Socialbots Whitewashing Contested Elections; A Case Study from Honduras

E. Gallagher, P. Suárez-Serrato and E. I. Velazquez Richards

Abstract We analyze socialbots active tweeting in relation to Juan Orlando Hernández, the recently reelected president of Honduras. We find a clear bimodal separation between humans and bots, using *Botometer* and its classifiers. Over one hundred separate communities of socialbots are identified and visualized, detected through the analysis of temporally coordinated retweets.

Keywords Social network analysis · Socialbots · Elections · Spanish · Honduras

1 Introduction

On November 26, 2017, a presidential election was held in Honduras. The Central American nation of 9 million people has been in a state of turmoil since the election. Multiple protests have ensued calling for a new election to take place and for the previous results to be invalidated. Violent clashes erupted, claiming several lives so far and remains a developing situation.[1]

In this political context, we obtained 41,288 tweets that mention the account of Juan Orlando Hernández (@JuanOrlandoH). These were first analyzed visually using Gephi to understand how the users mentioning this account were related to each other. It can be seen in Fig. 1 how the full network of mentions is distributed. Upon close examination of the dataset, it was clear that a significant amount of these accounts were managed through TweetDeck (22,519 tweets from our dataset).

[1] See http://bit.ly/2lKpIcR, http://fxn.ws/2DyUH3R, and http://bit.ly/2D8rLmx.

E. Gallagher
Pursuance Project 3419, Westminster Avenue #25, Dallas, TX 75205, USA

P. Suárez-Serrato (✉) · E. I. Velazquez Richards
Instituto de Matemáticas, Universidad Nacional Autónoma de México, Ciudad Universitaria, 04510 Mexico, Coyoacán, Mexico
e-mail: pablo@im.unam.mx

P. Suárez-Serrato
Department of Mathematics, University of California Santa Barbara, Goleta, CA, USA

X.-S. Yang et al. (eds.), *Third International Congress on Information and Communication Technology*, Advances in Intelligent Systems and Computing 797, https://doi.org/10.1007/978-981-13-1165-9_50

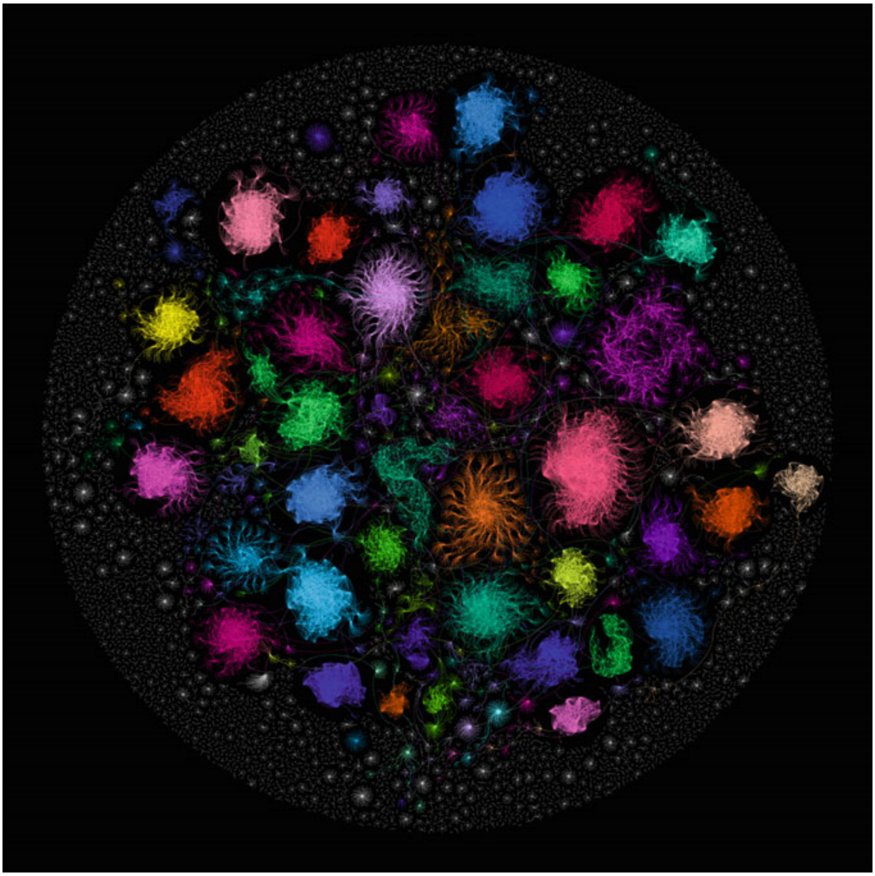

Fig. 1 Full network of Twitter users mentioning the account during the collection period: 41,288 tweets. Nodes: 26,363. Edges: 41,255. Communities: 4108

