

Disinformation Warfare: Understanding State-Sponsored Trolls on Twitter and Their Influence on the Web

Savvas Zannettou^{*}, Tristan Caulfield[†], Emiliano De Cristofaro[‡],
Michael Sirivianos^{*}, Gianluca Stringhini[†], Jeremy Blackburn[‡]

^{*}Cyprus University of Technology, [†]University College London, [‡]University of Alabama at Birmingham
sa.zannettou@edu.cut.ac.cy, {t.caulfield,e.decrisofaro,g.stringhini}@ucl.ac.uk
michael.sirivianos@cut.ac.cy, blackburn@uab.edu

Abstract

Over the past couple of years, anecdotal evidence has emerged linking coordinated campaigns by state-sponsored actors with efforts to manipulate public opinion on the Web, often around major political events, through dedicated accounts, or “trolls.” Although they are often involved in spreading disinformation on social media, there is little understanding of how these trolls operate, what type of content they disseminate, and most importantly their influence on the information ecosystem.

In this paper, we shed light on these questions by analyzing 27K tweets posted by 1K Twitter users identified as having ties with Russia’s Internet Research Agency and thus likely state-sponsored trolls. We compare their behavior to a random set of Twitter users, finding interesting differences in terms of the content they disseminate, the evolution of their account, as well as their general behavior and use of the Twitter platform. Then, using a statistical model known as Hawkes Processes, we quantify the influence that these accounts had on the dissemination of news on social platforms such as Twitter, Reddit, and 4chan. Overall, our findings indicate that Russian troll accounts managed to stay active for long periods of time and to reach a substantial number of Twitter users with their messages. When looking at their ability of spreading news content and making it viral, however, we find that their effect on social platforms was minor, with the significant exception of news published by the Russian state-sponsored news outlet RT (Russia Today).

1 Introduction

Recent political events and elections have been increasingly accompanied by reports of disinformation campaigns attributed to state-sponsored actors [8]. In particular, “troll farms,” allegedly employed by Russian state agencies, have been actively commenting and posting content on social media to further the Kremlin’s political agenda [25]. In late 2017, the US Congress started an investigation on Russian interference in the 2016 US Presidential Election, releasing the IDs of 2.7K Twitter accounts identified as Russian trolls.

Despite the growing relevance of state-sponsored disinformation, the activity of accounts linked to such efforts has not been thoroughly studied. Previous work has mostly looked at

campaigns run by bots [8, 11, 21]; however, automated content diffusion is only a part of the issue, and in fact recent research has shown that human actors are actually key in spreading false information on Twitter [23]. Overall, many aspects of state-sponsored disinformation remain unclear, e.g., how do state-sponsored trolls operate? What kind of content do they disseminate? And, perhaps more importantly, is it possible to quantify the influence they have on the overall information ecosystem on the Web?

In this paper, we aim to address these questions, by relying on the set of 2.7K accounts released by the US Congress as ground truth for Russian state-sponsored trolls. From a dataset containing all tweets released by the 1% Twitter Streaming API, we search and retrieve 27K tweets posted by 1K Russian trolls between January 2016 and September 2017. We characterize their activity by comparing to a random sample of Twitter users. Then, we quantify the influence of these trolls on the greater Web, looking at occurrences of URLs posted by them on Twitter, Reddit, and 4chan. Finally, we use Hawkes Processes [16] to model the influence of each Web community (i.e., Russian trolls on Twitter, overall Twitter, Reddit, and 4chan) on each other.

Main findings. Our study leads to several key observations:

1. Trolls actually bear very small influence in making news go viral on Twitter and other social platforms alike. A noteworthy exception are links to news originating from RT (Russia Today), a state-funded news outlet: indeed, Russian trolls are quite effective in “pushing” these URLs on Twitter and other social networks.
2. The main topics discussed by Russian trolls target very specific world events (e.g., Charlottesville protests) and organizations (such as ISIS), and political threads related to Donald Trump and Hillary Clinton.
3. Trolls adopt different identities over time, i.e., they “reset” their profile by deleting their previous tweets and changing their profile name/information.
4. Trolls exhibit significantly different behaviors compared to other (random) Twitter accounts. For instance, the locations they report concentrate in a few countries like the

USA, Germany, and Russia, perhaps in an attempt to appear “local” and more effectively manipulate opinions of users from those countries. Also, while random Twitter users mainly tweet from mobile versions of the platform, the majority of the Russian trolls do so via the Web Client.

2 Related Work

We now review previous work on opinion manipulation as well as politically motivated disinformation on the Web.

Opinion manipulation. The practice of swaying opinion in Web communities is a long-standing issue as malicious actors attempt to push their agenda. Kumar et al. [14] study how users create multiple accounts, called *sockpuppets*, that actively participate in some communities with the goal to manipulate users’ opinions. Using data from Disqus, a popular commenting platform, they find that sockpuppets exhibit different posting behavior when compared to benign users.

Mihaylov et al. [19] show that trolls can indeed manipulate users’ opinions in online forums. In absence of ground truth data, they label a user as troll if it is called out by multiple users of the community. In follow-up work, Mihaylov and Nakov [20] highlight two types of opinion manipulation trolls: those paid to operate and those that are called out as such by other users. Then, Volkova and Bell [28] attempt to predict the deletion of Twitter accounts because they are trolls, focusing on those that disseminated content related to the Russian-Ukraine crisis between 2014 and 2015. Among other things, they find that lexical features can assist in detecting such accounts with high accuracy.

Elyashar et al. [7] distinguish authentic discussions from campaigns to manipulate the public’s opinion, using a set of similarity functions alongside historical data. Also, Steward et al. [24] focus on discussions related to the Black Lives Matter movement and how content from Russian trolls was retweeted by other users. They build a retweet network and use community detection techniques to identify communities, finding one left-leaning and one right-leaning communities. By identifying the Russian troll accounts within the communities, they highlight that trolls infiltrated both communities, setting out to push specific narratives. Finally, Varol et al. [27] aim to identify memes (ideas) that become popular due to *coordinated* efforts, and achieve 75% AUC score before memes become trending and 95% AUC score afterwards.

False information on the political stage. Conover et al. [3] focus on Twitter activity over the six weeks leading to the 2010 US midterm elections and the interactions between right and left leaning communities. After building the retweet and mentions networks, they find that the retweet network shows limited connectivity between right and left leaning communities, which does not happen in the mentions network. This is because users engage others users with different ideologies and expose them to different opinions by using mentions to try change their stance on a political individual or situation. Ratkiewicz et al. [21] study political campaigns using multiple controlled accounts to disseminate support for an individual or opinion. They

use machine learning to detect the early stages of false political information spreading on Twitter and introduce a framework that considers topological, content-based, and crowdsourced features of the information diffusion.

