The 'Star Wars' botnet with >350k Twitter bots

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Abstract

A large number of Twitter users are bots. They can send spam, manipulate public opinion, and contaminate the Twitter API stream that underline so many research works. One of the major challenges of research on Twitter bots is the lack of ground truth data. Here we report our discovery of the Star Wars botnet with more than 350k bots. We show these bots were generated and centrally controlled by a botmaster. These bots exhibit a number of unique features, which reveal profound limitations of existing bot detection methods. Our work has significant implications for cybersecurity, not only because the size of the botnet is larger than those analysed before, but also because it has been well hidden since its creation in 2013. We argue that more research is needed to fully understand the potential security risks that a large, hidden botnet can pose to the Twitter environment, and research in general.

1 Introduction

Twitter is a popular online social media service. Twitter users can post short messages, called 'tweets', and they can 'follow' and receive other users' tweets. There are more than 313 million active users and about 500 million tweets are created per day [1]. Twitter plays an increasingly important role in modern society.

Twitter has been the subject of intensive study in recent years. For example, [14] studied the graph of Twitter users and [6] examined how to measure the influence of a Twitter user. A particular popular research trend is to analyse the real-time stream of tweets as means to predict or detect events, such as outbreak of epidemics [15], election results [28], earthquakes and typhoons [23].

1.1 Twitter bots and botnet

A Twitter bot is a Twitter user account whose functions are automatised and therefore require little or no human input. A botnet is a group of bots that are created and centrally controlled by a master, called 'botmaster' [5]. Some bots have benign purposes, for example to generate an automated tweet whenever a new article is published in a news website.

In this work we focus on the non-benign bots whose purposes include spamming, manipulating public opinion, and selling bots as fake followers. There are many research works on the behaviour and impact of Twitter bots. For example [17] studied how bots can gain influence; [9] evaluated how bots infiltrate the Twitter environment; [2] studied how bots can be used in political propaganda; [27] studied the black market for trading bots.

1.2 Threats of Twitter bots

Twitter bots have attracted a lot of attention [19] because they can pose serious threats to the health and security of Twitter as a popular public social and communication service.

Spamming Spammer bots can send a large amount of unsolicited content to other users. The most common objective of spam is getting users to click on advertising links with questionable value [12], or propagate computer viruses and other malware.

Fake trending topics If bots are able to pass as humans through Twitter's filters, they would be counted by Twitter for choosing trending topics and hashtags. This would allow the bots to create fake trending topics that are not actually being popular in Twitter.

Opinion manipulation A large group of bots can misrepresent public opinion. If the bots are not detected in time, they could tweet like real users, but coordinated centrally around a specific topic. They could all post positive or negative tweets skewing metrics used by companies and researchers to track opinions on that topics.

Astroturfing attack Bots can orchestrate a campaign to create a fake sense of agreement among Twitter users [4,21], where they mask the sponsor of the message, making it seem like it originates from the community itself.

Fake Followers Fake followers can be bought or sold online [31]. After receiving payment from a user, the botmaster of a botnet can instruct its bots to follow that user. Fake followers could make a user seem more important than it is [7,9,17]. One would expect that fake followers should try to appear like real users [11,12], however people rarely verify whether someone's followers are human or bots.

Streaming API contamination Many research works rely on analysing tweet data returned by Twitter's streaming API. It is reported [18] that the API is susceptible to an attack by bots, where bots can time their tweets in such a way that their tweets can be included in the API with a probability higher than the expected 1%, up to as high as 82%.

1.3 Detecting Twitter bots

The Twitter company has been actively identifying and removing suspicious users, many of which are spammer bots [26]. Researchers have also proposed many methods to detect Twitter bots [25–27]. For example, [29] used the Levensthein distance between tweets to identify bots; [32] and [16] aimed to classify bots quickly with minimum information: [4] discovered a botnet of 130 bots.

It is recognised that a major challenge to analyse and detect Twitter bots is the lack of ground truth data [25] as publicly available datasets of Twitter bots are small and contain mixed classes of bots.

In the paper we report our discovery of the Star Wars botnet, which contains more than 350k bots that are centrally controlled by the same botmaster.

