

A Socialbots Analysis-Driven Graph-Based Approach for Identifying Coordinated Campaigns in Twitter

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Abstract. Twitter is a popular microblogging platform, which facilitates users to express views and thoughts on day-to-day events using short texts limited to a maximum of 280 characters. However, it is generally targeted by socialbots for political astroturfing, advertising, spamming, and other illicit activities due to its open and real-time information sharing and dissemination nature. In this paper, we present a socialbots analysis-driven graph-based approach for identifying coordinated campaigns among Twitter users. To this end, we present some statistical insights derived from the analysis of logged data of 98 socialbots, which were injected in Twitter and associated with top-six Twitter using countries. In the analysis, we study and present the impact of socialbots' profile features, such as *age* and *gender* on infiltration. We also present a multi-attributed graph-based approach to model the profile attributes and interaction behavior of users as a similarity graph for identifying different groups of synchronized users involved in coordinated campaigns. The proposed approach is experimentally evaluated using four different evaluation parameters on a real dataset containing socialbots' trapped user profiles. The evaluation of identified campaigns in the form of clusters reveals the traces of spammers, botnets, and other malicious users.

Keywords: Social network analysis, Coordinated campaign, Socialbots infiltration, Socialbots characterization, Twitter spam.

1. Introduction

Nowadays, a majority of the people, particularly the younger generation, are registered on one or more Online Social Networks (OSNs) that facilitate them to connect and keep in touch with their family members, friends, acquaintances, and colleagues irrespective of their geographical location and boundary. People use OSNs generally for news propagation, entertainment, gaming, thought-expression, to raise social issues and awareness, information diffusion and so on [1,2,3,4]. On the contrary, affordable accessibility, wider reachability, and easy to use functions of OSNs attracted criminals and defaulters to use them for various il-

licit activities, such as spamming, cyberbullying, cyberstalking, identity theft, and so on [5,6]. Kayes et al. [7] described the threats and privacy issues faced by the OSN service providers and their users, including a description of the threats-generating entities. In addition, they also provided a detailed description of the existing mitigation strategies. Meanwhile, researchers have proposed various spammers and malicious accounts detection approaches for different OSNs [8,9].

1.1. Socialbots and Coordinated Campaigns in OSNs

In OSNs, cybercrimes and illicit activities are generally committed using fake profiles in various forms, such as *sybils*, and *sockpuppets* [10]. In *sybil attack*, an adversary creates multiple fake profiles in an OSN to compromise the trust network [11], whereas, in case

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of *sockpuppets*, adversary creates multiple fake profiles to deceive other users of the network to carry out opinion manipulation, astroturfing, and other sophisticated attacks [12]. Although, fake profile creation is very easy in OSNs, manually handling them is neither economically feasible nor scalable. Therefore, depending on the end objective, malicious users automate these profiles in different forms, such as spambots, clickbots, cyborgs, and so on [13]. Socialbots are computer programs to handle OSN profiles and emulate human behavior to pass themselves as real human beings to gain the trust of other users to further exploit it for malicious and illicit activities [14]. Socialbots that are especially injected in an OSN for spamming are called *social spambots*, whereas socialbots that are assisted by the human during their operations are called *cyborgs* [13]. In OSNs, socialbots are generally state/government-sponsored and used as a tool for political astroturfing, propaganda diffusion etc. against rivals [15,16]. *Twitter*, as a microblogging platform to express views and ideas on any topic of interest and get updated by others, seems ideal to socialbots for such sophisticated attacks as the prime objectives of these socialbots are generally opinion and behavior manipulation of network users. In addition, socialbots are also used to generate low-quality contents [17]. Therefore, to understand the socialbots' working behavior and their infiltration efficacy, categories of vulnerable users and their geographical regions, we injected 98 socialbots in *Twitter*, monitored them and logged their activities for analysis at different levels of granularity.

In OSNs, injected socialbots are assisted by existing fake profiles and socialbots. Fake accounts and socialbots are generally created in large numbers and operate in a coordinated manner to deceive benign users towards opinion manipulation, propaganda diffusion, and spamming [17,18,16]. These campaigns are operated by adversaries in such a way that they seem genuine. However, users involved in such campaigns have a certain level of similarity in terms of activity behavior, content, and account properties. The malicious socialbots operating in a coordinated manner are harmful to both OSNs and their users. Therefore, the characterization and detection of coordinated campaigns is a vital and challenging research problem. To this end, we have presented a multi-attributed graph-based approach for identifying coordinated campaigns in *Twitter*.

1.2. Our Contributions

In the existing literature, a number of socialbots injection experiments in different OSNs have been performed to observe their impact and infiltration efficacy [14,19,20]. To the best of our knowledge, none of them has ever analyzed the regional association of socialbot profiles on their infiltration performance. This work, which is an extension of one of our previous works [21], analyzes the regional association of socialbot profiles on their infiltration performance. On analysis, we noticed several interesting observations. While evolving as influential users in OSNs, socialbots are assisted by trapped users who could be either benign or malicious. Malicious users generally operate in coordination towards a certain campaign, such as political astroturfing and advertisement. Therefore, in order to detect coordinated campaigns among *Twitter* users, we present a multi-attributed graph-based modeling approach for identifying a synchronized group of users based on their profile attributes and activities. The multi-attributed graph is converted into a similarity graph and *Markov* clustering is applied to identify different groups of coordinated and synchronized users, such that the attribute and behavior similarity among the intra-cluster users is high and that among the inter-cluster users is low. The identified clusters are evaluated using four different evaluation metrics. The proposed approach is experimentally evaluated on a real *Twitter* dataset of socialbots' trapped users. Figure 1 presents a work-flow of the proposed approach. In short, the main contributions of this paper can be summarized as follows:

- A thorough statistical analysis of the infiltration capabilities of socialbots of different geographies, in terms of the impact of their profile features on infiltration.
- A multi-attributed graph-based approach to model users' profile features and activities for identifying coordinated campaigns in *Twitter*.
- A detailed analysis of identified user groups to reveal the traces of spammers and botnets operating in *Twitter*.