Wong et al. [30] aim to quantify political leaning of users and news outlets during the 2012 US presidential election on Twitter by formulating the problem as an ill-posed linear inverse problem, and using an inference engine that considers tweeting and retweeting behavior of articles. Yang et al. [31] investigate the topics of discussions on Twitter for 51 US political persons showing that Democrats and Republicans are active in a similar way on Twitter, although the former tend to use hashtags more frequently. They also find that Republicans are more clustered, as they tend to share more tweets regarding the party’s issues and agenda. Le et al. [15] study 50M tweets regarding the 2016 US election primaries and highlight the importance of three factors in political discussions on social media, namely the *party* (e.g., Republican or Democrat), *policy considerations* (e.g., foreign policy), and *personality* of the candidates (e.g., intelligent or determined).

Howard and Kollanyi [13] study the role of bots in Twitter conversations during the 2016 Brexit referendum. They analyze 1.5M tweets from 313K Twitter accounts obtained using specific hashtags related to the referendum. They find that most tweets are in favor of Brexit, that there are bots with various levels of automation, and that 1% of the accounts generate 33% of the overall messages. Also, Hegelich and Janetzko [11] investigate whether bots on Twitter are used as political actors. By exposing and analyzing 1.7K bots on Twitter during the Russia-Ukraine conflict, they uncover their political agenda and show that bots exhibit various behaviors, e.g., trying to hide their identity, promoting topics through the use of hashtags, and retweeting messages with particularly interesting content.

Finally, a large body of work focuses on social bots [1, 4, 9, 8, 26] and their role in spreading political disinformation, highlighting that they can manipulate the public’s opinion at large scale, thus potentially affecting the outcome of political elections.

Remarks. Unlike previous work, our study focuses on the set of Russian troll accounts that were suspended by Twitter and released by the US congress. To the best of our knowledge, this constitutes the first effort not only to characterize a ground truth of troll accounts independently identified by Twitter, but also to quantify their influence on the greater Web, specifically, on Twitter as well as on other communities like Reddit and 4chan.

3 Background

In this section, we provide a brief overview of the social networks studied in this paper, i.e., Twitter, Reddit, and 4chan, which we choose because they are impactful actors on the Web’s information ecosystem [32].

Twitter. Twitter is a mainstream social network, where users can broadcast short messages, called “tweets,” to their followers. Tweets may contain hashtags, which enable the easy index and search of messages, as well as mentions, which refer to

other users on Twitter.

Reddit. Reddit is a news aggregator with several social features. It allows users to post URLs along with a title; posts can get up- and down- votes, which dictate the popularity and order in which they appear on the platform. Reddit is divided to “subreddits,” which are forums created by users that focus on a particular topic (e.g., */r/The_Donald* is about discussions around Donald Trump).

4chan. 4chan is an imageboard forum, organized in communities called “boards,” each with a different topic of interest. A user can create a new post by uploading an image with or without some text; others can reply below with or without images. 4chan is an anonymous community, and several of its boards are reportedly responsible for a substantial amount of hateful content [12]. In this work we focus on the Politically Incorrect board (*/pol/*) mainly because it is the main board for the discussion of politics and world events. Furthermore, 4chan is ephemeral, i.e., there is a limited number of active threads and all threads are permanently deleted after a week.

4 Datasets

Russian trolls. We start from the 2.7K Twitter accounts suspended by Twitter because of connections to Russia’s Internet Research Agency troll farm. The list of these accounts was released by the US Congress as part of their investigation of the alleged Russian interference in the 2016 US presidential election, and includes both Twitter’s *user id* (which is a numeric unique identifier associated to the account) and the *handle*.¹ From a dataset storing all tweets released by the 1% Twitter Streaming API, we search for tweets posted between January 2016 and September 2017 by the user ids of the trolls. Overall, we obtain 27K tweets from 1K out of the 2.7K Russian troll accounts.

Note that the criteria used by Twitter to identify these troll accounts are not public. What we do know, is this is not the complete set of active Russian trolls, because 6 days prior to this writing Twitter announced they have discovered over 1K more troll accounts.² Nonetheless, it constitutes an invaluable “ground truth” dataset enabling efforts to shed light on the behavior of state-sponsored troll accounts.

Baseline dataset. We also compile a list of random Twitter users, while ensuring that the distribution of the average number of tweets per day posted by the random users is similar to the one by trolls. To calculate the average number of tweets posted by an account, we find the first tweet posted after January 1, 2016 and retrieve the overall tweet count. This number is then divided by the number of days since account creation. Having selected a set of 1K random users, we then collect all their tweets between January 2016 and September 2017, obtaining a total of 96K tweets.

We follow this approach as it gives a good approximation of posting behavior, even though it might not be perfect, since (1)

¹See https://democrats-intelligence.house.gov/uploadedfiles/exhibit_b.pdf

²See https://blog.twitter.com/official/en_us/topics/company/2018/2016-election-update.html

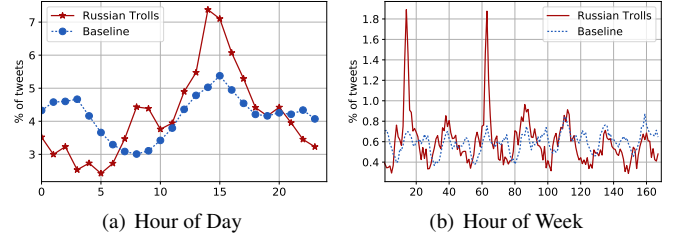


Figure 1: Temporal characteristics of tweets from Russian trolls and random Twitter users.

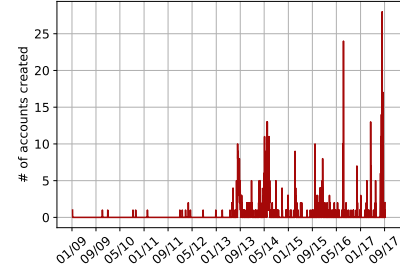


Figure 2: Number of Russian troll accounts created per day.

Twitter accounts can become more or less active over time, and (2) our datasets are based on the 1% Streaming API, thus, we are unable to control the number of tweets we obtain for each account.

5 Analysis

In this section, we present an in-depth analysis of the activities and the behavior of Russian trolls. First, we provide a general characterization of the accounts and a geographical analysis of the locations they report. Then, we analyze the content they disseminate and how they evolve from January 1, 2016 until their suspension by Twitter. Finally, we present a case study of one specific account.