2 Discovery of the Star Wars bots

2.1 Random uniform sample of 1% Twitter users

While a few studies collected complete datasets from Twitter [3,8], most studies relied on sampled datasets [13,24]. It is known that samples based on the random walk on the Twitter user graph can be biased towards users with large numbers of followers or friends¹; and samples based on Twitter's streaming API [20] can be biased towards

¹If user X follows user Y, X is a *follower* of Y, and Y is a *friend* of X.

users who are active and tweet frequently.

Twitter assigns each user a unique 32-bit ID². The random uniform sampling method [10,30] randomly chooses user IDs with a uniform probability.

We collected 1% of Twitter users using the random uniform sampling method. We obtained the profile of each valid user using the Twitter API, and filtered out non-English speakers ³. Thus we had a dataset of around 6 million random English-speaking users. In the following, this dataset is referred to as the 1% random users. In this following, unless specified, we only consider English-speaking users.

2.2 Abnormal distribution of tweet locations

A Twitter user can choose to tag their tweets with locations. Different from a user's registered location in its profile, the locations of a user's tweets should change when the user moves to different places. The tweet location is recorded in the format of latitude and longitude coordinates.

Twitter API can retrieve up to 3,200 of a user's most recent tweets, which usually includes all tweets of a user. The 1% random users have created 843 million tweets, of which around 20 million have a location tag.

Figure 4 shows the density distribution of tweet locations of the 1% random users on the map. We observed that although the tweet distribution is largely coincident with the population distribution, there are two rectangle areas around North America and Europe that are fully filled with non-zero tweet distributions, including large uninhabited areas such as seas, deserts and frozen lands.

These rectangles have sharp corners and straight borders that are parallel to the latitude and longitude lines. We conjectured that the figure shows two overlapping distributions. One is the distribution of tweets by real users, which is coincident with population distribution. The other is the distribution of tweets with faked locations by Twitter bots, where the fake locations are randomly chosen in the two rectangles – perhaps as an effort to pretend that the tweets are created in the two continents where Twitter is most popular.

2.3 Random quotations from the Star Wars novels

The blue-colour dots in the two rectangles were attributed to 23,820 tweets. We manually checked the text of these tweets and discovered that the majority of these tweets were random quotations from Star Wars novels. Many quotes started or ended with an incomplete word; and some quotes have a hashtag inserted at a random place. Here is an example:

Luke's answer was to put on an extra burst of speed. There were only ten meters #separating them now. If he could cover t

This quote was from the book *Star Wars: Choices of One*, where Luke Skywalker is an important character. We have found quotations from at least 11 Star Wars novels.

2.4 Definition of the Star Wars bots

It is known that Twitter bots often quote from books or online sources [11]. We examined the 4,942 users that are associated with the blue dots in the two rectangles, from which we identified 3,244 bots showing all of the following properties. We named them the Star Wars bots.

 $^{^2}$ Twitter recently extended the user ID space to 64 bits, but all existing users are in the range of [0, 232]

¹3Using the declared user interface language

- They only tweet random quotations from the Star Wars novels. Each tweet contains only one quotation, often with incomplete sentences or broken words at the beginning or at the end.
- The only extra text that can be inserted in a tweet are (1) special hashtags that are associated with earning followers, such as #teamfollowback and #followme; and (2) the hash symbol # inserted in front of a randomly chosen word (including stop words, like "the" and "in") in order to form a hashtag.
- The bots never retweet or mention any other Twitter user.
- Each bot has created <= 11 tweets in its lifetime.
- Each bot has <= 10 followers and <= 31 friends.
- The bots only choose 'Twitter for Windows Phone' as the source of their tweets.
- The user ID of the bots are confined to a narrow range between 1.5×10^9 and 1.6×10^9 . See Figure 7.

3 Detection of the Star Wars botnet

The above 3,244 Star Wars bots were manually identified from the 1% random users. Here we used a machine learning classifier to automatically detect *all* bots that belong to the Star Wars botnet.