2. Related Works

The large amount of data generated through OSN users' activities has opened the door for various research problems, such as sentiment analysis, predic-

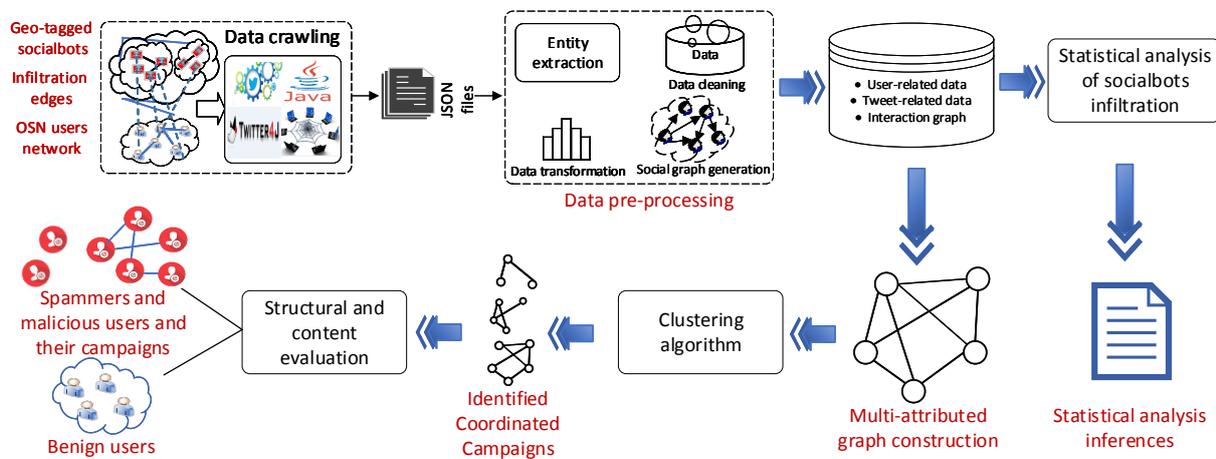


Fig. 1 Work-flow of the proposed approach for analysis and detection of coordinated campaigns among Twitter users

tive analytics, emotion analysis, and customer behavior analysis [22,23]. However, OSNs have also provided a very fertile ground for adversaries to carry out various illicit activities using different forms of malicious profiles. With the evolution of OSNs, a new breed of the bot called “socialbot” has proliferated these networks for illicit purposes [24]. In the existing literature, there is a number of instances, where socialbots and their misuse have been observed and reported in the form of propaganda diffusion, political astroturfing [16,17], identity theft [25], spear-phishing [18], fake news diffusion [26], and so on. As the problem evolved, researchers tried to conceive their working behavior and its impact on manipulating the structural properties and users’ discourse in different OSNs. To this end, some live competitions^{1,2} have been organized to inject and observe the impact of socialbots in social networks. Boshmaf et al. [14,27] presented a complete description of socialbots network creation and operation process and discussed the existing inherent vulnerabilities of OSNs which are exploited by the ill-intended spammers and bots. In [14], Boshmaf et al. thoroughly analyzed the economic feasibility of organizing the socialbots attack, and presented a categorization of different bot detection approaches. Meanwhile, Aiello et al. [28] injected and analyzed the efficacy of a socialbot to infiltrate users in aNobi, a popular OSN in Italy among book-lovers to manage and review the books. On analysis, the authors found that the injected socialbot having no reputation

reached among the top influential users of the network, just by browsing and investigating other users’ profiles. It proves that even passive socialbots can be infiltrative. On the contrary, authors in [20,29] used an active approach for infiltration and targeted the selected groups of users to analyze the infiltration performance. Elyashar et al. [20] injected socialbots to breach users of a technical organization using the information revealed by them on Facebook, demolishing the belief that security-aware users cannot be infiltrated. On the other hand, Zhang et al. [29] programmed socialbots to exploit the Twitter’s strategy to suspend only originators, not distributors of the spam messages and used it for users’ influence score manipulation. In another experiment, Freitas et al. [19] injected 120 socialbots in Twitter and operated them for 30 days. The authors performed the factorial experiment to find out effective infiltration strategy and inferred that highly active socialbots were more successful in infiltrating network users. Meanwhile, 38 socialbots were suspended by the Twitter. On analysis, authors found that socialbots posting automated tweets were more vulnerable to get detected and suspended by the Twitter’s defense mechanism. In another experiment, two socialbots were injected in Twitter and it is observed that they easily manipulated reputation metrics, such as *Klout-score* [30]. Authors also found that one of the two socialbots gained the *Klout-score* close to celebrities and influential users.

In an interesting observation while crawling tweets related to Syrian crisis, Abokhodair et al. [15] unearthed a social botnet network of 130 bots. In the paper, the authors presented their evolution in terms

¹<http://www.webecologyproject.org/>

²<http://ca.olin.edu/2008/realboy/index.html>

of activities and influence and analyzed their difference from benign users in terms of tweets' content. Cresci et al. [31] experimented with three different types of accounts – genuine, conventional spambots and social spambots, and found that though *Twitter* defense mechanism is efficient in detecting conventional spambots, but it fails to detect social spambots. Through crowdsourcing, they further concluded that even human users are not good enough in differentiating the social spambots from traditional spambots. Authors also characterized the users who are susceptible to be misled by socialbots. In this direction, Wald et al. [32] characterized and predicted users who can be easily persuaded to either interact with or reply to socialbots. They used various features ranking techniques to rank the characterizing features and found that *Klout-score* is the most effective feature to predict the users' interaction and reply with socialbots. In an approach, Fazil et al. [33] grouped the socialbots target into three categories – active, reactive, and inactive, depending on their connection formation behavior with the socialbots. Further, they trained machine learning-based classification models for the categorization of three categories of users. In the existing literature, researchers have also proposed several approaches to characterize and detect the socialbots on different OSNs [8,34]. Recently, *Conference and Labs of the Evaluation Forum (CLEF)* organized a competition [35] in which participants were asked to profile OSN users to classify them as bots or real-humans. The participants were also asked to present a gender prediction approach for the profiles detected as human. A total number of 56 teams participated in the competition and their approaches were evaluated over two datasets – one containing English language bots and the other containing Spanish language bots. Finally, 46 teams submitted the notebook paper. Over Spanish dataset, character and word n -gram features-based approach by [36] performed best with an accuracy of 93.33%, whereas Johansson's approach [37] showed the best performance with an accuracy of 95.95% over the English dataset. Towards coordinated campaign detection, Gao et al. [38] presented a posts similarity-based approach to characterize and detect the spam campaigns in *Facebook*. Authors created a graph based on the similarity of the content of posts and URLs that are further processed to identify the subgraphs, representing the different spamming and malicious campaigns.

3. Socialbots Injection Experiment

This section presents a detailed description of socialbots injection process – starting from profile creation to running the whole socialbots network for approximately four weeks including the description of activities performed by them.

