Coordinated Behavior on Social Media in 2019 UK General Election

Leonardo Nizzoli,12∗ Serena Tardelli,12∗† Marco Avvenuti,2 Stefano Cresci,1 Maurizio Tesconi1
1Institute of Informatics and Telematics, Pisa, Italy
2Dept. of Information Engineering, University of Pisa, Italy

Abstract
Coordinated online behaviors are an important part of information and influence operations, as they allow a more effective disinformation’s spread. Most studies on coordinated behaviors involved manual investigations and the few existing computational approaches make bold assumptions or oversimplify the problem to make it tractable.

Here, we propose a new network-based framework for uncovering and studying coordinated behaviors on social media. Our proposal extends existing systems and goes beyond limiting binary classifications of coordinated and uncoordinated behaviors. It allows to uncover different patterns of coordination and to estimate the degree of coordination that characterizes different communities. We apply our framework to a dataset collected during the 2019 UK General Election, detecting and characterizing coordinated communities that participated in the electoral debate. Our work conveys both theoretical and practical implications, and provides more nuanced and fine-grained results for studying online manipulation.

Introduction
In recent years, information or influence operations (IOs) have been frequently carried out on social media with the aim to mislead and to manipulate. IOs can take different shapes, target different individuals, online crowds or communities, and have diverse goals (Starbird, Arif, and Wilson 2019). Among the strategic tools used by perpetrators are fake news, propaganda, hateful speech, astroturfing, colluding users (e.g., paid trolls), and automation (e.g., social bots). Since the Donald Trump election and the Brexit referendum in 2016, each of these tools became the focus of extensive scientific attention. The ongoing endeavors have already led to a huge body of work on these issues and to a plethora of different solutions for solving them. Despite the efforts, the efficacy of the proposed solutions is debated, and IOs still appear to pose a serious threat to our democracies and societies (Barrett 2019).

Meanwhile, groundbreaking advances in specific areas of computing are causing profound changes to the online information landscape. Advances in artificial intelligence brought to the rise of deepfakes – synthetic media where the original source has been modified via deep learning techniques. Deepfakes allow crafting arbitrary texts that resemble the writing style of a target person, as well as to produce audio and video samples where a target person’s face and voice are used to make it look like the person said something that he or she actually never said. Unsurprisingly, these powerful techniques have already been used for creating fake news (Zellers et al. 2019), fake profile pictures for deceitful accounts1, and to impersonate famous characters and politicians on video. With deepfakes, detecting disinformation based on an article’s content, or detecting fake personas by analyzing their posts and pictures might not be feasible anymore (Boneh et al. 2019).

However, each IO must spread to and “infect” a large number of users for it to be successful, independently on its aims and the tools used to deceive. This often mandates large and coordinated social media efforts in order for the campaign to obtain a significant outreach, to exert influence, and thus to have an impact. In light of this consideration, since 2018 all major platforms showed great interest in studying coordinated inauthentic behavior (CIB)2. Despite often appearing together, coordination and inauthenticity are two distinct concepts. For example, activists and other grassroots initiatives typically feature coordinated but authentic behaviors. Conversely, one might maneuver a single fake account with the intent to mislead, thus exhibiting inauthentic but uncoordinated behavior. The majority of existing efforts for studying CIB involved a great deal of manual investigations and computational approaches are still few and far between. Among the challenges are the ambiguity and fuzziness of CIB itself: What exactly is a coordinated behavior? What is an inauthentic behavior? How many organized accounts are needed for a (meaningful) coordinated behavior to surface? Unfortunately, there are no agreed-upon answers

1https://www.wired.com/story/facebook-removes-accounts-ai-generated-photos/
2https://about.fb.com/news/2018/12/inside-feed-coordinated-inauthentic-behavior/
to these questions and, thus, operationalizing these concepts and developing computational methods for their analysis, represent open challenges. In particular, no successful attempt has been reported so far for automatically distinguishing between authentic and inauthentic coordination (Vargas, Emami, and Traynor 2020). Instead, a few interesting works have been recently proposed for the simpler task of detecting and studying coordinated behaviors, disregarding intent and authenticity. In the present work, we also focus on this task. To this end, the few existing techniques make bold assumptions or oversimplifications, such as using fixed thresholds to obtain a binary distinction between coordinated and uncoordinated behaviors (Pacheco et al. 2020). Coordination however is a complex, non-binary concept, similarly to automation (Cresci 2020) and inauthenticity (Starbird 2019).

Here, we go beyond existing approaches for studying coordinated behaviors by proposing a new network-based framework that relaxes previous assumptions, and that extends and generalizes existing works. Within our framework, coordination is defined as an unexpected, suspicious or exceptional similarity between any number of users. We do not provide a binary classification of coordinated vs uncoordinated users, but instead we estimate the extent of coordination. In practice, our framework builds a user-similarity network. Then, we obtain the multi-scale backbone of the network by retaining only statistically-relevant links and nodes. Next, we iteratively perform community detection on subsets of increasingly coordinated users. Our approach does not require fixed thresholds for defining coordination. Rather, it allows to study the whole extent of coordination found in the data, from weakly-coordinated users to strongly-coordinated ones. Finally, we experiment with a set of network measures for studying and characterizing coordinated communities. We test our framework on Twitter in the context of the 2019 UK General Election (GE), showing the usefulness of our approach.