5.1 General Characterization

Temporal analysis. We observe that Russian trolls are continuously active on Twitter between January, 2016 and September, 2017, with a peak of activity just before the second US presidential debate (October 9, 2016). Fig. 1(a) shows that most tweets from the trolls are posted between 14:00 and 15:00 UTC. In Fig. 1(b), we also report temporal characteristics based on hour of the week, finding that both datasets follow a diurnal pattern, while trolls’ activity peaks around 14:00 and 15:00 UTC on Mondays and Wednesdays. Considering that Moscow is three hours ahead UTC, this distribution does not seem to rule out that tweets might actually be posted from Russia.

Account creation. Next, we examine the dates when the state-sponsored accounts infiltrated Twitter, by looking at the account creation dates. From Fig. 2, we observe that 71% of them are actually created before 2016. There are some interesting peaks, during 2016 and 2017: for instance, 24 accounts are created on July 12, 2016, approximately a week before the Republican National Convention (when Donald Trump received the nomina-

Word	Name		Word	Description			
	(%)	4-gram (%)		(%)	Word bigram	(%)	(%)
news	1.3%	news	1.5%	news	10.7%	follow me	7.8%
bote	1.2%	line	1.5%	follow	10.7%	breaking news	2.6%
online	1.1%	blac	1.3%	conservative	8.1%	news aus	2.1%
daily	0.8%	bote	1.3%	trump	7.8%	uns in	2.1%
today	0.6%	rist	1.1%	und	6.2%	deiner stdt	2.1%
ezeziel2517	0.6%	nlin	1.1%	maga	5.9%	die news	2.1%
maria	0.5%	onli	1.0%	love	5.8%	wichtige und	2.1%
black	0.5%	lack	1.0%	us	5.3%	nachrichten aus	2.1%
voice	0.4%	bert	1.0%	die	5.0%	aus deiner	2.1%
martin	0.4%	poli	1.0%	nachrichten	4.3%	die dn	2.1%

Table 1: Top 10 words found in Russian troll screen names and account descriptions. We also report character 4-grams for the user names and word bigrams for the description.

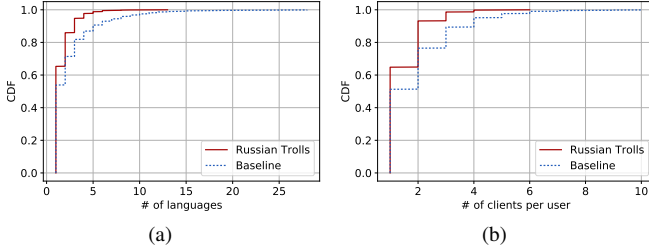


Figure 3: CDF of number of (a) languages used (b) clients used per user.

tion), while 28 appear on August 8, 2017, a few days before the infamous Unite the Right rally in Charlottesville [29]. Taken together, this might be evidence of coordinated activities aimed at manipulating users’ opinions on Twitter with respect to specific events.

Account characteristics. We also shed light on the troll account profile information. In Table 1, we report the top ten words appearing in the names and the descriptions of Russian trolls, as well as character 4-grams for account names and word bigrams for profile descriptions. Interestingly, a substantial number of Russian trolls pose as news outlets, evident from the use of the term “news” in both the name (1.3%) and the description (10.7%). Also, it seems they attempt to increase the number of their followers, thus their reach of Twitter users, by nudging users to follow them (see, e.g., “follow me” appearing in almost 8% of the accounts). Finally, 10.3% of the Russian trolls describe themselves as Trump supporters: “trump” and “maga” (Make America Great Again, one of Trump campaign’s main slogans).

Language. Looking at the language (as provided via the Twitter API) of the tweets posted by Russian trolls, we find that most of them (61%) are in English, although a substantial portion are in Russian (27%), and to a lesser extent in German (3.5%). In Fig. 3(a), we plot the CDF of the number of different languages for each user: 64% of the Russian trolls post all their tweets in only one language, compared to only 54% for random users. Overall, by comparing the two distributions, we observe that random Twitter users tend to use more languages in their tweets compared to the trolls.

Client. Finally, we analyze the clients used to post tweets. We do so since previous work [6] shows that the client used by official or professional accounts are quite different than the ones used by regular users. Table 2 reports the top 10 clients for both

Client (Trolls)	(%)	Client (Baseline)	(%)
Twitter Web Client	50.1%	TweetDeck	32.6%
twitterfeed	13.4%	Twitter for iPhone	26.2%
Twibble.io	9.0%	Twitter for Android	22.6%
IFTTT	8.6%	Twitter Web Client	6.1%
TweetDeck	8.3%	GrabInbox	2.0%
NovaPress	4.6%	Twitter for iPad	1.4%
dlvr.it	2.3%	IFTTT	1.0%
Twitter for iPhone	0.8%	twittbot.net	0.9%
Zapier.com	0.6%	Twitter for BlackBerry	0.6%
Twitter for Android	0.6%	Mobile Web (M2)	0.4%

Table 2: Top 10 Twitter clients (as % of tweets).

Russian trolls and baseline users. We find the latter prefer to use Twitter clients for mobile devices (48%) and the TweetDeck dashboard (32%), whereas, the former mainly use the Web client (50%). We also assess how many different clients Russian trolls use throughout our dataset: in Fig. 3(b), we plot the CDF of the number of clients used per user. We find that 65% of the Russian trolls use only one client, 28% of them two different clients, and the rest more than three, which is overall less than the random baseline users.

5.2 Geographical Analysis

Location. We then study users’ location, relying on the self-reported location field in their profiles. Note that users not only may leave it empty, but also change it any time they like, so we look at locations for each tweet. We retrieve it for 75% of the tweets by Russian trolls, gathering 261 different entries, which we convert to a physical location using the Google Maps Geocoding API.³ The API does not return results for 11 queries, as they correspond to non-existing locations (e.g., “block corner street”).

In the end, we obtain 178 unique coordinate locations for the trolls, as depicted in Fig. 4 (red circles). The size of the circles on the map indicates the number of tweets that appear on each location. We do the same for the baseline, getting 2,037 different entries, converted by the API to 894 unique locations (950 queries do not return results). We observe that most of the tweets from Russian trolls come from locations within the USA and Russia, and some from European countries, like Germany, Belgium, and Italy. Whereas, tweets in our baseline are more uniformly distributed across the globe, with many tweets from North and South America, Europe, and Asia. This suggests that Russian trolls may be pretending to be from certain countries, e.g., USA or Germany, aiming to pose as locals and better manipulate opinions. This explanation becomes more plausible when we consider that a plurality of troll account tweets have their location set as a generic form of “US,” as opposed to a specific city, state, or even region. Interestingly, the 2nd, 3rd, and 4th most popular location for troll accounts to tweet from are Moscow, St. Petersburg, and a generic form of “Russia.”