3.1. Profile Creation and Distribution

The presence of a person in an OSN is determined by an account having some of his/her personal information, such as name, address, age, gender. Accordingly, we manually created the socialbots' profiles and adjusted their features as per the requirements rather than purchasing profiles from third-party vendors or generating them using automated profile creation tools³. Profile attributes were adjusted to disguise them as real human beings. Created profiles were associated with top-six *Twitter* using countries⁴, in terms of their user-base (in millions). Figure 2 shows worldwide *Twitter* users' distribution of top-six countries in which the USA leads the list, followed by Brazil, Japan, and so on. Number of socialbots allocated to top i^{th} country C_i is proportional to its user-base (in millions) to the sum of user-bases of top-six countries as given in equation 1, where \mathcal{N}_i and \mathcal{U}_i are the number of assigned socialbots and user-base of top i^{th} country, respectively. Figure 3 shows the number of socialbots assigned to each country, where numbers are slightly different from calculated ones using equation 1 to make the socialbots count of each country be at least 10% of the total number of socialbots i.e. 98. Initially, it was 100 but right after the beginning of the operation, two profiles were not working properly. Therefore, we dropped those two socialbots and the rest of the experiment was performed with only 98 socialbots. Among the 98 socialbots, male and female profiles were 47 and 51, respectively following the *Twitter*'s gender distribution, though it provides no option to reveal the gender, which is implicitly revealed by name, profile picture and description, etc. Therefore, these characteristics were adjusted accordingly for every socialbot depending on his/her gender. Further, within a country, equal numbers of male and female socialbots were created. We used the profile picture to exhibit age except a few for whom the date of birth was provided. We adjusted the socialbots' age as

³<http://sick-profile-maker.soft112.com/>

⁴<http://www.adweek.com/digital/twitter-top-countries/>

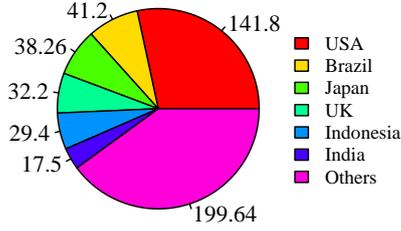


Fig. 2 Twitter user distribution (in millions)

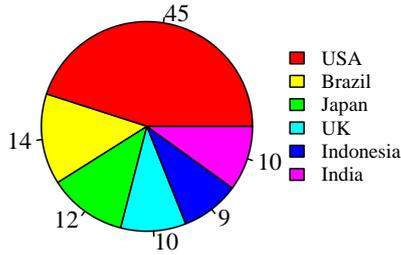


Fig. 3 Country-wise socialbots distribution

per the Twitter age distribution⁵. However, during every step of profile creation, we did our best to follow the Twitter distributions to determine the values of socialbots' profile attributes. Profiles were created between 1st November 2015 to 3rd January 2016. The pictures used in the profiles were crawled from the innermost pages of Google Image. We generally used pictures, which were little-bit blurred or face was not straight. However, to protect users' privacy, profile pictures were deleted after the experiment and not distributed to any third party/person. These profiles were operated through computer programs in a deceptive manner to imitate human behavior, and consequently to term them as socialbots. To this end, an application named TrueBot was developed and hosted on a Linux Apache web server.

$$\mathcal{N}_i = \frac{\mathcal{U}_i}{\sum_{i=1}^6 \mathcal{U}_i} \times 100 \quad (1)$$

$$Activity = \begin{cases} \text{follow 5-10 celebrities,} & \text{if } r=1 \\ \text{follow 10-20\% intra-country socialbots,} & \text{if } r=2 \end{cases} \quad (2)$$

3.2. Socialbots Injection and Operation

Once the socialbots profiles creation process was completed, we started operating them using the TrueBot computer program to manage their activities in Twitter. In a social network, activities of a profile can be performed either through the Web or through application programming interfaces (APIs) of the underlying platform. The APIs are generally provided by the OSN platforms to facilitate their access to the third-party applications. Twitter provides two types of APIs – REST API and Streaming API. Since socialbots are the computer programs to operate social media profiles, they access and operate profiles using the APIs.

As discussed in Section 3.1, we developed an application called TrueBot to access the Twitter platform. Profiles were authenticated using TrueBot application to access the Twitter network, generating a set of four keys and tokens – *consumer key*, *consumer secret key*, *access token*, and *access token secret* when the profiles were authenticated for the first time. Thereafter, future interactions of profiles with Twitter are authenticated using the keys and tokens of the respective profiles. In the experiment, following the first authentication, profiles were activated at any time between 30 minutes to 8 hours for the first-time activity. Activity \mathcal{A} at first-time activation was performed based on the value of a random variable r , as given in equation (2), where random number of celebrities between 5 to 10 were followed for $r=1$. Celebrity handles were chosen from a database having a large number of celebrities handles. In the alternate case of the equation (2), 10 to 20% of socialbots of his/her country were followed within a random period of 30 minutes to 2 days. Future activation times for profiles were determined at present activation. All activities were performed using the REST API functions. Target users of socialbots were crawled either from the followers list of a celebrity of their home country or from the followers list of one of their own followers. During the experiment, profiles were programmed to maintain the followers to followees ratio as at least 0.25 to evade existing socialbots detection approaches, which utilize network-based features. As a result, for a socialbot, whenever this ratio drops below 0.25, a number of *followed* users were *unfollowed* to adjust the ratio at 0.25. Similarly, socialbots were programmed to respond back every *following* request to build a trust relationship in the network. In the experiment, socialbots were programmed to tweet using either of the three approaches – (i) tweeting

⁵<http://www.pewinternet.org/fact-sheet/social-media/>

quotes from a database, (ii) crawling tweets related to trending topics and hashtags and tweeting them as their own with some tuning or just retweeting them, or (iii) crawling and posting tweets from the followers' timelines. Tweets were not generated using automated tweets generation techniques due to the fact that though advanced language technologies can generate tweets, they are not semantically good enough. Tweets generated using language technologies can easily be identified by benign users. The socialbots network was operated for approximately four weeks between January 6, 2016, to February 2, 2016.

3.3. Socialbots Evolution

In this section, we analyze the evolution of the socialbots during the experiment in terms of the number of grabbed followers. For this, we have divided the experiment duration in weeks and plotted the number of followers of each socialbot on the first day of each week of the experiment, which is shown in figure 4. It can be observed from this figure that socialbots fail to attract the sufficient number of followers in the first week as it was their evolution period and they were less interactive outside their network. Meanwhile, socialbots were programmed to establish trust through mutual followings. This figure also presents that the socialbots start trapping followers in the second week, and during the third and consecutive weeks they attracted a sufficient number of followers. On the contrary, some socialbots failed to attract users resulting in very few followers for them as shown in sub-figures of figure 4. In addition, socialbots associated with India, Brazil, and the USA grabbed more followers and grew frequently. Figures 4(e), 4(c) show slower growth rate for socialbots associated to Indonesia and Japan who were unable to attract users. Another interesting observation is that socialbots associated to the Brazil and UK started attracting a large number of followers in the fourth week until the suspension of the whole network by Twitter on the first day of the fifth week of the operation. We have also analyzed the effect of tweeting frequency on infiltration that the number of followers grabbed and did not found any correlation, which is contradictory to the result presented in paper [19]. A fascinating observation is that even very inactive users, in terms of tweeting frequency, were successful to grab a large number of followers, whereas highly active users failed to grab followers.