Our main contributions are as follows:

- We move beyond existing approaches for detecting coordination by proposing a more nuanced, non-binary, network-based framework.
- We uncover coordinated communities that operated during the 2019 UK GE, and we discuss them in light of their role in electoral debate.
- We find and discuss different patterns of coordination, that emerge from the behavior of different communities. This is made possible by our non-binary approach to coordination, and it demonstrates the power of our framework.
- We empirically demonstrate that coordination and automation are orthogonal concepts. Thus, our framework can complement long-studied techniques for detecting automation, manipulation and inauthenticity.
- We create and publicly share a large dataset for the 2019 UK GE, comprising 11M tweets shared by 1.2M users.

Related Work

Due to the many existing challenges, to date only few works have attempted to develop computational means to detect and characterize coordinated online behaviors. Among them, the most similar approach to our present work was proposed in (Pacheco et al. 2020; Pacheco, Flammini, and Menczer 2020), which we extend and generalize. Pacheco et al. propose to extract behavioral traces of online activity and use them to build a bipartite network. Then, they project this network onto the accounts, obtaining a user-similarity network. Next, they filter low-weight edges by applying a restrictive, arbitrary similarity threshold. The remaining connected nodes are so similar to be deemed coordinated. Finally, they compute and analyze the connected components of the filtered network, and each component is considered as a distinct group of coordinated users. We have several differences with respect to (Pacheco et al. 2020; Pacheco, Flammini, and Menczer 2020), the most impactful one being that we do not apply a similarity-based filter. Their choice results in a sharp definition of coordinated users, which are subsequently investigated, while uncoordinated ones are ignored. However, this sharp distinction is an artifact introduced to simplify the analysis. In our framework we do not apply a similarity-based filter, but we iteratively perform community detection at different levels of coordination. In this way, we are able to study the whole extent of coordination among the accounts, uncovering different patterns and dynamics of coordination that would not be visible with a simpler approach.

The work discussed in (Giglietto et al. 2020b; 2020a) focuses on a specific instance of CIB. Authors propose a 2-step process for the detection of coordinated link sharing behavior, and they test it on a Facebook dataset. In the first step, they detect groups of entities that all shared a given link, almost at the same time. In the second step, the coordinated networks are identified by connecting only those entities that repeatedly shared the same links. Inauthenticity is then manually assessed by analyzing shared domains and stories. The proposed algorithm requires two parameters: one for defining near-simultaneous link sharing, and the other for defining repetitive link sharing. Similarly to (Pacheco et al. 2020), these parameters represent fixed similarity thresholds used for filtering. Also Assenmacher et al. propose a 2-step framework for detecting IOs (Assenmacher et al. 2020b; 2020a). Initially, they apply unsupervised stream clustering and trend detection techniques to social media streams of text, identifying groups of similar users. Then, they propose to apply standard offline analyses, including manual inspection via visualizations and dashboards, for assessing inauthenticity. Another study leverages a ground-truth of coordinated accounts involved in a disinformation campaign to identify network measures for detecting IOs (Keller et al. 2020). Authors conclude that the traces left by coordination among astroturfing agents are more informative than the typical individual account characteristics used for other related tasks (e.g., social bot detection). In addition, they also develop an astroturfing detection methodology based on the previously identified coordination patterns. In (Fazil and Abulaish 2020) is proposed a multi-attributed graph-based approach for detecting CIB in Twitter. Authors model each user with a 6-dimensional feature vector, compute pairwise similarities obtaining a user-similarity graph and finally ap-
ply Markov clustering, labeling the resulting clusters as inauthentic coordinated groups. In (Fazil and Abulaish 2020), high coordination automatically implies inauthenticity.

Instead of proposing a new technique, the study in (Vargas, Emami, and Traynor 2020) focuses on determining the usefulness and reliability of previously-proposed network-based metrics of coordination. Several authors, including some of those previously mentioned, report positive results for the detection of inauthentic behavior via the analysis of suspicious coordination (Ratkiewicz et al. 2011; Keller et al. 2020; Fazil and Abulaish 2020). However, the results of (Vargas, Emami, and Traynor 2020) show that, when evaluated in non-trivial real-world scenarios, such previously proposed approaches are unable to distinguish between authentic (e.g., activists, fandoms) and inauthentic coordination. These results confirm that coordination and inauthenticity are different concepts, and that high coordination does not necessarily imply inauthenticity.

