Characterizing the Use of Images by State-Sponsored Troll Accounts on Twitter

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Abstract

Anecdotal evidence has emerged suggesting that state-sponsored organizations, like the Russian Internet Research Agency, have exploited mainstream social. Their primary goal is apparently to conduct information warfare operations to manipulate public opinion using accounts disguised as “normal” people. To increase engagement and credibility of their posts, these accounts regularly share images. However, the use of images by state-sponsored accounts has yet to be examined by the research community.

In this work, we address this gap by analyzing a ground truth dataset of 1.8M images posted to Twitter by called Russian trolls. More specifically, we analyze the content of the images, as well as the posting activity of the accounts. Among other things, we find that image posting activity of Russian trolls is tightly coupled with real-world events, and that their targets, as well as the content shared, changed over time. When looking at the interplay between domains that shared the same images as state-sponsored trolls, we find clear cut differences in the origin and/or spread of images across the Web. Overall, our findings provide new insight into how state-sponsored trolls operate, and specifically how they use imagery to achieve their goals.

1 Introduction

In the age of social media, social network users are constantly bombarded with digital content, being it life events from their friends, world news, or product advertisements. While the sheer amount of information users have access to was unthinkable just a couple of decades ago, the way in which people process that information has also evolved drastically. Users often feel overwhelmed with how much content they are exposed to [31], and pay attention to each piece of information for short amounts of time, with repercussion to their attention span [48]. Previous research has showed that 60% of social network users re-share articles on social media without having read them, basing their decision on limited cues such as the title of the article or the thumbnail image associated with it [22].

As a result, it is not surprising that social networks have become the battlefield for information warfare, with different entities attempting to disseminate content to achieve strategic goals, push agendas, or fight ideological battles. As part of this game, governments often employ “armies” of actors, operating from believable online accounts and posting content that aims to manipulate opinion or sow public discord by actively participating in online discussions. This is apparent from recent evidence extensively suggesting the involvement of state-sponsored accounts in divisive events, e.g., the Black Lives Matter movement [24] or the 2016 US elections [43], highlighting how these entities can be impactful both on the information ecosystem and in the real world.

In such an information-saturated society, the effective use of images when sharing online content can have a strong influence in whether content will catch people’s attention and go viral [13, 27, 29]. Therefore, as part of the efforts aimed to actively push agendas, state-sponsored accounts do not only use textual content, but also take advantage of the expressive power of images and pictures, e.g., using politically and ideologically charged memes [50]. In Figure 1, we report some examples of images pushed by state-sponsored accounts on Twitter, showcasing their unequivocally political nature and how they can be used to push agendas. Nonetheless, the role of images in information diffusion on the Web has attracted limited attention from the research community, which has thus far mainly focused on textual content [4, 52].

In this work, we begin filling this gap by studying the use of images by state-sponsored accounts, aka Russian trolls [23]. Our goal is to understand their targets, the content they aim
to disseminate, and where images shared by state-sponsored accounts appear on the Web. First, we expand on an image-processing pipeline presented by [50] in order to study images shared by state-sponsored trolls on Twitter; more precisely, we implement a custom annotation module that uses Google’s Cloud Vision API to annotate images in the absence of high-quality ground truth data or for images that are not bounded to a specific domain (e.g., memes). Then, we run the new pipeline on a dataset of 1.8M images from the 9M tweets released in October 2018 by Twitter as part of their effort to curb state-sponsored propaganda. These tweets were posted by 3.6K accounts identified as being controlled by the Russian Internet Research Agency (IRA).

Along with a first-of-its-kind characterization of how images are used by state-sponsored actors, our work yields a number of interesting and novel findings:

1. The sharing of images by the trolls is tightly coupled with real-world events. For instance, we find a peak in activity that is clearly in close temporal proximity with the Unite the Right rally in Charlottesville [45], suggesting their use to sow discord during dividing events. Also, changepoint analysis reveals statistically significant changes in posting behavior; e.g., Russian trolls started sharing images related to Syria by the time that Russian military forces started operations in Syria [40].

