Did State–sponsored Trolls Shape the US Presidential Election Discourse? Quantifying Influence on Twitter

Nikos Salamanos  
Cyprus University of Technology  
nik.salaman@cut.ac.cy

Michael J. Jensen  
University of Canberra  
Michael.Jensen@canberra.edu.au

Xinlei He  
Fudan University  
xlhe17@fudan.edu.cn

Yang Chen  
Fudan University  
chenyang@fudan.edu.cn

Costas Iordanou  
Cyprus University of Technology  
costas.iordanou@eecei.cut.ac.cy

Michael Sirivianos  
Cyprus University of Technology  
michael.sirivianos@cut.ac.cy

ABSTRACT

It is a widely accepted fact that state–sponsored Twitter accounts operated during the 2016 US presidential election, spreading millions of tweets with misinformation and inflammatory political content. Whether these social media campaigns of the so–called “troll” accounts were able to manipulate public opinion is still in question. Here, we aim to quantify the influence of troll accounts on Twitter by analyzing 152.5 million tweets from 9.9 million users, including 822 troll accounts. The data collected during the US election campaign, contain original troll tweets. From these data, we constructed a very large interaction graph; a directed graph of 9.3 million nodes and 169.9 million edges. Recently, Twitter released datasets on the misinformation campaigns of 8,275 state–sponsored accounts linked to Russia, Iran and Venezuela. These data serve as a ground–truth identifier of troll users in our dataset. Using graph analysis techniques along with a game–theoretic centrality measure, we quantify the influence of all Twitter accounts (authentic users and trolls) on the overall information exchange as is defined by the retweet cascades. Then, we provide a global influence ranking of all Twitter accounts and we find that only four troll accounts appear in the top-1000 and only one in the top-100. This along with other findings presents evidence that the authentic users were the driving force of virality and influence in the network.

KEYWORDS

Disinformation, information diffusion, Twitter trolls, social media

1 INTRODUCTION

The Russian efforts to manipulate the outcome of the 2016 US presidential election were unprecedented in terms of the size and scope of the operation. Millions of posts across multiple social media platforms gave rise to hundreds of millions of impressions targeting specific segments of the population in an effort to mobilize, suppress, or shift votes [10]. Trolls were particularly focused on the promotion of identity narratives [11], though that does not distinguish them from many other actors during the election [22]. The Special Counsel’s report described this interference as "sweeping and systematic" ([17], vol 1, 1). Russia demonstrated an impressive array of tactics to inflict significant damage to the integrity of the communication spaces where Americans became informed and discussed their political choices during the election [14].

While Russia’s efforts continue "unabated" [27], it is likely they and others will seek to target the American election in 2020 as well as to continue to target elections in Europe and elsewhere. It is important therefore, to characterize the operational tactics and impact of social media influence operations if we are to promulgate adequate defenses against them in the future.

There is considerable debate as to whether state–sponsored disinformation campaigns that operated on social media were able to affect the outcome of the 2016 US Presidential election. While there is a large body of work that tried to address this question from distinct disciplinary angles [4, 10, 22], a conclusive result is still missing. There are several obstacles that any empirical study on this subject has dealt with: (i) the lack of complete and unbiased Twitter data – the Twitter API returns only a small sample of the users’ daily activity; (ii) Tweets from deactivated profiles are not available; (iii) The followers and followees lists are not always accessible, hence the social graph is unknown. Moreover, the disinformation strategies that the operators of the state–sponsored accounts had employed are vaguely specified. A study of Russian social media activity has found that the majority of the communications are not obviously false [20]. It is equally possible that the operators had employed advanced manipulation techniques such as first building a reliable social profile, aiming to engage a group of followers. Subsequently, they transmitted factually correct, but otherwise deceptive and manipulative claims, advancing the political objectives of the disinformation campaign. Hence, text...
mining and machine learning techniques for veracity assessment might not perform well under this scenario.

In this paper we measure the impact of troll activities on the virality of the ambiguous political information that had been shared on Twitter during the 2016 US Presidential election. We consider as “troll” any account that deliberately spreads disinformation, tries to inflict conflict or causes extreme emotional reactions. A troll account could be human or operate automatically. An automated operated account is called “bot” and is controlled by an algorithm that autonomously performs actions on Twitter. The term “bot” is not synonymous to “troll” as benign bots do operate and have positive impact on users. In fact, Twitter has set specific rules for acceptable automated behavior.