**Dataset**

By leveraging Twitter Streaming APIs, we collected a large dataset of tweets related to the 2019 UK GE. Our data collection covered one month prior to election day, from 12 Nov to 12 Dec 2019, included. During that period, we collected each tweet that contained at least one hashtag from a list we created. Our list contains the most popular hashtags, both those used by the two main parties, as well as the neutral ones. Table 1 lists all hashtags used at this step, the corresponding political leaning (N: neutral, L: labour, C: Conservative), and the number of tweets, retweets, and replies we collected. The `tweets` column only counts quoted retweets if the quote text contains one of the hashtags in Table 1. The remaining quoted retweets are still included in our dataset, but they are not counted in Table 1. In addition to the aforementioned hashtags-based collection, we also collected all tweets published by the official accounts of the 2 parties and their leaders, together with all the interactions (i.e., retweets and replies) they received. Table 2 shows the accounts and the collected data. Our final dataset for this study is the combination of data shown in Tables 1, 2 and 3,642 2,521,499 1,046,063

| hashtag                | leaning | users         | tweets          |
|------------------------|---------|---------------|-----------------|
| #GE2019                | N       | 436,356       | 2,640,966       |
| #GeneralElection19     | N       | 104,616       | 274,095         |
| #GeneralElection2019   | N       | 240,712       | 783,805         |
| #VoteLabour            | L       | 201,774       | 917,936         |
| #VoteLabour2019        | L       | 55,703        | 265,899         |
| #ForTheMany            | L       | 22,966        | 40,116          |
| #ForTheManyNotTheFew   | L       | 8,170         | 13,381          |
| #RealChange            | L       | 78,285        | 2,742,54        |
| #VoteConservative      | C       | 52,642        | 238,647         |
| #VoteConservative2019  | C       | 13,513        | 34,195          |
| #BackBoris             | C       | 36,725        | 157,434         |
| #GetBrexitDone         | C       | 46,429        | 168,911         |
| total                  |         | 668,312       | 4,983,499       |

Table 1: Statistics about data collected via hashtags.

| account                 | production | interactions |
|-------------------------|------------|--------------|
| @jeremycorbyn           | L          | 788          | 1,759,823     | 414,158 |
| @UKLabour               | L          | 1,002        | 325,219       | 79,932 |
| @BorisJohnson           | C          | 454          | 284,544       | 382,237 |
| @Conservatives          | C          | 1,398        | 151,913       | 169,736 |
| total                   |            | 3,642        | 2,521,499     | 1,046,063 |

Table 2: Statistics about data collected from accounts.

2. **Select similarity measure.** Both in our framework and in previous work (Pacheco et al. 2020), unexpected similarity between users is used as a proxy for coordination. Similarity can be computed in many different ways. Hence, this step deals with the selection of a similarity measure. Examples of valid options are the cosine similarity between user feature vectors encoding account profile characteristics, as done in (Fazil and Abulaish 2020), or the Jaccard similarity between the sets of hashtags used by each user, or between the sets of followings or retweeted accounts.

3. **Build user similarity network.** In this step we compute pairwise user similarities between all users identified at step 1, by means of the metric selected at step 2. We leverage user similarities to build a weighted undirected user similarity network $G(V_i, V, W)$, that encodes behavioral and interaction patterns between users.

4. **Filter user similarity network.** When studying real-world datasets of large IOs, the network resulting from step 3 can be simply too big to analyze and even to visualize. Hence, a filtering step is needed. Contrarily to previous work, we avoid simple filtering strategies based on fixed edge weight thresholds. We recall that edge weights encode similarity, and to a certain extent coordination, between users. As such, applying a weight threshold $t$ and discarding all edges $e \in E$ whose weight $w(e) < t$ would mean to arbitrarily perform a binary distinction between coordinated behaviors ($w(e) \geq t$) and uncoordinated behaviors. For this reason, we instead employ Markov clustering, labeling the resulting clusters as inauthentic coordinated groups. In (Fazil and Abulaish 2020), high coordination automatically implies inauthenticity.

In this section, we describe our network-based framework for detecting coordinated behaviors. Our detailed methodology is composed of the following 6 main steps, summarized in Figure 1:

1. **Select starting set of users.** The first step concerns the selection of those users to investigate. For instance, given a large dataset, one might want to investigate most-active users, such as superproducers or superspreaders, or all users that tweeted with a particular hashtag, or even all followers of a given prominent user. Whatever the selection criterion, this step returns a list of users to analyze.

2. **Select similarity measure.** Both in our framework and in previous work (Pacheco et al. 2020), unexpected similarity between users is used as a proxy for coordination. Similarity can be computed in many different ways. Hence, this step deals with the selection of a similarity measure. Examples of valid options are the cosine similarity between user feature vectors encoding account profile characteristics, as done in (Fazil and Abulaish 2020), or the Jaccard similarity between the sets of hashtags used by each user, or between the sets of followings or retweeted accounts.

3. **Build user similarity network.** In this step we compute pairwise user similarities between all users identified at step 1, by means of the metric selected at step 2. We leverage user similarities to build a weighted undirected user similarity network $G(V_i, V, W)$, that encodes behavioral and interaction patterns between users.

4. **Filter user similarity network.** When studying real-world datasets of large IOs, the network resulting from step 3 can be simply too big to analyze and even to visualize. Hence, a filtering step is needed. Contrarily to previous work, we avoid simple filtering strategies based on fixed edge weight thresholds. We recall that edge weights encode similarity, and to a certain extent coordination, between users. As such, applying a weight threshold $t$ and discarding all edges $e \in E$ whose weight $w(e) < t$ would mean to arbitrarily perform a binary distinction between coordinated behaviors ($w(e) \geq t$) and uncoordinated behaviors ($w(e) < t$) and uncoordinated behaviors.
Perform coordination-aware community detection.