3.1 Machine learning classifier

A classifier is a machine learning technique that assigns a category to a new observation based on previous observations. In this work we used the Naive Bayes classifier, which has been successfully used to classify spam emails. It makes the assumption that features of word frequencies are independent.

One training dataset was the tweets of the 3,244 Star Wars bots that we had manually identified with high confidence. The other dataset was the tweets created by 9,000 real users⁴. Figure 10 illustrates the words that most frequently appeared in tweets of the Star Wars bots and the real users, respectively. It is clear the bots used many words that are characteristically related to the Star Wars stories, such as 'jedi', which are rarely mentioned by real users.

From the two training datasets, we removed all stop-words and non alphabetical characters except the # symbol. We obtained a set of 80k words that included 30k most frequent words tweeted by the bots and 50k by the real users. We created word count vectors, which represent the frequencies of the words in tweets. We trained the classifier with the word count vectors of the two training datasets. Then, we tested the classifier with 10-fold cross validation. We achieved >99% for precision, recall and F-measure on each of the folds. Furthermore, we tested using both a balanced (by resampling the bots 3 times) and an imbalanced training sets, and achieved practically identical results for all performance measures.

⁴It is known that real users are unlikely to follow bots. Thus friends of a real users are mostly real users. Starting from a known real user, we collected the friends that it follows, and then collected the friends of its friends. We collected four levels of friends using the breadth-first search and got two million users. We then randomly selected 9,000 English-speaking users.

Properties	Random users	Star Wars bots
Number of users	6,063,970	356,957
Location-tagged users	208,612	349,045
% of location-tagged users	3.4%	97.7%
Number of tweets	842,670,281	2,422,013
Location-tagged tweets	19,777,003	1,209,597
% of location-tagged tweets	2.3%	49.9%
Tweets in Europe	3,486,239	604,647
% of tweets in Europe	17.6%	50.0%
Tweets in N. America	8,950,941	604,912
% of tweets in N. America	45.2%	50.0%
Tweets elsewhere	7,339,823	38
% of tweets elsewhere	37.1%	0.0%
Tweet source		
Twitter for iPhone	31.1%	0%
Twitter Web client	17.2%	0%
Twitter for Android	14.9%	0%
Twitter for Blackberry	6.8%	0%
Mobile Web	0.99%	0%
Twitter for Windows Phone	0.02%	100%

Table 1: Properties of the Star Wars bots and the 1% random users.

3.2 Detection results

Our classification process is shown in Figure 11. According to the properties of the Star Wars bots defined in Section 2.4, we collected 14 million English-speaking Twitter users with IDs in the range of 1.5×10^9 and 1.6×10^9 . We then removed users with > 10 followers, > 31 friends, or > 11 tweets; we also remove users with any tweet source other than 'Twitter for Windows Phone'. From these Twitter users, our classifier identified in total 356,957 Star Wars bots (see Table 1).

Figure 12 is the location distribution of the tweets made by the Star Wars bots. This figure shows uniformly distributed rectangles, which are well defined. Only 38 tweets fall outside of these rectangles. This means our classifier is correctly identifying the Star Wars bots, and has little noise. The classifier uses no location information, and tweets and users are not filtered by location.

4 Properties of the Star Wars bots

Here we analyse the properties of the Star Wars bots in comparison against the 1% random users.

4.1 Daily count of total tweets

Figure [13] shows the total number of tweets created by the Star Wars bots and the 1% random users, respectively, in each day from 20 June to 14 July 2013. This time period corresponds to the window when user IDs between 1.5×10^9 and 1.6×10^9 were allocated to new users, including all Star Wars bots. The random users, as expected, produced a relatively stable amount of tweets, with minor fluctuations on a weekly period.

The Star Wars bots, however, started to tweet immediately after they were created. They produced more than 150,000 tweets per day. When the creation of new Star Wars bots stopped on 14 July 2013, all the bots suddenly fell silent and remained so ever

since. This unusual bursty behaviour suggests that the bots were orchestrated and centrally controlled by a botmaster.

4.2 Lifetime count of user tweets

Lifetime count of user tweets is the total number of tweets created by a user in its lifetime. Figure [13] shows that the lifetime count of user tweets for the random users follows a power-law distribution. 43% random users have never tweeted and only 30% have created more than 3 tweets; whereas a small number of random users have large numbers of tweets. This heterogeneous behaviour is typical of online social media systems with a massive number of users.

