On the Detection of Disinformation Campaign Activity with Network Analysis

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ABSTRACT
Online manipulation of information has become more prevalent in recent years as state-sponsored disinformation campaigns seek to influence and polarize political topics. While we are aware that these disinformation campaigns exist, detecting their online presence is still difficult. Previously, researchers have proposed detecting disinformation campaigns on Twitter by looking for specific coordination patterns amongst their users (e.g., sharing the same hashtag in a short time frame). The problem with this approach, however, is that while the proposed coordination patterns may have been unique to the studied disinformation campaigns, the patterns have not been thoroughly validated against non-random samples or across a diverse set of campaigns. As such, we examine the usefulness of these coordination patterns for identifying the activity of a disinformation campaign from other legitimate Twitter activity. We do this by rigorously testing the proposed coordination patterns on a large-scale dataset of ten state-attributed campaigns and various benign Twitter communities that are likely to coordinate and share information amongst themselves. Our results show that such patterns have significant limitations. First, coordination in Twitter communities is not uncommon, especially when the online world is reacting to real-world news (e.g., Brexit, US impeachment trials). Second, due to the COVID-19 pandemic, we found that political bodies noticeably increased their coordinated Twitter activity. Such an unexpected surge in coordination worsens the trade-off between usability and rate of detection. To identify most of the benign activity during the pandemic, the classifier misses nearly 25% of disinformation activity. Conversely, if the classifier achieves a high rate of detection for malicious coordination, it misclassifies 46% of legitimate coordinated activity. In doing this meta-analysis, we show that although coordination patterns could be useful for detecting disinformation activity, further analysis is needed to determine the community’s intention.

1 INTRODUCTION
The many forms of social media allow for the rapid and widespread dispersion of information. Whereas traditional channels for news were unidirectional, the open and participatory nature of these online worlds allows for information to be discovered and delivered faster than ever before. This change has been largely beneficial, allowing distant friends simple ways to reconnect, job seekers to learn information about potential opportunities, and special interest groups to easily come together.

Unsurprisingly, the source, provenance, and veracity of such information are often difficult to determine. State-sponsored actors, operating disinformation campaigns, exploit the swift and decentralized nature of modern social media to inject false or intentionally misleading information to manipulate and polarize public opinion. In response, many researchers have proposed a range of detection techniques [10, 12, 28, 37, 38], with recent efforts to identify coordination networks drawing significant attention because of their relatively high reported accuracy [26, 27]. Unfortunately, these solutions do not adequately consider the environment in which they would be deployed, making their practical utility unknown. Specifically, these techniques focus on detecting single accounts when disinformation campaigns rely on coordination to push a message and, when coordination is considered, it is unclear whether such patterns extend to other disinformation campaigns. Finally, even if they do extend to such campaigns, the coordination patterns are tested against trivial baselines that are likely to have little-to-no coordination. Given these shortcomings, it is unclear to what extent these coordination patterns are useful in detecting the activity of disinformation campaigns in a real setting.

In this paper, we aim to address the shortcomings mentioned above by performing the most extensive study to date of the characterization of coordination patterns used by disinformation campaigns. Primarily, we focus on determining to what extent previous network-based coordination metrics are useful in detecting disinformation campaign activity when compared against real-world benign communities found on Twitter. By better understanding the environment in which the proposed coordination patterns will be deployed, we gain insight into how useful they will be for detecting disinformation campaigns. We argue that comparing coordination patterns of disinformation campaigns against communities found on Twitter better represents the disinformation detection problem since Twitter communities likely share more characteristics with disinformation campaigns than random accounts. Namely, both disinformation campaigns and Twitter communities are composed of users that 1) share similar interests, and 2) are likely to coordinate amongst themselves to push a message to the online world, whether with malicious or benign intent. By making this comparison of coordination patterns, we observe the following findings:

- Largest Disinformation Detection Meta-analysis: We measure the effectiveness of previously proposed coordination patterns as a way to uncover disinformation campaigns on Twitter by examining over 51 million tweets from 10 state-attributed campaigns and 4 communities with varying levels of benign coordination.
- Characterize Coordination Patterns of Disinformation Campaigns: Communities with strong ties (especially political ones) can coordinate in ways indistinguishable to a
As Starbird et al. discuss, bad actors have leveraged social media search to discover how Russia’s Internet Research Agency (IRA) the open nature of social media sites. For example, previous re-

mation to the broader public while staying camouflaged. To reach a narrative and deliberately share misleading or confusing infor-
mation. Disinformation campaigns can be carried out by multiple state and non-state operators. The goal of these campaigns is to manipulate or inaccurate news for deception and manipulation of a narrative. Bad actors have exploited the open nature of social media sites as a way to share disinformation with minimal effort. Unlike misinformation, which refers to the spread of inaccurate news without ill-intent, disinformation seeks to deliberately spread misleading or inaccurate news for deception and manipulation of a narrative. As Starbird et al. discuss, bad actors have leveraged social media disinformation as a conduit of manipulation to reach and deceive millions of people in the online world as part of their Strategic Information Operations (SIO) campaigns [31]. Many examples of these campaigns have been discovered over the past decade. Some of these can be attributed to state-sponsored manipulation [2]. Others, however, target specific demonstrations (e.g., #BlackLivesMatter [1], #WhiteHelmets [40]) and try to masquerade as grassroots move-

ments (i.e., astroturfing) to appear more genuine to other online users. We used the term SIO throughout this paper to broadly refer to any coordinated effort to spread inaccurate information and influence public opinion, including specific disinformation efforts such as astroturfing.

2 DATA-DRIVEN DISINFORMATION

Bad actors have exploited the open nature of social media sites as a way to share disinformation with minimal effort. Unlike misinformation, which refers to the spread of inaccurate news without ill-intent, disinformation seeks to deliberately spread misleading or inaccurate news for deception and manipulation of a narrative. As Starbird et al. discuss, bad actors have leveraged social media disinformation as a conduit of manipulation to reach and deceive millions of people in the online world as part of their Strategic Information Operations (SIO) campaigns [31]. Many examples of these campaigns have been discovered over the past decade. Some of these can be attributed to state-sponsored manipulation [2]. Others, however, target specific demonstrations (e.g., #BlackLivesMatter [1], #WhiteHelmets [40]) and try to masquerade as grassroots move-

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2.1 Operating a Disinformation Campaign

Disinformation campaigns can be carried out by multiple state and non-state operators. The goal of these campaigns is to manipulate a narrative and deliberately share misleading or confusing information to the broader public while staying camouflaged. To reach this goal, disinformation campaigns have successfully exploited the open nature of social media sites. For example, previous re-

search discovered how Russia’s Internet Research Agency (IRA) and Iran’s state-sponsored apparatus launched social media dis-

information campaigns attacking the United State’s presidential election in 2016 [11, 25].