The detection of coordinated groups of users is often achieved via clustering and community detection. Given the crude approach to filtering adopted in previous work, the filtered user similarity network was considered to only contain highly-coordinated users. A single run of a community detection algorithm was thus enough to highlight coordinated networks. In our case, however, the filtered user similarity network still features diverse levels of coordination. As such, we need a more nuanced approach for surfacing coordinated behaviors. Our approach is based on an iterative process that takes into account increasing levels of coordination, as shown in Algorithm 1. We begin by performing community detection on the filtered network resulting from step 4, identifying the set $C_0$ of communities. Then, at each iteration we apply an increasingly restrictive similarity threshold $t_i$ to edge weights, thus removing certain edges and disconnected nodes, and we repeat community detection on this subnetwork $G^{c,v}_i$. At each iteration, the community detection algorithm is initialized with the set of communities $C_{i-1}$ found at the previous iteration. This guarantees that the starting communities are kept, to a certain extent, throughout the whole process. As a result of the “moving” threshold, we are able to study how the structure and the properties of coordinated communities change across the whole spectrum of coordination.

6. Study coordinated communities. To study the structure of coordinated communities and their patterns of coordination, we employ several network measures. In addition, we put communities into context, and we characterize their content production by applying natural language processing techniques. By leveraging our novel approach to the detection of coordinated communities described at step 5, we are able to obtain results of these analyses as a function of the extent of coordination between users.

The main novelties of our approach with respect to previous work, and particularly to (Pacheco et al. 2020), are steps 4 and 5. In turn, our nuanced coordination detection approach also enables more in-depth analyses at step 6.

### Surfacting coordination in 2019 UK GE

In the following, we describe how we implemented and applied the aforementioned framework to uncover coordinated behaviors on Twitter related to the 2019 UK GE. The content of this section roughly corresponds to steps 1 to 5 of our methodology, while step 6 (i.e., analysis of coordinated communities) is described in the next section.

**User similarity network.** For our analysis, we posed our attention on the activity of *superspreaders* – coarsely de-
defined as the most influential spreaders of information, including mis- and disinformation, in online social media (Pei et al. 2014). Here, we defined superspreaders as the top 1% of users that shared more retweets. This resulted in selecting for our analysis 10,782 users. Despite representing only the 1% of all users in the online electoral debate, superspreaders shared the 39% of all tweets and the 44.2% of retweets. Thus, by focusing on them, we investigated the most prolific users and a considerable share of all messages. Next, we characterized each superspreader with a TF-IDF weighted vector of its retweeted tweet IDs. In other words, each user is modeled according to the tweets she retweeted. The TF-IDF weight allows to reduce the relevance of highly popular tweets in our dataset, and to emphasize similarities that are due to retweets of unpopular tweets – a much more suspicious behavior (Mazza et al. 2019; Pacheco et al. 2020). Then, we computed user similarities as the cosine similarity of user vectors. Before studying the network, we applied the technique proposed in (Serrano, Boguñá, and Vespignani 2009) to retain only statistically-relevant edges, thus obtaining the multiscale backbone of our network, which we exploited for the remaining analyses. The resulting filtered user similarity network contains 276,775 edges and is shown in Figure 2. In addition, Figure 3 shows the distribution of edge weights in the filtered network. The filtering step preserved the rich, multiscale nature of the network.

Political leaning. In Figure 2, nodes are colored based on their political leaning, as inferred from the hashtags that they used. In particular, we employed a label propagation algorithm for assigning a polarity score to each hashtag in our dataset. The score for a given hashtag is inferred from its co-occurrences with seeds of known polarity. We used the 13 hashtags in Table 1 as the seeds for the label propagation.

Finally, a user’s polarity is computed as the term-frequency weighted average of the polarities of the hashtags used by that user.

Network interpretation. As shown in Figure 2, the user similarity network presents a visible structure characterized by several large communities and a few smaller ones. With respect to political polarization, all users can be grouped into 3 main classes: labourists (red-colored), conservatives (blue-colored), and neutral users (yellow-colored). We performed a first sanity check by comparing structural properties of the network with political ones. In particular, colors in the network appear to be clearly separated. In other words, communities derived from network structure appear to be extremely politically homogeneous, and we do not have any cluster that contains users with markedly different colors. Moving forward, the conservative cluster appears to be sharply separated from the rest of the network, while the labourist and neutral clusters are more intertwined with one another. This interesting property of our network closely resembles the political landscape in the UK ahead of the 2019 GE. Indeed, one of the main topics of the debate was Brexit, which lead to a strong polarization between conservatives and all other parties (Schumacher 2019). In addition, the first-past-the-post UK voting system also motivated anti-Tory electors to converge on the candidate of the party having the highest chances to defeat the conservative’s one in each constituency – a strategy dubbed tactical voting.³ Our rich and informative network clearly embeds and conveys these nuances.

