

Women's Reproductive Rights

Computational Propaganda in the United States

**The role of bots in spreading disinformation,
harassment, and divisiveness on Twitter in 2018**



ABSTRACT

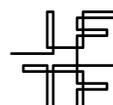
Women's reproductive rights have been a divisive political issue in the United States for decades. While social media holds great potential to support bipartisan engagement around politically contentious issues like reproductive rights, these platforms can also be co-opted by nefarious actors to perpetuate polarization.

Our research investigates the role of automated (bot) Twitter accounts in perpetuating polarization through the spread of disinformation, harassment, and divisiveness. Using the Twitter Search and Stream APIs, we used hashtags and handles (Twitter account names) focused on women's reproductive rights to capture over 1.7 million tweets corresponding to 463,261 unique handles from August 27 to September 7, 2018. Our preliminary results (from a combination of social network analysis, bot detection, and qualitative coding of tweets distributed by bots) indicate that both pro-choice and pro-life bots were highly centralized in our network. While pro-life bots were more likely to send and retweet harassing language, pro-choice bots were more likely to perpetuate political divisiveness. Our initial findings provide insight into new methods to identify and mitigate the impact of computational propaganda on politically contentious topics, and increase awareness and skepticism of the authenticity of extreme views that are widely disseminated on platforms. The next stage of this research will be to conduct a detailed analysis of the nature and scale of the spread of disinformation, harassment, and divisiveness on women's reproductive rights from both centralized bot and non-bot accounts in our dataset, including an evaluation of the interactions and influence between these accounts.

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ABOUT THESE PAPERS

This case study series explores the social implications of computational propaganda. Each report outlines how tools and tactics including bots, disinformation and political harassment were used over social media in attempts to silence social and issue-focused groups prior to the 2018 US midterm elections.



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introduction

“Abortionist holds head of his 20-week-old victim.” This title introduces a one-minute video featuring graphic imagery of an aborted human fetus. In one single tweet, the video has been viewed over 240,000 times and retweeted nearly 2,000 times.¹ In the thread that follows, individuals reply with pro-life² statements, such as, “the court [should] order these women to get fixed so they don’t have the right to murder innocent children,” and pro-choice tweets counter that the video is fake. Twitter is a battleground for fervent debate about women’s reproductive rights, and automated bot accounts are fueling the fire.

Social media services have become primary platforms for political discourse in America (Anderson, Toor, Rainie, & Smith, 2018). Despite their potential to support bipartisan engagement around contentious issues, social media has increased polarization and harassment (Bail et al., 2018). And no issue may be more polarizing between the Democratic and Republican parties than women’s reproductive rights, especially abortion.

In the lead-up to Justice Brett Kavanaugh’s confirmation to the U.S. Supreme Court on October 6, 2018, women’s rights and women’s reproductive rights were central in the debate over his fitness to serve on the Court. Allegations of sexual harassment and questions as to whether Justice Kavanaugh would overturn *Roe v. Wade* fueled a nationwide debate that dominated the mainstream news cycle and social media. Using the Twitter Search and Stream APIs, we captured over 1.7 million tweets from 463,261 unique handles from August 27 to September 7, 2018. This time frame encompassed the first Senate Judiciary Committee hearing for Justice Kavanaugh on September 4.

Our research analyzes the use of computational propaganda (“the use of algorithms, automation, and human curation to purposefully distribute misleading information”) and the spread of harassment and political

divisiveness targeting women’s reproductive rights issues on Twitter (Woolley & Howard, 2017, p. 6). We present preliminary results that provide quantitative and qualitative insights into the nature and scale of disinformation, harassment, and political divisiveness spread by highly influential automated bot accounts.

background

The politics of women’s reproductive rights

Since the 1960s, women’s reproductive rights have been a divisive political issue in the United States—reframed in myriad ways to leverage voter support by both Republican and Democratic parties. Republicans supported abortion in the 1960s under the pro-choice ideological framework of limited government control over individual liberties (Taranto, 2018). In the 1970s, tight elections shifted many Republicans to a pro-life stance, reframing abortion in moral and religious terms to appeal to undecided Catholic and evangelical voters, while the Democratic Party became more inclusive of feminist ideology in the wake of the *Roe v. Wade* Supreme Court decision (Taranto, 2018). Women’s reproductive rights have been used as political tools (deployed strategically by both parties to strengthen partisanship), and new media strategies have played a central role.