We also assess whether users change their country of origin based on the self-reported location. We find a negligible percentage (1%) of trolls that change their country, whereas for the baseline the corresponding percentage is 16%.

³<https://developers.google.com/maps/documentation/geocoding/start>

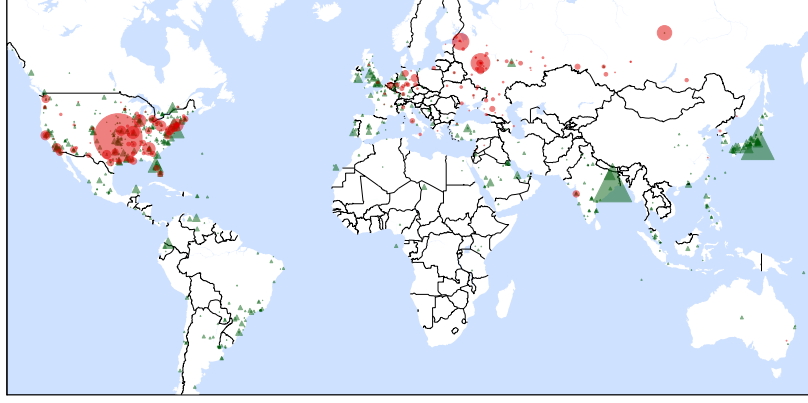


Figure 4: Distribution of reported locations for tweets by Russian trolls (red circles) and baseline (green triangles).

Timezone (Trolls)	(%)	Timezone (Baseline)	(%)
Eastern Time	38.87%	Athens	24.41%
Pacific Time	18.37%	Pacific Time	21.41%
Volgograd	10.03%	London	21.27%
Central Time	9.43%	Tokyo	3.83%
Moscow	8.18%	Central Time	3.75%
Bern	2.56%	Eastern Time	2.10%
Minsk	2.06%	Seoul	1.97%
Yerevan	1.96%	Brasilia	1.97%
Nairobi	1.52%	Buenos Aires	1.92%
Baku	1.29%	Urumqi	1.50%

Table 3: Top 10 timezones (as % of tweets).

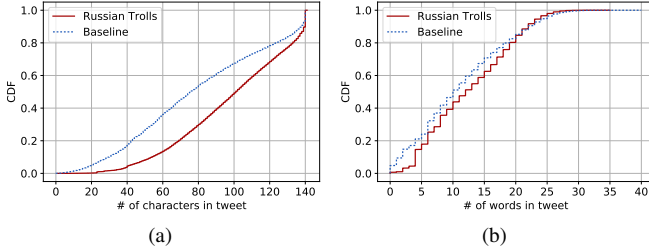


Figure 5: CDF of the number of (a) characters and (b) words in each tweet.

Timezone. We then study the timezone chosen by the users in their account setting. In Table 3, we report the top 10 timezones for each dataset, in terms of the corresponding tweet volumes. Two thirds of the tweets by trolls appear to be from US timezones, while a substantial percentage (18%) from Russian ones. Whereas, the baseline has a more diverse set of timezones, which seems to mirror findings from our location analysis. We also check whether users change their timezone settings, finding that 7% of the Russian trolls do so two to three times. The most popular changes are Berlin to Bern (18 times), Nairobi to Moscow (10), and Nairobi to Volgograd (10). By contrast, this almost never happens for baseline accounts.

5.3 Content Analysis

Text. Next, we quantify the number of characters and words contained in each tweet, and plot the corresponding CDF in Fig. 5, finding that Russian trolls tend to post longer tweets.

Media. We then assess whether Russian trolls use images and videos in a different way than random baseline users. For Rus-

Trolls			Baseline		
Hashtag	(%) Hashtag	(%) Hashtag	(%) Hashtag	(%) Hashtag	(%)
news	7.2% US	0.7% iHeartAwards	1.8% UrbanAttires	0.6%	
politics	2.6% tcot	0.6% BestFanArmy	1.6% Vacature	0.6%	
sports	2.1% PJNET	0.6% Harmonizers	1.0% mPlusPlaces	0.6%	
business	1.4% entertainment	0.5% iOSApp	0.9% job	0.5%	
money	1.3% top	0.5% JouwBaan	0.9% Directioners	0.5%	
world	1.2% topNews	0.5% vacature	0.9% JIMIN	0.5%	
MAGA	0.8% ISIS	0.4% KCA	0.9% PRODUCE101	0.5%	
health	0.8% Merkelmussbleiben	0.4% Psychic	0.8% VoteMainFPP	0.5%	
local	0.7% IslamKills	0.4% RT	0.8% Werk	0.4%	
BlackLivesMatter	0.7% breaking	0.4% Libertad2016	0.6% dts	0.4%	

Table 4: Top 20 hashtags in tweets from Russian trolls and baseline users.

sian trolls (resp., baseline accounts), 66% (resp., 73%) of the tweets include no images, 32% (resp., 18%) exactly one image, and 2% (resp., 9%) more than one. This suggests that Russian trolls disseminate a considerable amount of information via single-image tweets. As for videos, only 1.5% of the tweets from Russian trolls includes a video, as opposed to 6.4% for baseline accounts.

Hashtags. Our next step is to study the use of hashtags in tweets. Russian trolls use at least one hashtag in 32% of their tweets, compared to 10% for the baseline. Overall, we find 4.3K and 7.1K unique hashtags for trolls and random users, respectively, with 74% and 78% of them only appearing once. In Table 4, we report the top 20 hashtags for both datasets. State-sponsored trolls appear to use hashtags to disseminate news (7.2%) and politics (2.6%) related content, but also use several that might be indicators of propaganda and/or controversial topics, e.g., #ISIS, #IslamKills, and #BlackLivesMatter. For instance, we find among the tweets in our dataset some notable examples including: “We just have to close the borders, ‘refugees’ are simple terrorists #IslamKills” on March 22, 2016, “#SyrianRefugees ARE TERRORISTS from #ISIS #IslamKills” on March 22, 2016, and “WATCH: Here is a typical #BlackLivesMatter protester: ‘I hope I kill all white babes!’ #BatonRouge <url>” on July 17, 2016. Note that <url> denotes a link.

