Lateral Astroturfing Attacks on Twitter

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Abstract—Astroturfing attacks use automated accounts to artificially propel a chosen keyword to the top of Twitter trending topics. Lateral astroturfing is a sophisticated subset of such attacks in which the automated tweets 1) are posted by compromised accounts and 2) are deleted immediately after they are created. The former makes the attack more effective and the latter aids in evading detection. We present the first large-scale analysis of lateral astroturfing attacks. We detected over 20 thousand astroturfing accounts that were used between February 2019 and June 2019 to manipulate 3,710 unique keywords — at least 10% of daily trending topics in the region analyzed. Lateral astroturfing pollutes trending topics; allows for the manipulation of users’ opinions; and permits content that could otherwise be filtered by the platform, such as illicit advertisements. Our results aid in understanding user manipulation on social media and more generally shed light on the type of adversarial behavior that arises to evade detection.

I. INTRODUCTION

Social media is revolutionizing the way that we socialize, communicate, and participate in public discourse. Twitter is one of the most influential social media platforms operating today, with more than 100 million active daily users [28] relying on it for news, social interactions, and political discussions. The immense influence and popularity of Twitter naturally attracts adversaries who hope to artificially influence public opinion. Perhaps the most well-known example of adversarial social media manipulation is the alleged Russian influence on American and European elections, in which fake profiles, posts, and pages influenced the opinions of social media users. These attacks are believed to have influenced elections and referendums in the world’s largest democracies, including the United States and the United Kingdom [37].

One effective means of influence is through manipulation of trending topics on Twitter. Trending topics displays the most discussed topics (events, names, phrases, etc.) both globally and based on geographical area. It is an important part of the Twitter ecosystem, as it gives visibility to discussions and further boosts popular topics. In general, keywords rise to trending topics either due to an event that occurs, such as a sporting event, or from many users discussing a similar topic, e.g. in grass-roots organizing. In this paper, we focus on a class of attacks that aims to mimic the later. This type of attack is often referred to as astroturfing since it mimics grass-roots organizing but is artificial.

In most astroturfing attacks on trending topics, a set of bots tweet the target keyword, making it appear as though many users are discussing it. This artificially propels the keyword into trending topics. In this paper, we focus on a particular subset of this attack, lateral astroturfing. Lateral astroturfing attacks take specific measures to increase their effectiveness and avoid detection by the platform. First, this attack employs, among others, compromised, active accounts without the knowledge of the users who own these accounts. This causes the attack to appear natural and evades bot detection, since the original user continues to tweet, retweet, like, and direct message from the account. Second, the tweets involved in the attack are deleted directly after they are posted. This action not only allows the attack to evade Twitter detection algorithms, as we will show through the success of the attack, but also evades detection of the account owners.

This attack is related to “lateral movement” attacks, in which one or more compromised nodes in a network (e.g. an email account), is used to attack the system from within. The methods of evasion that are the cornerstone of lateral astroturfing attacks are also often present in other lateral movement attacks. For example, lateral phishing attacks 1) employ compromised email accounts within a company without the knowledge of the account owner and 2) delete the phishing email almost immediately after it is sent. Like in lateral astroturfing attacks, these actions make the attack more effective and more difficult to detect. [17]

This paper studies lateral astroturfing attacks on trending topics in Turkey, a country with one of the highest number of Twitter users. The contributions of this study are:

Identification of a new, ongoing attack on trending topics: lateral astroturfing (Section III). Lateral astroturfing attacks use compromised, but still active, accounts to artificially propel a chosen keyword to the top of Twitter trending topics. The tweets are then deleted immediately after they are created. We formally define this new attack.

Attack Detection (Section IV). We present our procedure to identify lateral astroturfing attacks and the bots that participate in them. We also compare this method against the state-of-the-art bot detection methods. We evaluate these existing bot-detection methods and explore why they fail to detect the bots that we have identified as participating in lateral astroturfing attacks.
Analysis of the success of the lateral astroturfing attacks (Section V-A). We analyze the lateral astroturfing attacks that we detect in order determine their success rate using a variety of metrics.

Analysis of new lateral astroturfing bots (Sections V-B and V-C). In order to better understand the ecosystem of the bots involved in lateral astroturfing, we classify the bots that take part in these attacks into different categories and reveal a new type of bot: an infected account in which the original user is unaware that their account is being used in an attack and continues to use it.

Analysis of the astroturfed trends (Section V-D). We reveal which trends this attack has been used to promote and categorize these trends.

Defenses (Section VI). We discuss why this attack is difficult to defend against, but present a number of potential platform-side defenses.

II. BACKGROUND AND RELATED WORK
A. User Manipulation Attacks

The wide adoption of social media platforms has attracted adversaries aiming to manipulate users on a large scale for their own purposes. Such manipulation attacks span from targeted advertising assisted by mass data collection to government sponsored trolling, propaganda, and spam. We are only now beginning to understand the impact that these types of attacks have, not only on individuals, but on society more broadly. Many of these manipulation attacks employ bots for bot-nets to execute, since wide deployment of the attack is often a necessary component. We focus on this class of bot-assisted manipulation attacks.

One clear example of manipulation efforts on social media is government censorship and propaganda. Traditional government censorship methods (i.e. blocking direct access to selected web pages) are becoming a less effective means of control as blocking an entire social media websites causes collateral damage and can even the inverse effect of an increase in the use of VPNs to circumvent the censor. As such, social media manipulation has become a new censorship strategy. While the focus of this paper is on bot-net attacks, this type of manipulation can also be done through the use of “troll armies.” These type of attacks have been observed on social media in many countries including, but far from limited to, Russia, Turkey, Mexico, Iran, and China.

In addition to government-sponsored attacks and manipulation, spammers and advertisers alike use similar methods to promote products and URLs. For example, accounts can take advantage of trending topics by including these keywords and hashtags into their messages in order to ensure a broad audience. This method can be used by advertisers to artificially cause users to read about certain brands by tweeting about popular trending topics. It is also used by spammers to encourage clicks on malicious URLs.

