Promoting Social Conventions across Polarized Networks: An Empirical Study

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Abstract—We investigate via simulation the conditions under which a new social convention promoted by a persistent minority can spread in a network polarized into two communities. Our experiments show how the fractional size of the persistent minority and its network location affect the network's tipping point. Specifically, we discover that i) previously research on the size of the critical mass need for widespread adoption does not apply in the presence of polarized communities; ii) spread is more affected by the position of the persistent minority than its size; and iii) topological properties of the nodes in the persistent minority, such as leverage centrality and degree, are relevant for the diffusion of the new social convention.

Index Terms—simulation, social convention, polarized network

This research is supported by the Office of Naval Research Grant N00014-18-1-2128, the U.S. National Science Foundation Grant IIS 1546453 and the DARPA SocialSim Program and the Air Force Research Laboratory under contract FA8650-18-C-7825.

I. INTRODUCTION

Today's digitally-mediated social interactions are often limited to a community of like-minded people and to the information that conforms to their social conventions and beliefs. Homophily, exacerbated by social media platforms with their business objectives implemented via technological solutions [1], generates polarized online environments [2]. Polarization segregates individuals holding different opinions to different groups that have little or no communication in between them. Interactions with only those of the same opinion reinforces existing social conventions: achieving widespread adoption of new conventions is challenging.

Previous research suggests that the critical mass of the committed minority needed to overturn an established convention is around 10-40% [3]–[7]. In a polarized network, diffusion is likely harder due to limited interaction between the communities, a network typology effect. Relatedly, the

placement of the persistent minority is likely crucial for the overturning of convention.

Our research uses simulation to investigate the conditions under which a new social convention promoted by a persistent minority located in one community of a polarized network may be adopted by members in both communities and thus by the majority of the population. Our test case is a network polarized into two communities – self-declared conservative or liberal bloggers – and variants created by rewiring.

The rest of the paper is structured as follows. Section II presents the relevant previous work in this area. Section III describes the dataset used in this study. Section IV explains the simulation protocols for adoption and for rewiring the test case to produce less polarized variants. Section V reports the results of experiments. Section VI summarizes the results and discusses real world applications and future work.

II. RELATED WORK

Xie et al. [3] use a *binary agreement model* to show that a committed and inflexible minority as small as 10% can rapidly change the global opinion in a population. Xie's conclusion differs from Centola et al. [4] who experimentally demonstrate with individuals interacting in a coordination game that a committed minority less than 25% of population cannot overturn an established convention. In research on dynamics on social innovation, Young [8] shows that the speed of emergence of a social convention depends on the topology of the network, the benefit an individual obtains from adopting the convention, and the existence of an autonomous group that adopts the innovation. His work demonstrates that local clustering can amplify the speed of social innovations diffusion. Centola [9] shows through another experiment that behavior spreads farther and faster in a clustered lattice network as compared to a random network.

Singh et al. [10] investigate how the spread of new convention is affected by changing network structure and shows that a committed minority increases time to consensus logarithmically with the network size. Nardini et al. [11] studies a variant of the voter model where agents can rewire their "unsatisfactory" connections and agents can adopt opinions from neighbors and shows how small modifications of the

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ASONAM '19, August 27-30, 2019, Vancouver, Canada

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ACM ISBN 978-1-4503-6868-1/19/08...\$15.00

<http://doi.org/10.1145/3341161.3342930>

interaction rules can drastically affect opinion formation and time to consensus.

Halu et al. [12] use opinion dynamics model to show that introducing a small committed minority of around 10% in a less connected network can reverse the outcome of an election.

Finally, two major diffusion models widely used are linear threshold and independent cascade models [13], [14]. In the first, an inactive user becomes active if the sum of the weights of the edges with active neighbors or fraction of active neighbors exceeds a threshold. In the independent cascade model, a node that becomes active has only one chance to activate its inactive neighbors. We use a variant of the linear threshold model, in which a user changes his/her existing convention when more than half of the neighbors adopt a new convention.