To assess the influence of trolls, we constructed a very large directed graph from the interactions between the users (tweet replies and mentions). The graph consists of 9.3 million nodes and 169 million edges and we constructed it based on two Twitter datasets: (i) A collection of 152.5 million tweets that was downloaded using the Twitter API during the US presidential election period (from September 21 to November 7, 2016). Hence, we have access to original troll tweets that have yet to be deleted by Twitter. (ii) A collection of original troll tweets which have been released by Twitter itself as part of the investigation on foreign interference in the 2016 US election – the misinformation campaigns of 8,275 state-sponsored accounts linked to Russia, Iran and Venezuela states. Using graph analysis techniques and Shapley–Value–based centrality – a game theoretic centrality measure – we are able to identify the group of users that were most probably the driving force of the viral cascades.

We address the following Research Questions (RQ):

RQ1: Who are the most influential authentic and troll users and can we rank them in order of contribution (impact) to the overall diffusion of information?

RQ2: Which are the viral retweet cascades of web and media URLs posted or retweeted by authentic users and specific troll accounts?

RQ3: What is the proximity of top-k influential authentic users from bot accounts?

Contributions: Our primary contributions are as follows:

- We introduce the notion of flow graphs – a natural representation of information diffusion that takes place in Twitter platform during the retweet process. This simple formulation allows us to apply a game-theoretic centrality for a fair estimation of users’ contribution on the information shared without requiring assumptions on the user behavior. Moreover, we estimate the retweet cascade trees where we measure how viral they are by the structural virality, and the influence each user has on the cascade tree by the influence–degree.
- By answering the research questions, we present strong evidence that troll activity was not the main cause of viral cascades of web and media URLs in Twitter. Our measurements show that the authentic users were in general the most active and influential part of the population and their activity was the driving force of the viral cascades. At the same time, we find that on average, troll accounts were tens of times more influential than authentic accounts. These findings further substantiate previously reported insights and unveil new influence characteristics.

Data availability: Our dataset will become publicly available under proper restrictions for compliance with Twitter’s ToS and the GDPR. The ground truth dataset is provided by Twitter.

2 RELATED WORK

In a seminal work on the general problem of disinformation on Twitter [26], the authors investigated the diffusion cascades of true and false rumors disseminated from 2006 to 2017; approximately 126,000 rumor cascades which have been spread by 3 million people. The rumors had been verified as true or false by six fact–checking organizations. The main finding of this study is that false news diffused faster and more broadly than the true ones and that human behavior contributes more to the spread of falsity than the trolls. These are in line with our main result that the authentic users had the dominant role on the viral cascades. Moreover, part of our methodology has been inspired by this work. We estimate the true retweet trees following the same methodology but we then apply the structural virality method for the identification of viral cascades. Since our main goal is to quantify the impact of users on the overall information exchange, we do not classify the tweets’ content as fake and non fake rumors. We use the URLs that spread through troll tweets to serve as “anchors” of retweet cascades that contain the same piece of information with the troll tweets.

In [5] a large-scale dataset is examined – 171 million tweets by 11 million users – collected during five months prior to the 2016 US presidential election. From this collection, the
authors analyzed 30 million tweets shared by 2.3 million users that contained at least one web–URL linking to a news outlet website. 25% of these news were either fake or biased representing the spreading of misinformation on Twitter. Then, in order to investigate the flow of information, the authors constructed retweet networks for each news category (based on URLs appeared in the tweet text) where the direction of edges indicates the flow of information. Furthermore, they estimate the most influential spreaders in the retweet network using the Collective Influence (CI) algorithm [16] which identifies the minimal set of users who are more likely to spread the information to the whole network (also see the influence maximization problem in [12]).

One of their findings is that the Trump supporters were the main group of users that spread fake news although it was not the dominant one in the whole network. We note that in [5], the overall retweet graph is constructed directly by the data as they were provided by the Twitter API. In our study, we enrich the raw Twitter data by considering all the possible information paths and at the same time we provide an estimation of the true retweet trees. Moreover, we treat every retweet cascade independently, providing an estimation of users’ influence as well as the users’ contribution on the information exchange.

Grinberg et al. [9] investigates the extent to which Twitter users were exposed to fake news during the 2016 US presidential election. Their data consists of tweets from 16.4K Twitter accounts that were active during the 2016 US election season along with their list of followers. They restrict their analysis on tweets containing a URL from a web site outside the Twitter. Moreover, the authors introduce the notion of users’ “exposures”, i.e., tweets from a user to his followers. This approach is roughly in line with the flow graphs that are presented in section 4.3. Finally, they investigate the group of users that have been exposed in certain URLs as well as the users who have spread URLs from fake news sources. The findings suggest that although a large part of the users had been exposed to fake news, only a small fraction of the population (1%) was responsible for the diffusion of 80% of the fake news.