In Fig. 3, the accounts that are being run through TweetDeck are visualized. More than half of the mentions of @JuanOrlandoH were generated by the accounts in this figure. Furthermore, these two networks are obtained by using timestamps of tweets as nodes and accounts that retweet these as edges, so that the clusters form when there are coordinated, timed, retweets. This type of padding, or political astroturfing, has been noticed and recorded before, but this is the first instance we know of where this scale of coordinated communities has been identified and visualized in a developing situation. A close reading of the accounts from Fig. 3 reveals that in some of the clusters the accounts even share a part of the username. The most notable in this sense are the Rivera and Santos teams. We also identified a group, which we called the Ladies team, of accounts with attractive women in their profile and whose main purpose is to emit sycophantic replies to @JuanOrlandoH (see Fig. 2).

This rudimentary bot creation and management strategy make these socialbots amenable to be identified. It is worrisome that the underlying message these socialbot

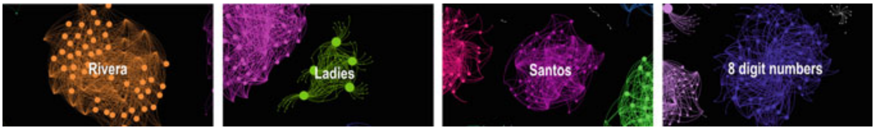

Fig. 2 Socialbot teams were created in batches. Santos cluster; December 6-8, 2017. Rivera cluster; December 7-8, 2017. Ladies cluster; June 10-17 of 2015. The socialbots follow each other and act in unison within their respective clusters. Each cluster retweets the same tweets at the same time. We were thus able to graph their activity based on the tweet's timestamps