B. Types of Bots on Twitter

Many manipulation attacks on Twitter are executed by bots. Broadly, bots are any automated agents, and on Twitter bots are any accounts with automated content. These Twitter bots can exhibit a variety of behaviors and be employed for many reasons. While this paper focuses on the attacks perpetrated by bots, much of the literature focuses on the bots themselves (e.g. buying and selling accounts, detection, their evolution). In order, then to related these bots to this work, we catalog the bot types found in the literature on social media bots and discuss, for each category, the types of attacks associated with them.

Spambots aim to promote specific malicious content. The most common type of attack that these bots execute is tracking trending topics and injecting these topics and hashtags into their tweets alongside the malicious content (e.g. malicious URLs). Spammers employ bot-nets to promote particular or malicious URLs en masse, in so-called “spam campaigns” with the goal of tricking users into clicking these links.

Fake followers are accounts that follow other users in order to boost perceived popularity and influence of these other accounts or simply to get followers in return. These bots can be used as part of another attack to make a fake account look more legitimate or simply be used by regular users in order to gain followers. In addition, some are users who deploy automated software to follows random accounts in order to promote themselves.

Social bots are those “designed to mimic human users on social media.” They aim to manipulate public opinion by spreading disinformation and creating artificial entities by boosting the impact of other users. These types of accounts are often involved in astroturfing attacks. They copy real identities (profile pictures, personal pictures, tweets), mimic the circadian rhythm of humans, gain followers by following each other, and mix malicious tweets with handcrafted tweets. CyboHuman bots, cyborgs, and humans assisted by bots, augmented humans, make bot detection even harder by blurring the line between bots and humans. As such, these accounts are increasingly difficult to identify both manually and automatically.

C. Bot Detection Techniques

In order to develop methods to detect bots, some ground truth is needed for validation. There are a variety of different methods in the literature for obtaining ground truth for bots, many of which are dependent on the type of bots that are being targeted. Common methods are 1) assuming suspended accounts were bots, 2) manual annotation by experts or crowd-sourcing annotations, and 3) using honeypot accounts. In this work, we develop another methodology for labeling bots. Instead of directly labeling bots, we detect that an attack is happening and then consider an account a bot if it is involved in an attack.

Once ground truth is established, much of prior work classifies new accounts with supervised learning methods trained on these known bot accounts using features based on meta-data and most recent tweets. Unsupervised learning methods can also be used to search for highly correlated activities by groups of bots.

Many methods for bot detection focus on a specific feature of the bot accounts that easily identifies them. In lateral
astroturfing attacks, content deletion is the identifying feature. Content deletion is rarely employed as a feature for detection, since it requires monitoring bots in real-time — deleted tweets are difficult to obtain on historical data. Varol et al. [29] and DeBot [4] listed content deletion recently as a bot feature, but used a proxy feature to capture deletions: a high recent tweeting rate but low number of tweets. Chavoshi et al. [5] discovered a set of Turkish bots with correlated deletion activity, although they did not have coordinated posting activity. Deletion is used to hide the bot-like behavior and maintain an average-looking profile.

D. Astroturfing

Prior work on astroturfing is scarce and focused on campaigns rather than trends. Ratkiewicz et al. [22] made the first attempt to detect and classify astroturfed political campaigns (memes). The authors use crowdsourcing to determine which campaigns were being astroturfed after the fact. Due to the deletion activity, lateral astroturfing attacks cannot be detected in this way — after the fact. Varol et al. [29] studied the early detection of promoted campaigns using the trends promoted by Twitter itself as a proxy for ground truth for artificial trends. However, the work does not give insight into the trends that were being astroturfed or about the strategies these bots used.

Conversely, Abu-El-Rub et al. [1] used the bots identified by DeBot [4] through coordinated activity to identify and study such artificial campaigns. They discovered that correlated bots indeed posted tweets with same hashtags, which, in turn, begin trending. However their method gives no indication as to whether the hashtags that made it to trending started organically, i.e. the bots were taking advantage of a trending topic, or artificially due to bot activity.

III. DEFINITION AND DESCRIPTION OF ATTACK

The goal of an astroturfing attack is simple: make a chosen keyword reach trending topics. Hundreds of topics and keywords reach trending topics every day in Turkey alone, so identifying which of these trends are organic vs manufactured is challenging. We are interested in studying a subset these attacks: lateral astroturfing. We therefore carefully define this attack and support the definition based on the differences between the organic trends/tweets and artificial trends/tweets we have collected.

A. Attack Summary

In a lateral astroturfing attack, a number of tweets are posted at the same time from a variety of different types of accounts, which we refer to generally as astrobots, all containing the same target keyword. These same tweets are then deleted in unison. Each tweet involved contains the target keyword, which in this context is an either a hashtag or an n-gram, and a selection of other random words. In addition, each account involved only tweets the target keyword once. If the target keyword reaches trending topics, which was the case in 90% of the attacks we observed, the attack has succeeded and the astrobots remain silent. Otherwise, the attack is repeated until it succeeds; this repeat attack usually only needs to occur one time before the attack is successful.

B. Formal Definition

We formally define this attack as follows. Consider a set of tweets $T = \{t_0, t_1, t_2, ..., t_n\}$ that are neither retweets nor contain mentions or urls in which each tweet $t_i$ is published at time $p_i \in P = \{p_0, p_1, p_2, ..., p_n\}$ and deleted at time $d_i \in D = \{d_0, d_1, d_2, ..., d_n\}$. Let $w$ be some promoted keyword. An attack $A$ occurs when there exists a $T$ s.t. every tweet $t_i$ contains $w$ along side a set of other random words and:

$$|T| > \kappa$$  \hfill (1)

$$\max(P) - \min(P) < \alpha_p$$  \hfill (2)

$$\max(D) - \min(D) < \alpha_d$$  \hfill (3)

$$d_i - p_i < \theta \quad \forall t_i \in T$$  \hfill (4)

That is, [1] there are at least $\kappa$ tweets involved in the attack, the tweets involved are created [2] and deleted [3] within a window of size $\alpha_p$ and $\alpha_d$ respectively, and [4] the tweets are deleted within $\theta$ after creation. We intentionally leave the parameters ($\kappa, \alpha_p, \alpha_d, \theta$) in the definition open and to be tuned.

C. Datasets

We collected two datasets of lateral astroturfing accounts to analyze this attack. First, we constructed the real-time dataset by following known astrobots using Twitter’s Streaming API in real-time. The real-time dataset contains recent data (2019). Second, we constructed the retrospective dataset from the historical 1% Twitter stream. The retrospective dataset contains data from 2018. The data collection methodology for these datasets is described in more detail in Section [IV].