3.4. Ethical Aspects

The socialbots injection experiment was conducted for academic research purpose in order to understand the impact of socialbots on the Twitter users of different geographies. In this experiment, we filtered radical and suspicious tweets during the tweets crawling from trending topics or followers timeline. Socialbots were programmed to retweet or tweet only those contents that were already floating on the Twitter. In addition, saved quotes were manually verified to not include inflammatory, racial, controversial, or provoking content. In light of the ethics-related issues discussed in [39], we have identified a set of ethical considerations which are presented in Table 1 that were complied during and after the experiment. In the experiment, socialbots did not followed any users for any illicit intention.

Moreover, the experiment was done after its clearance from the departmental research ethics committee. During or post-experiment, we have not shared any private or public information of the crawled users to any third party and further ensure that it will not be shared in the future as well. Throughout the experiment, we tried our best not to violate Twitter's terms of service⁶ and privacy policy⁷ at any level.

4. Infiltration Performance Analysis

In this section, we present an analysis of profile features efficacy towards manipulating network structure and affecting users trust. The exploratory data analysis is performed at two levels of granularity – *generic analysis* and *country-specific analysis*, which are further explained in following sub-sections.

4.1. Generic Analysis

This section presents statistical analysis results, considering all the socialbots as a single entity without any type of grouping. In the line, first, we analyzed the effect of socialbots profile picture and inferred age in tempting and persuading other users to follow them or follow back (if socialbot has followed first). In Twitter, users infer the age of other users based on their profile picture, bio descriptions, alphanumeric used in the handle, and so on [40,41]. Accordingly, at-

⁶<https://twitter.com/en/tos>

⁷<https://twitter.com/en/privacy>

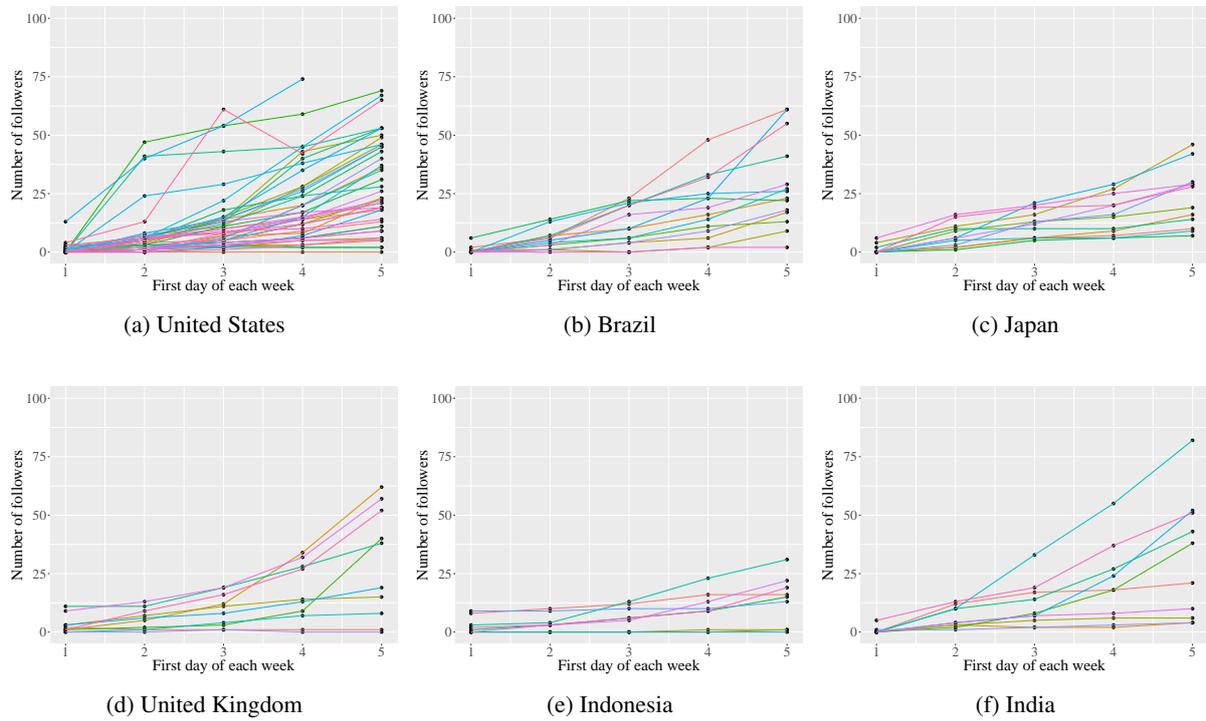


Fig. 4 Followers count growth for each socialbot across all six countries

Table 1

Ethical considerations and their compliance

S.no.	Ethical consideration	Compliance
1	User consent	We did not inform the users because that may affect their normal behavior in the network.
2	Indirect exposure	Since we did not crawl the information of the followers of socialbots' followers, there is no question of indirect exposure.
3	Exposure of human weaknesses	We identified certain human weaknesses towards socialbots or while accepting friend request from a known user.
4	Waste of resources	We did not create a large number of profiles that can make any burden on the Twitter network.
5	Impact on statistics	Creation of merely 98 socialbot profiles is negligible with respect to the existing Twitter user-base, and it cannot make any impact on the network statistics.
6	Exposure of sensitive information	We planted the socialbots using the APIs provided by Twitter. Therefore, we did not crawl information which is either sensitive or not provided by Twitter.
7	Confidentiality	We have not uploaded the data on any archive, and never shared it with any third person.
8	Anonymity	We have stored the crawled data in an encrypted format to ensure the privacy of the users.

tributes of the created socialbots profile were adjusted as per their age. Figure 5 shows the number of followers grabbed by the socialbots of different age. In the injection experiment, profiles were assigned age between 10 to 75 years, and socialbots were grouped into three age groups representing *young adult* (younger than 25 years), *matured adult* (between 25 and 50 years), and *old-age* socialbots (older than 50 years). On analysis, *matured adult* socialbots were found to be the most infiltrative with an infiltration rate of 38 users per socialbot. In contrast, *young adult* and *old* socialbots were mildly infiltrative with an average infiltration

rate of 28 and 30 users, respectively. High follower rate for *matured* and *old* socialbots represents that these users use Twitter for thought expression and to get updated with other users views rather than using it as an entertainment platform. Further, statistical significance analysis using *two sample t-test* was performed to analyze the difference in the infiltrative power of every pair of three socialbots groups. On significance analysis, the difference in the infiltration power of each pair of socialbots groups was statistically insignificant. To have a better understanding, the cumulative distribution of the number of followers grabbed by social-