In contrast, the Star Wars bots features a bell-shaped distribution, which peaks at 7 tweets and cuts off at 11. This homogeneous behaviour could be a result of a Binomial process, which can be conveniently generated by a computer.

4.3 Location-tagged tweets

Percentage of location-tagged users and tweets As shown in Table 1, only 3.4%random users have ever created location-tagged tweets; and 2.3% of all tweets of the random users have location tags. In sharp contrast, more than 97% of the Star Wars bots have location-tagged tweets; and half of all tweets of the bots have location tags.

Split between North America and Europe For the random users, 45% of their location-tagged tweets are in the North American rectangle, 17% in the European rectangle, and 37% are located in the rest of the world. For the Star Wars bots, however, all of their location-tagged tweets are strictly confined in the two rectangles, with an exact 50/50 split, which strongly indicates an artificial control.

Distance between consecutive tweets The Haversine distance [22] is defined as the surface distance between two locations taking into account the earth's sphere shape. We calculated the average Haversine distance between tagged locations of consecutive tweets for each bot and random user. Figure 15 shows the distribution of the average distance for the random users follows a power-law, whereas that for the Star Wars bots resembles a bell curve. Moreover, the average Haversine distance over all random users is only 39km, but that for the bots is a staggering 2,064km. This is another evidence that a Star Wars bot faked their tweet locations by choosing a random location in any of the two rectangles (with equal probability), such that it often has consecutive tweets located in different continents.

4.4 Tweet device

Table 1 shows that the random users tweeted from a variety of devices, called 'tweet source', where iPhone is the most popular device creating 31% of all tweets by the random users. In contrast, 100% of tweets of the Star Wars bots appeared to be created on a Windows Phone, which account for only 0.02% of random users' tweets.

4.5 Followers and Friends of the Star Wars bots

In graph theory, the degree of a node is defined as the number of connections the node has. A Twitter user's in-degree is defined as the number of its followers, and its out-degree is the number of its friends. Figure 16 shows the distributions of user in-degree and out-degree, respectively, for the Star Wars bots and the random users. For the random users, the degree distributions follow a power-law decay with a long

tail⁵. This means a small number of users have extraordinarily large numbers of friends and followers. For the Star Wars bots, the degree distributions drop significantly faster. 0.1% bots have more than 7 followers or more than 10 friends.

5 Discussion

5.1 The Star Wars botnet

Both the definition of the Star Wars bots in Section 2.4 and the properties shown in the above Section IV strongly support our conjecture that the Star Wars bots form a single botnet that were computer generated and centrally controlled by a botmaster.

The Star Wars botnet provides a valuable source of ground truth data for research on Twitter bots – not only a complete collection of a single botnet, but also the size of the botnet, which is tens of times larger than any public datasets. The Star Wars botnet dataset is available on request. Researchers can also collected data by themselves using details provided in this paper.

5.2 How can the Star Wars botnet hide so well?

There have been efforts to detect and remove bots from Twitter. However, there are a number of reasons why the Star Wars bots created in 2013 have not been detected so far.

Firstly it seems the Star Wars bots were deliberately designed to keep a low profile. They tweeted a few times, not too many, not too few. They avoided doing anything special. Secondly they only tweeted random quotations from novels. This helped the tweets appear like using real human's language. This invalidates the bot detection methods based on detecting language created by machines. Thirdly the bots were carefully designed to have 'normal' user profiles, and some even have profile pictures. This invalidates the detection methods based on profile analysis. Finally and more importantly, it seems the Star Wars bots were deliberately designed to circumvent many of the heuristics underlying previous bot detection methods. For example, contrary to previous assumptions, the Star Wars bots don't have any URLs in their tweets, they never mention or reply to other users, and they only follow a small number of friends.