In [29, 30] the authors analyzed the characteristics and strategies of 5.5K Russian and Iranian troll accounts in Twitter and Reddit. Moreover, using Hawkes Processes they compute an overall statistical measure of influence that quantifies the effect these accounts had on social media platforms, such as Twitter, Reddit, 4chan and Gab. One of their main results is that even though the troll accounts reach a considerably large number of Twitter users and are effective on spreading URLs on Twitter. However, their overall effect on the social platforms is not dominant. Our findings verify these results and support the fact that some trolls have above average influence.

In [3] the authors examined the Russian disinformation campaigns on Twitter in 2016. The analysis was based on 43 million posts shared on Twitter by 5.7 million users and 221 troll accounts (September 16 to November 9, 2016). The study focused on the characteristics of spreaders, namely the users that had been exposed and shared content published by Russian trolls. They constructed the retweet graph using edges that represent retweet actions. They applied the label propagation algorithm in order to classify Twitter accounts as either conservative or liberal. Finally, they used Botometer (a.k.a. BotOrNot) [7], in order to determine whether spreaders and non–spreaders can be labeled as bots. The Botometer is a publicly available platform for estimating whether existing Twitter accounts have the characteristics of Twitter bots. We also apply this technique in order to examine whether the top-k most influential users exhibit bot behavior.

Bovet et al. [6] propose a method for inferring the political opinions of Twitter users during the 2016 US presidential election. First, they constructed a directed social graph based on the actions from one user to another, namely replies, mentions, retweets and quotes. We have also used this approach for graph construction. Then, they monitored the evolution of three structural graph properties, the Strongly Connected Giant Component, Weakly Connected Giant Component, and the Corona. Subsequently, they build a labeled set of tweets where the hashtags reflect political opinions by which they train a machine learning classifier. This leads to a classification of the hashtags that reflect political opinions.

3 DATASETS
3.1 Ground–truth Twitter data
Twitter has released a large collection of tweets of the state–sponsored troll accounts as part of Twitter’s election integrity efforts4. We requested the unhashed version which consists of the tweets of Twitter accounts identified as Russian, Iranian and Venezuelan – 25M tweets shared by 8,275 troll accounts. In this study, we leverage only the troll user–IDs which served as ground–truth identifiers of the troll users in the tweets collection we present next.

3.2 Our Twitter dataset
Our analysis is based on 152.5M tweets from 9.9M users. The tweets were downloaded using the Twitter streaming (1%) API in the period before and up to the 2016 US presidential election – from September 21 to November 7, 2016 (47 days; we did not collect data on 02/10/2016). The tweets’ track terms were related to political content such as “hillary2016”, “clinton2016”, “trump2016” and “donaldtrump2016” – namely,

4https://about.twitter.com/en_us/values/elections-integrity.html
a list of phrases used to determine which Tweets are delivered by the stream (see\textsuperscript{3} for more details). The tweets were collected using a Python script utilizing the Tweepy module. In addition to the tweet text, user screen name, and user ID, we also collected metadata including the hashtags, the URLs and mentions that were included in the tweet text, as well as information on the account creation, user timezone, and user-supplied location and biographic information. Based on the ground-truth troll IDs, we identified 35.5K tweets from 822 troll accounts (see Table 1).

| Table 1: Twitter dataset |
|--------------------------|
| Authentic | Trolls |
| Unique Twitter accounts | 9,939,698 | 822 |
| Total tweets | 152,479,440 | 35,489 |
| Replies | 12,942,628 | 129 |
| Mentions | 172,145,775 | 33,627 |
| Retweets | N/A | N/A |

Even though the retweet labels (i.e., whether a given tweet is a retweet and of which original tweet-ID and author-ID) are missing in the initial dataset, in the next section we explain how we are still able to identify most of the retweets.

4 METHODOLOGY

4.1 The graph of interactions

We followed a graph-theoretic approach, namely, we map users to nodes and we also map the interactions between users to edges. We construct the graph based on the tweets collection we presented in the previous section – 152.5 million tweets collected during 47 days. The actions between the users are either replies or mentions. Each directed edge \((i, j)\) corresponds to a tweet-action from user \(i\) to user \(j\); either \(i\) had replied to a tweet of \(j\) or he had mentioned \(j\) in his tweet, or both. Both are actions from one user to another and represent the social relationship between the two. In other words, \(i\) is a “follower” of \(j\). We leverage this graph as an approximation of the true follower graph – the actual social network.

This produces a directed multigraph of users’ interactions, i.e. multiple edges are permitted between any pair of nodes, consisting of 169,921,912 edges, 9,321,061 authentic users and 821 trolls. Although the number of troll accounts is small, there are indications that some troll accounts might have substantial activity that is worth investigating further. For instance, we have 671K edges that point to 285 troll accounts; in other words, more than half million users had an interaction with troll accounts.