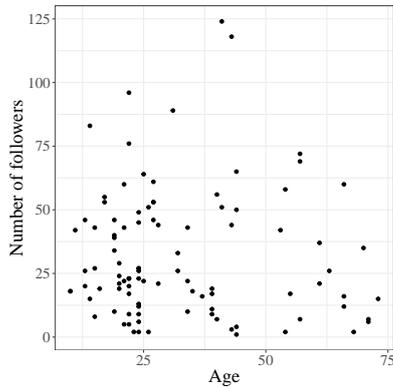


Fig. 5 Number of followers vs. age of socialbots

bots is shown in figure 6. It can be observed from the figure that it follows an exponential distribution and 58% of the socialbots have less than 25 followers.

Further, we analyzed the impact of socialbots' gender on their infiltration performance. Figure 7 represents the gender-based cumulative distribution of socialbots' followers count, which shows that gender does not have any significant contribution in followers grabbing, except the case of profiles with fascinating profile-picture and description to entice the users. The inferred conclusion that gender did not have any significant impact on infiltration is in-line with other similar results presented in [42,18].

4.2. Country-Specific Analysis

This section demonstrates the effect of socialbots features on intrusion by grouping the infiltration results based on socialbots countries, although there is no regional splitting of networks in *Twitter*. In the experiment, country assignment to a socialbot means that his/her location, time-zone, and other features were adjusted as per the attributes of the people of the assigned country. The average number of followers grabbed by the socialbots of each country is shown in figure 8. It can be inferred from the figure that socialbots infiltration is related to their regional association as socialbots associated to India were the most infiltrative by luring the highest number of users, whereas Indonesia associated socialbots were least.

In this analysis, all the results are grouped based on socialbots' country and it is found that socialbots with profile picture were more successful in grabbing followers with an average of 34 users in contrast to socialbots without profile-picture grabbing only 25 average numbers of followers. We divided the socialbots

into two age-groups – (i) younger than 30 years, and (ii) older than 30 years, to compare the infiltration performance of socialbots of each country on the basis of age in terms of the average number of grabbed followers. In this case, socialbots are divided into two age-groups because for three age-groups as done in Section 4.1, some groups were without socialbots or with very few socialbots. Figure 9(a) shows that there is no significant difference between the two groups in terms of the number of grabbed followers, except the UK where younger socialbots were more successful. In order to observe the exact impact of age on infiltration, an analysis is performed with only those profiles that have a profile picture, and results are shown using figure 9(b). Among the six countries, the UK is the only country where older socialbots have lower average followers count than the average follower count for all socialbots as shown in figure 9(c). Based on the analysis, it is inferred that *Twitter* users are influenced by the age of users while following, and older peoples are considered more reliable.

Further, we present an analysis of socialbots' gender effect on trapping the users and grouped the results based on socialbots' countries. In the analysis, only those socialbots that have profile picture have been considered. It can be inferred from Figure 10 that younger female and older socialbots from India and USA grabbed a large number of followers, whereas male socialbots from Japan showed good infiltration performance. Figure 11 portrays the average number of followers misled by the socialbots of two genders grouped by their associated country and shows that female socialbots from UK and Brazil are much dominating to their male counterpart. Critical analysis reveals the fact that few female profiles from these two countries were exposing and persuading; consequently grabbing a large number of followers. On the other hand, female socialbots from Indonesia have not used profile pictures except for one and therefore failed to grab users attention. It can be inferred that gender effect is conditional and depends on the geographical attachment of the profile and does not have a significant impact until used exposing profile picture. We can infer other interesting observations by analyzing the figure 10.

5. Proposed Approach for Identification of Coordinated Campaigns

Following a detailed discussion of statistical analysis in previous sections, this section presents a multi-

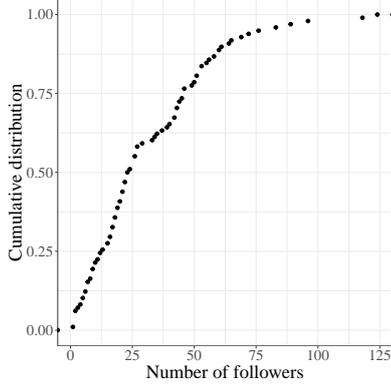


Fig. 6 Cumulative distribution of socialbots' followers count

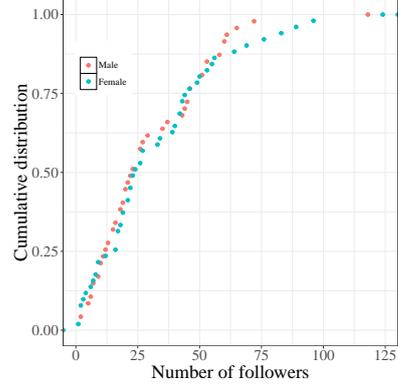


Fig. 7 Cumulative distribution of gender-wise socialbots' followers count

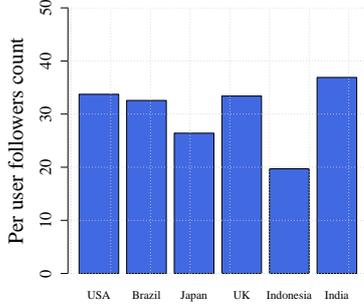


Fig. 8 Country-wise socialbots' average followers

attributed graph-based approach for modeling and identifying trapped users' clusters, representing behavioral pattern among them. A detailed description of the proposed approach is presented in the following subsections.