Coordinated communities. Building on these promising preliminary results, we are now interested in a fine-grained analysis of the communities found in the user similarity network. In (Pacheco et al. 2020), this step was carried out by analyzing the connected components of their similarity networks. As anticipated, in order to be reasonably sure about coordination, Pacheco et al. enforced very restrictive edge weight filters, so as to only retain edges with very large weights (e.g., users whose cosine similarity ≥ 0.9, on a 0 to 1 scale). As a consequence of this aggressive filtering, the networks were broken down into several disconnected communities.
components, hence the analysis of connected components. Instead, in our study the user similarity network features diverse degrees of similarity and coordination, as testified by the distribution of edge weights in Figure 3. Therefore, we carried out this analysis by applying community detection, and in particular the well-known Louvain algorithm (Blondel et al. 2008). This step in our analysis corresponds to line 1 of Algorithm 1. Detected communities (resolution = 1.5, minimum size at $t_0 = 20$) are outlined in Figure 4 and are briefly described in the following. Users exhibiting higher coordination with other users are assigned darker shades of color. For each community we also computed its TF-IDF weighted hashtag cloud, as shown in Figure 5, so as to highlight the debated topics.

1. **CON**: The community of conservative users that was clearly visible in Figure 2 was also detected by our community detection algorithm. It includes all major conservative users (e.g., @BorisJohnson and @Conservatives), and it is characterized by a majority of hashtags supporting the conservative party (voteconservative), its leader (backboris) and Brexit (getbrexitdone).

2. **LAB**: Similarly, also the dense group of labour users that we highlighted in Figure 2 has been identified as a distinct community of labourists. These users are characterized by hashtags supporting the party (votelabour), their leader (jc4pm), and traditional labour flags like healthcare (saveournhs) and climate change (climatedebate). Notably, the absence of Brexit-related keywords seems to confirm the alleged ambiguity of Jeremy Corbyn’s campaign on this topic.

3. **TVT**: The largest group of neutral users in Figure 2, tightly related to LAB users, was assigned to this community. These users debated topics related to liberal democrats (votelibdem), anti-Tory (liarjohnson), anti-Brexit (stopbrexit) and to the campaigns promoting tactical voting (votetactically, tacticalvote).

4. **SNP**: The remaining share of neutral users was assigned to this community, related to the Scottish National Party (SNP). The main hashtags used by members of this com-

---

6https://www.telegraph.co.uk/politics/2019/09/03/labours-policy-constructive-ambiguity-brexit-running-road/
munity support the party (votesnp) and ask for a new referendum for the independence from the UK (indyref2020). The traditional hostility of SNP against Brexit and Tories (Jackson et al. 2019) also explains the proximity of this cluster to the LAB and TVT ones.

5. **B60**: This small cluster identifies activists involved in the so-called *Backto60* initiative (backto60, 50swomen), which represents 4 million women born in the 1950s that are negatively affected by state pension age equalisation. Their instances have been addressed in the Labour manifesto, while Conservatives denied their support to the initiative despite Boris Johnson’s promises. The political connections of *Backto60* activists are well reflected in our network, as represented by the B60 cluster being linked to both the LAB and TVT clusters.

6. **ASE**: The tightly connected users in this cluster are all strongly leaning towards conservatives, as also clearly visible by their connections. However, their activities are mainly devoted towards attacking the Labour party and its leader, rather than to support the Tories. As confirmed from Figure 5f, some of the most relevant hashtags of this cluster are against labours (labourlies, nevercorbyn) and, in particular, are about the antisemitism allegations (labourantisemitism, votelabourvoteracism) that held the stage during the entire electoral campaign.

7. **LCH**: Finally, the last cluster is again composed of activists, similarly to the B60 cluster. This time activists were protesting against “loan charge”, a tax charge introduced to contrast a form of tax avoidance based on disguised remunerations. Anti-loan charge campaigners claim that it is a retrospective taxation that, due to the abnormally long period of application, caused involved people to return unsustainable amounts, also inducing several suicides.

The analysis of the communities detected in our user similarity network allowed to identify both large clusters, each corresponding to one of the major political forces involved in the election, as well as much smaller ones. The small clusters are related to highly organized activists (B60, LCH) and political campaigns (ASE). The previous analysis provided some first results into the presence of coordinated behaviors in the 2019 UK GE and, in particular, it allowed to uncover groups that featured at least a small degree of coordination. However, since our network embeds different degrees of coordination among its users, it still does not provide results towards the extent of such coordination and the patterns of coordination that characterize such groups. These crucial points are tackled in the next section.

---

7https://pensionsage.com/pa/Backto60-granted-leave-to-appeal.php

8https://www.thetimes.co.uk/article/revealed-the-depth-of-labour-anti-semitism-bb57h9pdz

9https://www.gov.uk/government/publications/disguised-remuneration-independent-loan-charge-review/guidance

---

**Analysis of coordinated behaviors**

In previous work, once detected, coordinated communities were visualized and manually inspected (Pacheco et al. 2020). In other words, existing pipelines for automatically studying coordinated behaviors stop at the detection of coordinated communities (step 5 in our framework), without providing insights into the patterns of coordination, which are left to human analysts. Contrarily, our multifaceted analysis allows our framework to produce results for estimating the extent and for investigating the patterns of coordination.