As we mentioned in Section 3.2, although we did not collect the original retweet labels (the original author of the tweet that has been retweeted is unknown) this information is still contained in the field “mentions” provided by the Twitter API. Hence the graph already contains the edges that represent the retweet actions, namely, that a given user has retweeted a user’s certain tweet.

4.2 Retweet Cascades

When a user retweets, we assume that she agrees with the context of the root-tweet, i.e., the original tweet that has been retweeted. For this reason, the analysis of the retweet cascades, that is the series of retweet actions, is important for the identification of the viral cascades as well as the influential users in them.

For these reasons, we have to identify the retweet labels in our dataset by leveraging the following facts:

1. The head of a retweet text always has a certain form: “RT @user screen name” where the “user screen name” refers to the screen name of the author of the original tweet.
2. The field “Entities” contains the sub-field “mention”, which includes the full list of the user IDs along with their screen names for all users mentioned in the tweet. Hence, in “mentions” there is always the root-user ID and screen name.
3. In addition, the “Entities” field provides the list of URLs that are embedded in the tweet text; web or media URL, namely the embedded media material such as videos and photos.

Based on the previous observations, we consider that a given tweet is a retweet when:

1. The tweet text starts with “RT @root screen-name”.
2. Contains at least one URL.
3. The tweet text, the root screen-name, the mentions and the embedded URLs are identical for a series of tweets that have been posted by at least 100 distinct users and all the user screen-names are different from the root screen name. For each of these candidate retweets, we parse the RT @root screen-name and we match it with the user screen name and the corresponding user ID that we have in the field “mentions”.

In conclusion, this process enables us to recover 46.4K retweet cascades with 19.6M tweets, which we present in Table 2. In the above process, we reconstruct only the retweet cascades where the root tweet-text contains at least one URL. The reason for that is that the URLs have a dual role. First, they are strong identifiers of the tweet-text equality by which we reconstruct the retweet labels. Secondly, in a retweet cascade, it is not only the actual tweet that has been diffused, but mainly the information it contains. So,
Figure 1: Toy example of retweet analysis. (a) The raw data provided by Twitter API along with the follower graph. The edges present the path of information that appears on the users’ timeline prior to their retweets. For instance, user c has retweeted on date \( t_2 \). At the same time user b, whom user c follows, has retweeted on date \( t_1 < t_2 \). Note that a given retweet contains both the name of the user who retweeted and the name of the root user who posted the original tweet. Hence, we have an edge from the root to any retweeter because the users have retweeted the root tweet even if they did not follow the root user. (c) The time-inferred cascade tree is constructed from the flow graph by making the assumption (see Section 4.3), that each retweeter has been influenced by the friend who just recently retweeted the original tweet.

4.3 Flow graphs & Retweet trees

Generally, the retweet data provided by the Twitter API are not well constructed and they do not represent the true retweet path. As we see in Figure 1(a) the raw data have the shape of a star tree where all the retweets point to the original tweet. This is not always the real-world case, since a user may have retweeted a retweet of a friend.

A widely used method for the reconstruction of the true retweet path is the time-inferred diffusion process [8, 25, 26]. It is based on the causality assumption that a given user before retweeting has been influenced by his “friend” who has recently retweeted the same original tweet. Moreover, since a user can retweet a tweet more than once, we assume

The URLs serve as “anchors” by which we connect distinct retweet cascades, considering that they are referring to the same piece of information (see also Section 5.3.1).

In order to verify the accuracy of this approach, we tried to recollect the tweets that have been identified as retweets by the previous method. Unfortunately, only 10M tweets out of 19.6M are still available while the rest have been deleted. Then, in these 10M tweets, we verified that indeed our mapping of retweets to root-user IDs is always correct.

Nevertheless, there were some discrepancies in 9,689 out of 10M tweets, regarding the mapping of retweets to root-tweet IDs. There are two cases that our approach is not able to capture: (i) The root–user could post the same tweet more than once. In this case, although the tweet text and all the other information are identical across the retweets, the root–tweet IDs are different; (ii) A given user might quote and retweet instead of just retweet. In this case, the quoted retweet will differ in the text compared to the other retweets even though the root–tweet IDs are identical.

Table 2: Retweet cascades with minimum 100 unique retweeters

|                    | Authentic | Trolls |
|--------------------|-----------|--------|
| Total users        | 3,633,457 | 233    |
| Root users         | 8,192     | 12     |
| Root tweets        | 45,986    | 423    |
| Retweeters         | 3,630,764 | 228    |
| Total retweets     | 19,588,072|        |
| Total URLs         | 43,989    |        |
that he has been influenced by another user on his first action. Hence, the final retweet path (see Figure 1(c)) is constructed by the raw data provided by Twitter in conjunction with the follower graph (Figure 1(a)). Thus, we have two rather extreme cases, the one is the star tree that we take from Twitter API where no real diffusion structure is present, and the other is the cascade tree where a specific hypothesis has been applied with respect to who was influenced by whom. The latter emphasizes the most recent friend whereas the former one always the root user.