Disinformation campaigns are usually composed of hundreds of accounts. As explained by Keller et al. [13], the operation of these campaigns can be roughly described by the principal-agent theory [18, 29], where the principal (campaign operator) conducts the agents (user accounts) to perform some task (spread false information). In the principal-agent problem, an issue arises when agents act for their own best interest, which is against the priorities of the principal. While carrying out the task of spreading disinformation, the agents are capable of making a decision that may hurt the camouflaging goal of the campaign operator by making use of automation. As such, disinformation campaigns need to balance the natural duality that exists between actively spreading misleading content and camouflaging their efforts to avoid detection. If the agents are purely automated, then it is easier for more agents to spread misleading messages. However, detecting the activity becomes a more manageable task due to the behavioral artifacts automation may leave behind (e.g., bulk account creation, temporal patterns, account inauthenticity) [4, 8, 15]. Conversely, if human agents control the accounts, then more resources are needed, and fewer accounts may be available to spread the message. However, even though there are fewer accounts, they have a higher chance of being more authentic to the human users the campaign wishes to manipulate, thereby camouflaging the disinformation campaign. Regardless of the type of agents (automated or human), the accounts that are part of the disinformation campaign may need to coordinate amongst themselves to push the message they wish to manipulate. This is seen by looking at the historical activity of the accounts that post similar messages at around the same time. It is this type of coordination that researchers have tried to exploit as a way to detect if a disinformation campaign is being executed [12, 26, 27].

In this work, we set out to analyze coordination found in Twitter communities with the goal of characterizing the issues coordination-based SIO detection tools may have. For an SIO detection tool, the ultimate goal would be to flag a user community (i.e., a network of accounts) that has spread disinformation in a coordinated fashion. This problem can be broken down into two main subtasks: identifying suspicious communities by looking at coordination patterns amongst the members and identifying the intent of the messages the accounts promote. The intent is usually determined by human analysts that understand the context of how/when the messages were shared. While some researchers have inferred the intent of a campaign based on offline data (e.g., email leakages [14], court filings [12]), such data sources are rarely available, making intent identification an open problem. We do not focus on the intent of disinformation and leave it to the analysis of the intelligence community. Instead, to arrive at our goal of carefully assessing coordination-based SIO classifiers, we conduct a large-scale analysis of the coordination patterns found in Twitter SIO campaigns using tweets from Twitter’s Information Operations Election Integrity report [36] as well as tweets from political and non-political Twitter communities that engage in legitimate coordination.
3 METHODOLOGY

In this section, we discuss the approach we take to characterize the coordination patterns that can be found in SIO campaigns and how they compare to other Twitter communities.

As mentioned earlier, researchers have looked into the task of flagging suspicious coordinated activity in service of SIO detection and have proposed discriminative patterns that appear to be characteristic of disinformation campaigns [13, 27]. These patterns usually rely on extracting network statistics of a graph, where nodes are accounts and edges represent coordination between accounts. For example, edges can be created when two accounts are tweeting the same message or retweeting the same person (more details in Section 4.1). While accounts that consistently participate in such behavior may certainly seem suspicious, the proposed patterns have only been tested against baseline activity of random Twitter users weakly linked by the political relevance of their tweets [27] or against no baseline activity at all [13]. We argue that the lack of carefully chosen Twitter communities for vetting coordination classification has failed to provide insight into how well these discriminative patterns would perform in the Twitter ecosystem. We base this argument on the assumption that weakly linked Twitter accounts (e.g., random accounts sharing the same trending hashtag) are not likely to coordinate amongst themselves. However, if the accounts are linked by a common interest or goal (e.g., accounts belonging to government officials of the same political party), then they are likely to form a community amongst themselves and share news about the community. Since the proposed patterns have yet to be tested in a classification setting where the baseline communities are likely to coordinate amongst themselves, it is unknown whether the coordination patterns are useful for detecting SIO campaigns or if they appear often in various Twitter communities. Therefore, to assist with our end goal of characterizing coordination patterns on Twitter as a means for SIO detection, we sought to answer two quantitative and qualitative guiding questions:

RQ1: Can we train a binary classifier to distinguish between the daily and weekly coordinated activity of the SIO campaigns from other Twitter communities?

RQ2: How is the classifier affected by an unexpected surge of activity that causes communities to disseminate more information?

RQ1 is concerned with measuring the ability of a classifier that uses coordination patterns to distinguish the activity of Twitter SIO campaigns from legitimate coordination. Our original hypothesis was that without additional context, these patterns are not discriminative enough to distinguish legitimate coordination within various closely linked communities from SIO campaign coordination. We show in Section 5 that this hypothesis is only partially correct: while a sufficiently powerful classifier is able to successfully identify coordination patterns from some of the baseline communities, it tends to confuse SIO-like activity exhibited by other communities.

Figure 1: Looking at the coordination patterns of a campaign at specific time periods can reveal “events” where the campaign pushes their messages. This information is lost when looking at the coordination patterns of a campaign as one network based on their full activity history.

RQ2 stems from recent observations that, due to the COVID-19 pandemic, governments (and other communities) have had to increase the rate of information dissemination (both politically motivated and health-related). This type of event brings massive paradigm shifts that cause predictive models trained on past data to fail, which is exactly when such tools are most needed to remove content polluters in real-time and at scale.

3.1 Classifying Coordinated Activity

To answer the questions mentioned above, we set up a meta-problem that focuses on detecting if the coordinated activity of a community can be classified as being SIO or non-SIO. Given a community, we train a binary classifier to predict if activity within a time period originates from an SIO campaign (positive class) or not (negative class) by solely looking at the networks generated by coordination.