**Visual inspection.** Regarding the extent of coordination, a visual inspection of Figure 4 already reveals interesting insights. For instance, large communities such as LAB and CON are simultaneously characterized by a multitude of weakly-coordinated users (light-colored) and by a smaller core of strongly-coordinated ones (dark-colored). Instead, other communities only feature either weakly- or strongly-coordinated behaviors. For example, the SNP and TVT communities appear to be characterized by mildly-coordinated behaviors, with only a few strongly-coordinated users that are spread out in the network and not clustered together. On the opposite, the small communities of activists (B60, LCH and ASE) appear to be almost completely characterized by strongly-coordinated behaviors, as represented by small, compact, and dark-colored clusters.

**Network measures.** In the following, we formalize these intuitions, and we propose a set of network measures for quantifying them. By applying steps 5 and 6 of our framework, we are able to produce these results automatically for each uncovered coordinated community. In particular, the *while*-loop in Algorithm 1 repeatedly performs community detection on subnetworks obtained by iteratively removing edges (and the resulting disconnected nodes) based on their weight. We begin by removing weak edges, and we proceed with stronger ones until we have removed all edges and nodes in the network. Since edge weight is a proxy for coordination, each subnetwork that we obtain with this process features a different degree of coordination. By studying the evolution of coordinated communities throughout this simulation, we are able to characterize their patterns of coordination. In the following, we present results for each coordinated community in terms of standard network measures, as a function of coordination. Our measure of coordination is the percentile rank of edge weights in the filtered network –
that is, the percentile rank of the distribution shown in Figure 3. Percentile rank is the proportion of values in a distribution that a particular value is \( \geq \) to. For example, a given result measured for a degree of coordination \( = 0.9 \), means that the result was obtained from a network that includes only the top-10\% of strongest edges.

The first aspect we consider is the size of coordinated communities. Figure 6 shows how the number and the percentage of nodes in each coordinated community changes, as a function of coordination. This analysis quantifies the observations we previously derived by visual inspection. It clearly shows that some communities are characterized by stronger coordination than others. This is reflected by the plateaux that strongly-coordinated communities, such as LCH and ASE, exhibit until some large values of coordination. On the contrary, communities such as B60, LAB and TVT exhibit a marked decreasing trend throughout all the spectrum of coordination. This analysis is also useful towards estimating a characteristic value of coordination for a given community. For instance, by using the elbow method, the LCH community could be described by a coordination value \( \simeq 0.9 \), since the vast majority of its members feature a degree of coordination \( \geq \) than that. Similarly, the ASE community could be characterized by a coordination value \( \simeq 0.55 \). These results also imply that, in general, each community has its own characteristic value of coordination, and that methods that applying the same arbitrary fixed threshold to all communities risk neglecting and erasing relevant patterns.

Next, we evaluate structural properties of coordinated communities. Density is a measure of the fraction of the actual connections between nodes in a network, with respect to all possible connections. This aspect is helpful towards assessing whether the most coordinated users are all linked to one another, or whether they act in different regions of their community. Results shown in Figure 7a highlight interesting patterns. First of all, some communities are overall more clustered than others, such as ASE and LCH. This is another indicator of strongly-coordinated behaviors. Then, we have rising and decreasing density trends. In detail, SNP exhibits a negative correlation between density and coordination, implying that the most coordinated users in that community are likely not colluded nor organized between themselves. On the contrary, the most coordinated members of B60 are likely well-organized together, as shown by the density spike observed when coordination \( \geq 0.8 \). Clustering coefficient, shown in Figure 7b, provides similar results with respect to density. In fact, it shows decreasing trends for SNP, LCH and TVT, as well as rising trends for CON and LAB and, to a much greater extent, for B60. Trends in density and clustering coefficient confirm that coordination \( \simeq 0.9 \) appears to be a representative value for LCH.

Finally, we evaluate the assortativity of coordinated networks. Here, assortativity measures the extent to which nodes with high degree are connected to other nodes with high degree, and vice versa. Again, different patterns emerge. In particular, some coordinated communities (e.g., ASE and LAB) are moderately disassortative. This result represents a situation where a few nodes with high degree are connected to many nodes with low degree, realizing a network structure that is similar to a star. In turn, this highlights a pattern of coordination characterized by a few hubs that are supported by many less important nodes – a pattern that was already found to be informative when studying online manipulations (Nizzoli et al. 2020). Conversely, the B60 community appears to be strongly assortative, especially when considering coordination in the region of 0.8. This finding represents a situation where many similar nodes are connected to each other, reinforcing the idea of a clique of coordinated peers. By combining all results shown in Figure 7, the B60 community appears to be well-described by a coordination value \( \simeq 0.8 \).