We also constructed a third dataset that contains tweets from normal, non bot users. We call this dataset the benign dataset. The benign dataset contains 115,423 tweets by real users, which we collected by monitoring 1,200 verified Turkish users that self-declared their profile on a popular Turkish website eksisozluk[6]. The benign dataset was collected using the Streaming API for 5 days.

D. Attributes of the Attack

1) Duration of Attack: The coordinated activity of the accounts involved in lateral astroturfing attacks is a primary feature that contributes to detection. The first aspect of this coordinated activity is that all of the tweets involved in a single attack are created and later deleted in an anomalously small window of time. That is, the attacker runs a script that causes all of the bots to publish a tweet containing the target keyword and then runs a script that causes all of the bots to delete that tweet. Figure [7] shows this coordinated activity. All of the tweets are posted together, on average within the same minute, and deleted together, on average in less than a minute.

[https://eksisoszuk.com/sozluclerin-twitter-sayfalari--2020198](https://eksisoszuk.com/sozluclerin-twitter-sayfalari--2020198)
2) Attack Tweet Lifetime: Since a major aspect of this attack is that the tweets involved are deleted in order to avoid detection, we study the total lifetime of tweets that are involved in an attack vs those that are not. We define the lifetime of a tweet as the difference between the creation and deletion date. Per our definition, all of the tweets involved in this attack are deleted within some time \( \alpha_d \).

Figure 2 shows the extent to which tweets that contain a promoted keyword have a shorter lifespan compared to other deleted tweets by the same set of users. Most tweets that contain a promoted keyword are deleted within the first 2 minutes, while most of the other deleted tweets are deleted after 30 minutes. This short tweet lifespan for tweets involved in an attack allow the attack to go undetected.

3) Lexicon-Based Content: Another marker of this attack is that the tweet contents, aside from the target keyword, appear to be sourced from a lexicon of words and parenthesized categories corresponding to each word. As each tweet in an attack is published, we add its contents to a bag of words before deletion to show the difference between normal tweets and the attack tweets. We refer to tweets with contents built from the lexicon as lexicon tweets.

Table 1 compares the most common words in the attack tweets we identified against the most common words in normal Turkish language Tweets. The non-attack Tweets are collected from archive.org from October 10, 2018 (the most recent date available), which contains 1% of Tweets.

| Attack Tweets | Translation | Realtime Sample | Translation |
|---------------|-------------|-----------------|-------------|
| bir | arany / one | bir | arany / one |
| bilimi | science (of) | ve | and |
| otu | plant (of) | bu | this |
| (iççe) | (district) | için | for |
| su | water | de | as well |
| taş | stone (of) | da | as well |
| açık | open | ne | what |
| bahşi | fish (of) | çok | a lot |
| iç | inner | kadar | as |
| bilimsel | scientific | ama | but |
| hava | air | o | it / that |
| kara | dark | ile | with |
| bilimci | scientist | en | most |
| yer | place | daha | more |

While the the most common words for normal tweets are, as expected, Turkish function words (e.g. this, for, also), the most common words in the attack tweets are words that commonly appear in noun phrases (some of which are also parts of common noun phrases in English, e.g. inner and science (of something)) and disambiguation indicator (e.g. district). This signifies that the content is nonsense at the sentence level and that the words are chosen in a somewhat random fashion.

4) Place Field Anomaly: Although not strictly part of the definition since many tweets do not contain a location attribute, another way that the tweets involved in the attack differ from normal tweets is that the location is much farther away from the previous tweet location.

The place field indicates the location (the city, country, and coordinates) of a geo-tagged tweet. This feature is off by default so users have to manually turn it on. However, third party applications and websites can post tweets with location.

Of the tweets that we identified as part of an attack, 10% had both a non-null place field and a different location than at least one other for the same user. Figure 3 demonstrates the extent to which the place field varies for attack tweets. This figure contains the tweets and users in the benign dataset vs those in the real-time dataset. We filtered out users with fewer than 2 geotagged tweets, yielding a total of 384 astrobots and 100 regular users. Figure 3 shows the total distance “traveled” in this 5 day span by summing the distances between two locations found in two consecutive geo-tagged tweets of a user. The median total distance traveled by the normal users that we monitored to over 5 days was 1 km, but the average distance traveled over the same days for the astrobot accounts was 24,582 km, which is a round trip flight from Istanbul to the capital, Ankara, 70 times.

5) Source of Tweets: The final field that we examine for the attack tweets is the source field. The source field contains information about where the tweet came from (e.g. which app
Fig. 3. The total distance covered by each user per type in five days. The astrobots traveled an average of 24,582km while normal users traveled just 1km.

was used). The tweets used in the attack were from Twitter for Android, Twitter for iPhone or Twitter for iPad. We have not identified any malicious Twitter application being used in this attack, as in the case of [12].

IV. BOT DETECTION PROCEDURE

The focus of this paper is on the observed lateral astrobot attack, not on bot detection or collection; however, to study this attack in detail we need a large collection of the bots and tweets involved. Here we describe our methodology for this data collection.

A. Real-time Detection

The real-time detection procedure requires three steps: 1) collection of a seed set of astrobots to monitor, 2) identification of an attack in progress and the keyword that attack is promoting, 3) tracking of these keywords to identify more astrobots, and 4) identifying new astrobots. Figure 4 illustrates the flow of our detection method.

Except for collecting seed accounts using a known astro-turfed trend, in which we made use of the Standard Search API[3] our bot detection system uses the Streaming API, which presents tweets in real-time. Since the rate limit of the Streaming API limits us to two streams, we are able monitor at most 5,000 astrobots and 400 promoted keywords. Since it is not possible, then, to track the all of the astrobots, we randomized the selection of astrobots to track maximum number of botnets.

1) Collection of Seed Accounts: The collection of seed accounts is a labor intensive, manual labeling process. We used multiple methods for building this initial data set. First we closely monitored recurrent keywords (e.g. ”TwitartrirCom” which promotes twitartrir.com, a Turkish fake follower market) to detect the attacks in real time using the Streaming API and confirmed manually that an attack was taking place. We also manually watched for a new trend to take affect, judged if it is part of an attack or not, and timely collected the tweets involved before they were deleted using the Search API.