Even before the advent of social media, activists on both sides have used broadcast and print media to elevate their messages and sow divisiveness regarding women’s reproductive rights. In the 1970s, large-scale campaigns were distributed by pro-life activists depicting graphic imagery of aborted fetuses, and pro-choice activists deployed images of deceased women from unsafe abortions (Erdreich, 2013; Staggenborg, 1999). In the 1980s, the pro-life video *The Silent Scream*

1. The account that sent the tweet has been confirmed as a bot account. The tweet and video are viewable at <https://twitter.com/ConserveMomUSA/status/1092270038302818304>. Warning graphic imagery.

2. In this paper “pro-life” categorizes sentiments that express opposition to all abortion and “pro-choice” categorizes sentiments that support a woman’s legal right to abortion.

claimed it used new ultrasound techniques to show a first-trimester abortion with narration purportedly describing outcries of pain from the fetus (Petchesky, 1987). In the 21st century, these campaigns have reached unprecedented virality through social media, often through the assistance of bot accounts.

The role of social media in spreading unconfirmed claims on women’s reproductive rights can have long-term detrimental effects when the claims influence public opinion and legislation. For example, five states require doctors to warn patients of a link between abortion and breast cancer, although both the American Cancer Society and the American Congress of Obstetricians and Gynecologists have stated that no such relationship exists (Traister, 2017). With facts left unchecked, unconfirmed claims on social media have the potential to gain momentum and influence state and federal law.

The Twitter public sphere: disinformation, harassment, and divisiveness

Building on Habermas (1989), Dahlgren (2005), a functioning public sphere is “a constellation of communicative spaces in society that permit the circulation of information, ideas, debates—ideally in an unfettered manner—and also the formation of political will (i.e., public opinion)” (Dahlgren, 2005, p. 148). Social media has redefined the scale of the public sphere to a “global public sphere” that is “built around the media communication system and internet networks, particularly in the social spaces of the Web 2.0, as exemplified by YouTube, MySpace, Facebook...” (Castells, 2008, p. 90).

Twitter is uniquely positioned to serve as an online public sphere because of four attributes: (1) all tweets are public by default; (2) hashtags enable the formation of conversations around a shared topic, enabling individuals to easily find, follow, and contribute to a conversation; (3) retweeting enables rapid sharing of information throughout a network; and (4) because Twitter does not require reciprocal connections (e.g.,

“friend” status on Facebook), the network structure supports development of central nodes of information sharing among disparate groups (Colleoni, Rozza, & Arvidsson, 2014).

While Twitter holds great promise to support a vibrant public sphere, it is also prone to influence political homophily, group cohesion, and polarization through the active role of bots in “manufacturing consensus”—creating an illusion of significant support for a particular political issue (Esteve Del Valle & Borge Bravo, 2018; Woolley & Guilbeault, 2017). The 2016 U.S. presidential election brought this issue to the fore, with widespread debate over the prevalence and impact of bots in shaping discourse and spreading disinformation on political issues. As a result of increased research and coverage, about two-thirds of Americans are now aware of social media bots and over half believe they are used for nefarious purposes (Stocking & Sumida, 2018), yet research still confirms that individuals are poor at detecting bots and computational propaganda tactics on their own (Yang et al., 2019).

The use of computational propaganda is on the rise globally, and being able to accurately identify it is critical. Nation-states are increasingly employing targeted online harassment and disinformation campaigns to intimidate, silence, and discredit political dissidents and opponents, fueling political divisiveness. These campaigns can be state-executed, state-directed or -coordinated, state-incited or -fueled, and state-leveraged or -endorsed (Nyst & Monaco, 2018). We extend this framework to non-state actors, lobbyists, and constituents vested in influencing politically contentious topics by perpetuating political divisiveness. These tactics are becoming increasingly common and women are especially targeted.

