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

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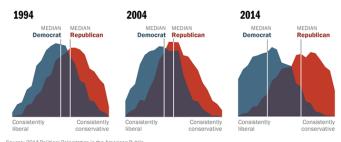
Abstract

This paper studies how political elites' polarization leads to mass polarization through Twitter. An agent-based model and computer simulation are applied. The model simulates the information flow and following and unfollowing mechanism of Twitter. The model features bounded confidence (how people are open to different opinions), controversialness of a specific and different influenceability between celebrities and ordinary people. The simulation shows that the controversialness of the issue is crucial to determine if elites' polarization can make the public polarized. A counterintuitive finding is that societies with very open-minded citizens are more likely to be affected by elites' polarization since different opinions more easily influence people.

1 Introduction

Figure 1 shows that political polarization between Democrats and Republicans become more severe than before. The polarization between political elites is especially McCarty et al. (2016) argues that severe. the elected representatives are more internally homogeneous but ideologically different from the opposite party. One noticeable difference in today's US politics and the past is the prevalence of social media, making it easy to connect with and access information from celebrities and ordinary people. Twitter is one of the most important social media platforms among them. However, whether and how the division between elites induces polarization

Democrats and Republicans More Ideologically Divided than in the Past Distribution of Democrats and Republicans on a 10-item scale of political values



Source: _024_Poilulear_poilulear_unit mit entender_pourch 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). PEW RESEARCH CENTER

Figure 1: Division Between Democrats and Republicans Over Time

within the public is still unclear and controversial. So, to solve this problem, this paper proposes

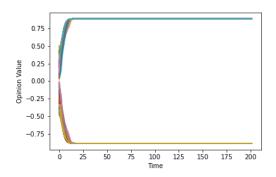


Figure 2: Opinion Evolution. The simulation time is 200.



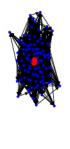


Figure 3: Final Network Structure. Red nodes represents influential nodes (i.e. celebrities) and blue nodes represent normal people. Edges between two nodes means one node follows another node.

an agent-based model to simulate the following and unfollowing mechanism and party polarization on Twitter. This paper uses the computer to simulate the model and develop several conclusions based on that model.

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. However, the situation now has been changed a lot since Fiorina & Abrams (2008) has been published. Robison & Mullinix (2016) analyzed how polarization is communicated to the public by news media. 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 use experiments or regression to study the impact of elite polarization on the mass public. The difference between this paper and the above papers is that an agent-based model and computer simulations are applied.

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." (Deffuant et al. (2000)). Their conclusion is similar to what this paper concludes: High confidence bound leads to convergence while low bound leads to several opinion clusters.

Hegselmann et al. (2002) also adopts this concept and studies the result of symmetric and asymmetric bounded confidence. Axelrod (1997), McPherson et al. (2001) and 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 is inevitable. They prove that, as long as people can change their opinions and connect with others, the social network with segregation and homogeneous communities are inevitable. The model of this paper 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 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." (Baumann et al. (2020)). Although Baumann et al. (2020) has similar conclusion with my paper. But, Baumann et al. (2020) takes the social network structure as given, and nodes cannot establish and remove edges with other nodes. This paper allows the social network to evolve. Baumann et al. (2021) uses the same model but with multidimensional opinion space.

The model of this paper considers the influence of celebrities (weight of elite), 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. A counterintuitive finding (Section 3.2) is that societies with very open-minded citizens are more likely to be affected by elites' polarization since they are inclined to be influenced by different opinions.

2 Model

The below model tries to model how information flow in Twitter through following and unfollowing mechanism.

- 1. In stage 0, the social network is created. Each node's opinion is drawn from a uniform distribution [-0.5, 0.5]. A certain amount of nodes would be selected as influential nodes.
- 2. After the network is created in stage 0, directed edges between nodes will be established. If there is an edge from i to j, it means $o_i(opinion_i)$ could affect $o_j(opinion_j)$. Take Twitter as an example. 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 is randomly selected, Suppose node i is an influential node. For each node j in this network $(j \neq i)$, if $|o_i - o_j| \leq \lambda$, there is μ probability that an directed edge from i to j will be established.

Suppose node i is non-influential node. For each node j in this network $(j \neq i)$, if $|opinion_i - opinion_j| \leq \lambda$, there is $1 - \mu$ percent probability that an directed edge from i to j will be established.

 λ 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 λ means that i is very open to and easily influenced by other opinions. Take Twitter as an 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 this is a very extreme opinion, and it is out of your opinion confidence interval. 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 opinion confidence interval.

 μ is the **weight of elite**. This is the key difference between my model and Baumann et al. (2020) and Sasahara et al. (2019). On Twitter, people are inclined to follow celebrities (i.e., influential nodes). Research shows that people conform readily to the wishes of authority figures even when those wishes are extreme(?). So, μ measures the weight that ordinary people give to celebrities (influential nodes) when forming their opinion. $1 - \mu$ will be the weight given to other ordinary people. Higher μ means that i is very easily influenced by the celebrities he follows.