III. DATASET

For experiments we used a publicly available dataset of a socially polarized network, Polblogs [15] between political blogs during the lead up to the 2004 United States presidential election. Each node (blog) is labeled as conservative or liberal and links are interactions between blogs such as citation, blogroll links etc.

Table I shows how the nodes and edges are distributed with respect to a larger, majority community and a smaller, minority community. Border nodes are nodes with edges to both communities while non-border nodes only have edges within their own community.

TABLE I: Node and edge distribution in Polblog. 'A' is the minority (liberal) and 'B' is the majority (conservative) community.

Nodes		Edges			Nodes in A	
1224		16718			588	
A%	B%	A-A%	B-B%	A-B%	Non border %	Border %
48	52	44	48	8	22	26

IV. EXPERIMENTAL METHODOLOGY

A. Adoption

Adoption is represented by a heterogeneous linear threshold model in which some nodes never change their state while others may change state depending on the states of their neighbors. Our experiments vary two parameters: p , the fractional size of the persistent minority, and M , node memory length.

In every round, a node who is not one of the persistent minority randomly chooses one of its neighbors and observes which convention the neighbor follows. The node adopts the convention of the majority of its last M observations. A non persistent minority node can oscillate between the old and new convention repeatedly while a node in the persistent minority stays with the new convention. Results are averages from 20 runs in each experiment.

B. Varying Polarization via Rewiring

We use the metric P proposed by Guerra et al. [16] to measure polarization. Positive index values indicate border nodes have more ties to own group than other group and negative index values indicate more ties to other group than own group. The exact formula is:

$$P = \frac{1}{|B|} \sum_{v \in B} \left[\frac{d_i(v)}{d_b(v) + d_i(v)} - 0.5 \right]$$

where B denotes border nodes; $d_i(v)$ and $d_b(v)$ represents internal edges and border edges respectively. The dataset we use (Polblogs) has $P = 0.18$. To vary polarization value, we use an edge rewiring procedure that preserves the overall degree distribution. For example, if R and S are in one community and X and Y are in another and there exist edges between R-X and S-Y then to increase polarization we rewire to R-S and then X-Y. We invert the procedure to decrease polarization.

Table II shows the polarization scores of the rewired graphs and their percentage of border nodes and percentage of edges between same type nodes.

TABLE II: The graph properties under different polarization indices.

Polarization P	Edge %			Border Node %	
	A-A %	B-B%	A-B%	% in A	% in B
0.44	48	51	1	3.3	5.9
0.42	48	51	1	6.3	6.4
0.36	47	51	2	9.7	9.8
0.27	46	49	5	15.9	16.5
-0.09	13	16	71	47.1	50.2
-0.12	13	17	70	46.7	49.9
-0.19	18	21	61	45.5	49.7
-0.24	26	29	45	44.2	47.3

V. EMPIRICAL EVALUATION

A. Tipping Points in the Polblog Network

A basic research question is whether the tipping point percentages proposed by Xie et al. [3] or by Centola et al. [4] apply to our network. Figure 1a to 1d shows a complete absence of tipping even when all non border nodes in the smaller community are in the persistent minority (22% of all nodes) for $M > 1$. In fact, less than 1% of the nodes in the larger community adopt the new convention when $M = 2$.

B. The Power of Border Nodes

Figure 1e to 1h shows that modest tipping occurs with border nodes as persistent minority: the new convention reaches above 50% of the population for a persistent minority of 20%. This result shows that the position of persistent minority is important for tipping in a polarized network. Our next experiments investigate how the selection of border nodes changes the chance of tipping: a smaller persistent minority, if placed strategically can change the majority convention even for memory larger than 1.

Fig. 1: Adoption by community: (a) to (d) all non-border nodes in smaller community are persistent minority nodes (22% of total); (e) to (h) border nodes in smaller community are persistent minority nodes (20% of total). Light shade is fraction of the population in the persistent minority (constant); medium shade is the fraction of the smaller community who adopt; dark shade is fraction of larger community who adopt.