While approximately four-in-ten Americans have experienced online harassment, women report greater incidences of gender-based harassment (21%) than men (9%) (Duggan, 2017). Women are increasingly facing multiple types of online harassment attacks, including doxxing (releasing private information with malicious intent); trolling (posting content that seeks

to annoy, provoke, or incite violence against women); sextortion (threatening the release of private and intimate images to extort photos, videos, or sexual acts); and revenge porn (disseminating intimate videos or images without permission)(United Nations Human Rights Council, 2018). Online platforms threaten to amplify sexual and gender-based discrimination rather than diminish it.

methods

Using the Twitter Search and Stream APIs, we captured over 1.7 million tweets from 463,261 unique handles from August 27 to September 7, encompassing the first Senate Judiciary Committee hearing for Justice Kavanaugh on September 2, 2018.³

Social network analysis

Twitter facilitates two primary interaction dynamics: mentions and retweets. A mention is a user's handle or hashtag included in another user's tweet, and a retweet is a tweet of another user's tweet. A mention network analysis enables identification of interactions between Twitter accounts; a retweet analysis enables identification of the virality of tweets as accounts rebroadcast messages to their networks.

In order to evaluate the interactions between handles (nodes), we constructed a mention network to explore their “betweenness centrality”—a measure of the number of mention connections between accounts in the network (Newman, 2010). Nodes with the shortest paths (i.e., nodes that directly share a message with many other nodes) have a high betweenness score, controlling information flow in a network because they are connected indirectly to many of the nodes acting as brokers. Betweenness centrality presumes that the nodes in the network have links in both directions, measuring how often they are mentioned by others and mention others in the network (Wasserman & Faust, 1994). Nodes in the center of a graph will display high levels on this measure, while perimeter nodes

will typically have very low values, representing the outer edge of a network. Mention networks tend to be politically heterogeneous with individuals of opposing political views interacting at a much higher rate than in the retweet network (Conover et al., 2011). Ratkiewicz et al. (2011, p. 302) found that “to generate retweeting cascades, the bots also coordinate mentioning a few popular users. When these targets perceive receiving the same news from several people, they are more likely to think it is true and spread it to their followers.” The hashtag mention network contained 498,928 nodes (handles) and 2,389,219 edges (mentions).