The above procedures will be repeated for each node i in this social network.

3. After the initial network and edges are established in stage 0, the opinion of each node will be updated. This opinion evolution equation follow (Baumann et al., 2020). Suppose the stage is t, the update of opinion follows the below equations,

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

$$(1)$$

$$I_{\lambda}(t), o_{j}(t)] = \begin{cases} 1 & \text{if } |o_{i}(t) - o_{j}(t)| < \lambda \\ 0 & \text{otherwise} \end{cases}$$
 (2)

$$r = \begin{cases} 20 & \text{if } i \text{ is influential node} \\ 1 & \text{otherwise} \end{cases}$$
 (3)

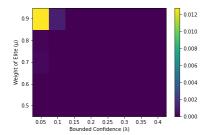
In equation 1, $o_i(t)$ refers to the opinion of node i in period t. r is the robustness of node i. More robust means it is harder for node i to change its opinion based on other people's opinions. For example, it is easier to persuade ordinary people than to persuade an adamant president. The definition of r is in equation 3. l means the number of nodes in this network. N is the number of nodes who have directed edge from j to i. α is the controversial parameter, measuring how controversial this issue is among the public. It controls the shape of sigmoidal

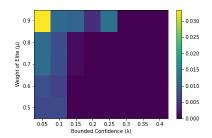
influence function taken to be $tanh(\alpha o_j)$. Its odd nonlinear shape guarantees that the social influence of extreme opinions is capped. This is suggested by Jayles et al. (2017). Also, higher α means it is hard to hold a moderate view regarding this issue. $I_{\epsilon}[o_i(t), o_j(t)]$ is a dummy variable. λ is the bounded confidence.

- 4. In stage t, the update of edges is based on the below rules,
 - (a) In time t, a node j is selected from i's predecessors who are not in i's bounded confidence $(|o_i o_j| \ge \lambda)$. There is a 1λ probability that the edge between them will be removed if j is an influential node and λ probability if not. The removal of edge means i decides to not follow j on Twitter.
 - (b) Once an edge is removed between j and i, a node k such that $|o_i o_k| < \lambda$ will be randomly selected and an edge between i and k will be established. This whole updating process simulation the following and unfollowing process on Twitter.

3 Simulation Results

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. Figure 7 shows that all the opinions are drawn uniformly from range (-0.5, 0.5). Figures 20 and other figures in the Appendix depicts the situations when initial opinion distribution are bimodal. The results do not change. 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 simulation time is 200 times.





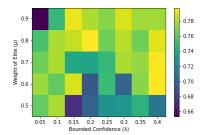


Figure 4: Controversialness = 0.2

Figure 5: Controversialness = 1

Figure 6: Controversialness = 1.6

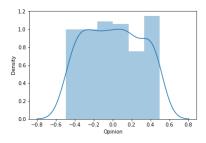


Figure 7: Uniform Distribution of Initial Opinion.

Figure 4 - 6 examines how final opinion variance evolves with λ (bounded confidence), μ (weight of elite) and α (controversialness). The x-axis represents the λ , and the y-axis represents μ . Higher λ means people are more tolerant of different opinions. Higher μ means there is a higher chance that people will follow celebrities and get influenced by their opinion. When μ 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 in terms of influentiality.

In each figure of Figure 4 - 6, given the value of α , I run the simulations with different values of α and μ . Each square cell in the figure represents a combination of α and μ . 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 4 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 weight of elite is 0.9 - the situation where polarized opinion is very likely - the final opinion variance is only 0.012. Figure 8 shows that there is not any opinion clusters in the final network. Edges and opinion distribution are very dense. The value of all the other cells in Figure 4 are deep dark, indicating that the divergence of final opinion is very low.

Figure 5 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 opinion will influence one's opinion without any fluctuation. The result in Figure 5 is almost the same with the result in Figure 4. The opinion polarization (i.e., the cell with the largest variance) happens when bounded confidence is 0.05, and the weight of elite is 0.9. Figure 9 also shows that there is no opinion clusters. Figure 5 also shows that, given the weight of elite fixed, the possibility of reaching social consensus is increasing with the bounded confidence. For example, the top row of cells in Figure 5 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). This pattern can be seen when the weight of the elite is 0.8 or 0.7.

Also, if the weight of the elite is low, even if bounded confidence is also low, social consensus could still be achieved. For example, when bounded confidence is 0.05 in Figure 5, final opinion variance is decreasing with the weight of elite.

Figure 6 describes the situation of a very controversial topic. α 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 6 shows that it is impossible to achieve social consensus. The value of each cell in Figure 6 is much higher than Figures 4 and 5. Even when people are very open to different views (bounded confidence is 0.4) and influential nodes cannot influence other people so much (weight of elite 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 10 describes this situation, showing that there is very clear opinion difference between two groups and no connection between two groups.