Themes and narratives. Until now we have only leveraged network measures to characterize coordinated communities. However, their content production can also reveal interesting insights into their preferred narratives. Here, we propose and briefly experiment with a text-based analysis that can be used to investigate the activity of coordinated groups. In particular, we are interested in highlighting the differences in the content produced by the coordinated users in a community, with respect to all other – less coordinated – users of that community. One way to reach our goal

Figure 7: Network measures computed for each coordinated community, as a function of the extent of coordination. By studying the whole extent of coordination among users, we are able to highlight the radically different patterns of coordination that characterize different communities, as highlighted by opposite trends in given network measures.
is by exploiting word shift graphs (Gallagher et al. 2020), which allow comparing two corpora by highlighting those terms that mostly contribute to differentiate them. We apply word shift graphs in our context by selecting all tweets shared by members of a community as the reference corpus, and all tweets shared by strongly-coordinated users in that community as the comparison corpus. Meaningful strongly-coordinated users from a community can be picked by leveraging results of our previous network-based analyses. For instance, the B60 community can be assigned a coordination value $\simeq 0.8$ while LCH can be characterized by coordination $\simeq 0.9$. Thus, in Figure 8 we highlight content production differences between all users in B60 and LCH, with respect to the users in those communities whose coordination $\geq 0.8$ and 0.9, respectively. In figures, words are ranked based on their contribution towards differentiating coordinated and non-coordinated users. Yellow-colored words (right-hand side of each word shift graph) are informative for coordinated users while blue-colored words (left-hand side) are informative for non-coordinated users. The informativeness of the different words towards characterizing coordinated users (i.e., their shift) is computed by means of Shannon entropy (Gallagher et al. 2020). As shown, this analysis reveals that coordinated users embrace much more specific narratives and themes with respect to non-coordinated users. In fact, while both B60 and LCH are characterized by generic labourist topics, coordinated users in those communities fight for 50s women’s rights and against the loan charge tax.

**Use of automation.** As a last experiment on coordinated behavior, we are interested in evaluating the relationship between coordination and use of automation. Detection of automation (e.g., social bots) has been a matter of study for years, and has been one of the most widely used approaches for investigating online deception and manipulation (Cresci 2020). Many bot detection techniques have been proposed (Chavoshi, Hamooni, and Mueen 2016; Varol et al. 2017; Cresci et al. 2018; Mazza et al. 2019), but their effectiveness towards tracking IOs and CIB is still debated\(^{10}\). For these reasons, we compared our assessments on coordination with the automation score provided by Botometer (Yang et al. 2019). We used the maximum of Botometer’s English and universal scores, both provided in the $[0,1]$ range, as our automation score. In addition, we also considered Twitter suspensions as an indicator of possible automation or inauthenticity. Then, similarly to our previous analyses, we reported the mean automation scores and the percentage of suspended users for the different coordinated communities, as a function of coordination. Figure 9 shows the results of this analysis. Automation appears to be almost completely uncorrelated with coordination. Independently of coordination, results do not show meaningful differences between our communities, with the sole exception of LCH for which we measured overall higher automation scores. Other communities are more affected by Twitter suspensions, such as both clusters of conservative users (CON and ASE). Interestingly, we notice a marked downward trend of suspensions for the B60 group, which might indicate an authentic, strongly-coordinated grassroots initiative.

Overall, our results confirm that coordination and automation are two different and orthogonal concepts. On the one hand, this suggests that using automation and bot detection to study CIB might be ineffective and leading to inaccurate results. On the other hand, it motivates to complement existing analyses on IOs with new results that are based on the study of coordinated behaviors.

**Conclusions**

We addressed the problem of uncovering coordinated behaviors in social media. We proposed a new network-based framework and we applied it for studying coordinated behaviors in the 2019 UK General Election (GE). Our work has both theoretical and practical implications.

From the theoretical standpoint of fighting IOs and CIB, our framework goes beyond a binary definition of coordinated vs uncoordinated behaviors, and it allows to investigate the whole spectrum of coordination. We reach this goal via an improved network filtering and a coordination-aware

---

\(^{10}\)https://blog.twitter.com/en_us/topics/company/2020/bot-or-not.html
community detection process. Our nuanced approach allows to uncover different patterns of coordination. We demonstrate that a certain extent of coordination is present in every online community, but that not all coordinated groups are equally interesting. Furthermore, while previous works blindly applied fixed coordination thresholds to whole networks, our approach allows to estimate the degree of coordination that characterizes each different community, opening up more accurate and fine-grained downstream analyses.

From the practical standpoint, we created and shared a Twitter dataset for the 2019 UK GE. Despite smaller numbers, we found that conservatives were overall more coordinated than labourists, and that they also featured a higher degree of automation and Twitter suspensions. However, the communities with the largest degree of coordination were not supporters of the main parties, but rather small groups of activists and political antagonists.

In summary, our work goes in the direction of embracing the growing complexity of important phenomena such as online deception and manipulation. Doing so would allow us to come up with better models of our complex reality, which would give us higher chances of providing accurate and reliable results. Despite still not being able to distinguish authentic coordinated behaviors from authentic ones, our work makes a step forward in this direction by providing more nuanced and more accurate results.

References

Assenmacher, D.; Adam, L.; Trautmann, H.; and Grimm, C. 2020a. Semi-automatic campaign detection by means of text stream clustering. In AAAI FLAIRS’20.

Assenmacher, D.; Clever, L.; Pohl, J. S.; Trautmann, H.; and Grimm, C. 2020b. A two-phase framework for detecting manipulation campaigns in social media. In SCSM’20.

Barrett, P. M. 2019. Disinformation and the 2020 Election: How the social media industry should prepare. White paper. Center for Business and Human Rights, New York University.

Blondel, V. D.; Guillaume, J.-L.; Lambiotte, R.; and Lefebvre, E. 2008. Fast unfolding of communities in large networks. Journal of statistical mechanics: theory and experiment 2008(10):P10008.