2. Our analysis provides evidence of their general themes and targets. For instance, we find that Russian trolls were mainly posting about Russia, Ukraine, and the USA.

3. The target of state-sponsored accounts varies over time, as evidenced by the entities detected in the images. For instance, Russian trolls were posting images related to Ukraine almost exclusively in 2014, and those related to Donald Trump mainly after 2016.

4. By studying the co-occurrence of these images across the Web, we show that the same images appeared in many popular social networks, as well as mainstream and alternative news outlets. Moreover, we highlight interesting differences in popular websites for each of the detected entities: e.g., images related to US matters were mostly co-appearing on mainstream English-posting news sites.

2 Related Work

Previous work has extensively focused on understanding the behavior, role, and impact of state-sponsored accounts in the US political scene. [15] perform linguistic analysis on posts by Russian state-sponsored accounts over the course of the 2016 US election; they find that right- and left-leaning communities are targeted differently to maximize hostility across the political spectrum in the USA. [46] investigate the behavior of state-sponsored accounts regarding the BlackLivesMatter movement, finding that they infiltrated both right- and left-leaning political communities to participate in both sides of the discussions. [28] find that, during the 2016 US election, Russian trolls were mainly interested in defining the identity of political individuals rather than particular information claims.

Other work has studied state-sponsored accounts’ behavior on, and use of, social networks. Specifically, [19] analyze the advertisements purchased by Russian accounts on Facebook. By performing clustering and semantic analysis, they identify their targeted campaigns over time, concluding that their main goal is to sway division on the community, and also that the most effective campaigns share similar characteristics. [52] compare a set of Russian troll accounts against a random set of Twitter users, showing that Russian troll accounts exhibit different behaviors in the use of the Twitter platform when compared to random users. In follow up work, [53] analyze the activities of Russian and Iranian trolls on Twitter and Reddit. They find substantial differences between them (e.g., Russian trolls were pro-Trump, Iranian ones anti-Trump), that their behavior and targets vary greatly over time, and that Russian trolls discuss different topics across Web communities (e.g., they discuss about cryptocurrencies on Reddit but not on Twitter). Also, [44] examine the exploitation of various Web platforms (e.g., social networks and search engines), showing that state-sponsored accounts use them to advance their propaganda by promoting content and their own controlled domains.

Finally, [5] use machine learning to detect Twitter users that are likely to share content that originates from Russian state-sponsored accounts.

Remarks. Overall, unlike previous work, we focus on content shared via images by state-sponsored accounts. Indeed, to the best of our knowledge, ours is the first study performing a large-scale image analysis on a ground truth dataset of images shared by Russian trolls on Twitter. Previous research [22] has showed that social network users usually decide what to share and consume content based on visual cues; therefore, as state-sponsored accounts tend to post misinformation [12], studying the images they share constitute an important step toward understanding the spread of false information on the Web.

3 Methodology

In this section, we describe our dataset and our methodology for analyzing images posted by state-sponsored trolls on Twitter.

Dataset. We use a ground truth dataset of tweets posted by Russian trolls released by Twitter in October 2018 [23]. The dataset includes over 9M tweets posted by 3.6K Russian state-sponsored accounts, and their associated metadata and media (1.8M images). Note that the methodology employed by Twitter for detecting/labeling these state-sponsored accounts is not publicly available, however, it is reasonable to assume that there are no false positives. Furthermore, to the best of our knowledge, this is the most up-to-date and the largest ground truth dataset of state-sponsored accounts and their activities on Twitter.

Ethics. We only work with publicly available data, which was anonymized by Twitter, and follow standard ethical guidelines [39], e.g., we do not try to de-anonymize users based on their tweets.

Image analysis pipeline. To analyze the images posted by these state-sponsored accounts, we build on the image processing pipeline presented by [50]. The pipeline relies on Percep-
clustering and medoid calculation

1. pHash Extraction
2. pHash-based Pairwise Distance Calculation
3. Clustering and Medoid Calculation
4. Cluster Annotation
5. Analysis of Annotated Dataset

Figure 2: Overview of our image processing pipeline. The pipeline is extended from [50].