5.1. Multi-Attributed Graph Construction

This section presents the theoretical background of the social graph and its construction. In the line, first, Twitter users are modeled as a multi-attributed graph, a type of graph in which vertices and edges are represented using multi-dimensional vectors. Mathematically, it is defined as $G_M = (V, E, \mathcal{F}_v, \mathcal{F}_e)$, where V is the set of vertices, E is set of edges between vertices, \mathcal{F}_v is a vertex-label function that maps each vertex $v \in V$ into an n -dimensional vector like $\forall v \in V. \mathcal{F}_v : v \rightarrow \mathcal{R}^n$, whereas \mathcal{F}_e is an edge-label function that represents the relationship between every pair of vertices of G_M using a m -dimensional vector like $\forall e \in E. \mathcal{F}_e : e \rightarrow \mathcal{R}^m$. In the proposed approach, ev-

ery vertex of the constructed graph G_M represents a user, which is labeled by a numeric node vector F of 6 features. The six features, namely, *Twitter age*, *time-zone*, *follower rate*, *followee rate*, *follower/followee ratio*, and *tweet rate* have been designed to track synchronization among the users' behavior and activities. Among the features, *Twitter age* of a user represents the number of days elapsed since the user has joined the network. It is important because user accounts related to a campaign will be created nearly the same point in time before starting a spam or smear campaign. *Timezone* is another important feature because users associated with a campaign will belong to the same region as they will be created by a single master. Other features are also important because they monitor synchronization among the users based on their average number of activities per day. Thereafter, a similarity metric is proposed to find the relationship strength between every pair of users $v_i, v_j \in V$ of the graph using their feature vectors. The similarity between two users is the average of similarities between corresponding feature values of the two users as represented in equation 3, where $I_{ij}(f)$ is an indicator variable representing the presence of attribute values for users. It is zero i.e. $I_{ij}(f) = 0$, if f^{th} feature's value for either of the two users is missing that is either $F_i(f)$ or $F_j(f)$ is zero or null; otherwise it is one, indicating that similarity for the given feature has been calculated. The similarity S_{ij} between users v_i and v_j for a feature $F(f)$ is calculated on the basis of its data type that is briefly described in the following paragraphs.

$$S_A = \frac{\sum_{f=1}^n I_{ij}(f) \cdot S_{ij}(f)}{\sum_{f=1}^n I_{ij}(f)} \quad (3)$$

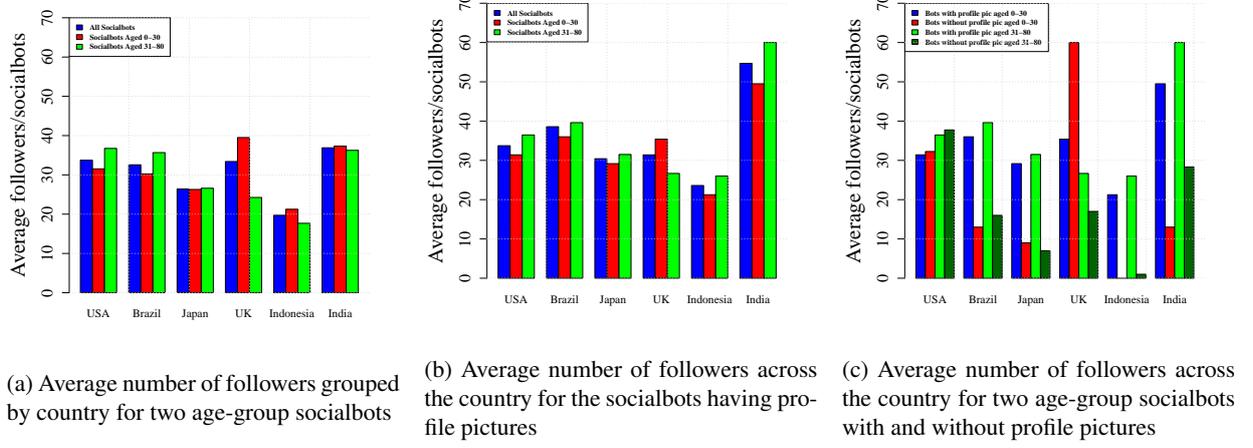


Fig. 9 Average number of infiltrated followers grouped by age and country of the socialbots

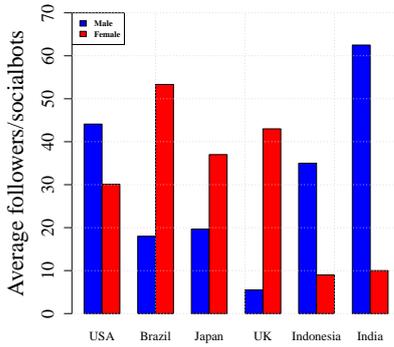
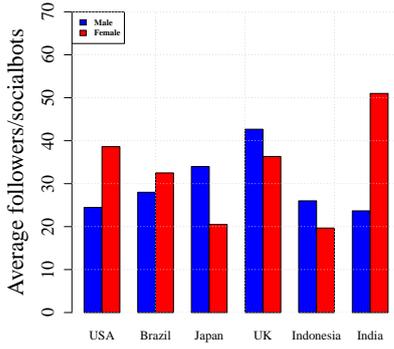


Fig. 10 Average number of followers gained by the socialbots for two age-groups (grouped on the basis of gender and country)

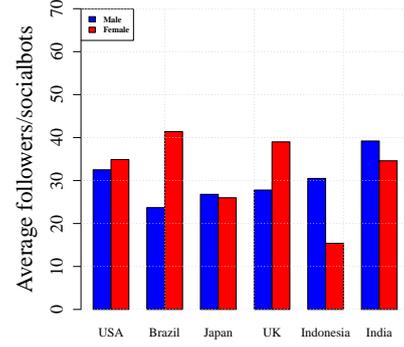


Fig. 11 Average number of followers for the two gender groups of socialbots across the country

- In case, $F(f)$ values are of nominal data type, S_{ij} between two users is calculated as given in equation 4, where \odot represents *Exclusive NOR* logical operation; which gives a value of 1 when both the input values are equal, otherwise 0.

$$S_{ij}(f) = F_i(f) \odot F_j(f) \quad (4)$$

- In case, $F(f)$ values are of the real type, similarity S_{ij} between the two users is calculated using Euclidean distance between them as given in equation 5, where denominator represents Euclidean distance between $F_i(f)$ and $F_j(f)$.

$$S_{ij}(f) = \frac{1}{\sqrt{(F_i(f) - F_j(f))^2}} \quad (5)$$

5.2. Coordinated Campaign Identification

Malicious users and bots generally operate in groups in a coordinated manner operated and controlled by a master. These users operate in a coordinated manner towards their master’s goal. An artificial and malicious campaign run by a group of coordinated users is called “coordinated campaign”. This section presents the identification of coordinated campaigns from multi-attributed graph G_M . Based on the similarity metric defined in equation 3, multi-attributed graph G_M is converted into a similarity graph G_S . Thereafter, a similarity matrix M_S is constructed from G_S and Markov clustering, a fast and scalable unsupervised clustering technique, is applied on it to identify the group of similar or coordinated users [43]. In clustering, each of the identified clusters represents the set of coordinated users. Markov clustering is an iterative algorithm that groups nodes of a graph in a way that maximizes the number of edges within clusters. In Markov clustering, two operations – *expansion* and *inflation* are performed; wherein *expansion* allows flow of weights in different parts of the graph and *inflation* controls the strengthening and weakening of existing connections. It can be applied on both weighted and unweighted graphs.