We also study when these hashtags are used by the trolls, finding that most of them are well distributed over time. However, there are some interesting exceptions, e.g., with #Merkelmussbleiben (a hashtag seemingly supporting German Chancellor Angela Merkel) and #IslamKills. Specifically, tweets

Trolls		Baseline	
Mention	(%)	Mention	(%)
leprasorium	2.1%	TasbiHstighfar	0.3%
zubovnik	0.8%	DLGreez	0.4%
realDonaldTrump	0.6%	DanaGeezus	0.4%
midnight	0.6%	ruopentwit	0.3%
blicqer	0.6%	Spoontamer	0.3%
gloed_up	0.6%	YouTube	0.3%
wylsacom	0.5%	ChrixMorgan	0.3%
TalibKweli	0.4%	sergeylazarev	0.3%
zvezdanews	0.4%	RT_com	0.3%
GiselleEvns	0.4%	kozheed	0.3%
		BaddiessNation	0.2%
		IGGYAZALEAO	0.1%

Table 5: Top 20 mentions in tweets from Russian trolls and baseline users.

with the former appear exclusively on July 21, 2016, while the latter on March 22, 2016, when a terrorist attack took place at Brussels airport. These two examples illustrate how the trolls may be coordinating to push specific narratives on Twitter.

Mentions. We find that 46% of trolls’ tweets include *mentions* (i.e., @user appears in the tweet) to 8.5K unique Twitter users. This percentage is much higher for the random baseline users (80%, to 41K users). Table 5 reports the 20 top mentions we find in tweets from Russian trolls and baseline users. We find several Russian accounts, like ‘leprasorium’ (a popular Russian account that mainly posts memes) in 2% of the mentions, as well as popular politicians like ‘realDonaldTrump’ (0.6%). The practice of mentioning politicians on Twitter may reflect an underlying strategy to mutate users’ opinions regarding a particular political topic, which has been also studied in previous work [3].

URLs. We then analyze the URLs included in the tweets. First of all, we note that 53% of the trolls’ tweets include at least a URL, compared to only 27% for the random baseline. There is an extensive presence of URL shorteners for both datasets, e.g., [bit.ly](#) (12% for trolls and 26% for the baseline) and [ift.tt](#) (10% for trolls and 2% for the baseline), therefore, in November 2017, we visit each URL to obtain the final URL after all redirections.

In Fig. 6, we plot the CDF of the number of URLs per unique domain. We observe that Russian trolls disseminate more URLs in their tweets compared to the baseline. This might indicate that Russian trolls include URLs to increase their credibility and positive user perception; indeed, [10] show that adding a URL in a tweet correlates with higher credibility scores. Also, in Table 6, we report the top 20 domains for both Russian trolls and the baseline. Most URLs point to content within Twitter itself; 13% and 35%, respectively. Links to a number of popular social networks, such as YouTube (1.8% and 4.2%, respectively) and Instagram (1.5% and 1.9%) appear in both datasets. There are also a number of news outlets linked from trolls’ tweets, e.g., Washington Post (0.7%), Seattle Times (0.7%), and state-sponsored news outlets like Russia Today (0.8%) in trolls’ tweets, but much less so from random accounts.

Sentiment analysis. We assess the sentiment and subjectivity of each tweet using the Pattern library [22]. Fig. 7(a) plots the CDF of the sentiment scores of tweets posted by Russian trolls and our baseline users. We observe that 30% of the tweets from Russian trolls have positive sentiment, and 18% negative. These scores are not too distant from those of random users

Domain (Trolls)	(%)	Domain (Baseline)	(%)
twitter.com	12.81%	twitter.com	35.51%
reportsecret.com	7.02%	youtube.com	4.21%
riaan.ru	3.42%	vine.co	3.94%
politexpert.net	2.10%	factissues.com	3.24%
youtube.com	1.88%	blogspot.com.cy	1.92%
vk.com	1.58%	instagram.com	1.90%
instagram.com	1.53%	facebook.com	1.68%
yandex.ru	1.50%	worldstarr.info	1.47%
infreactor.org	1.36%	trendytopic.info	1.39%
cbslocal.com	1.35%	minibird.jp	1.25%
livejournal	1.35%	yaadlinksradio.com	1.24%
nevnov.ru	1.07%	soundcloud.com	1.24%
ksnt.com	1.01%	linklist.me	1.15%
kron4.com	0.93%	twimg.com	1.09%
viid.me	0.93%	apparse.com	1.08%
newinform.com	0.89%	cargobayy.net	0.88%
infreactor.ru	0.84%	virralclub.com	0.84%
rt.com	0.81%	tistory.com	0.50%
washingtonpost.com	0.75%	twitcasting.tv	0.49%
seattletimes.com	0.73%	nytimes.com	0.48%

Table 6: Top 20 domains included in tweets from Russian trolls and baselines users.

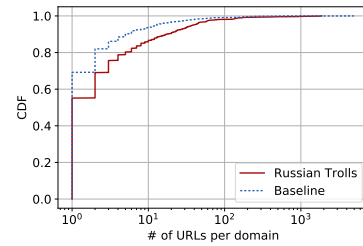


Figure 6: CDF of number of URLs per domain.

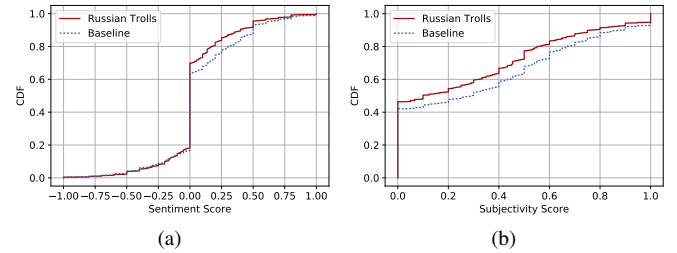


Figure 7: CDF of sentiment and subjectivity scores for tweets of Russian trolls and random users.

where 36% are positive and 16% negative, however, Russian trolls exhibit a unique behavior in terms of sentiment, as a two-sample Kolmogorov-Smirnov test unveils significant differences between the distributions ($p < 0.01$). Overall, we observe that Russian trolls tend to be more negative/neutral, while our baseline is more positive. We also compare subjectivity scores (Fig. 7(b)), finding that tweets from trolls tend to be more subjective; again, we perform significance tests revealing differences between the two distributions ($p < 0.01$).