Figure 3: CDF of the number of images per cluster. Image uniqueness is based on their pHash.

Figure 4: CDF of the number of images per troll account.

Running the pipeline. First, we extract a pHash for each image using the ImageHash library. This reveals that there is substantial percentage of images that are either visually identical or extremely similar as they have the same pHashes (43% of the images).

Next, we cluster the images by calculating all the pairwise comparisons of all the pHashes, as described by [50]. This results in 78,624 clusters containing 753,634 images. Then, for each cluster, we extract the medoid, which is the image that has the minimum average Hamming distance between all the images in the cluster, again following the methodology in [50]. Then, using each medoid, we perform “Web Detection” using the Cloud Vision API, which provides us with a set of entities and URLs, which we assign for each image in the cluster. This is doable since the average number of unique images per cluster is 1.8 with a median of 1 unique image per cluster (see Figure 3).

4 Results

We now present the main results of our analysis. First, we perform a general characterization of the images posted by state-sponsored accounts on Twitter; then, a temporal analysis of the tweets that contain images, an analysis of the content of the images and how it evolves over time. Finally, we study the occurrence of the images across the Web.

4.1 General Characterization

First, we look at the prevalence of images in tweets by state-sponsored trolls. Figure 4 plots the CDF of the number of images posted per confirmed state-sponsored account that had at least one tweet (4.5% of the identified trolls never tweeted). We find that only a small percentage of these accounts do not share images (9.7% of the Russian troll accounts). Also, some accounts shared an extremely large number of images, 8% of the Russian trolls posted over 1K images. Furthermore, we find an average of 502.2 images per account with a median number of images of 37.

Then, in Figure 5, we report the CDF of the number of images per tweet; we find that 19% of Russian trolls’ tweets in-
4.2 Temporal Analysis

We examine how tweets that include images are shared on Twitter, aiming to assess whether state-sponsored accounts change posting behavior over time. We also study whether statistically significant changes in their posting behavior are driven/influenced by real-world events using changepoint analysis [30].

In Figure 6, we plot the percentage of tweets that contained images for each day during our dataset. We observe two main time periods of increased posting behavior of images (during 2015 and end of 2016 to beginning of 2017), with a substantial dip of activity in the middle (between early- and mid-2016). This sheds some light on the campaigns these accounts took part in: for instance, Russian trolls’ posting behavior during 2015 is likely related to the Russia-Ukraine conflict, while the campaign after 2016 is likely related to the Russian interference on US politics. When looking at peaks of activity, we note that the single largest peak is in close proximity with the Unite the Right Rally in Charlottesville during August 2017 [45], which led to the death of one counter protester [16] and was a significant turning point in the use of online hate speech and anti-Semitism in fringe Web communities [21]. Other substantial peaks in image-related sharing by Russian trolls are during April 2017, which are in close proximity with American air strikes in Syria and Afghanistan [25, 18], and November 2015, after terrorist attacks in Paris by ISIS [17] and the shooting down of a Russian warplane by Turkey [8].

However, one important question is whether or not these peaks in activity are statistically significant w.r.t. the time series. To answer that, we perform changepoint analysis on the time series. Specifically, we use the Pruned Exact Linear Time (PELT) approach [30] to maximize the log-likelihood for the means and variances of the time series, using a penalty function for the number of changepoints: the penalty function also allow us to rank the changepoints according to their significance. Table 1 reports the detected changepoints and possible real-world events that are in close temporal proximity to the changepoint and are likely to coincide with the change in the time series. Looking at the results (Figure 6 and Table 1), we find several changepoints (changepoints 1-5) in 2014 and early 2015 that coincide with real-world developments related to the Russia-Ukraine conflict. Then, we find several changepoints in 2016 and 2017 that coincide with real-world politics events in the USA and France like Trump’s plans for his first day in presidency [10] and the Macron leaks during the French elections in 2017 [3]. In a nutshell, our changepoint analysis reveals that image related activity of Russian trolls on Twitter during 2014 and 2015 is driven by real-world events that happened during the Russia-Ukraine conflict, while from 2016 onwards, their activity is driven by events in the USA and Europe.