2) Keyword Detection: Once a set of seed astrobots is established, we next detect an attack as early as possible by tracking their activity. To this end, we use a rule based classifier to determine if a tweet is an attack tweet candidate.

Recall from Section III-D3 that the contents of the attack tweets appear to be selected at random from a lexicon and therefore do not make sense to a native Turkish speaker. We developed a simple rule based classification technique to identify these lexicon tweets and manually verified the results. This method achieved 100% precision on a set of lexicon and normal tweets of astrobots. These rules are:

- No @ (so no RT or mention/reply)
- Is between 25 and 90 characters
- Does not start with an uppercase letter
- Has no url (no ’http’)
- Has no punctuation
- Has a minimum 3 tokens and maximum 7 tokens
- Contains a maximum of one hashtag including the promoted keyword
- Does not contain Turkish pronouns or other common short function words (e.g. ’ne’, ’de’, ’bu’, ’her’, ’mi’)

Any tweet which complies with these rules is a candidate lexicon tweet and therefore a candidate attack tweet.

In order to classify when an attack is happening, we combine the rules from the lexicon tweet detector with a threshold (κ) on the number of consecutive tweets sorted by creation date containing the same keyword. We set κ to be 4 after observing that κ > 4 is simply redundant. We then update the second connection to Streaming API, in which we track the most recent 400 keywords we’ve identified and collect the tweets that contain those keywords.

3) New Bot Detection: Updating keywords just when astrobots start to promote a new keyword allow us to collect some of the lexicon tweets. We assume that any user who tweeted a lexicon tweet with a promoted keyword is an astrobot and we add them to astrobots list. However, as seen in Figure 5 the rules alone do not guarantee that the accounts are correctly classified. In order to reduce false positives we require that a tweet also both proceeds and follows another lexicon tweet candidates within the same second. We manually verified that this method guarantees 100% precision, however there are likely false negatives that are unaccounted for.
compared to its neighbors. Finally we filtered out the tweets sum as those with at least a difference of 4 tweets in height algorithm for this. We then detected the peaks in the rolling creation time of attack tweets. We use Scipy’s peak detection of 120 seconds so that the peak of the signal is the mean number of tweets posted per second containing that keyword. For each promoted keyword, we create a timeseries based on the promoted keyword. Elimination of such noise is also necessary to participate in attacks by 23 June 2019. Astrobot Tweets (4,683) are those tweets which are posted by accounts that participate in lateral astroturfing, but not as part of an attack. Astrobot Tweets (115,423) are from the benign dataset described in the previous section. Finally, the lexicon tweets (11,710) are those that we label as appearing to be selected form a lexicon.

Using this method, we detected 20,055 astrobots between 15 December 2018 and 17 March 2019. Of the 5,000 astrobots we monitored, 3,182 of them were still active and participating in attacks by 17 March 2019 and 1,630 of them were still active and participating in attacks by 23 June 2019.

4) Classifying Attack Tweets and Eliminating Noise: Once we have detected promoted keywords, we then classify whether a tweet containing the keyword is part of the attack. We find that astrobots may tweet with a promoted keyword, but not all of their tweets are part of the attack. This implies that they are employed in other kind of bot activity as well, suggesting that the network of bot activity is quite complex. It is also possible that they participate in organic activity with the promoted keyword. Elimination of such noise is also necessary to precisely compute when an attack begins and ends. To this end, we leverage the fact that attack tweets are posted in a very short time frame.

To reduce this noise, we perform peak detection to determine which tweets are outside of the attack area. That is, for each promoted keyword, we create a timeseries based on number of tweets posted per second containing that keyword. Then we take a rolling sum using a triangular window size of 120 seconds so that the peak of the signal is the mean creation time of attack tweets. We use Scipy’s peak detection algorithm for this. We then detected the peaks in the rolling sum as those with at least a difference of 4 tweets in height compared to its neighbors. Finally we filtered out the tweets that were not within 150 seconds of the peak. We determined that 150 seconds was sufficient through inspecting multiple attacks. We classify every peak as a standalone attack.

B. Comparison with Bot Detection Tools

While this paper does not focus on bot detection techniques or claim to have created an efficient methodology for such, comparison to prior work on bot detection is useful in determining if other methods would flag the bots that we are tracking as bots or humans.

1) Botometer [10]: Botometer is a bot detection method that relies on a snapshot of a profile (i.e. the last 200 tweets, follower count, like count etc.) in the time of querying the api. Therefore, it cannot take deleted tweets into account. It also classifies users in isolation therefore cannot detect accounts that participate in an attack with other accounts.

Botometer has 2 possible scores as an indicator for whether a user is a bot. We use the universal score for bots since it does not take content features into account and the bots we have detected tweet in Turkish. The scores with respect to identified types are given in Figure [IV-B1]. As seen in the figure, botometer, having no access to deletions, performs poorly. Without deletions, astrobots are difficult to identify, even to a human. The authors state that they use high recent tweet rate but low number of tweets overall as a proxy for content deletion, under the assumption that the recent tweets will get deleted in the future [35]. However, both the deletions explained and the the behavior they describe are quite different than what we have here; astrobots do not have high recent tweet rate and their tweets are deleted immediately.

The system seems to work for the astrobot type “inactive”, possibly because algorithm’s bias towards inactive users. Note that for the bots whose timeline are completely empty (kept clean by deletions) the botometer could not produce a score, so they are not included.

2) DeBot [4]: Debot is an unsupervised tool to detect correlated bot activity. It follows a similar procedure to ours, first collecting a seed set based on correlated keyword activity, then adding those accounts to a list of potential bots to listen to and flag other correlated activity.

The major difference is that because DeBot uses certain keywords to filter data, it suffers from poor recall when it uses keywords that are too general. In lateral astroturfing, the accounts use random words alongside the keyword they are promoting, so it is impossible to detect them using frequent words. The API they provide is on top of a model which uses...
keyword filtering. This model model yields no match with the astrobots we discovered.

Listening to the keywords the astrobots promote would yield 100% recall but it introduces a cold start problem, as it is not possible to predict which keyword will be promoted by an attack before such attack happens and displayed in trends. A few keywords are boosted by subsequent attacks after the keyword reaches trending, but the astrobots we track are mostly idle after the initial attack, making it impossible to detect them by listening to the keyword they promote.