6. Experimental Setup and Results

This section presents experimental details about the proposed approach for identifying coordinated campaigns. A detailed description of the dataset and experimental results are presented in the following subsections.

6.1. Dataset

The proposed approach for identifying coordinated campaigns is evaluated on the dataset extracted from the socialbots injection experiment, discussed earlier in Section 3. In the experiment, a total number of 2907 users were trapped, out of which 671 users were either suspended or protected or do not have followers/followees and other related information. As a result, we do not have any information related to these

users. Final dataset of trapped users has the profile and other information of 2236 users. We also crawled a maximum number of 5000 tweets and their related metadata information from the timeline of each of these 2236 users. All the non-English tweets were filtered during the pre-processing step. In the remaining paper, all the experiments have been performed on this final dataset.

6.2. Experimental Results

Following the dataset curation process of 2236 users, a similarity graph is constructed as defined in Section 5. Thereafter, we applied Markov clustering on the similarity graph to group users who exhibit similar characteristics. Markov clustering converts similarity matrix M_S into a transition matrix M , also called Markov matrix, where every element represents transition probability between the corresponding pair of users. In the Markov clustering, *expansion* and *inflation* operations are performed iteratively in a interleaved manner until $|M_t - M_{t-1}| \leq \epsilon$, where M_t and M_{t-1} are the Markov matrix at t^{th} and $(t-1)^{th}$ iterations respectively. We have chosen $\epsilon=0.0001$ at different value of inflation parameter r . The number of clusters at different value of r is given in Table 2, where each identified cluster represents a coordinated campaign. In the table, we have reported the clusters having more than 10 users because cluster with less than 10 does not seem relevant for a campaign. It can be observed from the table that as we increase the value of r , the number of clusters increases, as per expectation. One important observation is that as the number of clusters increases, some clusters fade away, such as cluster having user 5 as the attractor, whereas some cluster emerges such as clusters with users 1158 and 2023 as attractors. However, increasing the value of r beyond 5 converges most of the clusters as it can be observed from the last few rows of Table 2. It can be observed from 8th, 9th, and 10th rows of the table that most of the clusters have converged except few, who are still expanding or shrinking and which are generally clusters with a large number of users. Based on empirical analysis, we have chosen clusters identified at $r=8$ as the final cluster. Among the 12 identified clusters of size greater than 10 at $r=8$, 3 are significantly large, representing approximately 88% of the users. In the remaining part of this paper, all the analyses are performed on these 3 large clusters namely, C_3 , C_5 , and C_{10} as given in Table 3. Further, we performed content and structural analysis of the users of these

Table 2
Identified clusters among trapped users

Inflation Parameter (τ)	#Clusters	Cluster Size (Attractor)
1	1	2236(477)
2	19	2211(5)
3	53	1064(5), 788(1158), 227(1583), 36(2023)
4	72	13(771), 21(5), 1895(1158), 15(661), 44(1730), 79(2023), 10(1128), 10(1137)
5	93	15(771), 12(5), 1770(1158), 37(661), 97(1730), 94(2023), 10(710), 11(1769)
6	114	15(771), 11(1951), 1611(1158), 51(661), 123(1730), 91(2023), 10(710), 10(1769), 10(2221), 78(1475)
7	140	13(771), 11(1285), 850(1158), 53(661), 248(1730), 83(2023), 10(710), 18(1951), 10(2221), 645(1475), 12(980), 11(2092)
8	169	13(771), 12(1285), 672(1158), 62(661), 253(1730), 78(2023), 12(1249), 24(1951), 12(1141), 752(1475), 15(980), 11(2092)
9	192	13(771), 13(1285), 689(1158), 64(661), 240(1730), 73(2023), 12(1249), 23(1951), 21(1141), 658(1475), 38(980), 10(2092), 13(14), 13(2071), 12(1584)
10	207	12(771), 12(1285), 799(1158), 65(661), 241(1730), 67(2023), 12(1249), 22(1951), 29(1141), 493(1475), 40(980), 10(2092), 16(14), 19(2071), 14(1584), 10(1477), 10(1931)

three clusters to observe their spamming and malicious nature.

6.3. Coordinated Campaign Evaluation

This section presents the evaluation of identified campaigns in the form of clusters using different evaluation measures. A detailed description of the evaluation measures and corresponding results is presented in the following sub-sections.

6.3.1. Evaluation Parameters

This sub-section presents different evaluation measures to evaluate the efficacy of the proposed approach towards coordinated campaign detection. The identified campaign(clusters) have been evaluated using a number of techniques and evaluation parameters, such as the number of suspended users in each campaign, url ratio, use of malicious keywords, and so on. A detailed description of the evaluation parameters is presented in the following paragraphs.

Suspended Users:

One of the important characteristics of a fabricated campaign is that it will be run by a group of users controlled by single master [29]. Accordingly, in case of a fabricated campaign, a group of users will be suspended rather than individual, reflecting the coordination and ill-intention of the users. In the analysis, we have chosen suspended users as those who are either suspended or not found on the platform, representing that users have deleted the accounts. Therefore, we verified the users of identified clusters to find the ratio of active and suspended users. To this end, we called Twitter API to verify the current status of users.

Timezone:

Another important characteristic of the users of coordinated campaigns is that they generally belong to the same timezone because the master user creates multiple sybil profiles from the same location. We have

chosen timezone rather than location because, during the profile creation process on Twitter, users are prompted to adjust their location. As a result, sybil creator can change it to a different location for a different user or can skip it. However, even if the creator assigns different locations to the different profiles, they generally chose the different cities of his/her own country having the same timezone. Additionally, users hardly adjust timezone available in account setting, which is by default adjusted by Twitter, therefore giving the same timezone to all the profiles created from the same location/country. We have not chosen the location of the tweets due to the fact that the majority of the tweets do not have a location because users generally have their global positioning system turned off. Therefore, we have analyzed the timezone of users to observe their suspicious and coordinated behavior.

Keywords Distribution:

The type of words used in users posts also reflects their intention and nature. It is another very important indication to track spam campaigns among clustered users. To this end, we have taken a maximum of 200 tweets from every user of each cluster. Thereafter, aggregated tweet set of each cluster is passed to Natural Language Understanding (NLU)⁸ for keywords extraction. NLU is a natural language processing service by IBM to perform sentiment analysis, entity extraction, topic extraction, and so on, on a given text corpus. In the process, we extracted 100 keywords from tweets corpus of the users of each cluster.