4.3 Entities Analysis

We now explore the content of images with a special focus on the entities they contain, which allows us to better understand what “messages” images were used to convey. To do so, we use the image processing pipeline presented by [50] to create clusters of visually similar images but leverage Google’s Cloud Vision API to annotate each cluster (as discussed in the Methodology section). Then, for each image, we assign the entity with the highest confidence score as returned by the Cloud Vision API. We also associate the tweet metadata to each image (i.e., which image appears in which tweet). The final annotated dataset allows us to study the popularity and evolution of entities over time for state-sponsored accounts on Twitter.

Popular Entities. We first look at the popularity of entities for the trolls: Table 2 reports the top 20 entities that appear in our image dataset both in terms of the number of clusters, as well as the number of images within the clusters. We observe that the two most popular entities for Russian trolls are referring to Russia itself (i.e., “Russia” and “Vladimir Putin” entities). Also, trolls are mainly focused on events related to Russia, Ukraine, USA, and Syria (their top entities correspond to these countries). Moreover, several images include screenshots of news articles (see entity “Web page”) as well as logos of news sites.
entities and the interplay between them, we also build a graph, 

Graph Visualization. To get a better picture of the spectrum of communities worth noting are those including comics and various other screenshots (emerald). Other outlets (pink) that are tightly connected with communities related to Donald Trump/Hillary Clinton (green), Ukraine/Petro Poroshenko (light blue), and Sergey Lavrov (gray). Also, we find a non-negligible percentage of images and clusters that show memes, highlighting that memes are exploited by such accounts to disseminate their ideology and probably weaponized information via memes, as previously noted by [50].

Table 2: Top 20 entities found in images shared by Russian troll accounts. We report the top entities both in terms of the number of clusters and of images.

| Top entity   | # clusters (%) | Top entity   | # images (%) |
|--------------|----------------|--------------|--------------|
| Russia       | 2.783 (3.5%)   | Russia       | 30,426 (4.0%)|
| Vladimir Putin| 1.377 (1.7%)   | Vladimir Putin| 15,718 (2.0%)|
| Donald Trump | 1.281 (1.6%)   | Breaking news| 15,071 (2.0%)|
| Car          | 1.262 (1.6%)   | Donald Trump | 13,807 (1.8%)|
| U.S.A.       | 1.031 (1.3%)   | Car          | 10,236 (1.3%)|
| Ukraine      | 907 (1.1%)     | Ukraine      | 10,169 (1.3%)|
| Barack Obama | 823 (1.0%)     | U.S.A.       | 8,638 (1.1%) |
| Petro Poroshenko | 621 (0.8%) | Barack Obama | 8,380 (1.1%) |
| Document     | 530 (0.6%)     | Petro Poroshenko | 6,654 (0.9%) |
| Moscow       | 495 (0.6%)     | Logo         | 6,017 (0.8%) |
| Hillary Clinton| 479 (0.6%)     | Moscow       | 5,524 (0.7%) |
| Meme         | 461 (0.6%)     | Syria        | 4,540 (0.6%) |
| Logo         | 456 (0.6%)     | Public Relations | 4,459 (0.6%) |
| Product      | 422 (0.5%)     | Police       | 4,301 (0.6%) |
| Public Relations | 416 (0.5%) | Hillary Clinton | 4,167 (0.5%) |
| Illustration | 393 (0.5%)     | Document     | 4,060 (0.5%) |
| Syria        | 372 (0.5%)     | Meme         | 3,886 (0.4%) |
| Web page     | 310 (0.4%)     | Product      | 3,256 (0.4%) |
| Advertising  | 295 (0.3%)     | Saint Petersburg | 2,870 (0.4%) |
| Police       | 290 (0.3%)     | Illustration | 2,862 (0.4%) |

Table 1: Detected changepoints for the timeseries of image activity of Russian trolls on Twitter. For each changepoint, we report corresponding real-world events that are likely linked with activity that lead to the changepoint.