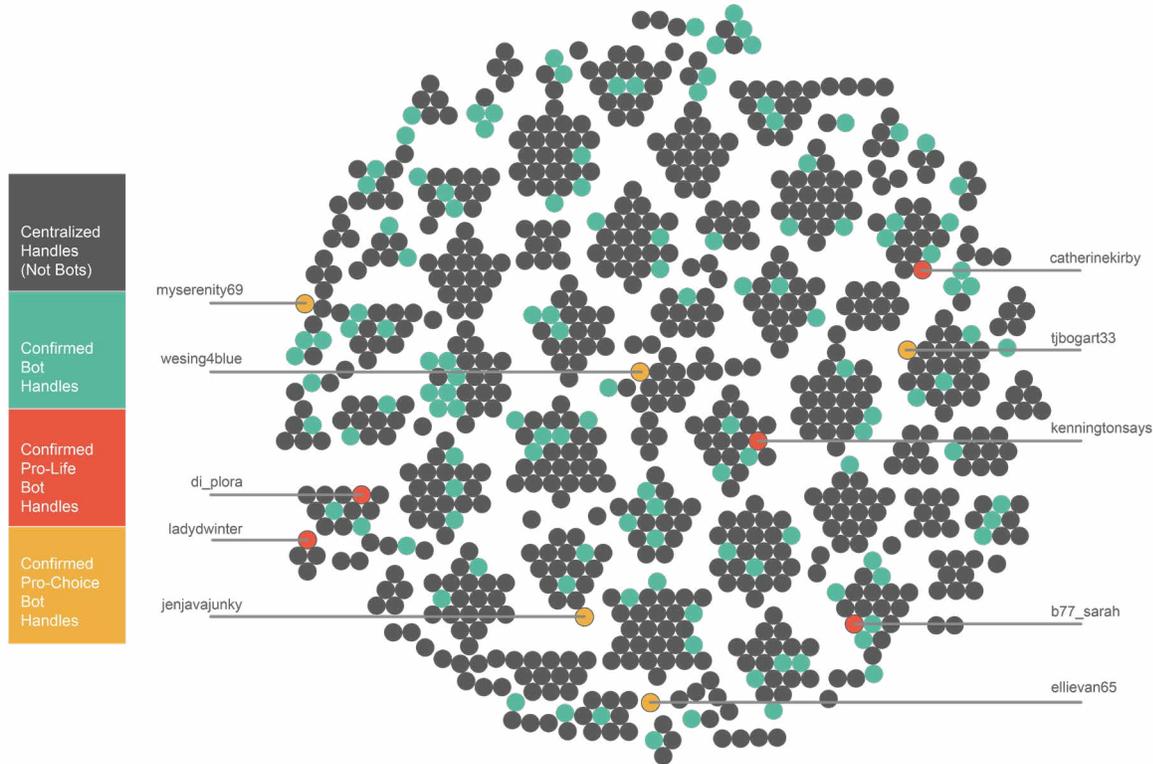
Identifying bots

Our team utilized the Botometer API (formerly BotOrNot) provided through the Network Science Institute and the Center for Complex Networks and Systems Research at Indiana University (<https://botometer.iuni.iu.edu>). Botometer utilizes supervised machine learning to produce a bot score, which calculates the likelihood (from 0 to 1) that an account is controlled entirely or in part by software (Davis et al., 2017; Yang et al., 2019). Botometer extracts over 1,000 features on an account from data provided through the Twitter API. These features are used to create six subscores, each of which is produced by a model that evaluates distinct sets of features. The six subscores include content, friends, network, sentiment, timing, and user metadata. These six subscores form the basis of the overall bot score.

In order to confirm the prevalence of bots with high centrality in our network, we first performed a “mention” social network analysis to identify accounts with high betweenness centrality scores (indicating that they frequently mention and are mentioned by others in the network). The mention social network identified 836 nodes (handles) with high betweenness centrality. All 836 handles were run through Botometer, and those with a score greater than or equal to 0.6 were classified as bots in our network. We identified 137 handles with a bot score greater than or equal to 0.6 (Figure 1, page 5).

3. A full list of the hashtags and handles used to collect tweets and a full list of all hashtags and handles found in tweets collected are viewable at <http://tiny.cc/WRRData>.

Figure 1. Social network mention analysis of 836 most centralized handles out of which 137 accounts were bots (colored teal, red, and yellow). Of the 10 most centralized bots, 5 exhibit a pro-life stance (colored red) and 5 exhibit a pro-choice stance (colored yellow).



In Figure 1 we present the mention network of the 836 handles including the 137 centralized bot handles colored in teal, red, and orange. Of the top 10 most influential bots in the mention network, 5 were pro-life (highlighted in red) and 5 were pro-choice (highlighted in yellow). The 10 most influential bots distributed 872 tweets. All 872 tweets were coded for whether they expressed harassment (including hate speech) and political divisiveness. The top 20 accounts with high betweenness centrality scores are detailed in Table 1 (page 6), which includes 6 of the most influential bot accounts in our network.

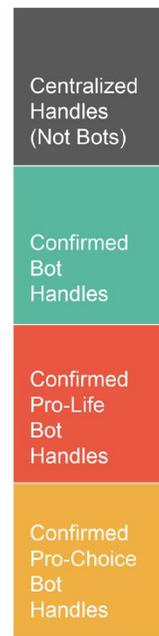
Coding disinformation, harassment, and divisiveness

We analyzed the role of bots in spreading disinformation, and the role of bots in perpetuating harassment and divisiveness.⁴ It is likely additional instances of disinformation were spread throughout the network; however, this analysis is left for future research. We follow the UNESCO Handbook for Journalism Education and Training to identify instances of disinformation by cross-checking claims with verification sites like PolitiFact.com and Snopes.com (Ireton & Posetti, 2018).

4. We follow Fallis' (2015) definition of "disinformation" as inaccurate information that is meant to deceive.

Table 1. Top 20 accounts with high betweenness centrality scores (in z-scores).