5.3 Reflection on our discovery

We were really luck to discover the Star Wars bots by accident. The fact that the bots tagged their tweets with random locations in North America and Europe was a deliberated effort to make their tweets look more real. But this camouflage trick backfired – the faked locations when plotted on a map seemed completely abnormal. It's important to note that this anomaly could only be noticed by a human looking at the map, whereas a computer algorithm would have a hard time to realise the anomaly.

It was also a 'mistake' for the bots to use the Star Wars novels as the sole source of their tweets. So when we studied the abnormal tweets, the Star Wars theme was easy to see. Furthermore, it was this feature of the tweets that allowed us to create an automatic classifier to uncover all Star War bots. In addition, the fact that all of the bots were created during a relatively small period of time, gave us the additional convenience to test only users registered in that period.

⁵On the out-degree distribution, there is a spike at out-degree 2,000. This is because Twitter restricts the maximum number of a user's friends at 2,000 unless the user has more than 2,000 followers.

5.4 Thoughts on detection of future botnets

Inspired by the properties of the Star Wars bots, we have recently discovered another botnet with more than 500k bots, which will be reported shortly.

However, the process of discovering these botnets is unique. It is unlikely that we can repeat our luck, because future botnets could easily be programmed to avoid the design 'mistakes' of the Star Wars bots. For example bots do not need to tag their locations at all, because most users do not; and bots can quote from all sorts of sources, including other series of books, magazines, web pages, or even social media postings.

Indeed, future bots can learn 'lessons' from every new detection method proposed. It will inevitably become more and more difficult to detect future botnets. There is perhaps only one thing that bots cannot easily achieve by themselves – bots from the same botnet can follow each other, but it is hard to make users outside the botnet to follow them. However, it is not clear yet how this feature could be effectively used to detect new botnets.

5.5 Potential threats of the Star Wars bots

The low tweet count and the long period of inactivity of the Star Wars bots might look like a reason to think they are harmless. The years-long inactivity may make one wonder whether the bots have been forgotten by their master, or the access credentials were lost, or the bots were created only for fun? However, it takes effort and resources to create such a large number of bots as the Star Wars botnet. What if the master of the botnet deliberately make them hidden for a long time?

It is highly possible that the master still has the ability to reactivate all of the 350k Star Wars bots at any time of their choice. When that happens, the bots can pose all the threats discussed in Section 1.2, including spam, fake trending topics, opinion manipulation, astroturfing attack, fake followers and sample contamination. The fact that the Star Wars botnet has so many bots makes its potential threats serious, perhaps more serious than we have ever seen before.

5.6 Implications for cybersecurity

It is known there are millions of bots on Twitter. But the Star Wars botnet is perhaps the first evidence that a single botnet can be as large as such. It is shocking that a botmaster was determined to create so many bots, and the botnet has been well hidden for three years.

It is irresponsible to assume that the botmaster does not have any cynical or malign purpose. In fact, the best we can hope for is that the botnet was created purely for commercial gains. It is known [27] that pre-aged bots could be sold at a premium on the black market. This means the Star Wars bots are perfectly suited to be sold as fake followers because they are already three years old and therefore more 'valuable'. Indeed, we have observed that up to 15k Star Wars bots have been following a small number of Twitter users outside the botnet. The only plausible explanation is that these bots have already been sold as fake followers.

But, what if the botmaster wants more? What if someone offers a good price for purchasing the *control* of the whole botnet? The cybersecurity community must appreciate and assess the potential threats of such event, so that proper remedial procedures can be developed.

6 Conclusion

This work has multiple contributions. Firstly it presents the discovery of a large botnet, which provides a valuable source of ground truth for research on Twitter bots. Secondly it reveals the profound limitations of existing bot detection methods. Thirdly, it suggests that new detection methods are needed to detect other hidden bots and the future bots that will look more and more like normal users. Finally and most importantly, although the Star Wars bots have been hidden and inactive for three years, the cybersecurity community should not underestimate their potential threats, especially given the size of the botnet. We call for more research to assess the possible damage that such a massive botnet could cause and to investigate measures to mitigate such threats.

