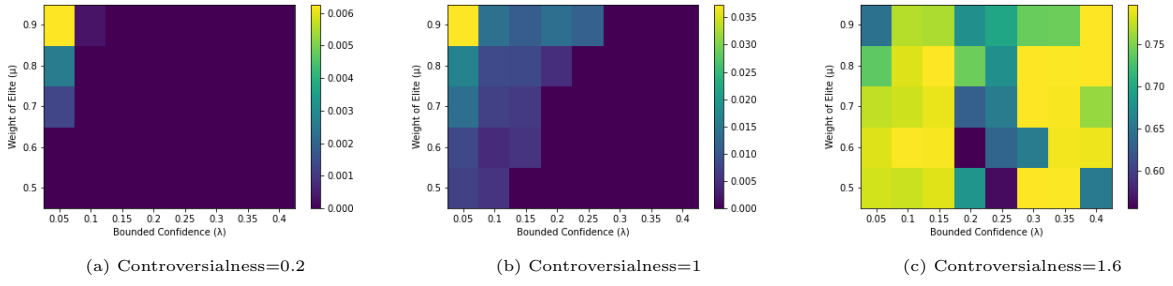


Figure 23: Bounded Confidence = 0.05, Controversialness = 1, robustness (influential nodes) = 10