Although not implemented in the authors’ official API, DeBot can also use a sample of 1% of real time tweets in theory. However this yields a small recall. To verify this, we fetched these real time tweets on May 30, 2019 for 9.5 hours (the time suggested in the original paper) starting from 12:00. In the original paper, deletions are not taken into account in [4] but the authors state it could be added in [5]. We reproduced DeBot to include deletions and it yielded 1,209 “suspicious users” for further inspection. Out of 1,704 users that we already know to be attacking that day, DeBot only discovered 107 of them, which yields a recall of 6.27%.

Figure 7 depicts the timeseries of attacks observed by 1% sample versus by listening to the known astrobots via the Streaming API. While attack tweets can go up to 923, 1% realtime data shows only up to 72, rendering bot detection very slow due to low recall.

![Figure 7](https://archive.org/details/twitterstream)

Fig. 7. Number of tweets gathered by using Streaming API versus the number collected via the 1% sample (Spritzer) every 15 minutes.

To improve the results of DeBot on the types of astrobots involved in lateral astroturfing attacks, an extra listener can be added to the architecture which would identify the content being promoted by the correlated activity of the bots that are being listened to. Then the collector can track the activity related to that promoted content to detect more bots using the rest of the DeBot architecture. Here, promoted content is not restricted only to keywords being astroturfed, but also tweets that are being retweeted, liked, or users who have purchased followers. Since such a framework is out of scope of this paper, we leave it as a future work.

C. Retrospective Detection

Once we identified the characteristics of this attack and confirm the definitions via real-time analysis, we developed a methodology to detect past lateral astroturfing attacks using the 1% of tweets on Twitter Stream, which is partially available on archive.org. This collection of tweets contains 1% of all tweets posted between April and October 2018, including deleted tweets, which are identified by a notice. This makes it possible to detect prior attacks using this data. To classify these prior attacks we reproduce the procedure we used for attack detection. We collect the deleted tweets and classify them as lexicon tweets using the rules outlined earlier in this section. We use a conservative approach and only consider that an attack has happened if four adjacent lexicon tweets candidates contain the same keyword. We then extended this initial set by applying peak detection as explained above. Note that we did not perform this detection on data in the same period as the real-time dataset because this data was not available.

From this retrospective detection, we find 2,904 unique keywords that were the target of a lateral astroturfing attack and 26,162 accounts that were involved in at least one such attack. We refer to the user accounts and trends found in this way as the retrospective dataset.

In contrast to the real-time dataset, the retrospective dataset is collected in a non-biased way. That is, due to the detection methodology, all of the data in the real-time dataset are related to the starting set of astrobots. While the retrospective dataset is gathered using the same criteria for determining if an attack is happening, it does not rely on a seed set and is therefore not biased to accounts related to the initial seed set. The drawback of the retrospective dataset, however, is that it only contains data that are of the 1% sample of the Twitter Stream.

V. ATTACK ANALYSIS

In this section we detail our quantitative analysis of lateral astroturfing attacks using the real-world attacks recorded in both datasets. We leverage the fact that we have two partial views of this attack in the form of the two datasets in order to get a more complete picture of the attack. For each set of analysis we the most illExcept where explicitly stated, we use the real-time dataset since it better captures the extent of each attack as it is not limited to the 1% Twitter Stream.

A. Measuring the Success of the Attacks

For completeness, we use multiple metrics to measure the success of the lateral astroturfing attacks. First we measure in terms of the success of the attacks on an individual level. For this we use the real-time dataset, because it contains a higher number of accounts that participate in each attack since it is not limited to 1% of tweets. Second we measure prevalence of the attacks in general using both datasets.

We consider an attack successful if the target keyword appears in trending topics, which contains 50 keywords at a time and is updated every 5 minutes. We fetched all trending keywords, regardless of their origin (astroturfed or organic), between 17 June 2019 and 16 July 2019. In this time frame, there were 764 target keywords in the real-time dataset. That is, we detected 764 unique keywords being manipulated by the astrobots that we monitored between these dates. Of these keywords, 97% made it into trending topics. Furthermore, 88% of all promoted keywords trended for longer than 1 hour and 85% trended more than 1 hour in top 10 trends. While our seed
data collection may be biased towards successful attacks, the rest of the data collection listens for the behavior of an attack from the astrobots we identify, so it is not biased towards successful attacks.

Although almost all of the attacks eventually succeed in reaching trending topics, it is not always the case that an attack is successful in its first try. We find that only 90% do so on their first try of the day. For the remaining 10%, the attack is tried a second time. Once a keyword reaches trending, only 17% of keywords are promoted again in the same day, and only 4% are re-promoted more than one time.

In the end, only 3% of keywords fail to reach trending topics. We manually inspected these cases and labeled the potential reasons: 1) only a substring of the keyword trended, i.e. promoting “Ağaç Bayramı” (Tree Fest) is intended, but “Ağaç” (Tree) actually trended, 2) the keyword includes swear words, 3) the keyword has a typo, 4) the keyword is an ad about creating artificial trends, 5) the keyword is very long.

Since almost all of the attacks we observe are successful, we next measure the degree of success for each attack by determining its position in trending topics for the duration of the attack, essentially how well an attacks succeeds. Figure 8 shows the maximum and mean trend rank of the set of keywords promoted by astrobots against a set of other trending topics. The attack keywords generally reach a higher position in trending than other topics and remain in the top ranks for a longer amount of time.

Another measure of how well an attack succeeds is how long it stays in the trending topics list. Figure 9 shows how much longer the attack trends are able to stay in trending topics than other keywords. Because some keywords reach trending topics multiple times in one day, we use the longest lifetime, this eliminates fluctuations such as going into the top 50 and out for 2 minutes. Here there is some contrast in the lifetime; the astroturfed trends spend a longer amount of time in trending topics list.