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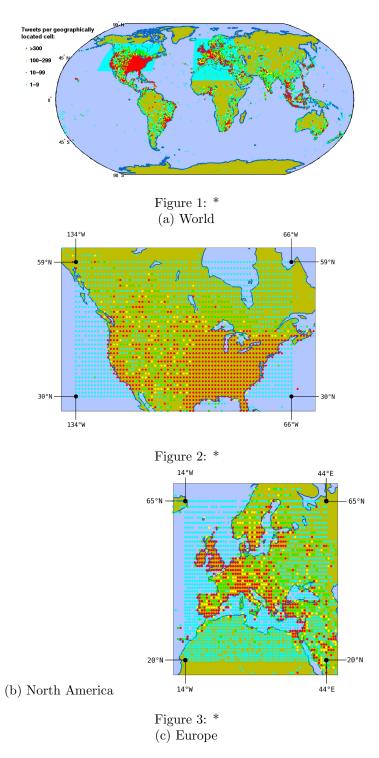


Figure 4: Distribution of tweet locations of the 1% random Twitter users. The map is divided into cells of 1 latitude and 1 longitude. The number of tweets in each cell are shown as a colour-coded dot.

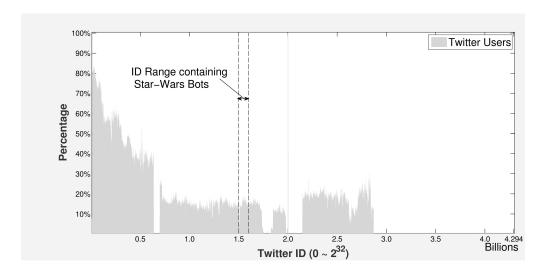


Figure 5: *
(a). All users

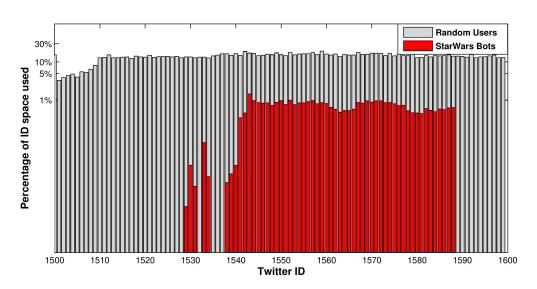


Figure 6: * (b). Star Wars bots with y axis in log scale.

Figure 7: Distribution of Twitter users over the user ID space. We show the percentage of user IDs that have been allocated to users in each bin of 1 million IDs.

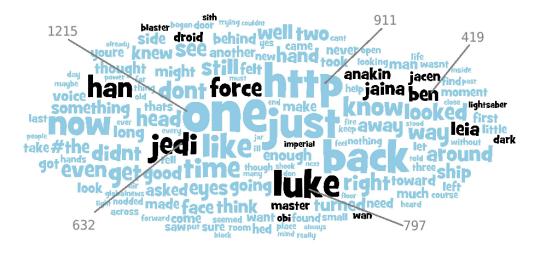


Figure 8: * (a). The Star Wars bots



Figure 9: * (b). The real Twitter users

Figure 10: Tag cloud illustrations of the words most frequently tweeted by (a) the Star Wars bots and (b) the real users. The size of a word indicates the frequency of appearance in tweets, where the frequency of selected words are shown in the pictures.

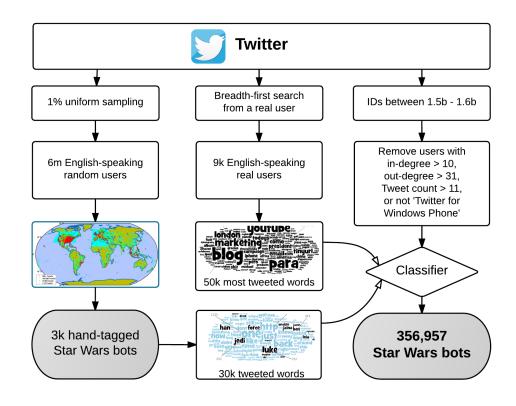


Figure 11: Discovery and detection of the Star Wars bots

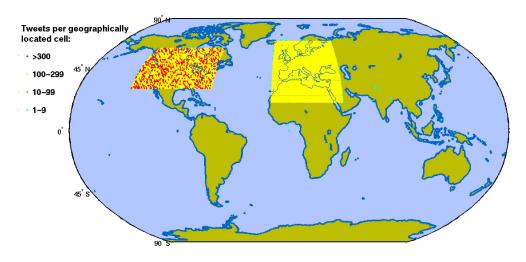


Figure 12: Geographic distribution of location tagged tweets made by the Star Wars bots