URL Ratio:

In the existing literature, another important characteristic for observing spamming behavior in users content is the analysis of url ratio in content [38,42,44]. In the case of Twitter, normal users generally use

⁸<https://www.ibm.com/watson/services/natural-language-understanding/>

Table 3
Users statistics among trapped users

Cluster	Cluster Size	Attractor	#Suspended Users	#Active Users	Suspended Users (%)
C_1	13	771	4	9	0.3076923077
C_2	12	1285	8	4	0.6666666666
C_3	672	1158	170	502	0.2529761905
C_4	62	661	9	53	0.1451612903
C_5	253	1730	118	135	0.4664031621
C_6	78	2023	30	48	0.3846153846
C_7	12	1249	4	8	0.3333333333
C_8	24	1951	2	22	0.0833333333
C_9	12	1141	2	10	0.1666666667
C_{10}	752	1475	153	599	0.2034574468
C_{11}	15	980	2	13	0.1333333333
C_{12}	11	2092	1	10	0.0909090909

url to share the article, news, and other third-party documents. In general conversation and thought expression, normal users generally do not use URLs, whereas spammers and malicious users are dedicated for promotion, advertisement, and fabricated propaganda, therefore they keep on using URLs of the specified brand, product, or service in their tweets/posts. In order to track this kind of behavior, we analyze the URLs use in tweets of clustered users by using url ratio for every user of the cluster. Thereafter, we find the average of the url ratio of every user of each cluster, representing the url ratio of the cluster.

6.3.2. Evaluation Results

To observe spamming nature of the users of each of the three identified campaigns C_3 , C_5 , and C_{10} , we performed experimental analysis of their behavior in terms of evaluation metrics defined in the previous section. In the line, a detailed description of evaluation results in terms of various evaluation metrics is presented in following sub-sections.

Cluster Analysis:

This section presents the evaluation results of the proposed approach in terms of evaluation metrics defined in Section 6.3. In the line, we present evaluation results for each of the three large clusters C_3 , C_5 , and C_{10} to observe their spamming nature at group-level granularity. We have performed the evaluation of only active users rather than suspended users due to the fact they are already suspended by the Twitter due to some sort of suspicious behavior. Therefore, we consider that suspended users are already malicious and their further analysis is of no use. To this end, first, we analyzed the coordinated campaign among the alive users of cluster C_3 . In the verification process through Twitter, it is found that 170 out of 672 users have been suspended or not found on the platform, which is approximately 25% as shown in the third row of Table 3. Timezone analysis shows very scattered distri-

bution among 502 active users who belong to 72 different timezones. However, *Pacific Time (US & Canada)*, *London*, and *Central Time (US & Canada)* are the most dominating timezones with 75, 30, and 23 users, respectively. During timezone and age analysis, we do not find any kind of coordination or synchronization among these accounts. Further, we extracted the top 100 representative keywords from the tweets of these users which are shown in figure 12(a), where keywords size is proportional to its relevance score, representing its relevance in the corpus. It can be observed from this figure that the two most important keywords are *music* and *video*, which are generally used to promote newly released music and songs. On analysis of users tweets, it is found that users were talking about and recommending songs and videos of singers, representing their personal views. Similarly, significant numbers of tweets were personal thoughts, views, and updates of daily activities. This is reflected and further verified while we performed *url ratio* and *spam word ratio* analysis on the tweets corpus. On analysis, *url ratio* and *spam word ratio* is found to be 0.50 and 0.012, respectively, which are moderately lower and can be said to fall under the benign category.

Further, we performed coordinated campaign analysis among the users of C_5 cluster. To this end, first, we identified the suspended users and found that 118 out of 235 users have been suspended. On analysis, we found that all the suspended users belong to the same timezone and created nearly the same time. In addition, their tweets writing style and bio-description were nearly similar. Further, we analyzed active users of the cluster by crawling their timezone information from Twitter and found that 95 out of 135 belong to same timezone *Pacific Time (US & Canada)* as that of suspended users, raising the doubt that they are controlled by the same master, whereas 34 users have not exposed their timezone. Further, we analyzed the aggregate thematic structure of the cluster's users by selecting a maximum of 200 tweets from tweets set of each user. Figure 12(b) represents keywords-cloud of the 100 keywords, where size is proportional to their relevance in the corpus. As shown in the figure, *security*, *mayor*, *camera* are the most discussed keyword among the users, representing the security concerns expressed by the people of a city. Further, we analyzed url usage behavior in the users' tweets, which has been exploited in various existing spammer detection techniques. On analysis, *url ratio* is found to be at 0.42, which is not high and can be said to be acceptable.

cluster analysis, we found a suspicious spam campaign represented by cluster C_5 which was eventually suspended by the `Twitter`. Apart from this, we did not find any other coordinated campaign, though a number of users were associated to same time-zone.

Therefore, on the basis of discussions mentioned above, it can be concluded that socialbots were not only successful in infiltrating influential and benign users; rather, they also attracted a significant number of spammers and bots. In addition, the trace of a coordinated campaign was also found.

8. Conclusion and Future Work

In this paper, we have presented a statistical analysis describing the impact of socialbots' profile features on their infiltration performance, with respect to the dataset collected through the injection of 98 socialbots in `Twitter`. We have presented a thorough analysis of the infiltration efficacy of the socialbots at different levels of granularity, and some key findings can be listed as follows – (i) socialbots can easily infiltrate `Twitter` users, (ii) infiltration performance of socialbots is found to be related to their regional association, (iii) most significantly, even verified users are at the risk of being trapped by socialbots as 5 verified users started following the socialbots. Among them, 3 are the prominent actors and songwriters – *Tay Zonday*, *Dylan Gardner*, and *Scott Maslen* having 581K, 39.3K, and 237K followers, respectively. In addition, one verified user has approximately 1.72 million followers, which is a very significant number in `Twitter` (iv) gender of a socialbot do not play any significant role, except on certain geographies and having young and exposing profile picture, (v) among the mislead followers, footprints of fake and malicious profiles such as spammers, bots, and content polluters were observed. We have also presented a multi-attributed graph-based approach for identification of coordinated campaigns among the `Twitter` users. The proposed approach has been experimentally evaluated on the `Twitter` dataset of socialbots' trapped users. In the evaluation, we identified three groups of users, one of them having a coordinated social botnet, which was later suspended by the `Twitter`. Presently, we are developing an integrated tweet analysis system for profiling mislead users and analyzing their topical evolution. Studying the multifaceted emotional aspects of socialbots, such as emotional behavior analysis, emotion-based socialbots de-

tection, and emotion-based analysis of socialbots' followers seems one of interesting future directions of research.

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