![Fig. 8. Histograms of the maximum (top) and mean (bottom) trend rank for the target keywords of an attack and benign keywords. The target keywords are those that are artificially pushed into trending topics. The other keywords are trends that we did not record being involved in a lateral astroturfing attack. Many more target keywords reach the top 5 than the other keywords and they remain there longer.](image)

![Fig. 9. Maximum lifetime of non-astroturfed trends (top) versus astroturfed trend (bottom). Astroturfed trends tend to stay in the trending list for longer.](image)

Now that we have shown how successful the attacks are individually, we estimate the prevalence of this attack in terms of the percentage of daily trending topics that are manipulated using both datasets. Because we are not able to obtain and analyze every single Turkish tweet posted and are limited by the APIs, we can only provide a lower bound for this metric. We use both datasets for this analysis, however, in order to get as complete a picture as possible of the prevalence of lateral astroturfing attacks.

To measure the prevalence, we record how many unique target keywords are pushed per day in each dataset and compare these words to the total number of trending topics on the same day. Figure 10 shows these results for both datasets. On the left is the retrospective dataset. Recall that this dataset is collected from a stream of tweets containing 1% of all tweets. For the retrospective data from 2018, data on the position of each keyword in trending topics was not available, so we consider all keywords that appear in trending topics (top 50 trends) for any length of time. On average, the target keywords that we found to be part of a lateral astroturfing attack made up 13.47% of trending topics per day. Because we only have access to 1% of the data from this period, there are likely attacks that we have missed.

The right side of Figure 10 shows a similar analysis with the real-time dataset, which is biased towards bots that from the same networks, but not limited to the 1% stream. For 2019, we have finer grained data on the position of each keyword in trending topics, so we consider only those keywords that appear in the top 10 trending topics for any length of time. We then also consider target keywords of an attack that reached the top 10 trends. On average, the target keywords made up 32.960% of the top 10 trending topics per day. In the same period, all target keywords that made it into the top 50 trending topics made up 12.55% of trending topics per day.

The previous metrics focused on how well the target keywords reach trending topics. However, these metrics ignore the core goal of an astrobot, to impact those who see their keyword. To capture this, we measure how the target keyword was able to catch the attention of Twitter users. For this, we use surplus as a proxy. We define surplus as the number of tweets related to the target keyword that are not deleted. Since these tweets are not deleted, they are not part of the attack, but instead show the influence of these attacks on the Twitter users that saw them enter trending topics.
Recall that, in part, the real-world dataset is collected by detecting that an attack is happening and then collecting all of the tweets containing the target keyword for the duration of the data collection. While the tweets involved in an attack are deleted by the attackers, those that are not deleted are not part of the attack. For this metric, we use this set of not deleted, keyword containing tweets collected between 17 February 2019 and 23 March 2019.

First, we determine which tweets have not been deleted via the Twitter API’s GET statuses/lookup endpoint on 9 April 2019. As we saw in [III] most attack tweets are deleted in 3 minutes after their creation, so the tweets that we observe here are not part of a lateral astroturfing attack. Therefore, we assume that the tweets that still exist by 9 April show the effect of a promoted keyword on Twitter users who observed them in trending topics. That is, the tweets related to the keyword that are not deleted are not part of the attack, but instead show the influence of these attacks on the Twitter users that saw the attack.

Figure [11] shows the results of this analysis. In short, this analysis shows that most of the hashtags have little to no surplus tweets. That is, aside from the tweets that are part of the attack, very few trends are tweeted about in the hours or days after the keyword successfully trends.

In addition, many of the remaining tweets appeared to be part of an orthogonal attack in which spammers use the keywords in trending topics (organic or manufactured) to gain visibility. That is, we see other types of bot accounts that create tweets that consist of a few of the top trending topics and a spam link in order to boost the visibility of the tweet.

**B. Astrobots’ Behavior Categories**

In order to better understand the ecosystem of the bots involved in this attack, we manually labeled a subset of 1,160 of the bots that were still active on March 12, 2019. Of these accounts 87 became unavailable during the 2 month period of qualitative analysis. Two of the accounts were temporarily unavailable due to Twitter’s Media Policy, 57 were not available because the user disabled the account temporarily or deleted it, 28 were suspended, and 42 accounts become protected (private). We present the results for the remaining 1,031 accounts.

We discovered three distinct categories of profiles which make up 92% of the samples. The samples were annotated independently by two native Turkish speakers familiar with fake accounts; one expert annotated all 1,031 accounts and the other 100 samples in order to confirm consistency. The inner-annotator agreement was 82% with kappa score 0.707 (substantial agreement). Here we present the categories of accounts that participate in the attacks:

**Human** “Human” accounts appear strongly to be used by a real person due to their sophisticated, original, recent tweets and conversations with other users on the platform. Here, we defined sophisticated as containing real sounding sentences that convey meaning and have standard grammar (while accounting for the fact that these are tweets). These accounts are compromised and do take part in the attacks, but the owners are generally unaware that their accounts have been compromised, since they are unable to see the tweets that have been posted and subsequently deleted.

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Fig. 10. Number of keywords promoted per day by the astrobots we monitored. The histogram on the leftmost section of the figure shows the number of attacks per day between 21 July and 16 October 2018, which comes form the retrospective dataset, which contains only 1% of tweets. The pink line (\(\sim\)) shows the percentage of trending topics (top 50) that these target keywords make up. The histogram on the right section of the figure shows the number of attacks per day between 17 June and 16 July 2019 that made it into the top trends. The attacks that made it into the top 10 are shown in green (■), the percentage of the top trending topics these target keywords make up for top 10 (\(\sim\)) and top 50 trends (\(\sim\)).

Fig. 11. Box plot of astroturfed keywords’ surplus. The median value is 55 tweets, that is, a median of 55 tweets are published that contain the astroturfed trend, excluding those involved in the attack. Although the target keywords made it into trending topic, the astroturfed keywords do not receive much attention.
**Retweeter:** These accounts consist almost entirely of retweets with little to no sophisticated tweets. These accounts may be legitimate compromised accounts or may be Sybil accounts created to boost the impact of the other accounts in the attack. Most of them have pictures of humans but do not have many or any original tweets.

**Inactive:** Inactive accounts are those whose users have either abandoned their account or never used it all. Their recent activity is hidden by the deletions that are a cornerstone of this attack. These may be legitimate but compromised accounts or Sybil accounts, but they do not have enough activity to evaluate. Some of these accounts have a human profile picture but do not have many sophisticated recent tweets and some have default profiles with no activity. Of those accounts a small subset (5%) had a not-deleted lexicon tweet as a last tweet (likely caused by a bug in the attacker’s program), and all other tweets are not recent.