There are two important distinctions to discuss about the proposed meta-problem. First, this detection problem is not the same as bot detection, which is a more clearly defined classification problem (determining if an account is a human or robot) without issues of determining intent, and is more thoroughly studied [28, 38]. Second, rather than flagging accounts, we focus on flagging suspicious coordinated activity. We consider activity classification, rather than account detection, because SIO campaigns are often coordinated efforts that involve many accounts which arguably leave traces that can be detected with network analysis techniques [13, 27].

We classify a community’s Twitter activity by following similar steps taken by other researchers, in that we use network analysis to extract specific coordination patterns [13, 26, 27]. However, instead of using the entire history of a community’s tweets to generate one monolithic coordination network, we generate multiple networks by looking at daily or weekly activity (Figure 1). Daily activity of

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1We consider a disinformation campaign to be a community since the accounts that compose it share similar interests.

2For this paper, legitimate coordination refers to the coordination found in our Twitter community baselines. We address them as legitimate since Twitter has not suspended the accounts.
SIO has also been studied in the context of a campaign targeting the 2012 South Korean presidential election [12]. We define daily coordination as a set of coordination networks where all network edges represent coordination between accounts that occurred on the same day. Coordination at the weekly level is considered by aggregating all of the daily coordination networks within a week, which consists of keeping the unique set of accounts from that week and taking the union of all of the edges from each day.

Viewing the coordination of a community as time slices, rather than as a single time-independent network, can help interpret why having a monolithic view of a community may lead to misclassification. Notice in Figure 1 that a coordination network made using the activity within a specific time period is a subgraph of the coordination network generated based on the entire history of the community. While it may seem like our classification setup ignores temporal dependencies within SIO campaigns that span across multiple days or weeks, characterizing these temporal patterns to develop such a detection system is left as a promising direction for future works.

### 3.2 Datasets

In this section, we discuss how we collected the ground truth Twitter activity for SIO campaigns as well as the four baseline communities. We use the coordination networks extracted from these communities as a way to understand if previously proposed coordination patterns are a unique structure to SIO campaigns. We acknowledge that SIO campaigns also exist in other online platforms (e.g., Facebook, Reddit). We chose to base our analysis on Twitter since many detection tools have already been proposed for this platform, and Twitter also provides SIO-related data to the open public for research purposes.

#### 3.2.1 Twitter SIO Campaigns.

For our SIO ground truth, we accessed all the data archives of Twitter’s Information Operations Election Integrity reports [36] up to September 2019. Each data archive contains all tweets, media shared, and descriptions of accounts that were part of a potentially state-backed information operation campaign. For each campaign, we grouped the archives based on the state-sponsor attribution (source) Twitter provided as well as which countries (targeted) were attacked by the SIO campaign\(^3\) (e.g., Iran state-sponsored targeting the United States). We did not consider campaigns from Saudi Arabia, Spain (source), and Bangladesh as they contained too few accounts and tweets. Such campaigns were short-lived and did not have enough activity to analyze. All coordination graphs (and features) mentioned in Section 4.1 were generated based on this combination of data archives in their respective source/target campaigns. The high-level statistics of the SIO campaigns are shown in Table 1.

#### 3.2.2 Legitimate Twitter Community Activity.

To compare SIO activity to other potentially legitimate coordination present on Twitter, we collected four community baselines that have varying levels of coordination amongst their members by using the Twitter API which provides an account’s most recent 3200 tweets. These four baselines are broadly categorized as either political or non-political Twitter communities. We make this categorization to characterize the similarities/differences that SIO campaigns have to Twitter communities that engage in politically-charged discussions and other communities that mainly discuss non-political topics.

For the political baselines, we collected the Twitter activity of accounts from the members of the United States Congress as well as the Members of Parliament (MPs) in the United Kingdom. These two baseline communities were chosen since their members are likely to discuss political topics that have polarizing viewpoints as well as coordinate amongst themselves to pass/support legislation.

The two non-political communities we collected were accounts of academic/professional security researchers and a random set of accounts. We chose this academic baseline as an example of a legitimate Twitter community since many of the members may show coordinated behavior (e.g., tweet about a conference, promote a paper) and are assumed to more limited political discussion. We claim that our academic baseline is representative of other Twitter communities composed of accounts that share a similar interest, such as other academic fields or users that are fans of the same sports team. In addition to the academics baseline, we collected a random set of accounts as previous studies have done. We collect this control baseline by first querying tweets that are part of a randomly chosen trending hashtag, then randomly picking one account from the results, and finally doing a random walk from account to account based on whom they follow. This random baseline is expected to have minimal (if any) shared interests or coordination. Statistics on our set of baseline communities are provided in Table 1.

### 4 IMPLEMENTATION

We now discuss how we extract feature vectors from coordination found in SIO campaigns and the baseline communities. We also discuss the implementation details of our classifier.

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\(^3\)Exact mapping based on the archive to state-sponsored attribution can be found in Appendix A.
4.1 Network Generation and Feature Engineering

Our methodology focuses on the coordination behavior of a community. Coordination of a community can be measured by mapping the tweet activity to a network analysis problem where the nodes are accounts and edges represent some prescribed coordination pattern that may exist between two accounts. In our case, we consider six coordination patterns that have been previously proposed as indicators of SIO [13, 26, 27]:

- **retweet**: an account retweeting another account in the same community [13, 27]
- **co-tweet**: two accounts tweeting (not retweeting) the same content (url excluded) within a time threshold [13]
- **co-retweet**: two accounts retweeting accounts that may/may not be part of the community within a time threshold [13]
- **co-hashtag**: two accounts tweeting the same hashtag within a time threshold [27]
- **co-mention**: two accounts mentioning the same user within a time threshold [27]
- **co-url**: two accounts sharing the same url within a time threshold [27]

While some of the patterns mentioned above are common behaviors in Twitter, Keller et al. [13] argues that accounts tweeting/retweeting messages with similar content within a short time frame can be seen as suspicious activity, and so we use a time threshold for all types except for the retweet networks. Retweeting is a simple way to spread false information and, more generally, to signal-boost a specific message. Time thresholds were not enforced for the retweet coordination pattern in either of the previous studies [13, 27] and hence we follow suit. Conversely, two or more tweets using the same hashtag may not necessarily mean that these accounts are coordinating. However, if those accounts tweet the same hashtag within a time threshold (e.g., 1 minute) of each other, then the behavior starts to appear more suspicious. The timing is important since short time between two messages with the same content could mean automation or an individual controlling multiple accounts. For all coordination patterns, the pattern is defined by what they share and the time between messages (except retweet).