LDA analysis. We also use the Latent Dirichlet Allocation (LDA) model [2] to analyze tweets’ semantics. We train an LDA model for each of the datasets and extract 10 distinct topics with 10 words, as reported in Table 7. Overall, topics from Russian trolls refer to specific world events (e.g., Charlottesville) as well as specific news related to politics (e.g., North Korea and Donald Trump). By contrast, topics extracted from the random sample are more general (e.g., tweets regarding birthdays).

Topic	Terms (Trolls)	Topic	Terms (Baseline)
1	trump, black, people, really, one, enlist, truth, work, can, get	1	want, can, just, follow, now, get, see, don, love, will
2	trump, year, old, just, run, obama, breaking, will, news, police	2	2016, july, come, https, trump, social, just, media, jabberduck, get
3	new, trump, just, breaking, obamacare, one, sessions, senate, politics, york	3	happy, best, make, birthday, video, days, come, back, still, little
4	man, police, news, killed, shot, shooting, woman, dead, breaking, death	4	know, never, get, love, just, night, one, give, time, can
5	trump, media, tcot, just, pjnet, war, like, video, post, hillary	5	just, can, everyone, think, get, white, fifth, veranomt2016, harmony, friends
6	sports, video, game, music, isis, charlottesville, will, new, health, amb	6	good, like, people, lol, don, just, look, today, said, keep
7	can, don, people, want, know, see, black, get, just, like	7	summer, seconds, team, people, miss, don, will, photo, veranomt2016, new
8	trump, clinton, politics, hillary, video, white, donald, president, house, calls	8	like, twitter, https, first, can, get, music, better, wait, really
9	news, world, money, business, new, one, says, state, 2016, peace	9	dallas, right, fuck, vote, police, via, just, killed, teenchoice, aldubmainecelebration
10	now, trump, north, korea, people, right, will, check, just, playing	10	day, black, love, thank, great, new, now, matter, can, much

Table 7: Terms extracted from LDA topics of tweets from Russian trolls and baseline users.

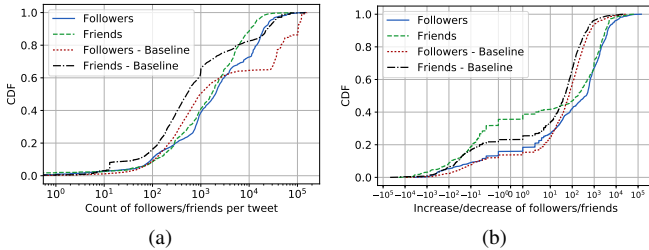


Figure 8: CDF of the number of (a) followers/friends for each tweet and (b) increase in followers/friends for each user from the first to the last tweet.

5.4 Account Evolution

Name changes. Previous work [18] has shown that malicious accounts often change their profile name in order to assume different identifies. Therefore, we investigate whether state-sponsored trolls show a similar behavior, as they might change the narrative with which they are attempting to influence public opinion.

Indeed, we find that 9% of the accounts operated by Russian trolls change their screen name, up to 4 times during the course of our dataset. Some examples include changing screen names from “OnlineHouston” to “HoustonTopNews”, or “Jesus Quintin Perez” to “WorldNewsPolitics,” in a clear attempt to pose as news-related accounts. In our baseline, we find that 19% of the accounts changed their Twitter screen names, up to 11 times during our dataset; highlighting that changing screen names is a common behavior of Twitter users in general.

Followers/Friends. Next, we look at the number of followers and friends (i.e., the accounts one follows) of the Russian trolls, as this is an indication of the possible overall impact of a tweet. In Fig. 8(a), we plot the CDF of the number of followers per tweet measured at the time of that tweet. On average, Russian trolls have 7K followers and 3K friends, while our baseline has 25K followers and 6K friends. We also note that in both samples, tweets reached a large number of Twitter users; at least 1K followers, with peaks up to 145K followers. These results highlight that Russian troll accounts have a non-negligible number of followers, which can assist in pushing specific narratives to a much greater number of Twitter users.

We also assess the evolution of the Russian trolls in terms of the number of their followers and friends. To this end, we get the follower and friend count for each user on their first and last tweet and calculate the difference. Fig. 8(b) plots the CDF of the increase/decrease of the followers and friends for each Russian troll as well as random user in our baseline. We observe

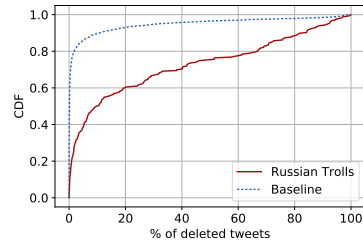


Figure 9: CDF of the number of deleted tweets per observe deletion.

that, on average, Russian trolls increase their number of followers and friends by 2,065 and 1,225, respectively, whereas for the baseline we observe an increase of 425 and 133 for followers and friends, respectively. This suggests that Russian trolls work hard to increase their reachability within Twitter.

Tweet Deletion. Arguably, a reasonable strategy to avoid detection after posting tweets that aim to manipulate other users might be to delete them. This is particularly useful when troll accounts change their identity and need to modify the narrative that they use to influence public opinion.

With each tweet, the Streaming API returns the total number of available tweets a user has up to that time. Retrieving this count allows us to observe if a user has deleted a tweet, and around what period; we call this an “observed deletion.” Recall that our dataset is based on the 1% sample of Twitter, thus, we can only estimate, in a conservative way, how many tweets are deleted; more specifically, in between subsequent tweets, a user may have deleted and posted tweets that we do not observe. In Fig. 9, we plot the CDF of the number of deleted tweets per observed deletion. We observe that 13% of the Russian trolls delete some of their tweets, with a median percentage of tweet deletion equal to 9.7%. Whereas, for the baseline set, 27% of the accounts delete at least one tweet, but the median percentage is 0.1%. This means that the trolls delete their tweets in batches, possibly trying to cover their tracks or get a clean slate, while random users make a larger number of deletions but only a small percentage of their overall tweets, possibly because of typos.

We also report the distribution, over each month, of tweet deletions in Fig. 10. Specifically, we report the mean of the percentages for all observed deletions in our datasets. Most of the tweets from Russian trolls are deleted in October 2016, suggesting that these accounts attempted to get a clean slate, by deleting their previous tweets, a couple of months before the 2016 US elections.

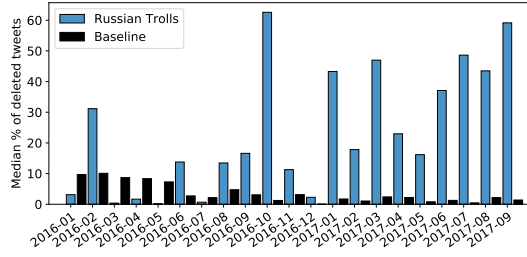


Figure 10: Average percentage of observed deletions per month.