**Korean:** The final category of Tweets are an artifact of the attack. These accounts are only promoting South Korean celebrities such as BTS. The accounts appear to be Turkish fans of such celebrities or fake accounts make to appear as such. Some of the accounts have sophisticated activity and some only have retweets, and it is not clear if those accounts are fully or partially automated. These accounts do, however, also participate in the lateral astroturfing attacks in Turkey. Our hypothesis is that these accounts are rented from a Turkish account market by Korean celebrities or their fans to participate in other forms of attacks on Twitter realted to Korean celebrities (e.g. [3]), but the same accounts are also rented to participate in lateral astroturfing in Turkey. The number of such accounts is small (41), so we did discarded the from the analysis.

The statistics of the type of astrobots in our dataset is shown in Figure 12. The median activity is reported not on the whole timeline of a user but during their activity during the period of our data collection.

1) **Creation Date:** Not all of the accounts in this attack are new accounts. In fact the oldest astrobot account that we detected was created in 2009. Figure 13 shows the creation dates of the astrobots in our dataset. Since this attack involved compromised accounts, we see that accounts involved can be created at any time. However, we have observed some anomalous peaks that suggest that some of the accounts are artificially created by the attackers, so not all accounts are compromised accounts.

2) **Last Activity of Users:** Here we see the overall churn of the accounts in our dataset. Out of 5,000 users that we detected (and later chose to track) between December 17, 2018 and March 17, 2019, 3,182 users were still active by March 17. 1,630 users were still participating in the attacks in 23 June, the day of the 2019 Turkish Election Rerun in Istanbul. Figure 14 shows the date of last attack for the astrobots we monitored. Most accounts that we monitored continue being part of the attacks, with the number becoming more stable as our data-collection continued. This suggests that there are a set of core astrobots used in the attack and a set of other accounts that the attackers use a throwaway accounts.

3) **Number of Attacks Per Account:** Because the turnover rate for the bot-net is quite low, most accounts have participated in many attacks. Figure 15 shows a histogram of the number of attacks per account. Here the spikes show the presence of a number of stable bots involved in the same attacks. For example, 300 users participated in between 570 attacks together and 150 participated in 340 attacks.

**C. Network of Astrobots with Respect to Their Behavior**

In order to gain insight into which astrobots are used together in attacks, we construct the botnet in a network graph. The nodes in the network are astrobots and an edge
Fig. 14. The Day of Last Attack by Users. This graph shows the last known attack that each astrobot we monitor was involved in. Note that a large group of accounts stop their attacks at the same time.

Fig. 15. This graph shows the number of attacks that each account was involved in. There appear to be a few core accounts that are involved in many attacks and then a number of support accounts.

between two astrobots indicates that those astrobots attacked to same keyword in the same day. The edges weights are the total number of such keyword-date pairs. Here we use the retrospective dataset as it gives a less biased sample than the real-time dataset since the data collection has not been done using seed users which could be in a particular cluster and would therefore not give information on other clusters.

Since we are interested in which types of astrobots are participating in the same attacks, we need to label the accounts by their types. We start with the 981 manual labels on the three main categories of accounts (human, retweeter, and inactive). We use this set as training data and build a classifier to label to remaining 13,668 bots active in the retrospective dataset. From the remaining unlabeled data, we labeled an additional small test set of 158 users consisting of 81 humans, 22 retweeters, 16 inactive accounts and 39 others which are discarded. For all three data sets, training, testing, and unlabeled, we collected each user’s current profile and most recent 200 tweets. The features we extracted from these profiles are displayed in Table V-C. We standardized the features pertaining to counts, as this method achieved slightly better results. For classification we trained a random forest with 700 trees. The features and their importances computed by scikit-learn are given in V-C.

The model achieved 82.2% 5-fold cross validation, 86.9% accuracy on test set and 82.775% out of bag performance. These results are in line with the error in the manual labeling. In both cases, the confusion comes from distinguishing between humans and retweeters.

The network for October 2018 is shown in Figure 15 and the communities and their composition are given in V-C. Using Force Atlas 2 by Gephi for network spatialization, we observe two main clusters, one of which mostly contains suspended accounts. The other cluster is segregated into two clusters in which one is big and homogeneous with respect to astrobots’ predicted behavior class and the other smaller cluster is mostly composed of astrobots predicted as human accounts.

Perhaps most interesting about this network is that there are no independent clusters. We assume that if there is more than one organization offering this service that they would use different bots to promote different keywords and therefore not be connected in the network. There are a number of possible explanations. The first is that only one company offers this service. It is also possible that at least a few clients chose to go to both companies and therefore there is a loose connection between the clusters. Finally, these services may share accounts.

D. Trend Analysis

We measure the impact of these attacks not only through their success in dominating the trending topics list, but also through the types of keywords that they promote. In contrast to the quantitative methods used in the previous section, here
we employ qualitative methods to characterize and categorize the types of target keywords that are manipulated in the lateral astroturfing attacks that we recorded. From this, we are able to also measure the success of the campaigns from a third angle: did the attack succeed at provoking others to tweet about the keyword.

In an iterative fashion, one expert labeled 1,113 target keywords with one to two pattern types that describe the keyword. Similar patterns were then merged (e.g. football and entertainment) and weak patterns were discarded. This process was repeated until each target keyword fit into exactly one pattern. In the end, this analysis ended with seven distinct categories that all 1,113 target keywords were labeled as one of. Confirmation was completed by another expert who labeled a random sample of 100 of the sample keywords, given the list of seven types. Inner-annotator agreement yielded an accuracy of 89% and Cohen’s kappa was 0.745 (substantial agreement). The disagreement primarily took two forms: implicit campaign slogans that require research before annotation and disagreement over what qualifies as entertainment. The results of this analysis are displayed in Table IV. Next we detail each of the categories.

Advertisement: Advertisements made up the largest proportion of the target keywords, with 36.9% of the keywords being labeled as advertisements. These keywords were advertisements by companies to promote their business. A majority belong to gambling websites or advertise Twitter specific scams, like follower markets.