Handle	Betweenness Centrality	In-degree	Out-degree
bannerite	7.6	1,265	356
womensmarch	5.7	23,634	333
sfpelosi	4.9	368	31
jambie61	3.4	97	318
gayleasher1	2.2	1,285	227
Myserenity69 (bot)	1.9	3,188	249
eagle1776n	1.8	1,639	4,016
alpinegoodtime	1.6	121	147
funder	1.4	35,579	104
archeology_girl	1.3	146	127
Jenjavajunky (bot)	1.0	711	261
shareitarie10	1.0	63	246
abramson1234	1.0	197	44
rcasonr	1.0	1,646	5,468
Ellievan65 (bot)	1.0	1,936	391
Di_plora (bot)	0.9	307	78
Kenningtonsays (bot)	0.9	234	8
Wesing4blue (bot)	0.8	230	450
lsfarmer311	0.5	91	255
jeppsaddison	0.4	1,082	324



Note: Accounts showing signs of automation are highlighted. Those highlighted in red exhibit a pro-life stance. Those highlighted in yellow exhibit a pro-choice stance.

The Twitter Abusive Behavior and Hateful Conduct Policies were used to guide our coding of tweets for harassment, including identifying whether tweets expressed hate speech (Twitter, 2019). Tweets exhibiting offensive, vulgar, aggressive, or insulting language were coded as expressing harassment. Tweets that expressed harassment “on the basis of race, ethnicity, national origin, sexual orientation, gender, gender identity, religious affiliation, age, disability, or serious disease” were coded as expressing hate speech (Twitter, 2019). Politically divisive speech was identified as speech intended to cause polarization between the

parties. For example, calling to party loyalty: “You’re only a true Democrat if you support pro-choice.” Tweets were coded by a team of 16 individuals trained in the detection of harassment and hate speech on social media at the Human Rights Center at UC Berkeley.⁵ Each tweet was coded by two individuals to better ensure intercoder reliability. Cohen’s kappa⁶ was calculated to determine agreement between coders on harassment and divisiveness coding. There was high agreement between coders on harassment ($\kappa = .989$) and on divisiveness ($\kappa = .993$).

5. <https://humanrights.berkeley.edu/>

6. Cohen’s kappa ranges from -1 to +1 and is a measure of the proportion of agreement over and above chance. A kappa of 1 is an indication of perfect agreement between coders.

results

Disinformation

We identified two disinformation campaigns that were particularly prominent in our dataset: (1) claims that the founder of Planned Parenthood, Margaret Sanger, established the organization to engage in race-based targeting of abortion, and (2) claims that fetal tissue collected from Planned Parenthood is sold for a profit.

A quote credited to Sanger, insinuating that her intention when establishing the organization was to “exterminate the Negro population,” was posted by over a dozen bots in our dataset and retweeted thousands of times. Figure 2 shows two tweets that spread this quote, engaging both bot and non-bot accounts.

According to Snopes (Wirestone, 2015), this claim is not true. Sanger’s full quote provides more nuance, indicating that she feared rumors that the organization may have nefarious intentions would be spread within the Black community.

“The ministers work is also important and also he should be trained, perhaps by the Federation as to our ideals and the goal that we hope to reach. We do not want the word to go out that we want to exterminate the Negro population and the minister is the man who can straighten out that idea if it ever occurs to any of their more rebellious members.”

**—Margaret Sanger,
Founder of Planned Parenthood⁷**

Figure 2. Screenshots of tweets from pro-life bot account claiming that the founder of Planned Parenthood, Margaret Sanger, practiced race-based targeting of abortion.



7. Margaret Sanger’s quote in the original letter she wrote to Dr. C.J. Gamble is viewable in the Smith College Archive at <https://libex.smith.edu/omeka/items/show/495>

In July 2015, The Center for Medical Progress, a pro-life nonprofit focused on ending federal funding for Planned Parenthood, produced an undercover video claiming to prove Planned Parenthood was engaging in deceptive and illegal practices to perform abortions for the purpose of harvesting and selling fetal tissue for profit (Carroll, 2015). According to the House Committee on Oversight and Reform (hereafter “Committee”), Planned Parenthood does receive reasonable reimbursement for tissue donation in accordance with the law. The Committee reviewed the video distributed by The Center for Medical Progress and the original unedited version, and concluded that the video was heavily edited to omit vital information that showed Planned Parenthood representatives stating the organization does not profit from its tissue donation program (House Committee on Oversight and Reform, 2015).