| Changepoint | Events                                                                 |
|-------------|------------------------------------------------------------------------|
| 1 – 2014/04/07 | 2014/04/06: Pro-Russian demonstrators occupy a government building in Donetsk, Ukraine [7]. |
| 2 – 2014/06/05 | 2014/06/03: Fight between the Ukrainian army and pro-Russia militias take place at Sloviansk, Ukraine [6]. |
| 3 – 2014/09/06 | 2014/09/05: Ukrainian government and pro-Russia rebels agree to cease fire. However, fighting continues [33]. |
| 4 – 2014/12/20 | 2014/12/19: President Obama imposes sanctions in Crimea by forbidding exports of US goods to Crimea [47]. |
| 5 – 2015/01/20 | 2015/01/17: Fights between the Ukrainian army and pro-Russia rebels intensifies in Donetsk [1]. |
| 6 – 2015/09/25 | 2015/09/24: 29 people are killed in a mosque during prayers in Yemen [2]. |
| 7 – 2015/09/27 | 2015/09/25: Ukraine bans Russian airlines from flying to and over Ukraine [36]. |
| 8 – 2015/12/29 | 2015/12/29: US military announces that they killed an ISIS leader with ties to the 2015 Paris terrorist attacks [32]. |
| 9 – 2016/09/16 | 2016/09/16: Official announcement of the first presidential debate that invites Trump and Clinton [38]. |
| 10 – 2016/11/21 | 2016/11/21: President-elect Donald Trump announces his plans for his first day in office [10]. |
| 11 – 2017/03/13 | 2017/03/06: Donald Trump signs the immigration ban executive order [37]. |
| 12 – 2017/03/10 | 2017/03/10: US Attorney General Jeff Sessions asks for the resignation of 46 Obama-era federal prosecutors [41]. |
| 13 – 2017/07/27 | 2017/07/24: Ukrainian President demands that Russia stops supplying weapons to pro-Russia rebels [49]. |
| 14 – 2017/08/31 | 2017/08/31: The US State Department orders Russia to close their consulate in San Francisco [11]. |
| 15 – 2017/10/05 | 2017/10/02: Shooting in Las Vegas leads to the death of 59 people [35]. |

Main Communities. From Figure 7, we observe a large community (sapphire) that corresponds to clusters related to Vladimir Putin and it is tightly connected with communities related to Donald Trump/Hillary Clinton (green), Ukraine/Petro Poroshenko (light blue), and Sergey Lavrov (gray). Also, we observe that other big communities include logos from news outlets (pink) that are tightly connected with communities including screenshots of articles (brown), images of documents (light green), and various other screenshots (emerald). Other communities worth noting are those including comics and var-
Changepoints. We also assess how the entities in the images change over time with respect to detected changepoints. We first split our dataset into changepoint intervals, which are time periods between two changepoints (in total we have 14 changepoint intervals). For instance, the first changepoint interval is the time period between the first and second changepoint as reported in Figure 6). Then, for each changepoint interval, we calculate the top N entities and their Jaccard similarity with the next interval and plot that in Figure 8 (since we have 14 changepoint intervals, there are 13 comparisons). This allows us to understand when state-sponsored accounts substantially changed the content of the images they shared. Between changepoint intervals 1-7, there are minor differences w.r.t. the top entities. Whereas, the most substantial shifts are between changepoint intervals 7 and 8 (2015/09-2015/12 vs 2015/12-2016/09), 9 and 10 (2016/09-2016/11 vs 2016/11-2017/03), and 11 and 12 (2017/03-2017/05 vs 2017/05-2017/07). The shift between intervals 7 and 8 are likely related to the end of the Russia-Ukraine conflict campaign, while the shift between intervals 9 and 10 is likely related to their involvement in the US presidential elections. Finally, the shift between intervals 11 and 12 is likely related to (possible) interference in US politics after the election of Donald Trump.