Boneh, D.; Grotto, A. J.; McDaniel, P.; and Papernot, N. 2019. How relevant is the Turing test in the age of sophists? IEEE Security & Privacy 17(6):64–71.

Chavoshi, N.; Hamooni, H.; and Mueen, A. 2016. DeBot: Twitter bot detection via warped correlation. In IEEE ICDM’16.

Cresci, S.; Di Pietro, R.; Petrocchi, M.; Spognardi, A.; and Tesconi, M. 2018. Social Fingerprinting: Detection of Spambot Groups Through DNA-Inspired Behavioral Modeling. IEEE TDSC 15(4).

Cresci, S. 2020. A decade of social bot detection. CACM 63(10).

Fazil, M., and Abulaish, M. 2020. A socialbots analysis-driven graph-based approach for identifying coordinated campaigns in Twitter. Journal of Intelligent & Fuzzy Systems 38:2961–2977.

Gallagher, R. J.; Frank, M. R.; Mitchell, L.; Schwartz, A. J.; Reagan, A. J.; Danforth, C. M.; and Dodds, P. S. 2020. Generalized word shift graphs: A method for visualizing and explaining pairwise comparisons between texts. arXiv preprint arXiv:2008.02250.

Garlaschelli, D., and Loffredo, M. I. 2008. Maximum likelihood: Extracting unbiased information from complex networks. Physical Review E 78(1):015101.

Giglietto, F.; Righetti, N.; Rossi, L.; and Marino, G. 2020a. Coordinated link sharing behavior as a signal to surface sources of problematic information on facebook. In SMSociety’20.

Giglietto, F.; Righetti, N.; Rossi, L.; and Marino, G. 2020b. It takes a village to manipulate the media: coordinated link sharing behavior during 2018 and 2019 italian elections. Information, Communication & Society 1–25.

Jackson, D.; Thorsen, E.; Lilleker, D.; and Weidhase, N. 2019. UK Election Analysis 2019: Media, Voters and the Campaign. Technical report, Bournemouth University.

Keller, F. B.; Schoch, D.; Stier, S.; and Yang, J. 2020. Political astroturfing on twitter: How to coordinate a disinformation campaign. Political Communication 37(2):256–280.

Mazza, M.; Cresci, S.; Avvenuti, M.; Quattrociocchi, W.; and Tesconi, M. 2019. RTbust: Exploiting temporal patterns for botnet detection on Twitter. In ACM WebSci’19. ACM.

Nizzoli, L.; Tardelli, S.; Avvenuti, M.; Cresci, S.; Tesconi, M.; and Ferrara, E. 2020. Charting the landscape of online cryptocurrency manipulation. IEEE Access 8:113230–113245.

Pacheco, D.; Hui, P.-M.; Torres-Lugo, C.; Truong, B. T.; Flammini, A.; and Menczer, F. 2020. Uncovering coordinated networks on social media. arXiv preprint arXiv:2001.05658.

Pacheco, D.; Flammini, A.; and Menczer, F. 2020. Unveiling coordinated groups behind white helmets disinformation. In WWW’20 Companion.

Pei, S.; Muchnik, L.; Andrade Jr, J. S.; Zheng, Z.; and Makse, H. A. 2014. Searching for superspreaders of information in real-world social media. Scientific reports 4:5547.

Ratkiewicz, J.; Conover, M. D.; Meiss, M.; Gonçalves, B.; Flammini, A.; and Menczer, F. M. 2011. Detecting and tracking political abuse in social media. In AAAI ICWSM’11.

Schumacher, S. 2019. Brexit divides the UK, but partisanship and ideology are still key factors. Technical report, Pew Research Center.

Serrano, M. Á.; Boguná, M.; and Vespignani, A. 2009. Extracting the multiscale backbone of complex weighted networks. PNAS 106(16).

Starbird, K.; Arif, A.; and Wilson, T. 2019. Disinformation as Collaborative Work: Surfacing the Participatory Nature of Strategic Information Operations. In ACM CSCW’19.

Starbird, K. 2019. Disinformation’s spread: bots, trolls and all of us. Nature 571:449–449.

Tumminello, M.; Micciche, S.; Lillo, F.; Piilo, J.; and Mantegna, R. N. 2011. Statistically validated networks in bipartite complex systems. PloS one 6(3):e17994.

Vargas, L.; Emmi, P.; and Traynor, P. 2020. On the detection of disinformation campaign activity with network analysis. arXiv preprint arXiv:2005.13466.

Varol, O.; Ferrara, E.; Davis, C. A.; Menczer, F.; and Flammini, A. 2017. Online human-bot interactions: Detection, estimation, and characterization. In AAAI ICWSM’17.

Yang, K.-C.; Varol, O.; Davis, C. A.; Ferrara, E.; Flammini, A.; and Menczer, F. 2019. Arming the public with artificial intelligence to counter social bots. Human Behavior and Emerging Technologies 1(1).

Zellers, R.; Holtzman, A.; Rashkin, H.; Bisk, Y.; Farhadi, A.; Roessler, F.; and Choi, Y. 2019. Defending against neural fake news. In NeurIPS’19.