C. Local Structures of Power

To explore the effectiveness of border nodes, Figure 2 shows how the connectivity to the larger community affects the tipping behavior. We select 10% of the nodes in the graph (122 nodes) from the border nodes in two ways: the border nodes with the highest number of ties to the larger community and, respectively, with the lowest number of such ties. When the persistent minority is the first set, the new convention is more widely adopted (Figures 2e to 2h) but even then only in the smaller community.

In the next experiment we select the border nodes based on the leverage centrality [17] of their neighbors in the majority community. Leverage centrality measures the relative influence of a node on its neighbors as a function of the number of its neighbors and the number of neighbors its neighbors have. Formally,

$$l(v) = \frac{1}{deg(v)} \sum_{v_i \in N_v} \frac{deg(v) - deg(v_i)}{deg(v) + deg(v_i)},$$

where v_i denotes v 's neighbors and N_v the set of all v 's neighbors.

Figure 3 shows that a persistent minority connected to high leverage nodes in the larger community is less successful than one connected to low leverage nodes. However, even when success occurs it is limited to spread in the smaller of the two communities and there is limited spread to the larger community. That a property of how nodes in the smaller community are connected to the larger community can affect adoption in the smaller community but not in the larger community is a puzzle. The puzzle is resolved by noting that when border nodes are effective it is because the connectivity property to the outside is correlated with the degree of those nodes to their own community. It is this higher degree of connectivity to own community that accounts for successful spread within it.

D. The Effect of Network Polarization on Diffusion

We use the previously described rewiring scheme to build variants of the empirical network with different degrees of polarization. Table III verifies the leverage result from analysis of the real Polblogs dataset (Figure 3). It presents spread in those rewired networks where the 10% persistent minority can be completely selected from border nodes in the smaller community. It shows that a persistent minority which connects to low leverage nodes in the majority community achieves a high adoption rate overall, while those connected to high leverage cross neighbors achieve little adoption. **However, the most striking finding is that spread to the larger community depends on the network being much less polarized than observed.**

TABLE III: Adoption by community when persistent minority are border nodes with edges to low (or high) leverage centrality nodes in larger community.

Polarization index P	Memory M	%adoption in minority community		%adoption in majority community	
		Low leverage in majority community	High leverage in majority community	Low leverage in majority community	High leverage in majority community
-0.24	1	38	27.9	52	32.3
	2	38	0.4	52	0.1
	3	38	0.4	52	0.06
	4	38	0.3	52	0.0
-0.19	1	38	25.7	52	34.9
	2	38	0.13	52	0.04
	3	38	0.10	52	0.03
	4	38	0.08	52	0.01
-0.12	1	38	23.7	52	31.1
	2	38	0.0	52	0.04
	3	38	0.0	52	0.03
	4	38	0.0	52	0.2
-0.09	1	38	21.1	52	28.7
	2	38	0.01	52	0.06
	3	38	0.01	52	0.03
	4	38	0.01	52	0.03

VI. SUMMARY AND DISCUSSION

This paper investigates a series of questions related to the position and critical mass of a persistent minority in a polarized network. Practical implications of these results are stopping fake news by injecting fact checking information in strategic positions in the network or limiting the spreading of viruses in a computer network by isolating the border nodes.

Fig. 2: Adoption by community with a persistent minority of $p = 10\%$ selected from border nodes in the smaller community: (a) to (d) represent the border nodes with few ties to the majority community; (e) to (h) represent the border nodes with many ties. See Fig. 1 for meaning of colors.

Fig. 3: Adoption by community with a persistent minority of $p = 10\%$ selected from border nodes in the smaller community: (a) to (d) selection based on low leverage centrality; (e) to (h) selection based on high leverage centrality. See Fig. 1 for meaning of colors.

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