Finally, we select the union of the top 10 entities across all changepoint intervals and plot their occurrence over the whole time span of our dataset in Figure 9. We observe varying behavior for different entities: some are persistent in that they span across multiple changepoint intervals, while others are mainly shared within a specific changepoint interval. For instance, images related to Ukraine (Figure 9(c)), Russia (Figure 9(d)), and Vladimir Putin (Figure 9(e))) span across multiple changepoint intervals, mainly between changepoints 1-8. Similarly, entities related to Donald Trump are persistent over time and they are shared mostly between changepoints 8 and 14 (see Figure 9(a))). Also, for entities that span to a specific changepoint interval, we find Syria (see Figure 9(d))), which is mostly shared between changepoints 8 and 9, and coincides with the start of Russian operations on Syrian soil [40]. Another notable example is the entity of John McCain, which appears between changepoints 13 and 14. Overall, these findings highlight that state-sponsored accounts change their targets over time and they change the content they share substantially over time.
4.4 Images Occurrence across the Greater Web

Our last set of measurements analyze the co-occurrence of the images posted by Russian state-sponsored accounts across the greater Web. Recall that the Cloud Vision API also provides details about the appearance of an image across the Web. This is useful when studying the behavior of state-sponsored accounts, as it either denotes that they posted the images on other domains too, or they obtained the image from a different domain, or that other users on the Web posted them on other domains too. Thus, studying the domains that shared the same images as state-sponsored accounts allows us to understand their behavior and potential impact on the greater Web. For instance, this information can be used to detect domains that are exclusively controlled by state-sponsored actors to spread misinformation.

In Table 3, we report the top domains, both in terms of number of clusters and number images within the clusters, that shared the same images as the state-sponsored accounts. Unsurprisingly, the most popular domains are actually mainstream social networking sites (e.g., Pinterest, Twitter, YouTube, and Facebook). Also, among the popular domains we find popular Russian news outlets like ria.ru and riafan.ru, as well as Russian owned social networking sites like livejournal.com and pikabu.ru. This highlights the efforts by Russian trolls to sway public opinion about public matters related to Russia. We further find both mainstream and alternative news outlets like theguardian.com and sputniknews.com, respectively (we use the list provided by [51] to distinguish mainstream and alternative news outlets). This provides evidence that the efforts of

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3Although founded in the US, LiveJournal was sold to a Russian company in 2007, and all servers have been located in Russia since 2017.
Table 3: Top 20 domains that shared the same images as the Russian trolls. We report the top domains both in terms of number of clusters and number of images within the clusters.

| Domain          | #clusters (%) | Domain          | #images (%) |
|-----------------|---------------|-----------------|-------------|
| pinterest.com   | 9,433 (12.0%) | pinterest.com   | 76,231 (10.1%) |
| twitter.com     | 5,481 (7.0%)  | twitter.com     | 46,609 (6.1%)  |
| youtube.com     | 4,132 (5.2%)  | youtube.com     | 40,540 (5.4%)  |
| wordpress.com   | 3,329 (4.2%)  | riafan.ru       | 35,497 (4.7%)  |
| ria.ru          | 3,260 (4.1%)  | ria.ru          | 31,153 (4.1%)  |
| riafan.ru       | 2,734 (3.4%)  | wordpress.com   | 30,464 (4.0%)  |
| blogspot.com    | 2,432 (3.0%)  | blogspot.com    | 20,890 (2.7%)  |
| livejournal.com | 2,381 (3.0%)  | sputniknews.com | 20,558 (2.7%)  |
| pikabu.ru       | 2,073 (2.6%)  | livejournal.com | 20,227 (2.6%)  |
| me.me           | 1,984 (2.5%)  | pikabu.ru       | 17,250 (2.2%)  |
| sputniknews.com | 1,943 (2.4%)  | rambler.ru      | 15,227 (2.0%)  |
| reddit.com      | 1,826 (2.3%)  | me.me           | 14,675 (1.9%)  |
| theguardian.com | 1,527 (1.9%)  | theguardian.com | 14,111 (1.9%)  |
| rambler.ru      | 1,524 (1.9%)  | reddit.com      | 14,025 (1.8%)  |
| facebook.com    | 1,336 (1.7%)  | wikipedia.org   | 12,897 (1.7%)  |
| dailymail.co.uk | 1,271 (1.6%)  | wikipedia.org   | 12,081 (1.6%)  |
| imgur.com       | 1,210 (1.5%)  | facebook.com    | 12,012 (1.6%)  |
| wikipedia.org   | 1,051 (1.3%)  | dailymail.co.uk | 9,854 (1.3%)  |
| pinterest.co.uk | 1,027 (1.3%)  | imgur.com       | 9,381 (1.2%)  |
| wikipedia.org   | 996 (1.2%)    | cnn.com         | 8,606 (1.1%)  |