In this paper, we introduce the notion of flow graph which represents an intermediate case and consists of the time-inferred edges that we actually use in order to estimate the true retweet tree. The flow graph presents the diffusion of information that has taken place in the Twitter platform – the direction of all possible influence between the retweeters. Let us consider the toy example in Figure 1. Before constructing the retweet tree in Figure 1(c), we first have to identify all the time-inferred edges from the users that retweeted in time \( t \) to the users who will retweet in \( t + 1 \). The edges direction indicates the information flow on the Twitter platform and is based on the fact that when a user retweets a given tweet, his action appears on his followers’ timeline. For instance, when user \( b \) retweets the root tweet in \( t_1 \), he is transmitting this information to his followers \( c \) and \( d \). Finally, we add an edge from the root user to any of the retweeters because in any given retweet, the author’s screen name is always visible. In our case, the construction of the flow graph is a little more complicated since we do not have the original follower graph but a representation of it, namely, the graph of interactions, where the edges are time inferred. So, in a given time \( t_i \), a given user \( i \) receives information from the users he had already started following at a certain time \( t_j < t_i \).

The flow graph together with the retweet tree are the two main graph structures we leverage in this paper in order to evaluate the impact of users in the overall information exchange. In summary: 
**Flow graph:** We measure the contribution of the users to the overall diffusion of information by the Shapley Value–based centrality – a game theoretic centrality measure.
**Retweet cascade tree:** We measure the influence of the users on this particular retweet tree by the influence–degree, and the overall virality of the tree by the structural virality.

In the next sections we present the measures mentioned here, in detail.

### 4.4 Shapley Value–based centrality

Towards evaluating the users in terms of the influence/impact they had on the retweet cascades we have to create a consistent ranking where the top-k users are the most influential ones. One way to do so, is to use a centrality measure that fits well in our problem. Here, we apply the Shapley–Value–based degree centrality [1, 2, 15] one of the game–theory–inspired methods of identifying influential nodes in networks [18, 19, 23]. These methods are based on the Shapley Value [21], a division scheme for fair distribution of gains or costs in each player of a cooperative game. The Shapley Value of each player in the game is the average weighted marginal contribution of the player over all possible coalitions. Hence, the problem of computing the Shapley Value in a \( N \) player game has in most cases exponential complexity, since the possible coalitions are \( 2^N \).

In this paper, we apply the Shapley Value–based degree centrality introduced by Michalak et al. [1, 15] which is further refined in [2]. First, in [1, 15] the authors provide a linear time algorithm for the exact computation of the Shapley Value in the following game. Given a directed graph \( G(V, E) \), with \( V \) nodes and \( E \) edges, the set of players are the nodes in \( V \) and each coalition is a subset of \( V \). The value of a coalition \( C \) is defined by the size of the set \( fringe(C) \) i.e. the set that consists of the members of \( C \) along with their out–neighbors. This set represents the sphere of influence of the coalition \( C \). Moreover, we define that the value of the empty coalition is always zero. The exact closed form solution of the Shapley Value of a node \( u_i \) is

\[
SV(u_i) = \sum_{u_j \in \{u_i \} \cup N_{out}(u_i)} \frac{1}{1 + \text{indegree}_G(u_j)} - \frac{1}{1 + \text{indegree}_G(u_i)}
\]

Hence, the algorithm for computing the Shapley Values has running time \( O(|V| + |E|) \) (see Algorithm 1 in [1, 15]). In fact, the Shapley Value is the sum of probabilities that the node contributes to each of its neighbors and itself.

This formulation is very similar to what we want to measure in the flow graphs. In our case, the value of a coalition is the set of users that have been informed from the members of the coalition about a given root–tweet. Having said that, we cannot directly apply the above formulation since a node cannot inform itself. This very problem has been addressed by the authors in [2] to solve the influence maximization problem. They refined the previous formulation so that the value of a coalition \( C \) is the size of the out–neighbors of the members in \( C \), i.e. the number of nodes that can be directly influenced by \( C \). In conclusion, we compute the Shapley Value for all nodes in any flow graph using the following formula (see [2] for more details):

\[
SV(u_i) = \sum_{u_j \in N_{out}(u_i)} \frac{1}{1 + \text{indegree}_G(u_j)}
\]