5.5 Case Study

While the previous results provide a quantitative characterization of Russian troll account behavior, we believe there is value showing a concrete example of the behavior exhibited and how techniques played out. We start on May 15, 2016, where the troll with screen name ‘Pen_Air’, was posing as a news account via its profile description: “National American news.” On September 8, 2016 as the US presidential elections approached, ‘Pen_Air’ became a Trump supporter, changing its screen name to ‘Blacks4DTrump’ with a profile description of “African-Americans stand with Trump to make America Great Again!” Over the next 11 months, the account’s tweet count grew from 49 to 642 while its follower count rose from 1.2K to nearly 9K.

Then, around August 18, 2017, the account was seemingly repurposed. Almost all of its previous tweets were deleted (the account’s tweet count dropped to 35), it gained a new screen name (‘southlonestar2’), and was now posing as a “Proud American and TEXAN patriot! Stop ISLAM and PC. Don’t mess with Texas” according to its profile description.

When examining the accounts tweets, we see that most are clearly related to politics, featuring blunt right-wing attacks and “talking points.” For example, “Mr. Obama! Maybe you bring your girls and leave them in the bathroom with a grown man! #bathroombill #NOBama <url>” on May 15, 2016, “#HiLIARy has only two faces! And I hate both! #NeverHillary #Hillaryliesmatter <url>” on May 19, 2016, and “RT @TEN.GOP: WikiLeaks #DNCLeaks confirms something we all know: system is totally rigged! #NeverHillary <url>.” on July 22, 2016.

5.6 Take-aways

In summary, our analysis leads to the following observations. First, we find evidence that trolls were actively involved in the dissemination of content related to world news and politics, as well as propaganda content regarding various topics such as ISIS and Islam, between February, 2016 and September, 2017. Moreover, several state-sponsored trolls were created or repurposed a few weeks before notable world events, including the Republican National Convention meeting or the Charlottesville rally.

We also find that the trolls deleted a substantial amount of tweets in batches and overall made substantial changes to their accounts during the course of their lifespan. Specifically, they changed their screen names aiming to pose as news outlets, experienced significant rises in the numbers of followers and

		/pol/	Reddit	Twitter	Trolls
URLs	Russian state-sponsored	6	13	19	19
	Other news sources	47	168	159	192
	All	127	482	861	989
Events	Russian state-sponsored	19	42	118	19
	Other news sources	720	3,055	2,930	195
	All	1,685	9,531	1,537,612	1,461
Mean λ_0	Russian state-sponsored	0.0824	0.1865	0.2264	0.1228
	Other news sources	0.0421	0.1447	0.1544	0.0663
	All	0.0324	0.1557	0.1553	0.0753

Table 8: Total URLs with at least one event in Twitter, /pol/, Reddit, and Russian trolls on Twitter; total events for Russian state-sponsored news URLs, other news URLs and all the URLs; and mean background rate (λ_0) for each platform.

friends, etc. Furthermore, our location analysis shows that Russian trolls might have tried to manipulate users located in the USA, Germany, and possibly in their own country (i.e., Russia), by appearing to be located in those countries. Finally, the fact that these accounts were active up until their recent suspension also highlights the need to develop more effective tools to detect such actors.

6 Influence Estimation

Thus far, we have analyzed the behavior of the Russian trolls on the Twitter platform, and how this differs from that of a baseline of random users. Allegedly, their main goal is to ultimately manipulate the opinion of other users and extend the cascade of disinformation they share (e.g., other users post similar content) [5]. Therefore, we now set out to shed light on their impact, in terms of the dissemination of disinformation, on Twitter and on the greater Web.

To assess their influence, we look at the URLs posted by four groups of users: Russian trolls on Twitter, “normal” accounts on Twitter, Reddit users, and 4chan users (/pol/ board). For each unique URL, we fit a statistical model known as Hawkes Processes [16, 17], which allows us to estimate the strength of connections between each of these four groups in terms of how likely an event – the URL being posted by either trolls or normal users to a particular platform – is to cause subsequent events in each of the groups. For example, a strong connection from Reddit to /pol/ would mean that a URL that appears on Reddit is likely to be seen and then re-posted on /pol/; whereas, a weak connection from Russian trolls to normal users on Twitter indicates that a URL posted by Russian trolls is less likely to be re-tweeted or re-posted by the latter. We fit the Hawkes Processes using the methodology presented by [32].

To study the dissemination of different types of content, we look at three different sets of URLs: 1) The complete set of all URLs posted by Russian troll accounts; 2) The subset of URLs for Russian state-sponsored news, namely, RT (Russia Today); and 3) The subset of URLs from other news sources, including both mainstream and alternative, using the list provided by [32]. Note that we initially planned to also include Sputnik news as a Russian state-sponsored outlet, but we did not find many instances of Sputnik URLs.

Table 8 summarizes the number of URLs, number of events

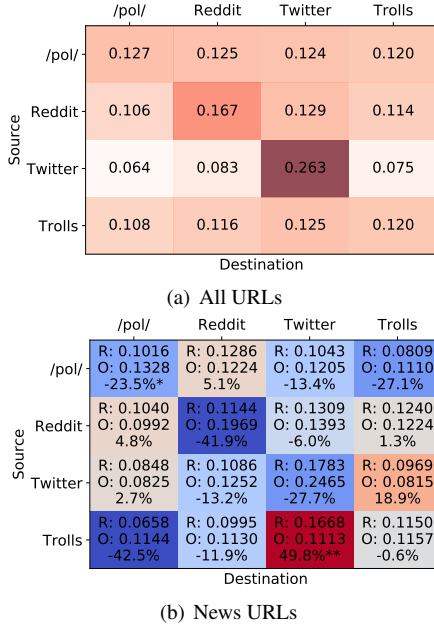


Figure 11: Mean weights for (a) all URLs in our dataset and (b) news URLs categorized as Russian state-sponsored (R) and other mainstream and alternative news URLs (O). We also show the percent of increase/decrease between the two categories (also indicated by coloration). Note that * and ** refer to statistical significance with, resp., $p < 0.05$ and $p < 0.01$.

(i.e., occurrences of a given URL) as well as the mean background rate for each category and social network. The background rate defines the rate at which events occur excluding the influence of the platforms included in the model; the background rate includes events created spontaneously on each network, such as by a user reading the original article and then posting a link to, or those generated by another platform not monitored by us, such as Facebook. The number of events for Russian state-sponsored news sources is substantially lower than the number of events from other mainstream and alternative news sources. This is expected since the former only includes one news source (RT), however, it is interesting that the background rates for these URLs are higher than for other mainstream and alternative news, meaning that events from Russian state-sponsored news are more likely to occur spontaneously, either from platforms we do not measure or posted by users directly.