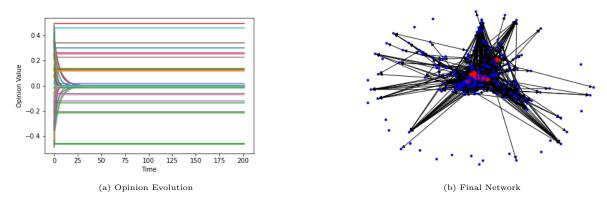


Figure 8: Bounded Confidence = 0.05, Weight of Elite = 0.9, Controversialness = 0.2

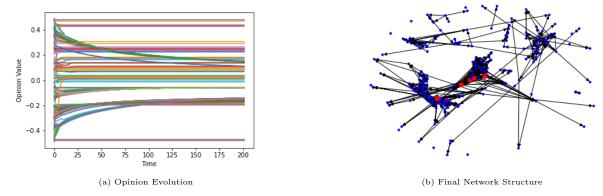


Figure 9: Bounded Confidence = 0.05, Weight of Elite = 0.9, Controversialness = 1

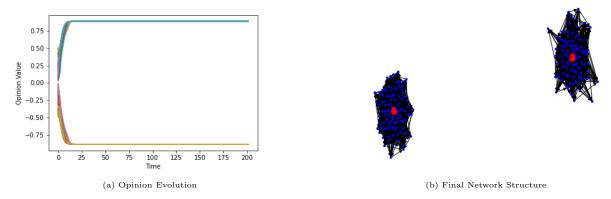


Figure 10: Bounded Confidence = 0.4, Weight of Elite = 0.6, Controversialness = 1.6

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 12 and 13 represents different initial opinion difference (δ) 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 12 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 13 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 11 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 in the network. In the appendix, Figures 17 - 20 shows the similar result with bimodal initial opinion distribution.

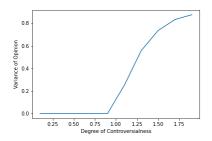


Figure 11: Opinion Variance and Controversialness

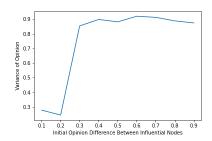


Figure 12: Controversialness = 1.6

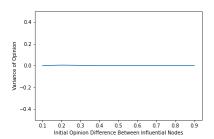


Figure 13: Controversialness = 0.2

3.2 Bounded Confidence and Polarization

Section 3.1 shows that the controversialness (α) will greatly determine the final opinion polarization among public. This section tests the relationship between bounded confidence (λ) and polarization. Figures 14 - 16 describes the situation when controversialness is 1 and the opinion of influential nodes are 0.4 and -0.4.

Figure 14 shows that, when bounded confidence is very low (0.1), people will only interact with a small circle of people who share identical opinion with themselves. The weight of elite in 14 is 0.9. So, even when people's opinions are greatly affected by two groups of polarized influential nodes, social consensus is not achieved finally. Figures 15 and 16 show that, when bounded confidence are higher, it is more likely to achieve social consensus.

Also, the final opinion is very diversified in Figure 14. Although there is no social consensus, the differences between each cluster of opinions are not huge. Compared with Figures 15 and 16, a diversified opinion distribution like Figure 14 is better for democracy to function well. This counterintuitive finding indicates that, when political elites have already been polarized, a society with more open-minded citizens is more likely to be polarized massively. More open people will listen to more diversified opinions and thus more likely to be affected. Conversely, if citizens are very close-minded, it is hard for the polarized elites to influence them.

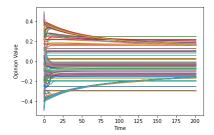


Figure 14: Bounded Confidence = 0.1

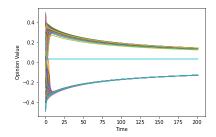


Figure 15: Bounded Confidence = 0.4

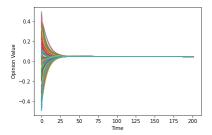


Figure 16: Bounded Confidence = 0.6

4 Conclusion

This paper studies the situation where political elites' polarization would induce public polarization. I find that the crucial factor of mass polarization is the controversialness of the issue. Simulation (Figures 4 - 13) shows that controversialness is more important than bounded confidence, weight of elite and initial opinion difference between two parties. A counterintuitive finding (Section 3.2) is that societies with very open-minded citizens are more likely to be affected by elites' polarization since they are inclined to be influenced by different opinions. Conversely, there will be many opinion clusters without significant differences in society with more close-minded citizens.

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Appendices

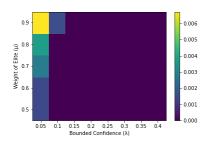


Figure 17: Controversialness = 0.2

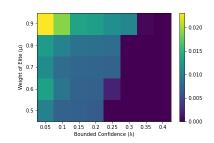


Figure 18: Controversialness = 1

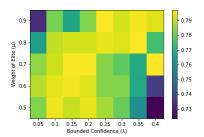


Figure 19: Controversialness = 1.6

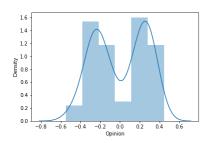


Figure 20: Bimodal Distribution of Initial Opinion. The two modes are 0.2 and -0.2.