Bot accounts in our dataset frequently referenced this video, using the hashtag #PPSellsBabyParts and sharing links to the video (Figure 3). A sub-campaign has emerged stating that fetal tissue composed of human embryonic kidney 293 cells (HEK 293) collected by Planned Parenthood is sold to companies for inclusion in vaccines and to produce food flavor enhancers. The tweet on the left in Figure 4, page 9, was retweeted by one of the most influential bot accounts in our network. This claim is not uncommon on Twitter. A search of #HEK293 on Twitter returns thousands of tweets, most of which are promoting this claim.⁸

According to the fact-checking site Snopes, human embryonic kidney 293 cells (HEK 293) were derived from an aborted embryo in the 1970s and are widely utilized in biological research, including for investigations of human cellular signaling pathways and generation of recombinant proteins, among other uses (Mikkelsen, 2012). The cell line has been used in commercial research for characterization of taste receptors expressed by HEK 293 cells that are stimulated by the addition of bitter and sweet ligands. This process, known as “cell culture,” is used to test molecules without the requirement of animal models. Furthermore, it is the cellular response itself in the culture that is tested—HEK 293 cells and their constituents are not added to commercial food products (Mikkelsen, 2012).

Harassment and divisiveness

We analyzed all 872 tweets spread by the 10 most centralized bot accounts in our network. All tweets were coded for the prevalence of harassment (including hate speech) and political divisiveness.

Incidences of harassment were identified in 103 tweets, and hate speech appeared once. Tweets expressing political divisiveness appeared 181 times (Table 2, page 9). An example tweet distributed by a pro-life bot account that contained both harassment and divisiveness is presented in Figure 5 (Page 10).

Figure 3. Screenshot of tweet from confirmed pro-life bot account stating that Planned Parenthood sells tissue for profit.



8. Tweets using the hashtag #HEK293 can be viewed at <https://twitter.com/search?f=tweets&vertical=default&q=HEK%20293&src=typd>

An example pro-life bot tweet expressing harassment and hate speech is presented in Figure 6. This tweet was retweeted by one of our most centralized pro-life bot accounts (@catherinekirby) and by 4 additional pro-life bot accounts in our mentions network constructed of the 836 most centralized handles. The tweet claims that Hillary and Bill Clinton “support the extermination of minority babies” (Figure 6).

Accounts expressing a pro-choice stance on abortion were often retweeted by pro-choice bot accounts. For example, one tweet targeting Justice Kavanaugh and his pro-life stance was retweeted by two of our top 10 most centralized pro-choice bot accounts (@Ellievan65 and @myserenity69) and by an additional 3 pro-choice bot accounts in our mentions network constructed of the 836 most centralized handles (Figure 7, page 11).

Members of Congress were frequently mentioned in bot tweets. For pro-choice bot accounts, the majority of these tweets informed constituents how to contact their Congressional representative to share their stance on Kavanaugh’s confirmation, (Figure 8, page 11). For pro-life accounts, most tweets were directed at oppositional party members of Congress to express disagreement with their pro-choice stance (Figures 9a, 9b, page 11). Within our mention network analysis of the 836 most centralized handles, the tweet in Figure 9a was retweeted by 10 confirmed pro-life bot accounts and the tweet in Figure 9b was retweeted by 6 confirmed pro-life bot accounts.

Figure 5. Screenshot of tweet sent by a confirmed pro-life bot account, expressing both harassment and political divisiveness.



Note: The graphic imagery has been blurred for inclusion in this paper. As of early March 2019, the original tweet and image were still online and viewable at http://tiny.cc/b77_sarahtweet

Figure 6. Screenshot of tweet sent by a confirmed pro-life bot account, expressing both harassment and hate speech. This tweet was retweeted by 5 of our confirmed pro-life bots active within the 836 most centralized handles in our mention network.



Figure 7. Screenshot of tweet sent by a confirmed non-bot account expressing pro-choice sentiments. This tweet was retweeted by 5 confirmed pro-choice bots active within the 836 most centralized handles in our mention network.



Figure 8. Screenshot of tweet sent by one of the most centralized pro-choice bots in our network (@wesing4blue). This tweet was retweeted by 5 confirmed pro-choice bots active within the 836 most centralized handles in our mention network.



Figures 9a and 9b. Screenshots of tweets sent by confirmed pro-life bot accounts to oppositional party members, expressing disagreement with their pro-choice stance.