To generate the daily/weekly feature vectors that we use to train the classifier, we first collect all the tweets from a community within a given time period (e.g., day, week). Second, for each coordination pattern mentioned above, we generate the coordination network using the tweet content and time to determine which accounts require an edge between them based on the specified coordination requirements. Once the coordination networks are generated, we extract the seven statistical properties mentioned in Table 2 for each of the six networks that measure the amount of activity (e.g., number of nodes and edges) and the connectivity (e.g., average connected component sizes, average node degrees). We concatenate all the high-level statistics into a 42-dimensional vector (seven metrics for each of the six coordination networks) as the representation of the coordination activity of the community for a given time period. Finally, we discard any daily/weekly feature vectors consisting of all zeros (i.e., no coordination activity was observed based on the six patterns we consider). These feature vectors are used to train/validate the classifier discussed in Section 4.2.

| Coordination Network Features |
|-----------------------------|
| nodes | # of nodes |
| edges | # of edges |
| largest_cc | Size of the largest connected component |
| mean_cc | Avg. size of connected components |
| std_dev_cc | Std. dev. of the sizes of connected components |
| mean_deg | Avg. node degree |
| std_dev_deg | Std. dev. of node degree |

Table 2: The seven features extracted from each of the six types of coordination networks from the SIO campaigns and baseline communities. We concatenate them to form 42-dimensional feature vectors.

We note that results based on co-url activity are limited due to link shortener/redirection services. While for the collected baselines, we can extract the exact links that were posted by the user, the URLs that are part of the Twitter SIO archives do not have such information present. Instead, a non-negligible amount of URLs are shown as their shortened URL (e.g., bit*ly, dlvr*it). While the correct approach to solve this issue is to look for the redirection of the shorten URLs manually, we noticed that some end domains no longer existed at the time of our analysis. Thus, instead of redirecting us to the originally posted URL, we get redirected to the domain registrar (e.g., www*hugedomains*com). Basing edge creation on these misleading redirects could add non-existent edges to the network. As such, we decided to be conservative and use the URLs found in the dataset instead of the redirected values.

4.2 Classifier Implementation

For the binary classifier, we use a Random Forest (RF) [3] with 100 trees implemented using scikit-learn [24]. RFs are widely considered to be a strong baseline classifier and have recently been employed for bot detection [41] and disinformation website detection [10] at scale. Compared to deep learning approaches, RFs learn similar highly nonlinear decision boundaries but produce more interpretable results, are more robust to unnormalized features, and generally handle low to medium amounts of training data better. We emphasize that although we are interested in assessing the ability of a classifier to separate Twitter SIO campaign coordination from non-SIO coordination, our primary goal is to characterize the coordination patterns found in our datasets, which leads us to favor interpretability over maximizing classifier performance.

The question arises of how to properly evaluate the classifiers for our study. Our proposed solution is to consider the classifier performance at two distinct decision boundaries. First, to fully characterize model performance at all decision boundaries, we show precision-recall (P-R) curves, which are better suited for imbalanced datasets than receiver operating characteristic (ROC) curves. Then, we assess the classifier when labels are decided by majority voting across the ensemble of 100 trees (Voting). This is the standard decision rule for RFs, and generally trades off precision (P) and recall (R) quite well. However, to reflect the desire of a low number of false positives, we also propose to show classifier performance at a
high threshold so that the classifier achieves a precision of 0.975 (P-Threshold). Note that this value is assumed by the authors, and we use it to simulate an acceptable number of false positives for our problem. The practice of evaluating classifiers by examining relevant score thresholds has also recently been used in a bot detection meta-analysis to highlight a severe false positive problem [28]. We can also provide some context for choosing a precision of 0.975 with the following example from our dataset. Suppose that for 350 instances of non-SIO daily activity and 500 instances of SIO daily activity the SIO discovery rate is 0.96. Then a model that achieves P = 0.975 or better can have no more than 12 false positives. Precision is sensitive to the number of true instances of SIO activity in the dataset, and although our dataset is not reflective of the unknown distribution of non-SIO to SIO activity in the real-world, note that if we reduce the amount of SIO instances by 10% to 450 and maintain the discovery rate, the number of allowed false positives at P = 0.975 will decrease to 11.

We note that we do not use PR-AUC or ROC-AUC scores to quantify model performance in this study, and instead report F1 scores computed with the two aforementioned decision rules. AUC scores average over many decision thresholds and can overestimate model performance [28]. Also, AUC scores are useful for comparing competing models and checking whether a model can successfully rank a majority of positive samples higher than negative samples. Based on visualizations of the data that we show in Figure 3, it can be seen that much of the non-SIO data should be easily classifiable by the RF; ROC-AUC scores are less informative when the overall true negative rate (TNR) is already expected to be high.

To train our RF classifier, the daily and weekly coordination network feature vectors extracted from the ten SIO campaigns (all assigned a label of 1) and four baseline communities (all assigned a label of 0) are combined into training and validation sets for cross-validation (CV) in the following way. For each campaign and baseline, we sort chronologically the days/weeks containing non-zero amounts of coordination and set aside the first 85% of days/weeks for training and the latter 15% for validation. We split the data temporally to simulate a realistic scenario of having to use past data to predict new coordination activity, and choose to use only the last 15% days/weeks for validation as most of the datasets display increasing amounts of coordination over time (see Section 5.1). We individually split each of the four baseline communities into non-overlapping time periods for training and validation; the split occurs on 2019-2-27 for UK Parliament, 2019-3-6 for US Congress, 2019-10-26 for Random, and 2018-9-28 for Academic. The validation set consists of the days between these dates and 2020-2-29; we reserve all days of political community activity after 2020-3-1 to use as a held-out set for the COVID-19 case study. We perform 10-fold cross-validation four times, holding out one of the four baseline communities to validate each time. For each fold, we train on five randomly selected SIO campaigns and three baseline communities and validate on the held out baseline community as well as on two randomly selected SIO campaigns not observed during training (this way we approximately maintain a 4:3 ratio of positive to negative labels during training and validation). Altogether, we train 240 models by considering 1, 5, and 10 minute coordination time thresholds (Section 4.1), and daily and weekly coordination aggregation. We refer to models by the held-out baseline community it was validated on (e.g., “UK Parliament” is a model trained on US Congress, Academics, and Random coordination activity as well as five randomly selected SIO campaigns and validated on UK Parliament along with two other randomly selected SIO campaigns).