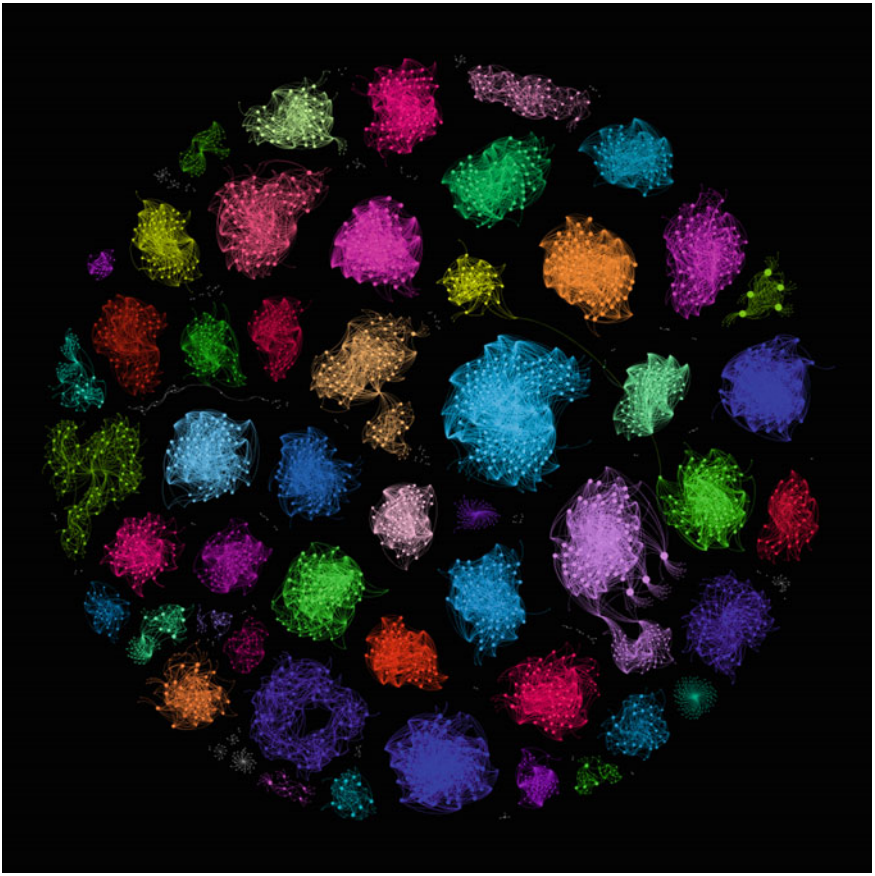

Fig. 3 Subnetwork of Twitter users mentioning the account during the collection period whose accounts were managed using TweetDeck. TweetDeck Only: 22,519 tweets. Nodes: 3767. Edges: 22,519. Communities: 124

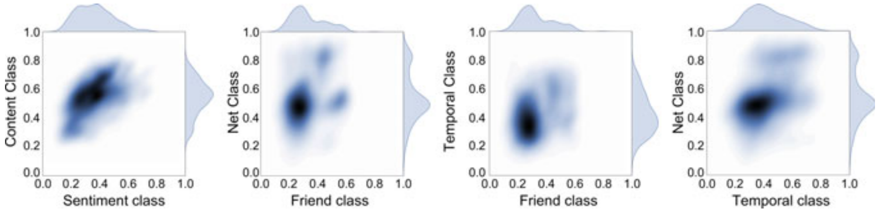

Fig. 4 2D kernel decomposition estimate for Content-Sentiment, Network-Friend, Temporal-Friend, and Network-Temporal pairwise classifiers from Botometer, for Twitter users mentioning the account, for the sample obtained through Twitter's streaming API containing a total of 2,367 unique accounts

accounts promote is that of good news, prosperity, and tranquility in Honduras. While in fact there are violent outbursts in the streets and widespread discontent with the way in which the last election's results are being imposed internally and accepted internationally.

In order to validate the presence of socialbots, we evaluated the accounts collected through *Botometer*. We find a considerable amount of bots acting, and we identify a bimodal separation between human and bot users using kernel decomposition estimate in two dimensions. Through the combination of non-language specific classifiers of *Botometer*, pairwise comparing its different classifiers, shown in Fig. 4.

1.1 Background

A review of *Botometer*, its effectiveness and design can be found in [6]. The use of socialbots for political purposes and for spam can be found in [14], [7]. Other methods of bot detection have also been successful [1–3, 5]. However *Botometer* provides public API access which allows work like this to be carried out. An extensive presentation of the features of this tool, as well as a review of how it compares to, and surpasses, previous methods can be found in [4] and [11]. This system has proven useful in identifying bots and their influence in online dialogue in other places in Latin America when analyzing tweets that are mainly in Spanish (see [10] and [13]). Recent studies have found this kind of activity present in marketing and propaganda [12].

2 Data Analysis

Data preparation. The total dataset comprises 41,288 tweets that mention the handle @JuanOrlandoH, collected via Tweet Archivist. Dates/Times of capture; Start: 12/25/2017 at 03:55:22 UTC; End: 01/01/2018 at 19:19:22 UTC. Out of the total dataset 22,519 tweets were sent using TweetDeck. The graphs from Figs. 1 and 3 are directed, layout algorithms OpenOrd and Force Atlas 2 were used in Gephi for visualization of both these datasets.

Network Analysis. We evaluated the centrality of the accounts being run with Tweetdeck and found that the eigenvector centrality created a proxy to naturally cluster

Table 1 Table of accounts with highest eigenvector centrality, indicating that they are possible botmasters

Andres_Arguet	1.0	AzulCerrato	0.882353
RicardoDuron15	0.970588	lauraso10566447	0.852941
JeffreyChavez_	0.970588	genesismargotc1	0.852941
MelanyBulnes	0.941176		

different teams of accounts. We include in Table 1 the accounts with the highest eigenvector centrality, as it is possible that these accounts are controlling the rest, acting as botmasters and leaders whose activity is then mimicked by the rest of the bots. It would be interesting to compare this standard measure of centrality to other proposed measures tailored to the study of similar social phenomena [8]. Given the protests that took place at the time of collection and in relation to the main account, the clusters of bot accounts are not typical of the collective responses that have been observed and described in these kinds of situations [9].