Figure 9a



Figure 9b

conclusion

Our preliminary results indicate that bot accounts employed computational propaganda tactics to spread disinformation, harassment, and divisiveness related to women's reproductive rights issues on Twitter. Both pro-choice and pro-life bots were highly centralized in our network, indicating their likely influence in shaping how women's reproductive rights issues were framed. While pro-life bots were more likely to send and retweet harassing language, pro-choice bots were more likely to perpetuate political divisiveness by promoting politically charged content.

Our research provides quantitative and qualitative evidence on the ways bots utilize computational propaganda tactics to target women's rights issues. We believe this work provides insight into new methods to identify and mitigate the spread of computational propaganda. It will also help alert social media users to the prevalence of bots and increase awareness and skepticism of the authenticity of extreme views that are widely disseminated on these platforms.

However, our research has some limitations. While Botometer is commonly applied in this type of research, Echeverria et al. (2018) caution that bot detection systems like Botometer can be error-prone because

of two primary drawbacks: (1) bot creators can avoid detection by quickly employing new tactics that are not recognized by the model, and (2) bot detection models can be biased to detect certain types of bots as they are often built on training datasets composed of bots exhibiting similar behaviors. Therefore, we may have false positive and false negative detection of bots in our network.

Finally, since we only coded tweets distributed by bot accounts, we do not have a full understanding of whether the behavior of bot accounts is reflective of non-bot accounts that were also highly centralized in our network. The next stage of this research will be to conduct a detailed analysis of the nature and scale of the spread of disinformation, harassment, and divisiveness on women's reproductive rights issues by conducting both retweet and mention network analyses and coding tweets from highly centralized bot and non-bot accounts within our Twitter dataset.

references

- Anderson, M., Toor, S., Rainie, L., & Smith, A. (2018, July 11). Activism in the Social Media Age. Retrieved October 15, 2018, from <http://www.pewinternet.org/2018/07/11/public-attitudes-toward-political-engagement-on-social-media/>
- Bail, C. A., Argyle, L. P., Brown, T. W., Bumpus, J. P., Chen, H., Hunzaker, M. B. F., ... Volfovsky, A. (2018). Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences of the United States of America*, 115(37), 9216–9221. <https://doi.org/10.1073/pnas.1804840115>
- Carroll, L. (2015, July 17). The Planned Parenthood video in context. PolitiFact. Retrieved from <https://www.politifact.com/truth-o-meter/article/2015/jul/17/planned-parenthood-video-context/>
- Castells, M. (2008). The new public sphere: Global civil society, communication networks, and global governance. *The Annals of the American Academy of Political and Social Science*, 616(1), 78-93.
- Colleoni, E., Rozza, A., & Arvidsson, A. (2014). Echo Chamber or Public Sphere? Predicting Political Orientation and Measuring Political Homophily in Twitter Using Big Data. *Journal of communication*, 64(2), 317-332.
- Conover, M. D., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., & Flammini, A. (2011, July). Political polarization on Twitter. In *Fifth international AAAI conference on weblogs and social media*.
- Dahlgren, P. (2005). The Internet, Public Spheres, and Political Communication: Dispersion and Deliberation. *Political Communication*, 22(2), 147-162.
- Davis, C. A., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. (2016, April). BotOrNot: A system to evaluate social bots. In *Proceedings of the 25th International Conference Companion on World Wide Web* (pp. 273-274). International World Wide Web Conferences Steering Committee.
- Duggan, M. (11 July 2017). *Online harassment 2017*. Pew Research Center. Retrieved from <http://www.pewinternet.org/2017/07/11/online-harassment-2017/>
- Echeverría, J., De Cristofaro, E., Kourtellis, N., Leontiadis, I., Stringhini, G., & Zhou, S. (2018). LOBO--Evaluation of Generalization Deficiencies in Twitter Bot Classifiers. *arXiv preprint arXiv:1809.09684*.
- Erdreich, S. (2013). *Generation Roe: Inside the Future of the Pro-choice Movement*. New York, NY: Seven Stories Press.
- Esteve Del Valle, M. & Borge Bravo, R. (2018). Echo chambers in parliamentary Twitter networks: The Catalan case. *International Journal of Communication*, 12, 1715-1735. Retrieved from <https://ijoc.org/index.php/ijoc/article/viewFile/8406/2325>
- Fallis, D. (2015). What is disinformation?. *Library Trends*, 63(3), 401-426.
- Habermas, J. (1989). The Structural Transformation of the Public Sphere, translation Thomas Burger. *Cambridge: MIT Press*, 85, 85-92.
- House Committee on Oversight and Reform (2015). The Facts vs. Fiction on Planned Parenthood. Retrieved from <https://oversight.house.gov/planned-parenthood-fact-v-fiction>
- Iretton, C. & Posetti, J. (Eds.) (2018). Journalism, 'fake news' & disinformation: Handbook for journalism education and training. United Nations Educational, Scientific and Cultural Organization (UNESCO) Series on Journalism Education. Retrieved from <https://en.unesco.org/fightfakenews>
- Mikkelsen, D. (2012, March 18). Were food companies caught using aborted babies in flavor additives? *Snopes*. Retrieved from <https://www.snopes.com/fact-check/senomyx-flavor-additive/>
- Nyst, C. & Monaco, N. (2018). State-sponsored trolling: How governments are deploying disinformation as part of broader digital harassment campaigns. *Institute for the Future*. Retrieved from http://www.iff.org/fileadmin/user_upload/images/DigIntel/IFTF_State_sponsored_trolling_report.pdf
- Newman, M.J. (2010). *Networks: An Introduction*. Oxford: Oxford University Press.
- Petchesky, R. (1987). Fetal Images: The Power of Visual Culture in the Politics of Reproduction. *Feminist Studies*
- Ratkiewicz, J., Conover, M. D., Meiss, M., Gonçalves, B., Flammini, A., & Menczer, F. M. (2011, July). Detecting and tracking political abuse in social media. In *Fifth international AAAI conference on weblogs and social media*.
- Staggenborg, S. (1991). *The pro-choice movement: Organization and activism in the abortion conflict*. New York, NY: Oxford University Press.
- Stocking, G. & Sumida, N. (15 Oct. 2018). *Social media bots draw public's attention and concern*. Pew Research Center. Retrieved from <http://www.journalism.org/2018/10/15/social-media-bots-draw-publics-attention-and-concern/>