In total, from the 51.9M tweets across all disinformation campaigns and baseline communities, 281K coordination networks were generated to represent daily coordination activity.\(^4\) Computing these networks took 3 days on a 40 core/512GB RAM server.

5 ANALYSIS

To answer the research questions posed in Section 3, we conduct a series of empirical studies. First, we qualitatively characterize how coordination changes in communities. Then, to answer RQ1, we measure the ability of our binary classifier to correctly identify the daily/weekly coordinated tweet activity by the considered Twitter SIO campaigns and baseline Twitter communities. We interpret the trained models by visualizing the coordination feature vectors using t-SNE [17] and discuss feature importance using SHAP plots [16]. We address RQ2 by presenting a case study on COVID-19 Twitter activity collected from members of the UK Parliament and the US Congress. Our case study shows how a massive global event has lead to an increase in SIO-like Twitter coordination from political communities, which in turn negatively impacts the ability of classifiers to identify SIO campaigns.

5.1 Characterization of Coordination

5.1.1 Setup. Before we analyze the guiding questions mentioned in Section 3, we first do a high-level characterization of the coordination found in both the SIO campaigns as well as our baselines. In Figure 2, we show examples of the coordination patterns exhibited by some of the SIO campaigns and baselines. We generated the coordination networks for each pattern discussed in Section 4.1 using daily aggregation with a 1-minute time threshold. We then counted how many accounts participated in each coordination pattern within their respective communities in a given day (i.e., the number of nodes in the coordination network). Note that each column represents the coordination patterns for one campaign, and the y-axis of the columns are different. Due to space limitations, we show the rest of the coordination patterns in Appendix A. Furthermore, to check how separable SIO and non-SIO coordination activity is, we visualize t-SNE plots of the training set feature vectors corresponding to daily/weekly aggregation at a 1-minute time threshold in Figure 3. We found that PCA [35] was unable to produce an interpretable representation of the variety of coordination activity in our data; t-SNE is a more expressive dimensionality reduction tool for visualizing high dimensional data in a 2-D plane. The features can be colored by class label to help reveal similarities across distinct classes in the dataset.

5.1.2 Key Results. We find that the usage of each type of coordination pattern differs from one community to the next. From Figure 2, we can see that coordination in SIO campaigns appear to be more orchestrated. For example, in the Iranian campaign (Figure 2(a)), the community appears to make use of co-tweeting (yellow) in late 2015 but then stops soon after. They then switch to coordinating by using

\(^4\)In addition to daily coordination networks, weekly networks are also generated by including all edges in a 7-day time period.
Figure 2: Examples of coordination activity for four communities (two disinformation campaigns and two of the manually collected baselines). Each community appears to have different behavior characteristics such as high levels of co-tweeting (Venezuela (commercial) or diversity in employed coordination patterns (Iran). A variety of coordination patterns can be seen more extensively in political communities (e.g., US Congress) than non-political (Academics), but both types of baselines show increasing amounts of coordinated activity over time.

Figure 3: Visualizing t-SNE plots of the training set coordination feature vectors for SIO campaigns and baselines (political and non-political) shows that the feature vectors generally appear to be separable at (a) daily aggregation and even more so with weekly aggregation (b). However, on days when a community is reacting to specific events (e.g., US SOTU addresses, UK general election), coordination from political communities blends in with SIO-like activity. This can be clearly seen by looking at baseline events (indicated by stars) that are near the vicinity of SIO activity, and by seeing that in b) the various weeks of heavy political activity (e.g., US SOTU addresses) become even more dissimilar from other baseline activity.

low amounts of retweeting (red) and high amounts of co-retweeting (green) for the majority of 2017. Conversely, coordination for the Venezuela (commercial) campaign (Figure 2(b)) posted the same message from each account (co-tweeting). These SIO campaigns show relatively constant coordinated activity, whereas other SIO campaigns (Appendix A) show different bursty behaviors (i.e., intermittent levels of high activity and little to no activity).

For the baseline communities, we can see that retweeting is the most used coordination pattern. This is not surprising as retweeting is one of the most common actions that a user can take on Twitter as
it only takes one click. Additionally, accounts within a community may desire to signal boost each other by retweeting if they share similar goals (e.g., legislative or academic). The amount of coordination also varies for the baselines, with political communities (the UK Parliament and the US Congress) showing more coordination than our non-political communities (Random and Academics). Finally, we note that while co-tweeting patterns are minimal in all of the baseline communities, some SIO campaigns rarely employ co-tweeting, thereby preventing the use of only co-tweeting metrics as a simple rule for identifying SIO activity.

Additionally, in Figure 3, we observe that the feature vectors of coordinated activity appear to cluster into SIO, political, and non-political for both daily and weekly coordination patterns. We first note that days and weeks of low coordination activity are present in the training sets for both SIO campaigns and the baselines. These low activity days manifest in the t-SNE plots as tight, isolated clusters where data points from all three clusters overlap. Another noticeable aspect is that there are several isolated days/weeks of political activity (green) that are spread through the SIO activity. Many of these days turn out to correspond to events of note such as the 2018 and 2019 US State of the Union (SOTU) addresses (we investigate further in Section 5.3). The proximity of these political days to SIO coordination feature vectors shows that during community events, some baselines appear to have SIO-like activity patterns. Finally, we find that increasing the temporal aggregation from daily to weekly greatly increases the separation between non-political and SIO coordination. While certain amounts of political coordination now resemble non-political nor SIO activity (2017 UK general elections in Figure 3(b)), other instances (2018 and 2019 US SOTU) appear even more strongly to be SIO activity.

5.1.3 Takeaways. As expected, coordination appears to be more prevalent and orchestrated in SIO campaigns than in the baseline communities. However, the type of coordination, as well as the behavior based on it, differs for each campaign and community. These variations can make it hard for detection mechanisms to learn generalizable patterns to detect SIO-like activity, which is worsened by the observation that the amount of coordination tends to increase over time. Moreover, the activity from days where a legitimate community reacts to a specific event appears to closely resemble SIO-like coordination patterns.

