Bots sustain and inflate striking opposition in online social systems

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ABSTRACT

Societies are complex systems which tend to polarize into sub-groups of individuals with dramatically opposite perspectives. This phenomenon is reflected – and often amplified – in online social networks where, however, humans are no more the only players, and co-exist alongside with social bots, i.e. software-controlled accounts. Analyzing large-scale social data collected during the Catalan referendum for independence on October 1 2017, consisting of nearly 4 millions Twitter posts generated by almost 1 million users, we identify the two polarized groups of Independentists and Constitutionalists and quantify the structural and emotional roles played by social bots. We show that bots act from peripheral areas of the social system to target influential humans of both groups, mostly bombarding Independentists with negative and violent contents, sustaining and inflating instability in this online society. These results quantify the potential dangerous influence of political bots during voting processes.

Societies consist of agents engaging in multi-modal social actions with one another in a complex system¹. This “society-as-system” metaphor inspired many computational studies aimed at identifying, at a microscopic level, how social interactions might lead to emergent global phenomena such as social segregation², spreading of information³ and behavior⁴,⁵. The recent advent of digital communication systems has dramatically shifted the investigation from empirical social interactions in the physical world to online social platforms and technology-mediated interactions⁶. Online platforms revolutionised the “society-as-system” metaphor⁷ by providing detailed datasets suitable for large-scale investigation of patterns reflecting real-world social phenomena such as the presence and role of influencers in information diffusion⁸–¹², the effect of emotions on social ties¹³,¹⁴, or the polarization of agents according to stances¹⁵–¹⁷. Social media yield an invaluable source of information for learning the mechanisms behind social influence and social dynamics¹⁸–²¹. However, digital systems are not populated only by humans but also by software-controlled agents, better known as bots, programmed to pursue specific tasks, from sending automated messages to assuming specific social or antisocial behaviors²²,²³. Similarly to human interactions, bots might be able to affect structure and function of a social system²¹. Understanding how human-bot dynamics drive social behavior is of utmost importance: as postulated by the theory of embodied cognition¹⁹,²⁴, the presence of robots in a social system affects the way human perceive social norms and how they interact one another and with the robots.

Here, we show how social bots play a central role in the collective dynamics taking place on online social systems during a voting event, namely the Catalan Referendum of October 1, 2017. To this end, we monitored the discussion on a popular microblogging platform (Twitter) from September 22, 2017 to October 3, 2017. We discovered that bots generated specific content with negative connotation that targeted at the most influential individuals among the group of Independentists (i.e., those supporting Catalan independence). For our analysis, we first detect bots by using cutting-edge scalable approach and find that nearly one in three users in this conversation is not a human (see Materials and Methods).
Results

By disentangling the observed social interactions in Retweets (who re-shares the content posted by whom), Replies (who responds to whom) and Mentions (who attracts the attention of whom), we find that humans and bots share similar temporal behavioral patterns in the volume of messages. Both groups display daily excursions resembling a circadian rhythm, with a dramatic increase in the activity rate on October 1 (cf., Fig. 1). Figure 1 (lower panel) shows that bots produced 23.6% of the total number of posts during the event (Retweets and Mentions show comparable values). Notably, the percentage of Replies generated by bots increases to 38.8%, suggesting that during this event bots preferred this form of targeted responses.

To better characterize the nature of the observed interactions, we investigate the targets of such intensive social activities. Figure 2A summarizes the structure of human-bot interactions. While humans interact mostly with other humans, 19% of overall interactions are directed from bots to humans mainly through Retweets (74%) and Mentions (25%), as shown in Fig. 2(B–D). This finding highlights the potential influence over human users exerted by software-controlled agents and by their hidden programmers.

To shed light on the nature of these human-bot interactions we focus on the semantic content of posted messages. A sentiment analysis (see Materials and Methods) reveals interesting differences in emotional trends between humans and bots (Fig. 3). Retweets directed to bots do not display any evident deviation from neutrality (0 sentiment score), while interactions directed towards humans display marked positive and negative trends of sentiment intensity. An analogous behavior happens also for mentions (light colors). These differences strongly indicate that bot-targeted interactions are not significantly influenced by the underlying social dynamics and hence the analysis should focus more on human-targeted interactions (i.e., human-to-human and bot-to-human).

Figure 1. Social activity of humans and bots over time. Upper panel shows the volume per minute for different social actions (Tweet, Retweet, Mention and Reply). Lower panel shows the fraction of volume generated by bots. Shaded areas highlight the 1st October 2017, day of the Catalan referendum.
Figure 2. Twitter interactions among humans and bots. (a): Flowchart of human-bot Twitter interactions across the whole time window. 19% of the considered interactions are from bots to humans. (b-d): Bow-tie charts for Replies (b), Retweets (c) and Mentions (d) where edge thickness is normalized against the total volume of Tweets displayed in (a). The thicker edges in (c) indicate that most of the Twitter actions are Retweets. More in detail, Retweets from bots to humans and among humans are the most frequent actions in the analysed dataset.