Appeals to Government: 18.7% of the target keywords were labeled as “appeals to government.” These keywords appeal to the government for policy changes. They are used by stakeholders to give the impression that many citizens are asking for the policy change or to further boost a campaign.

Election Campaign: Similar in volume to the appeal campaigns, election campaigns make up 18.1% of the target keywords. The real-time dataset leads up to the March 31, 2019 Turkish local elections, so it is not surprising that we found keywords related to political campaigns. Many hashtags in this category were merely campaign slogans of specific parties or candidates of any political party. We found out that astroturfed trends do not necessarily follow a specific party or an ideology, contrary to hypothesis of [5].

Entertainment: Entertainment keywords, which make up 11.5% of the keywords, are broadly related to entertainment. Keywords in this category supported certain football teams, television shows, or were part of so called “hashtag” games.

Cult Slogans: Cult slogans made up 6.1% of the keywords. These keywords were in support of cult leader Adnan Oktar, who was arrested in the middle of the real-time dataset collection in July 2019.

Opinion Manipulation: Aside from political and appeal campaigns, we also categorizes 5.4% of tweets as pertaining to other political manipulation, including spreading disinformation.
Defamation: Keywords that are started by stakeholders to defame a brand or individual or a group made up just 3.8% of trends.

In order to determine which type of trends are the most successful in gaining the attention of Twitter users, we revisit the surplus analysis from Section V.D. For each successful astroturfed trend we calculate the surplus. Figure 17 shows the keywords with the highest surplus as well as the category.

The keywords with biggest surplus are political keywords (categorised as either election campaign or opinion manipulation). These keywords come from both the government and opposition. Television related keywords (categorised as entertainment) and appeals have also a large surplus. We believe that these keywords are both augmented by other kinds of bots (i.e. spammers), stakeholders (i.e. those who have political gains) and users who participate in organic discussion (i.e. TV show fans). These results are detailed in Figure.

VI. SECURITY IMPLICATIONS AND COUNTERMEASURES

In this section we discuss the implications of the findings described throughout the paper with respect to the security and privacy of large scale social networks. We also discuss potential platform-side defenses against lateral astroturfing.

A. Security Implications

Lateral astroturfing is a threat to the authenticity and integrity of trending topics on Twitter. We found that at least 10% of twitter trends per day in Turkey and at least 30% of the Top 10 trending topics were induced by the bots that we monitored. In addition, these topics reached higher and trended longer than organic trends, so their impact is even greater than their volume suggests. As with any system, when authenticity is compromised, trust in the system diminishes, e.g. the price of bitcoin falls after a hack and the prevalence of credit card fraud causes a mistrust of credit cards. If trending topics fails to display authentic trends and instead displays only artificial trends, trust in trending topics and Twitter as a whole is threatened.

Lateral astroturfing attacks also promote a market for compromised accounts, especially those accounts which have active users. As long as lateral astroturfing remains effective, more compromised accounts will be needed to boost the target keywords which inevitably leads to more attacks on Twitter users. However, the fact that there is a very easy way to detect this attack means that otherwise difficult to detect compromised accounts can be identified. Because of the deletion activity used in lateral astroturfing attacks, the fact that an account is compromised is often unknown even to the account user, so the accounts are rarely reported. An additional advantage is that once a set of compromised accounts is identified, these accounts can be used to track down how the accounts were compromised. We believe that determining what these accounts have in common (e.g. a rogue third party application or the same operating system version) can lead to understanding how the accounts were compromised.

Lateral astroturfing also has real-world, offline security implications beyond Twitter. Most notably, many of the target keywords we tracked were an attempt to damage election integrity by astroturfing strategic arguments in political discussions. For example, one notable target keyword was #HırsızEkrem “Thief Ekrem,” which accuses Ekrem, a candidate of the 2019 Istanbul Election Run, of being a thief and stealing votes. This type of automated, large scale astroturfing campaign supplements traditional internet censorship such as restricting access to certain web pages. At its core, censorship is about silencing. This includes over-promoting your own narrative or disinformation in order to drown out any undesired content.

B. Countermeasures

Because of the use of “real” compromised accounts, defenses against lateral astroturfing attacks are inherently challenging. Simply detecting and removing the accounts associated with these attacks means deleting accounts of real, active, otherwise non-malicious users. Otherwise these attacks fit an easily detectable pattern and can easily be detected. We outline two main paths for defenses: detecting and inoculating. The methods outlined in Section IV can be used to detect when an attack is occurring and which accounts are involved. That is, listen for deletions of recently posted tweets with the same keyword across different users and then flag these users accounts. Then, inspect the accounts and determine if they are otherwise benign (belong to a normal user) or are purely used for astroturfing attacks and can be deleted immediately. For
the human accounts, a forced password reset and a warning about third party apps may suffice.

The second option is to render the attack useless. The fact that these attacks are successful implies that the Twitter trending algorithm does not consider the deletion of tweets. A simple defense, then, is to account for deleted tweets when computing trending topics.

VII. ETHICS AND REPRODUCIBILITY

All of the data used in this research was collected from Twitter using the API and respecting the rules and limits of the system. This includes deletion of the content of Tweets that were deleted from the platform. The Development Agreement requires users of the Twitter API to not store deleted, protected, or suspended content. Classification of the contents of the deleted tweets could be performed in real time, as described in Section IV so no deleted content needs to be stored.

We also do not to reveal the accounts involved in this attack, especially because some of those users are legitimate human accounts. However, the study is reproducible given a seed set and using the procedure we describe. The seed set can be found by timely querying the Search API when a new keyword enters trending topics and then collecting the authors of the lexicon tweets that obey the rules we describe.

We have notified Twitter about the presence and volume of lateral astroturfing attacks on their platform and provided details and solutions. However, Twitter denies that this attack indicates a specific vulnerability and instead is a “Defense-In-Depth” measure and declined to make any specific changes.

VIII. CONCLUSION

In this study we have revealed and described an active attack on the Twitter Trending algorithm that accounts for at least 10% of daily trending topics in Turkey, a country with 8.6 million active Twitter users. We observe an overall success rate of 97% and find that these artificial trends last longer and rise higher than organic trends. These attacks employ, in part, a set of accounts that are otherwise normal human users, but are compromised to be used in parallel as bot accounts to astroturf trends. These accounts evade detection, even to their original owners, through almost immediate deletion of attack tweets.

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