In this way, the “leaf” nodes have always zero Shapley Value since they did not inform anyone in the flow graph. The advantage of this approach is that it provides a linear
time computation of Shapley Values and also works for disconnected graphs. In fact, this is the case that we face here, since the overall information flow is represented by the flow graphs i.e. a set of disjoint graphs. Moreover, we can compute the overall Shapley Value for any subset of retweet cascades that a user is part of. As we will show in Section 5.3.1 we use this property in order to evaluate trolls and users together, only in a subset of retweet cascades. The intuition of this approach is that Equation 1 computes in a fair way the users’ contribution in informing the other members of the graph for a given piece of information, which in our case is the original root–tweet and the URL it contains. We note that from the method in [2] we use only the part that computes the Shapley Values and not the whole process (influence maximization). Our goal is to compute the users’ contribution without assumptions regarding the influence process.

Finally, the global Shapley Value of a user in the overall information exchange is the summation of his Shapley Values in the flow graphs (FG) he participates in. Hence:

\[ SV_{global}(u) = \sum_{FG \in \{FG\}_u} SV(u, FG) \quad (2) \]

### 4.5 Structural virality & influence-degree

Structural virality is a method for evaluating how viral a retweet cascade tree is [8]. The structural virality of a cascade tree \( T \) with \( n > 1 \) nodes is the average distance between all pairs of nodes in a cascade. That is:

\[ v(T) = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} \quad (3) \]

where \( d_{ij} \) is the shortest path between the nodes \( i \) and \( j \). The \( v(T) \) represents the average depth of nodes when we consider all nodes as the root of the cascade.

The structural virality measures how viral a retweet cascade is. We expect that the tree of a viral cascade will have many sub–trees, which represent many generations of a viral diffusion process in a smaller scale. On the other hand, a cascade tree with many leaves, directly connected with the root, represents a “broadcast” – where in a single diffusion process the material has been transmitted to many nodes (see Figure 1(a) an example of a broadcast). Even though the structural virality is a measure for the cascade tree, it also reflects the collective influence of the nodes in the tree, meaning that not only the root but also other intermediate nodes should have been influential, since the material has been transmitted in several regions of the network. So, we expect to find influential nodes in cascades with large structural virality. Hence, in order to measure the influence on individual level, we define the influence–degree. The influence–degree measures the direct influence a node had on a cascade tree. It is defined as the number of users that have been influenced by user \( i \) in the cascade tree. For instance, in Figure 1(c) the influence–degree of node \( a \) is 2 because he has influenced both \( b \) and \( e \).

The global influence–degree is the total number of users that have been influenced by \( i \) in all the cascade trees that \( i \) has participated in.

### 5 RESULTS

The analysis is based on the comparison of the influence of two groups of users: (i) the trolls; (ii) the rest of the users in the graph. First, we provide general statistics about the structure of the overall directed multigraph, as well as the corresponding directed simple graph (where only one edge is allowed between each pair of nodes). The simple graph is necessary in order to compute certain topological features such as the largest connected component and the k–core decomposition. Next, we focus on the analysis of the retweet cascades trees and their corresponding flow graphs. We provide general statistics and we compute the Structural Virality of each cascade tree along with the nodes’ influence–degree. Moreover, we compute the nodes’ Shapley Value in the flow graphs. Finally, we provide global rankings where we identify the top-k influential users (authentic or troll).

#### 5.1 Graph topology

##### 5.1.1 Degree distribution

Figure 2 presents the empirical complementary cumulative distribution (CCDF) of the in–degree and out–degree for each user (authentic or troll) in the directed multigraph as well as in the directed simple graph. Both graphs consist of 9,321,061 authentic users and 821 trolls. In the simple graph (or graph, for brevity) only one edge is allowed for each pair of nodes that is already connected in the multigraph. Moreover, the multigraph has been constructed by the users’ actions (replies and mentions) on other Twitter accounts and posts. Hence, the in–degree represents the user’s popularity, i.e. the followers that are interested in the posts (tweets) of the user in question. On the other hand, the out–degree is a measure of a user’s sociability/extroversion, i.e., how active a given user is by interacting with other Twitter accounts. Furthermore, it is important to compare the degree distributions in both graphs (multigraph and graph) because users with a high degree in the multigraph do not necessarily have a large degree in the graph. For instance, one might have a large in–degree in the multigraph only because she is popular to a small group of people which is highly engaged with her Twitter account;
they perform a large number of actions on her tweets while their population size is not significantly large.

Figure 2(a) & (c) presents the in–degree distributions where we observe that: (i) 285 trolls and 2.3M authentic users have non zero in–degree; (ii) the degree distributions for both graphs are very similar; and (iii) 11 troll accounts out of 285 have in–degree larger than 1K. On the other hand, we have 9.2K and 34 authentic users with in–degree larger than 1K and 10K, respectively. The top-3 trolls have large in–degrees, i.e., 38K, 45K and 89K. On the other hand, the top-3 authentic users have in–degrees 385K, 1.1M and 1.8M.