The sentiment of human-to-human interactions displays marked trends in different phases: (i) a trending positive average sentiment score in the days before September 30 (Fig. 3, HH upper panel); (ii) a sudden drop in sentiment starting from the midnight of October 1 (Fig. 3, HH lower panel) after negative contents start getting reshared; (iii) a peak of negative sentiment on the midday of October 1 and (iv) a later increase in sentiment towards neutrality. These sentiment scores and their related content both indicate that human-to-human interactions are a powerful proxy of the dynamics of underlying real-world social system. Furthermore, the drastic drop of sentiment score from positive to negative among more than 300k human users strongly indicates the presence of polarization in the social system, due either to opposing factions exchanging positive/negative messages or rather to the influence of non-humans.

Identifying user polarization, i.e., users being in favour or against a given event or topic, cannot be performed with sentiment only. We overcome this limitation by exploiting a synergy between the network structure of social actions and their emotional intensities, with the aim of identifying stances focused on the voting event in our dataset: Constitutionalists and Independentists to the Catalan referendum. Notice that our network-enhanced stance detection analysis has two major elements of novelty compared to previous approaches, as it not only considers semantic features of messages but also the structure of their exchanges and the nature of their recipients (i.e., bots and humans).

In order to capture pivotal trends in the structure of social interactions we focus on the core of the network of social interactions (see Materials and Methods). It is well documented that people tend to retweet each other as a form of social endorsement. To filter out spurious or infrequent interactions, we consider the available multi-modal information and focus on strong social interactions, i.e. those actions where users perform at least a retweet and either a reply or a mention, during the considered time window. We use strong ties to identify the network core, shown in Fig. 4. To determine the two underlying polarized groups, we look for a partition that minimizes inter-group interactions and use the Fiedler vector approach for an efficient estimation (cf. Methods). The results are shown in

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1Examples: Protest against the Guardia Civil and injured demonstrators (goo.gl/sS4Jyd, sentiment score -0.431), the Police using violence against demonstrators (goo.gl/7ZrvVz, sentiment score -0.2687 and goo.gl/9sBABV, sentiment score -0.2856).
Figure 3. Sentiment evolution before, during and after the Catalan referendum. Average sentiment scores for Retweets (full color) and Mentions (lighter colors) over time for human-to-human (HH), human-to-bot (HB), bot-to-human (BH), bot-to-bot (BB). The grey box in the above plots highlights the day before the Catalonia ballot. While bot-to-bot and human-to-bot display no clear trend over time, human interactions display a positive pattern of sentiments until September 30, after which a drop in sentiment up to negative values appears in human-to-human and bot-to-human interactions. In the lower-right sub-panel, negative tweets are generated around 1:00 AM of October 1 but they start spreading only in the morning, after 7:00 AM. Positive tweets start spreading after noon.

Fig. 4(A). Each group includes about 6300 users, with 18% (12%) of them being bots in Group 1 (Group 2). Within both groups, human-to-human interactions are the most frequent ones, followed by bot-to-human, see Fig. 4(B). Remarkably, humans in Group 1 direct towards bots almost 100 times more social interactions than in Group 2, suggesting a larger influence of bots on the social dynamics in Group 1 rather than in Group 2. Furthermore, bot-bot interactions across the two groups are absent, with bots mostly interacting with humans.

To understand the importance of humans and bot in this network, we calculate Google’s PageRank, a widely used measure of user’s importance in online networks. On average, we find that humans are 1.8 times more central than bots, highlighting that the latter tend to act from the periphery of the social system. Interestingly, despite their peripheral position, bots target their interactions strategically, mostly directing their activity towards human hubs, playing an influential role in the system. If we define the indegree of a user as the number of its incoming interactions, then the indegree of humans with respect to interactions incoming only from bots correlates positively with the indegree with respect to interactions incoming only from humans (Kendall Tau $\kappa \approx 0.62$, p-value $< 10^{-4}$), indicating that bots tend to target their interactions mainly with the most connected humans. Analogously, also humans tend to interact mainly with the most connected bots (Kendall Tau $\kappa \approx 0.75$, p-value $< 10^{-4}$). To verify if these effects are genuine, we have performed the same analysis on randomized realizations of the network while preserving the empirical degree distribution. In this test, the observed correlations are no more present, providing significant evidence for a strategic targeting of social interactions. Since hubs in online social networks like Twitter characterize broadcasters and influencers, the above results strongly indicate that bots interacting with human
Figure 4. Network of Twitter interactions. (a): Visualization of the network among users accurately classified with respect to faction and botness. Nodes indicate users and links encode their social interactions (Retweet and Reply or Mention). Top: sub-networks corresponding to the factions consisting of humans. Bottom: sub-networks corresponding to factions consisting of bots. Colors encode interactions started by humans (blue) or bots (red). (b): Total traffic of Twitter interactions among humans and bots. Thicker edges indicate higher traffic volume. (b): Median sentiments of Twitter interactions among factions. Interactions with average negative (positive) sentiment are in dark red (green). Black corresponds to interactions on average compatible with neutrality. Distributions of sentiments are tested against neutrality (i.e. 0 sentiment score) with a sign test at a 95% confidence level.
hubs can influence the social dynamics of both groups, while remaining in the periphery of the microblogging social system.