Russian trolls had an impact on, or were inspired by, content shared on a wide variety of important sites in the information ecosystem on the Web.

Next, we aim to provide a holistic view of the domains while considering the interplay between the entities of the images and the domains that they also shared them. To do this, we create a graph where nodes are either entities or domains that were returned from the Cloud Vision API. An edge exists between a domain node and an entity node if an image appearing on the domain contained the given entity. Then, we perform the operations (1) and (2) as described in the entities analysis section (i.e., community detection and layout algorithm). We do this for the images posted by the trolls and present the resulting graph in Figure 10. This graph allows us to understand which domains shared images pertaining to various semantic entities. We find popular Web communities like Twitter, Pinterest, Facebook and YouTube in the middle of the graph, constituting a separate community (light blue), i.e., they are used for sharing images across all entities. Entities mainly related to Russia are shared via Russian state-sponsored outlets like sputniknews.com (see orange community). Entities that are related to the USA and political persons like Donald Trump, Barack Obama, and Hillary Clinton are part of a separate community (pink) with popular news outlets like washingtonpost.com and nytimes.com. Fi-
nally, for matters related to Ukraine (green community) most of the images co-appeared on popular Russian owned social networks like livejournal.com and pikabu.ru.

Overall, our findings indicate that the same images often appear on both their feeds and specific domains. Thus, state-sponsored trolls might be trying to make their accounts look more credible and push their agenda by targeting unwitting users on popular Web communities like Twitter.

5 Conclusion

This paper presented a large-scale analysis of 1.8M images shared by Russian state-sponsored accounts on Twitter. Our work is motivated by the fact that social network users put little effort in verifying information and that are driven by visual cues, e.g., images, for re-sharing content [22]. Therefore, as state-sponsored accounts tend to post misinformation [12], analyzing the images they share represent a crucial step toward understanding the spread of false information on the Web, and its impact in our societies.

By extending an existing image processing pipeline [50], we clustered the images and annotated them using Google’s Cloud Vision API. Also, by leveraging changepoint analysis, we were able to detect points in time where significant changes happen with respect to the image sharing behavior of these accounts. Our analysis shed light on the content and targets of these images, finding that Russian trolls had multiple targets that varied across time. During their early days (before 2016), they disseminated images related to Russia and Ukraine, possibly in an attempt to influence public opinion related to Russian matters and the Russia-Ukraine conflict. Later on, we observe a shift in the content they shared, as they focused on disseminating images related to USA and the candidates of the 2016 US election.

Overall, our findings demonstrate that state-sponsored accounts pursue political agenda and aim to influence users on Web communities w.r.t. specific world events and individuals (e.g., politicians). Also, the fact that they change their targets over time suggest that detecting them is not straightforward, thus prompting the need to design and develop advanced detection techniques to mitigate their impact. Some of our findings confirm previous analysis performed on the text of the tweets [53], hence highlighting that state-sponsored actors post images that are conceptually similar with their text, possible in an attempt to make their content look more credible.

As part of future work, we plan to study the use of news articles and social network posts from state-sponsored accounts with a particular focus on detecting possibly doctored images. Furthermore, we intend to assess how influential were images shared by state-sponsored trolls to other popular Web communities like Twitter, Reddit, 4chan, and Gab. To do this, we plan to use Hawkes Processes that allow us to assess the root cause of an event (in this case it is the posting of an image). Finally, we aim to build on top of the work presented in the previous section in an attempt to detect domains that are controlled by state-sponsored actors and aim to push specific (disinformation) narratives on the Web.

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