REFERENCES (CONT.)

Taranto, S. (2018, January 22). How abortion became the single most important litmus test in American politics. *Washington Post*. Retrieved from <https://www.washingtonpost.com/news/made-by-history/wp/2018/01/22/how-abortion-became-the-single-most-important-litmus-test-in-american-politics/>

Traister, R. (2017, January 17). Fake news, fake science and why doctors lie about abortion. *The Cut*. Retrieved from <https://www.thecut.com/2017/01/what-happens-when-fake-news-about-abortion-becomes-law.html>

Twitter (2019). Rules and Policies. Retrieved from <https://help.twitter.com/en/rules-and-policies#twitter-rules>

United Nations Human Rights Council [UNHRC]. (June 2018). Report of the Special Rapporteur on violence against women, its causes and consequences on online violence against women and girls from a human rights perspective. Retrieved from https://www.ohchr.org/EN/HRBodies/HRC/RegularSessions/Session38/Documents/A_HRC_38_47_EN.docx

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (vol. 8). Cambridge University Press: Cambridge, UK.

Wirestone, C. (2015, Oct. 5). Did Margaret Sanger believe African Americans “should be eliminated”? *Snopes*. Retrieved from <https://www.politifact.com/new-hampshire/statements/2015/oct/05/ben-carson/did-margaret-sanger-believe-african-americans-shou/>

Woolley, S. C., & Guilbeault, D. R. (2017). Computational propaganda in the United States of America: Manufacturing consensus online. *Computational Propaganda Research Project*, 22.

Woolley, S. C., & Howard, P. N. (2017). *Computational propaganda worldwide: Executive summary*. Working Paper, (11. Oxford, UK), Computational Propaganda Research Project.

Yang, K. C., Varol, O., Davis, C. A., Ferrara, E., Flammini, A., & Menczer, F. (2019). Arming the public with artificial intelligence to counter social bots. *Human Behavior and Emerging Technologies*, e115.

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