In order to harness the emotional structure of the links in the network core, we perform a sentiment analysis of the interactions among humans and bots in the two groups, see Fig. 4(C) and Materials and Methods. The resulting atlas of emotional interactions indicates that the average sentiments of human-to-human and bot-to-human interactions are negative within Group 1 and positive within Group 2. This substantial difference in sentiment suggests that the two identified groups endorse their exchanged messages in a different way. In fact, Group 1 preferentially endorses negative content. To characterize the semantic nature of this content (e.g. aggressive, pessimistic, etc.) we build and analyze networks of hashtag co-occurrences (see Materials and Methods), providing a proxy of users’ mindset, i.e. the way users perceive and associate concepts.\textsuperscript{30–32}

A consistency analysis indicates that the two groups post messages about a common set of 4132 hashtags but associate the corresponding concepts in different ways. Figure 5 shows how the same hashtags co-occur differently in Group 1 and Group 2. Capitalizing on this finding, we focus on those specific concepts that are most important for one group but most peripheral in the other one. We quantify the importance of concepts by identifying the hashtags with highest degree, strength and closeness centrality – characterizing the number of different associations, the total frequency of co-occurrences and how closely hashtags are associated, respectively.\textsuperscript{30,33–36}

![Figure 5. Hashtag ecosystem reveals group identity. Hashtags are coupled together if they appear simultaneously in a message, building a network of concepts. Analyzing the hashtag networks obtained from each group, we identify the hashtags which are ranked (A) similarly and (B) very differently in the two groups, to visualize the corresponding neighboring concepts. In (A), low-ranked hashtags coexist in both groups and do not allow to identify the underlying ideology of each group. In (B) top-ranked hashtag that exist only in Group 1 are strongly related to concepts of freedom, independence, fight, shame against the Spanish government, dictatorship and blame against police violence, providing evidence that Group 1 consists of Catalan Independentists. Remarkably, concepts related to “sonunesbesties” (tr. “they are beasts”) – highlighted in (B) – are posted by bots only, whereas the other hashtag networks have contributions by both humans and bots.]
In Group 1, concepts of “freedom” and “independence” are dramatically associated with “fight”, “shame” against the Spanish government, “dictatorship” and blame against “police violence”. In Group 2, these associations are missing, providing strong quantitative evidence that Group 1 consists of Independentists. To test the way bots influence Independentists, we further distinguish between associations coming from bots and humans. Negative associations for the content of Group 1 comes exclusively from bots interactions, highlighting that bots act on humans by bolstering instability and hatred-driven content.

Discussion

Through the synergy of cutting-edge techniques in bot detection, multi-language sentiment analysis, network partitioning and semantic network analysis we find strong evidence of two opposing factions on an online social media platform during a large-scale voting event. We provide quantitative findings that the captured online trends in the dataset mirror meaningful events in the real world concerning the voting timeline. Harnessing the structure and the semantic content of social actions within a large-scale dataset, we identify factions as groups of people having opposite stances during the Catalan referendum of October 1 2017, i.e. Independentists and Constitutionalists.

Our results demonstrate that bots sustain each faction from the periphery of the online social network structure by mainly targeting human influencers. This finding is further corroborated by showing that bots tend to target human Independentists with messages evoking negative sentiments and associating hashtags with negative connotations. Importantly, we show that bots provide semantic associations, in messages directed to the Independentists, that inspire fight, violence, shame against the government and the police.

While software-controlled agents might be beneficial to online networked systems, e.g. by improving the collective performance of human groups, their improper use can have dramatic effects. Our findings provide quantitative evidence that bots might not only influence information in social media systems, but rather provide a dangerous contribution in bolstering diffusion of violence from online platforms to the real world. This concerning trend, coupled with the ability to control time-varying networks such as online social systems, further motivates the crucial need for the development of quantitative techniques like the one proposed here for unmasking the social manipulation enacted by bots in socio-technical systems.