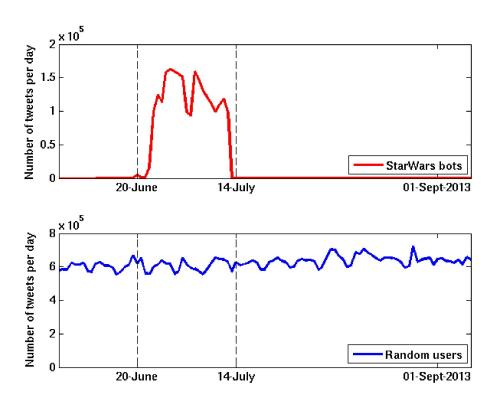


Figure 13: Daily count of total tweets created by the Star Wars bots and the random users in summer 2013.

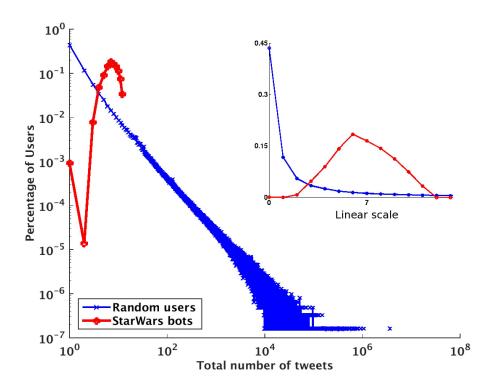


Figure 14: Distribution of lifetime count of user tweets for the Star Wars bots and the random users.

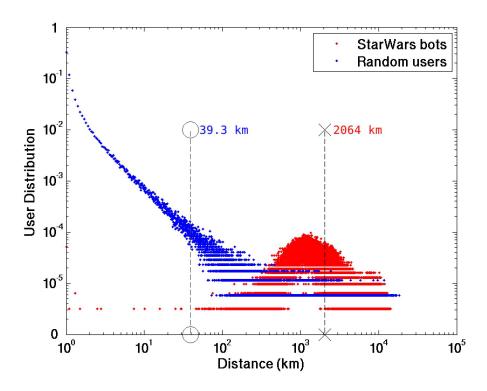


Figure 15: Distribution of users as a function of a user's average Haversine distance between locations of consecutive tweets. The two dashed vertical lines show the average Haversine distance over all the bots and the random users, respectively.

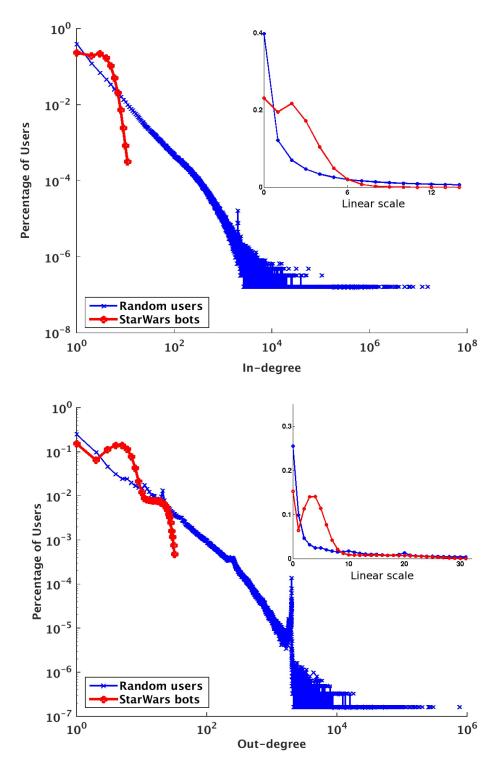


Figure 16: Distributions of in-degree (followers) and out-degree (friends or followees) for the Star Wars bots and the random users. The insets show the same distributions in linear scale.