5.2 RQ1: Coordination Activity Classification

5.2.1 Setup. Using the cross-validation data splits described in Section 4.2, we now train all of the binary classifiers and analyze their ability to distinguish daily/weekly coordinated activity from our SIO and non-SIO Twitter communities. In Table 3, we show F1 (Voting) and F1 (P-Threshold) scores computed by averaging over the 10 cross-validation folds, political communities (UK Parliament and US Congress), and non-political communities (Academics and Random) with 95% confidence intervals (CI) shown. For each of the 10 folds, we evaluate F1 (P-Threshold) at the threshold corresponding to P = 0.975. To select one model from the 10 folds for displaying precision-recall curves, we compute the average PR-AUC score across the 10 models and select the one whose PR-AUC score is closest to the mean. We do this rather than selecting the model that achieves the highest PR-AUC score across the 10 folds since we observed the best PR-AUC score consistently fell outside of the 95% CI of the mean, and is likely to overestimate the results. The daily / 1-minute precision-recall curves are shown in Figure 4, with the remainder of the curves shown in Appendix A. For a more fine-grained examination of the performances, sensitivity vs. specificity for the daily / 1-minute models is shown in Table 4.
Table 3: 10-fold CV F1 scores. F1 scores are averaged across 10 folds with 95% (upper, lower) confidence intervals around the mean estimate shown. F1 (P-Threshold) scores are evaluated at the threshold corresponding to P = 0.975 along the P-R curve.

| F1 (P-Threshold) | Activity | Political | Non-political |
|------------------|----------|-----------|---------------|
| **Voting**       |          |           |               |
| Daily / 1-min    | 0.91 (0.89, 0.92) | 0.94 (0.92, 0.97) |               |
| Daily / 5-min    | 0.86 (0.84, 0.88) | 0.92 (0.88, 0.96) |               |
| Daily / 10-min   | 0.83 (0.81, 0.86) | 0.91 (0.86, 0.95) |               |
| **Weekly / 1-min** | 0.89 (0.87, 0.91) | 0.97 (0.95, 0.98) |               |
| Weekly / 5-min   | 0.83 (0.81, 0.85) | 0.94 (0.91, 0.96) |               |
| Weekly / 10-min  | 0.80 (0.79, 0.82) | 0.94 (0.91, 0.97) |               |
| **P-Threshold**  |          |           |               |
| Daily / 1-min    | 0.83 (0.76, 0.90) | 0.94 (0.91, 0.98) |               |
| Daily / 5-min    | 0.62 (0.52, 0.72) | 0.86 (0.75, 0.97) |               |
| Daily / 10-min   | 0.52 (0.40, 0.65) | 0.91 (0.85, 0.97) |               |
| Weekly / 1-min   | 0.66 (0.55, 0.78) | 0.99 (0.99, 1.0)  |               |
| Weekly / 5-min   | 0.45 (0.31, 0.59) | 0.98 (0.97, 0.99) |               |
| Weekly / 10-min  | 0.42 (0.28, 0.55) | 0.98 (0.97, 0.99) |               |

Table 4: TPR = true positive rate (recall), TNR = true negative rate (specificity). Here, TPR measures the ability of the classifier to correctly identify coordination from the US Congress (N = 361) and the UK Parliament (N = 367).

| 10-fold CV                      | TPR / TNR P-Threshold | TPR / TNR Voting |
|---------------------------------|-----------------------|------------------|
| Political (daily / 1-min)       | 0.75 / 0.98           | 0.93 / 0.87      |
| Political (daily / 5-min)       | 0.49 / 0.99           | 0.90 / 0.77      |
| Political (daily / 10-min)      | 0.40 / 0.99           | 0.88 / 0.72      |

5.2.2 Key Results. The daily / 1-minute models all attain F1 (Voting) scores greater than or equal to 0.91, and when increasing aggregation to weekly / 1-minute, the F1 (Voting) scores for non-political communities increases to 0.97. Strikingly, the F1 (P-Threshold) scores at weekly / 1-minute for non-political communities reach 0.99. Conversely, when moving from daily to weekly, the classifier either has low recall when achieving the threshold on false positives for political communities (F1 (P-Threshold) = 0.66) or sacrifices precision to maintain a high F1 score (F1 (Voting) = 0.89).

By requiring P = 0.975, the specificity for the political communities at daily / 1-minute is acceptable (TNR = 0.98) but the trade-off is a lower recall (R = 0.75). On the other hand, using voting to decide labels achieves a more balanced trade-off of specificity (TNR = 0.87) and recall (R = 0.93), but a TNR of 0.87 does not reflect our desire for a sufficiently low rate of false positives.

5.2.3 Takeaways. We conclude that by adequately tuning the decision threshold and using weekly aggregation, the RF classifier can achieve near-perfect separation of non-political coordination from SIO coordination. However, the same cannot be said about political communities. While the F1 scores (both Voting and P-Threshold) for the political communities appear high, there is still a false positive problem when achieving desirable recall levels. More broadly, these results show that disinformation detection based on network analysis must balance effectiveness for usability. With a loose restriction on the number of allowable false positives, a classifier can identify almost all of the SIO activity, but such a system would be deemed impractical as it would flag a high amount of benign activity. Therefore, our response to RQ1 is that a classifier using only network analysis features is unable to distinguish daily/weekly activity as SIO or non-SIO at desirable levels for all Twitter communities.

We noticed that many of the errors causing the false positives surrounded days/weeks, which contained significant political events (see Section 5.3). We also note that increasing the time thresholds to 5 and 10 minutes tended to reduce model performance, suggesting that the added coordination captured by higher time thresholds has the effect of further blurring the line between legitimate coordination found in Twitter communities and SIO activity.

To further probe the classifier’s decision-making process, we produced a SHAP summary plot of RF feature importances (Figure 5). As our focus is on assessing the broad use of network analysis features for our detection task, we do not analyze the features in further detail by examining e.g., partial dependence plots or multicollinearity in this study. The classifier mostly relies on various statistics of the retweet network to separate SIO and non-SIO data. A high average node degree in the retweet network is a main indicator of SIO activity, however. Other important coordination features that strongly indicate similarity to SIO activity include the number of nodes in the co-tweet network, as well as the average size of connected components of the co-url and co-mention networks. Co-tweeting rarely appears in the non-SIO training data, causing the classifier to label almost all data points containing any amount of co-tweeting as SIO. Overall, stronger connectivity amongst nodes increases the likelihood that the classifier labels the activity as SIO.