Materials and Methods

Data collection

By following a consolidated strategy, we manually selected a set of hashtags and keywords to collect messages (tweets) posted to a microblogging platform (Twitter). The list contains various general Catalan issue-related terms: #Catalunya, #Catalonia, #Catalogna, #1Oct, #votarem, #referendum, #1O.

We monitored the Twitter stream and collected data by using the Twitter Search API, from September 22, 2017 to past the election day, on October 3, 2017: this allowed us to almost uninterruptedly collect all tweets containing any of the search terms. The data collection infrastructure ran inside FBK servers to ensure resilience and scalability. We chose to use the Twitter Search API (https://dev.twitter.com/rest/public/search) to make sure that we obtained all tweets that contain the search terms of interest posted during the data collection period, rather than a sample of unfiltered tweets: this precaution avoids incurring in known sampling issues related to collecting data using the Twitter Stream API (https://dev.twitter.com/streaming/overview) rather than the Twitter Search API.

This procedure yielded a large dataset containing approximately 3.6 million unique tweets, posted by 523 thousand unique users.

Building the Twitter network

People from the same faction tend to retweet each other as a form of social endorsement, as documented in the relevant literature, while cross-faction retweets are less likely. Considering only retweets would pose the question of how to get rid of spurious or infrequent interactions, possibly by identifying a given retweet threshold. Identifying a threshold would be problematic, as the final network structure might greatly vary with small perturbations on the considered threshold, as it can happen on co-occurrence networks. We address this issue by considering strong
social interactions: Twitter interactions were users perform at least one retweet but also at least another type of Twitter interaction, be it a mention or a reply during the considered time window. Notice that mentions and replies do not express the same social endorsement of retweets but they can help in identifying the core interactions in the considered social system.

The resulting Twitter Core Network (TCN) included 12 thousands users and 16 thousands directed strong social interactions. Notice that the TCN aggregates together interactions happening over the whole considered time window. However, the frequency of Twitter interactions strongly correlates with the indegree on the TCN (Kendall Tau $\tau = 0.81$), thus indicating that the aggregated network topology is a valid proxy for investigating patterns of Twitter interactions.

**PageRank centrality of humans and bots**

In the Twitter Core Network we used the average PageRank centrality$^{28}$ as a measure of centrality of human and bot users quantifying how important individual nodes are for information flow in a given network topology. We computed PageRank centrality in Mathematica, which provides normalised values indicating the probability of a random walker to visit a given node. We used 0.85 as dampening factor, as in Google’s Page Rank. On average human users displayed a PageRank of $8.1 \cdot 10^{-4}$ while bots displayed an average PageRank of $4.6 \cdot 10^{-4}$. Hence, on average human users tended to be almost 1.8 times more central than bots in terms of information flow on the Twitter Core Network.

**Newtwork partitioning**

In order to detect the two groups in the Twitter Core Network we used the Fiedler vector, a widely used heuristic in spectral graph partitioning$^{40}$. The Fiedler vector of a given graph is the eigenvector corresponding to the smallest non-zero eigenvalue (i.e. the algebraic connectivity) of the Laplacian matrix $L = D - A$ of the graph represented by the adjacency matrix $A$ and by the diagonal matrix $D$. Negative and positive entries in the Fiedler vector partition the corresponding network nodes in two sets. One can prove analytical that this heuristic for graph partitioning is a valid approximation for solving the minimum cut problem on general graphs, i.e. partitioning nodes in two groups so that the number of edges across groups is minimized.

We applied spectral clustering on the undirected version of the TCN and then built randomized partitions. Through direct sampling, we show that the modularity of the Fiedler’s partitioning is optimal compared to randomizations even on the original TCN (see SI).

**Building the hashtag co-occurrence network**

Hashtags are strings of characters starting with the hash ($) character and representing the main semantic content of a tweet$^{41}$. The literal meaning of hashtags is already considered in the sentiment analysis. Co-occurrence of different hashtags can provide important additional information on the semantic content of tweets, as it was recently shown$^{42}$. Analogously to other association networks in psycholinguistics$^{31,32}$, networks of hashtag co-occurrences represent a powerful proxy of the cognitive profile of users, i.e. the way concepts are perceived and associated by users.

From our Twitter dataset, we build semantic networks of hashtag co-occurrence where nodes represent hashtags and they are linked when co-occurring in at least one tweet. This network definition is in agreement with previous large-scale studies$^{42}$. We build one network of hashtag co-occurrences per group. Group 1 (Group 2) co-occurrence network includes 8451 (7107) unique hashtags and 29694 (23644) links. The two networks overlap for 4132 hashtags, on which the consistency analysis is performed (see SI).

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