University of Copenhagen
Department of Political Science
Social Network Analysis (ASTK18106U)
Yevgeniy Golovchenko

Title

Ole Fechner, Johannes Kopf

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Boddinstr. 15
12053 Berlin
ole.fechner@fu-berlin.de

MA Politcal Science

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1 Introduction

2 Agenda-building and astroturfing

The process of trying to move an actors agenda to the agenda of other actors, especially policymakers, is defined as *agenda-building* (Linvill/Warren 2018: 3). This can also be extended to the question of how the public views certain issues, usually by analyzing media coverage of those issues: “Agenda-building research examines how certain groups, such as those in politics and business, influence what issues journalists cover as well as how the public views issues” (Parmelee 2014: 434). Since the rise of social media platforms like Twitter and Facebook, agenda-building takes place in those environments. This is due to journalists drawing heavily on Twitter for their job and, on the other hand, research shows that Twitter is the most popular social media platform for participating in political discussions, which from there are often taken to other media (Parmelee 2014: 435, 437). Influencing the citizens of another country through the use of media is nothing new, rather it is regularity used in conflicts or during war. “However, Russia’s work on social media has taken agenda-building efforts by nations into a new context” (Linvill/Warren 2018: 3).

Closely linked to agenda-building is a second phenomenon called (political or/and online) *astroturfing*, which can be characterized as the “creation of a false or exaggerated impression of grassroots support” (Harcup 2014). It describes the strategic and coordinated approach of a group with the aim to create the impression of a certain public opinion, that might not exist in that way. On social media, those groups use many different accounts that post and interact with regular users to create the desired impression. For the purpose of this paper, we see astroturfing as a strategy of agenda-building. The anonymity provided by platforms like Twitter, as well as the covert structure of those groups, make them very hard to discover (Yang et al. 2017: 564). This paper will therefore take the structure of the IRA as a staring point, instead of the presumed agenda behind the organization. Social network analysis, which will be introduced in the next section, offers an excellent tool box to conduct this task.

3 Methodology/Operationalisation/Research design

3.1 Data

In early 2018, NBC news published a dataset of 203,451 Tweets by 453 troll accounts between July 2014 and September 2017, which were linked to the Russian IRA by an official document handed over to US Congress by Twitter. Twitter justifies this linking by referring to "third party sources", which makes it possible to reconstruct or evaluate their method. This paper will assume those accounts' links to the IRA to be correct, as it is the best evaluation there is. We will use a Social Network Analysis approach to investigate the behaviour of these Russian troll accounts, which is why only relational data will be taken into account within our analysis.

Retweets contain relational information about one user retweeting another, therefore creating a directional tie between the two. First, we drop any of the Tweets in the dataset that are not retweets, which leaves us with 147,428 Retweets by 333 troll accounts. There were 120 trolls, who did not retweet and were therefore dropped. Each of these Retweets represents a tie between two users and an edge in our graph, as will be shown later. We define a Retweet sender as the person retweeting an original Tweet by another person, who, accordingly, is the Retweet receiver.

Our dataset revolves around a set of 333 unique troll Twitter handles, who are retweeting others. A Twitter handle is the screen name of a Twitter account and can be changed by the users. A variable stating the unique User ID is used to validate unique users, showing that there are no duplicate User IDs in the dataset. There is information about who these 333 accounts did retweet, but not by whom they were retweeted. This makes it an ego-centred network around the group of 333 trolls. Of these 333 trolls, 151 (around 45%) retweeted others and were themselves retweeted by other trolls, thus being both sender and receiver. 182 (around 55%) trolls only retweeted others, but were not retweeted themselves, making them only senders. A third group of 71 trolls was found by looking at who was retweeted by the original group of trolls in the data, thus increasing the number of trolls in our data to a group of 404. These 71 trolls were retweeted by others, though did not send retweets themselves. Finally, the big body of users in the dataset consists of 36,485 users, who are retweeted by the trolls, but are not themselves categorized as trolls by Twitter. Overall, there are 36,889 unique twitter users in the dataset, 404 classified trolls and 36,485 non-trolls, which together represent 36,889 nodes in our network.

To further extend our data and our scope of analysis, we are adding additional qualitative information on the IRA trolls, provided by Darren Linvill and Patrick Lee Warren (2018) via the online news outlet FiveThirtyEight (citation). Linvill and Warren conduct a qualitative analysis, categorizing a sample of 1,133 IRA troll accounts by examining the Tweets' content and the account names, applying a temporal analysis of the trolls tweeting behaviour after. They "[...] identified five categories of IRA-associated Twitter handles, each with unique patterns of behaviors: *Right Troll*, *Left Troll*, *Newsfeed*, *Hashtag Gamer*, and *Fearmonger*." (Linvill/Warren 2018: 6). In addition, there are three categories, which are not used within their analysis, those being *Non-English*, *Commercial* and *Unknown*. The categories *Right Troll* and *Left Troll* need little explanation, as they include users who broadcasted right-leaning populist and socially libral messages. *Hashtag Gamers* are users who are playing word games on Twitter, mostly non-political, though sometimes including left- or right-leaning messages. *Newsfeed* Trolls are posing as local US News Agencies, mostly linking to legitimate news content, often with a pro-Russian perspective. Fearmongers spread news of crisis events such as Tweets about salmonella infections. The *Non-English* troll category includes users who tweeted in other languages than English, predominately Russian, some German and little French and Spanish. *Commercial* Trolls are not included in our dataset. Finally, users were categorized as *Unknown*, if they could not be assigned to other categories for lack of information in their tweets. These categories will be included in this paper's analysis, since might be interesting to see how they interact with the other trolls. We are appending Linvill and Warren's account categories to our data, finding categories are available for 394 of the 404 troll handles in our dataset, meaning that around 98% of the trolls in our dataset are categorized.

As another attribute, we are appending information on the count of followers of the troll accounts from a second dataset provided by NBC news. The information on the count of followers provided only includes one figure and does not vary over time, without specification of when these follower counts were obtained. We will assume that they are at least to some degree representative and use them as a heuristic.

Lastly, we are using the full time period of Retweets, from July 2014 to September 2017. This paper is not interested in a time period preceding a specific event, like an election or a specific trending discussion, but rather strategic behaviour of the trolls in general. That is why it seems to be the right approach to include all of the Tweets in the analysis.

User	N	Senders	Receivers
Troll	404	182	222
Non-Troll	36,485	0	36,485
Total	36,889	333	36,707

Table 1:

User	N	Senders	Receivers
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Table 2: Troll Statistics

Category	N	Senders	Receivers	Average_Followers
Right	101	75	90	4649
Left	110	104	48	1783
Hashtag Gamer	61	43	60	3021
Non-English	106	100	7	2127
Newsfeed	11	1	10	16446
Fearmonger	4	0	4	0
Unknown	11	10	3	3306
Total	404	333	222	4476

4 Methods

5 Discussion

6 Conclusion

7 Code (not included in word count)

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