5.3 RQ1: Examples of Misclassification

5.3.1 Setup. We now turn our attention to understanding why coordination activity of legitimate communities can get misclassified as SIO activity, due to the emphasis we place on minimizing false positives. To do that, we look at the days that were consistently misclassified by the daily / 1-minute models across each of the 10 folds in cross-validation. More concretely, we only consider days in this analysis if they were misclassified across all 10 CV folds. We found 0 days from Academics, 9 days for Random, 16 days for the US Congress, and 13 days for the UK Parliament. We then extract all information from the tweets that were used to generate the coordination network for that given day. Finally, we manually looked at both the tweets that caused the misclassification to occur as well as the news for that specific date that may have affected the coordination patterns of the community.

5.3.2 Key Results. Unsurprisingly, the models that validated their ability to classify non-SIO activity on non-political communities did not make many misclassifications. Mainly, we noticed that the coordination networks based on co-url and co-hashtag appeared to be more active while other networks (e.g., retweet network) had minimal (if any) activity. For the dates that were misclassified, we
could not determine any specific event that caused the error. As discussed in Section 5.2, by increasing the temporal aggregation to weekly / 1-minute, the RF can reduce misclassifications to nearly 0.

Conversely, for the political baselines, we noticed that the misclassifications occur when the community is reacting to a specific community event. For example, in the US Congress dataset, we saw that the US Congress Twitter activity surrounding the impeachment hearings of President Donald Trump was mostly misclassified as having SIO-like coordination patterns. These misclassified dates include the announcement of a formal impeachment inquiry [19], many days during the testimonial hearings [21], and the House vote to pass the Articles of Impeachment [20]. Furthermore, as Figure 3 demonstrates, the coordination pattern surrounding events like the 2018 and 2019 SOTU address appears similar to SIO coordination. Indeed, the 2020 SOTU was also consistently misclassified. In Figure 6, we show the coordination activity as well as the generated networks of US Congress during the SOTU address of 2020. Note that highly coordinated tweet activity occurs at the same time as the event is on the air. The UK Parliament was no different in regards to misclassification. Many days misclassified included Prime Minister Boris Johnson becoming the leader of the Conservative Party, updates on the UK withdrawing from the European Union (i.e., Brexit), or debates regarding the general elections for the UK.  

5.3.3 Takeaways. The findings above may have profound implications beyond the classification of coordinated community activity. The coordination networks are subgraphs of the monolithic coordination network generated on the entire activity of the whole community. SIO community detection systems are likely to have many false positives if they are based on monolithic networks that naively aggregate over long time periods since legitimate communities would appear as highly coordinated, even though the coordination may only occur around community events, which are expected to be common occurrences across Twitter. Information on those events, however, is lost since the monolithic network ignores the temporal nature of the activity.

5.4 RQ2: Case Study—Political Coordination During the COVID-19 Pandemic

5.4.1 Setup. While conducting this study, we observed a shift in the coordination patterns of the political communities around the time the COVID-19 pandemic began to impact western countries (late February 2020). This enabled us to conduct a unique case study to test the generalization ability of our trained models in a novel context.
Table 5: Classifier specificity/TNR on post-COVID-19 Twitter activity for UK Parliament (N = 32) and US Congress (N = 51). TNR = true negative rate.

|                         | TNR P-Threshold | TNR Voting |
|-------------------------|-----------------|------------|
| UK Parliament (daily / 1-min) | 0.68            | 0.45       |
| UK Parliament (daily / 5-min) | 0.8             | 0.31       |
| UK Parliament (daily / 10-min) | 0.7             | 0.26       |
| US Congress (daily / 1-min) | 0.92            | 0.64       |
| US Congress (daily / 5-min) | 0.97            | 0.42       |
| US Congress (daily / 10-min) | 0.79            | 0.45       

5.4.3 Takeaways. The increase in political coordination exhibited by the US Congress and even more so by the UK Parliament due to the COVID-19 pandemic is reflected by a corresponding sharp decrease in our trained models ability to identify non-SIO coordination. By increasing the detection threshold, the classifier can somewhat identify political activity as non-SIO, but a broader discussion about an acceptable recall for detecting SIO activity must be held. Note that in our training dataset, we have slightly more positive labels than negative labels (4:3 ratio), which implies that maintaining the $P = 0.975$ with a more imbalanced dataset would lead to even lower recall scores. Hence, in response to RQ2, we show that the extent at which such a global event affects our network analysis-based classifier highlights that bad actors that try to take advantage of time periods such as these to deploy an SIO campaign are less likely to be detected.

6 DISCUSSION

6.1 Limitations

While the SIO coordination patterns examined were previously proposed [13, 27] and to some extent represent normal behavior of Twitter users, other coordination patterns likely exist. For example, a common behavior that may be heavily used by Twitter communities—but is not included in our analysis—is sharing the same image or video. We also note that our ground truth data for SIO activity is based on discovered SIO campaigns Twitter has published. Likely, many more SIO campaigns are still operating on the Twitter platform. Some of the coordination patterns present in those communities are likely unaccounted for by our analysis.

6.2 Coordination as a Spectrum

As we showed in our experiments, coordination is not a unique phenomenon that only occurs in SIO campaigns. Each of the four collected baselines shows varying levels of coordinated activity, with political baselines exhibiting both SIO-like and non-SIO coordination patterns. Since other benign communities (e.g., governments, political activists) likely share similar behaviors as our political baselines, it is essential to note that their SIO coordination activity should be seen as a spectrum and not a binary state. Forcing a classifier to
make a binary decision between SIO and non-SIO based on coordination can lead to an overestimation of accounts that are part of disinformation campaigns. These overestimations would flag the activity of legitimate accounts as suspicious and possibly lock or suspend them, thereby degrading the usability of Twitter.