Regarding the out–degree (Figure 2(b) & (d)): (i) 675 trolls and 8.5M authentic users have non–zero out–degree; (ii) the troll activity is not substantial, i.e., 33 accounts have out–degree larger than 100 and the top-3 between 900 to 3.2K; (iii) the authentic users appear to be quite more active, i.e., 8.6K accounts have out–degree larger than 1K and 47 between 5K to 12.6K. In conclusion, it seems that in our dataset the troll activity is not dominant compared to the activity of authentic users.

Finally, Table 3 presents the average values for in–degree and out–degree for trolls and authentic users in both graphs. Even though the authentic users are the dominant part of the population, the trolls attracted, on average, considerably larger amount of traffic (actions by other users on their accounts). For instance, the trolls’ average in–degree is 45 times higher than the authentic users’ average in–degree.

5.1.2 Connected components. Here we examine the structure of the undirected version of the graph by identifying the connected components. Since we have only a sample of the total activity, we examine the undirected version of the graph where all the edges (social relationships) are reciprocal.

A connected component is a subgraph where for each pair of nodes i, j there is an undirected path – a graph traverse – from i to j. Since the subject of this study is the diffusion of

| Table 3: Average values: Authentic users vs Trolls |
|--------------------------------------------------|
| Multigraph | In-degree | 18.16 | 821.22 |
|            | Out-degree | 18.23 | 38.97  |
| Graph      | In–degree  | 8.99  | 258.63 |
|            | Out–degree | 9.02  | 22.48  |
| Largest Comp. Coreness | 9.22 | 31.75 |
| RT Cascades | Shapley Value | 3.21 | 269.02 |
|            | Infl. Degree | 5.35 | 382.71 |
|            | Ranking by Shapley | $1, 82 \cdot 10^6$ | $1, 61 \cdot 10^6$ |

Figure 2: Multigraph & simple graph: CCDF of the non–zero in–degree and out–degree of all nodes. Authentic users are denoted as simply “users” for brevity.
information, the connectivity of a region implies that there is a possible path for information flow between the nodes that belong to this region.

The undirected graph consists of 9.3M nodes and 82.8M reciprocal edges. We identify 104,954 connected components. Figure 3 presents the number of connected components for a given component size (i.e., number of nodes in the component) in a log–log plot. The largest part of the graph is well–connected. The largest connected component consists of 9M nodes and 82.7M edges while the second largest has only 223 nodes. In other words, we have a giant connected component along with thousands very small ones.

5.1.3 $k$–core decomposition. We compute the $k$–core decomposition of the nodes in the largest connected component. The $k$–core decomposition is the process of computing the cores of a graph $G$. The $k$–core is the maximal subgraph of $G$ where each node has degree at least $k$. The $k$–shell is the subgraph of $G$ that consists of the nodes that belong to $k$–core but not to $(k + 1)$–core. A node has coreness (or core number) $k$ if it belongs to the $k$–shell. In other words, each node is assigned to a shell layer of the graph $G$. The graph $k$–core number is the maximum value of $k$ where the $k$–core is not empty. It has been proved that the coreness is one of the most effective centrality measures for identifying the influential spreaders in a complex network [13]. Nodes with larger coreness are more likely to be more central in the graph.

In Figure 4, we present the empirical complementary cumulative distribution (CCDF) of the coreness values for troll and user accounts, respectively. The graph $k$–core number is 854. The majority of nodes in the larger $k$–shells are the users, since their population is larger than that of the troll accounts. There are only eight trolls with large coreness; seven accounts are part of the largest 854–shell and one account is part of the second largest 853–shell. This is an indication that these accounts were probably influential. Regarding the authentic users, 3,710 and 250 of them belong to the largest and second largest $k$–shell, respectively. Finally, from Table 3 we observe that the average coreness of trolls is three times larger than the coreness of authentic users.

Summary of Results: The graph of interactions is well connected. Based on the overall graph structure, few trolls have substantial number of followers (in–degree), activity on other accounts (out–degree) and structural position in the network (coreness). Generally, the dominant part of the population consists of the authentic users. On the other hand, on average, the trolls attracted tens of times more traffic than the average user.

5.2 Retweet Cascades

We now turn our attention to the retweet cascades and we provide general statistics about the popularity of the root tweets posted by authentic users and trolls.