Bot Analysis. In Fig. 4, we plot the bivariate kernel density estimatation of pairwise classifiers from *Botometer*. This technique allows us to extract a more complete picture of the distribution of human versus automated accounts. As Twitter's public API only allows approximately 10% of mentions to be collected, through this statistical method we can infer the amount of socialbot accounts given our sample.

3 Conclusions

We found over one hundred clusters of coordinated socialbots acting to provide a positive social media fog in what turned out to be a violent post-electoral circumstance. While the socialbot accounts and the way in which they are managed is rudimentary, the implications for freedom of expression and control of dissenting voices in Honduras should be cause for concern. This study further highlights the need for social media companies to continuously monitor the abuse by automated accounts. Our findings underscore the need for tighter controls of social media abuse by regimes that seek to quell their opposition through a fake positive atmosphere online.

Acknowledgements We thank the OSoMe team in Indiana University for access to *Botometer*, and also Twitter for allowing access to data through their APIs. PSS acknowledges support from UNAM-DGAPA-PAPIIT-IN102716, UC-MEXUS-CN-16-43, and DGAPA-PASPA program.

References

1. Chavoshi N, Hamooni H, Mueen A (2016) Identifying correlated bots in twitter. In: International conference on social informatics. Springer International Publishing pp 14–21

2. Chu Z, Gianvecchio S, Wang H, Jajodia S (2010) Who is tweeting on twitter: human, bot, or cyborg? In Proceedings of the 26th annual computer security applications conference. ACSAC '10, ACM, New York, NY, USA pp 21–30
3. Clark EM, Williams JR, Jones CA, Galbraith RA, Danforth CM, Dodds PS (2016) Sifting robotic from organic text: a natural language approach for detecting automation on twitter. J Comput Sci 16:1–7
4. Davis CA, Varol O, Ferrara E, Flammini, A, Menczer F (2016) BotOrNot: a System to Evaluate Social Bots. In: Proceedings of the 25th international conference companion on world wide web, WWW '16 Companion, 2016, International World Wide Web Conferences Steering Committee pp 273–274
5. Dickerson JP, Kagan V, Subrahmanian V (2014) Using sentiment to detect bots on twitter: are humans more opinionated than bots? In: 2014 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM) 00(undefined), pp 620–627
6. Ferrara E, Varol O, Davis C, Menczer F, Flammini A (2016) The rise of social bots. Commun. ACM 59(7):96–104
7. King G, Pan J, Roberts ME (2013) How censorship in china allows government criticism but silences collective expression. American Political Science Review 107(2(May)), 1–18 (2013), please see our followup article published in Science, "Reverse-Engineering Censorship In China: Randomized Experimentation And Participant Observation."
8. Steinert-Threlkeld Z (2017) Longitudinal network centrality using incomplete data. Political Anal 25(3):308–328
9. Steinert-Threlkeld Z (2017) Spontaneous collective action: peripheral mobilization during the Arab spring. Am. Political Sci. Rev. 111(2):379–403
10. Suárez-Serrato P, Roberts ME, Davis C, Menczer F (2016) On the influence of social bots in online Protests. In: Spiro E, Ahn YY (eds) Social informatics. SocInfo 2016. Lecture Notes in Computer Science, vol 10047. Springer, Cham
11. Varol O, Ferrara E, Davis CA, Menczer F, Flammini A (2017) Online human-bot interactions: detection, estimation, and characterization. In: Proceedings of the eleventh international conference on web and social media, ICWSM 2017, Montréal, Québec, Canada, May 15-18, 2017, 280–289
12. Varol O, Ferrara E, Menczer F, Flammini A (2017) Early detection of promoted campaigns on social media. EPJ Data Sci 2193–1127
13. Velázquez E, Yazdani M, Suárez-Serrato P (2018) Socialbots supporting human rights, to appear in Proceedings AAAI-ACM international conference on artificial intelligence ethics and society
14. Woolley S (2013) Automating power: social bot interference in global politics. First Monday 21(4)