Fitting a Hawkes model yields a weight matrix, which characterizes the strength of the connections between the groups we study. Each weight value, represents the connection strength from one group to another and can be interpreted as the expected number of subsequent events that will occur on the second group after each event on the first. The mean weight values over all URLs, as well as for the URLs from Russian state-sponsored outlets and other mainstream and alternative URLs are presented in Fig. 11.

In Figure 11(a), which shows the mean weights for all URLs, we observe that for /pol/, Reddit, and normal users on Twitter, the greatest weights are from each group to itself, meaning that reposts/retweets on the same site are more common than shar-

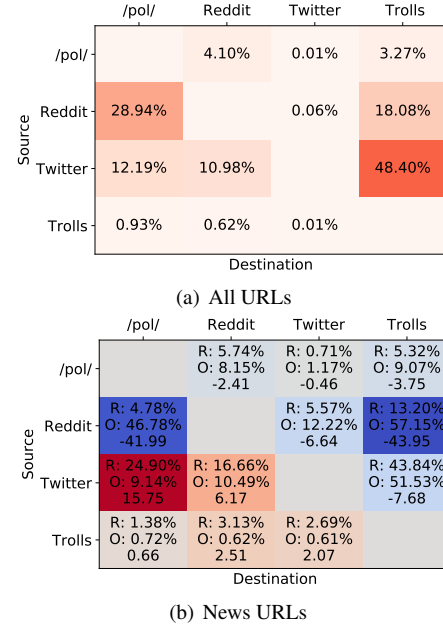


Figure 12: Estimated mean percentages of events created because of other events for (a) all URLs and (b) Russian state-sponsored URLs (R) and other mainstream and alternative news URLs (O). We also show the difference between the two categories of news (also indicated by coloration).

ing the URL to the other platforms. For the Russian Trolls on Twitter, however, the weight is greater from the trolls to Twitter than from the trolls to themselves, perhaps reflecting their use as an avenue for *disseminating* information to normal Twitter users.

From Figure 11(b), we observe that, in most cases, the connections are stronger for non-Russia state-sponsored news, indicating that regular users are more inclined to share news articles from mainstream and alternative news sources. Looking at the Russian trolls and normal Twitter users, we see that the trolls are more likely to retweet or repost Russian state-sponsored URLs from normal Twitter users than other news sources; conversely, normal Twitter users are more likely to retweet or repost Russian state-sponsored URLs from the troll accounts.

In order to assess the significance of our results, we perform two-sample Kolmogorov-Smirnov tests on the weight distributions for the Russian state-sponsored news URLs and the other news URLs for each source-destination platform pair (depicted as stars in the Fig. 11(b)). Small p value means there is a statistically significant difference in the way that Russian state-sponsored URLs propagate from the source to the destination platform. Most of the source-destination pairs have no statistical significance, however for the Russian trolls–Twitter users pair, we find statistically significance difference with $p < 0.01$.

In Fig. 12, we report the estimated total impact for each pair of platforms, for both Russian state-sponsored news, other news sources as well as all the observed URLs. We determine the impact by calculating, based on the estimated weights and the number of events, the percentage of events on a destination platform caused by events on a source platform, following

the methodology presented by [32]. (We omit the details due to space constraints.)

For all URLs (Fig. 12(a)), we find that the influence of Russian trolls is negligible on Twitter (0.01%), while for /pol/ and Reddit it is slightly higher (0.93% and 0.62%, respectively). For other pairs, the larger impacts are between Reddit–/pol/ and Twitter–Russian trolls, mainly due to the larger population of users. Looking at the estimated impact for Russian state-sponsored and other news sources (Fig. 12(b)), we note that the Russian trolls influenced the other platforms approximately the same for alternative and mainstream news sources (0.72%, 0.62%, and 0.61 for /pol/, Reddit, and Twitter, respectively). Interestingly, Russian trolls have a much larger impact on all the other platforms for the Russian state-sponsored news when compared to the other news sources: approximately 2 times more on /pol/, 5 times more on Reddit, and 4 times more on Twitter.

Take-aways. Using Hawkes processes, we were able to assess the degree of influence Russian trolls had on Twitter, Reddit, and /pol/ by examining the diffusion of information via URLs to news stories. Our results indicate that their influence is actually quite limited. With the exception of news originating from the Russian state-sponsored news outlet RT (formerly Russia Today), the troll accounts were generally less influential than other users on Reddit, Twitter, and 4chan. However, our analysis is based only on 1K troll accounts found in Twitter’s 1% stream, and, as mentioned previously, Twitter recently announced they had discovered over 1K more troll accounts and more than 50K automated accounts.

With that in mind, there are several potential explanations behind this limited influence. For example, there might be a lot of influence attributed to regular Twitter users that belongs to newly announced troll accounts. Considering that Twitter announced the discovery of “only” 1K more troll accounts, we suspect that this is not really the case. Another, more plausible explanation is that the troll accounts are just not terribly efficient at spreading news, and instead are more concerned with causing havoc by pushing ideas, engaging other users, or even taking both sides of controversial online discussions [24]. This scenario makes more sense considering that, along with 1K new troll accounts, Twitter also announced discovering over 50K *automated* accounts that might be more efficient in terms of driving traffic to specific URLs.

7 Conclusions

In this paper, we analyzed the behavior and use of the Twitter platform by Russian state-sponsored trolls during the course of 21 months. We showed that Russian trolls exhibited interesting differences when compared with a set of random users, actively disseminate politics-related content, adopted multiple identities during their account’s lifespan, and that they aimed to increase their impact on Twitter by increasing their followers. Also, we quantified the influence that Russian trolls have on Twitter, Reddit, and /pol/ using a statistical model known as Hawkes Processes. Our findings show that trolls’ influence

was not substantial with respect to the other platforms, with the significant exception of news published by the Russian state-sponsored news outlet RT (Russia Today).

Our study also prompts some directions for future work. For instance, the consistent reinventing of troll accounts’ identities, batch message deletion, and aggressive collection of friends and followers could prove useful for designing detection and mitigation techniques. In particular, we believe our findings motivate the need for more sophisticated measurements of influence. Our analysis indicates that the troll accounts were *not* terribly effective in spreading disinformation, but it is likely that these curated troll accounts left simple information diffusion to automated bots, focusing, instead, on more nuanced methods of manipulation.

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