6.3 Detection Outside the Closed World

We use the COVID-19 case study to illustrate two crucial problems with deploying machine learning systems in the real world. First, current machine learning techniques make a strong assumption that the future will resemble the past. In adversarial environments that are constantly changing, this assumption rarely ever holds. Second, events that are inherently unpredictable pose significant challenges for even anomaly-detection systems, which are trained to identify abnormal data points, as examples of the “novel” data points do not yet exist at training time [30]. This problem is akin to the “hindsight is 20/20” expression which tells us that decisions made in the past are easy to understand once we look back at them but hard to justify as they are happening. We emphasize that research into SIO detection must prioritize gaining insight over improving the numerical results.

6.4 Future Work

In this work, we focus on separating the activity of Twitter communities, whether SIO campaigns or legitimate users, based on their daily and weekly coordination patterns. While these time periods give us insight into how coordinated a community is for a specific day and week, they do not include information as to how their activity changes. Future research in this field could expand into finding ways to incorporate temporal dependencies into SIO coordination classifiers. By looking at the evolution of coordination, more behavior patterns of SIO campaigns and Twitter communities may emerge, such as cycling of accounts or measuring the burstiness or continuous coordination fingerprint of a community.

7 RELATED WORK

Disinformation campaigns have received much attention from various research disciplines since they play on human influence [2], political messaging [33], and platform manipulation [40, 44, 45]. While online social media platforms like Twitter have presented yet another landscape for the dissemination of disinformation, such platforms have also served as a way to keep a historical record that allows researchers to perform post-mortem analysis of the measures taken by the campaign operators. By focusing on the activity of accounts of one SIO campaign, researchers have been able to infer various campaign characteristics such as: what political leaning the community takes (e.g., left-leaning, right-leaning) [33], the divisive content they share [43], their possible presence in other platforms [33, 43, 44], the coordination efforts made by the community [42], or influence [13]. More closely related to the work in this paper, other researchers have also looked into cross-campaign comparisons to characterize various disinformation activities [23, 45]. While we use a similar dataset, we focus on explaining SIO coordination tactics rather than characterizing campaign content.

Identifying content pollution on social media has become a challenging problem due to the rapid and immense scale at which information diffuses in real-time. As a result, there is an increased interest in automating the moderation of such spaces using carefully designed algorithms [6, 7, 9, 34]. Such content moderation can be done through bot detection systems like Botometer [37, 38] or disinformation website detection systems like Disinfotron [10]. Additionally, network-based detection mechanisms have also been used to uncover Sybil accounts that wish to abuse online platforms [5, 39, 46]. Bot detection, which seeks to determine if an account is a human or robot, does not necessarily suffer from SIO detection challenges like identifying the intent behind a political community’s motivations for coordinating. Notably, current bot-detection methods are still lacking in that they exhibit high false-positive rates [28], and recent studies have sought to improve the generalization capabilities of detection systems by careful data selection during training [41].

Though the bot detection problem involves flagging individual accounts, other detection mechanisms focus on flagging networks based on their behavior. Truthy [26, 27] is an example of an early attempt at developing an automated system for detecting astroturfing campaigns. The primary function of Truthy is to flag networks of users extracted from Twitter as suspicious based on a list of weak indicators. Once flagged, the final determination of whether the coordinated user activity can be considered as astroturfing is left to end-users due to the difficulty of automatically capturing intent. Though helpful, the binary classifier with features designed to measure information network connectivity is trained on a small dataset of individual hand-labeled networks obtained via the Truthy web service [27]. Additionally, while Truthy provides evidence that political astroturfing tends to contain patterns of coordination, it lacks rigorous validation on large-scale datasets with non-random legitimate coordination baselines for comparison. Other recent developments in the automatic extraction of Twitter communities likely to be engaged in astroturfing campaigns have mainly focused on tweet coordination networks [12, 13, 22], text-based analysis [12], and specific temporal patterns [22]. As we set out to show in the current study, a careful examination of the extent to which legitimate political communities coordinate reveals that coordination network statistics are insufficient to distinguish Twitter SIO campaigns from other instances of coordination.

8 CONCLUSION

Strategic Information Operations have exploited online social media sources to deceive and manipulate online rhetoric. Detecting these SIO campaigns, however, is still an open problem. Previous works have suggested using coordination patterns that were present in the specific disinformation campaign as a way to uncover other SIO campaigns or compare disinformation to non-realistic baselines. In this work, we address previous shortcomings by focusing on answering a broader question: how generalizable are these patterns and do they have any pitfalls as detection mechanisms. As our results show, coordination patterns on Twitter are not uncommon. In fact, communities (specifically political ones) are likely to have coordination patterns that are similar to those of SIO campaigns. The analysis performed in this paper shows that coordination patterns are not enough to detect these campaigns, and further analysis is needed to gain more insight into disinformation coordination.
### Table 6: This table shows how we mapped the data release from Twitter’s Election Integrity Hub to the disinformation campaign in our study.

| Disinformation Campaign | Release Date       |
|-------------------------|--------------------|
| China → Hong Kong       | August 2019        |
|                         | September 2019     |
| Iran → Geopolitics      | June 2019          |
| Russia (IRA) → USA      | October 2018       |
|                         | January 2019       |
|                         | June 2019          |
| UAE → Qatar/Yemen       | September 2019     |
| Iran → USA              | October 2018       |
|                         | January 2018       |
| Venezuela → Venezuela   | January 2019       |
| Ecuador → Ecuador       | September 2019     |
| Venezuela (commercial) → Venezuela | January 2019 |
|                         | June 2019          |
| UAE/Egypt → Qatar/Iran  | September 2019     |
| Catalonia → Spain       | June 2019          |

### APPENDIX

In this Appendix, we first show how we map the data from Twitter’s Election Integrity archives [36] to the source/target disinformation campaign labels used in the study (Table 6). Next, in Figure 8, we show the high-level coordinated activity of the remaining disinformation campaigns and baselines that are not shown in Figure 2. Finally, Figure 9 shows the P-R curves at varying levels of time thresholding (e.g., 5, 10 minutes).
Figure 8: This Figure shows the coordination patterns of the remaining eight disinformation campaigns and the two community baselines not shown in Section 5. Note the y-axis are not the same values for different campaigns.
Figure 9: P-R Curves for daily/weekly 5-minute and 10-minute models. Models shown are the ones that are closest to the mean PR-AUC score across the 10 folds.