In Figure 5 we present the CCDF of the number of unique retweeters and the CCDF of the total number of retweets per retweet cascade. From the 423 retweet cascades that have been initiated by troll accounts, 18 of them have more than 1K retweeters. In addition, the two largest cascades have 5.2K and 7.5K retweeters (Figure 5(a)). Regarding the cascades that started by authentic accounts, in 2,890 of them the number of retweeters is larger than 1K; 101 cascades have more than 10K retweeters and the top-5 have between 40K to 83.2K. Regarding the number of retweets per cascade, the findings are similar to the previous ones. The most popular root tweets have been posted by authentic users instead of trolls (Figure 5(b)). Moreover, in the largest four cascades, the number of retweets is between 83K to 111K, which renders them considerably larger than the number of unique retweeters. This indicates that the root tweets of these four cascades were very popular and they have been retweeted multiple times by the same users.


![Retweet Cascades](image)

**Figure 5:** CCDF of retweet cascades in terms of unique number of retweeters and total number of retweets. Authentic users are denoted as “users” for brevity. The retweeters might have retweeted the same tweet more than once, hence the number of retweets is larger than the number of retweeters.

### 5.2.1 Structural virality

The previous results depict that the cascades initiated by trolls were not considerably large. However, the results are based on the unstructured raw data provided by Twitter API, where all the retweets point to the original tweet (see the example in Figure 1(a)). Here, we aim to measure how viral the cascades were by using the measure of structural virality (see Section 4.5). For the computation of Equation 3, we use the networkx\(^6\) Python package (Dijkstra’s algorithm).

In Figure 6 we compare the structural virality of cascade trees for: (i) the cascades initiated by trolls (423, see Table 2); and (ii) the 45,986 cascades initiated by other users. We can see that the users were the source of the most viral cascades. The top troll cascade has 13.95 structural virality. On the other hand, 138 user cascades have structural virality larger than 13.95.

One would expect that cascades with large structural virality, should also have large number of participants (retweeters). In other words, we should expect a positive correlation between these two variables. However, this does not seem to be the case in our dataset. Specifically, in Figure 7 we present the scatter plots of structural virality versus the number of nodes in the cascade tree. We observe that cascades with very small virality have a quite large number of users (Figure 7(a)). This means that the majority of users retweeted the original tweet and not so often the retweet of another user. For the cascades that were initiated by troll accounts, the situation is different (Figure 7(b)). There are cascades with very large virality and a large number of users (authentic or troll). A possible explanation is that the community around the trolls was more dense, with users retweeting each other and forming an “echo chamber” where political polarization took place.

### 5.3 Top-k influential users

We conclude the analysis by identifying the most influential Twitter accounts – either trolls or authentic users. We estimate their influence based on two measures, the Shapley Value–based centrality and the influence–degree. First, we produce the global ranking of all accounts that are part of the retweet cascades and then report the rank of the troll accounts and the most influential authentic users. In addition, we measure how close to a Twitter bot the profiles of the top-1000 authentic users were. In order to estimate this we use the Botometer API \([24, 28]\) which has been used in the literature for identifying Twitter bots \([5, 6]\). Our goal is to examine whether the behavior of top ranked accounts deviate

\(^6\)https://networkx.github.io/
Figure 7: Scatter plot of structural virality versus number of retweeters for retweet trees which have either trolls or authentic users as root (the author of the original tweet).

Figure 8: CCDF of the non-zero Shapley Value for troll and authentic user accounts. For brevity, authentic users are denoted as “users”.

Figure 9: Botometer scores CAP(English, universal) for the top-1000 most influential users. Plots for $CAP \geq 0.2$ and global ranking based on Shapley Value centrality.

from a human operated account. As we mentioned in Section 1, an account can be automated (having a high Botometer score) and at the same time can be benign. In other words, being a Twitter bot does not coincide with being a troll. On the other hand, a high bot–score raises questions about the authenticity of the account.

Botometer\textsuperscript{7} classifies Twitter accounts as bot or human with 0.95 AUC classification performance \cite{24}. It uses various machine learning models and more than a thousand features which have been extracted from the publicly available

\textsuperscript{7}https://botometer.iuni.iu.edu
data of the account in question, such as friends, accounts’ profile or language. When we check an account, the Botometer API returns various scores where the more general one is the Complete Automation Probability (CAP) – the probability that a given account is completely automated. For a given account, two CAP scores are provided, one based on its English language tweets and one for universal features. For instance, if we know that a user is from China and the majority of her tweets are written in Chinese, then we can consider the CAP(universal) score as the estimator of that account being a bot.

5.3.1 Shapley Value–based centrality. We compare the 233 trolls with the 3.6M users in terms of the impact they have on the diffusion of information which in our case is the tweet context. As we mentioned in Section 4.3, for each retweet cascade there is a corresponding flow graph which formalizes the overall information exchange that has taken place between the users who retweet a given tweet. Here, based on the flow graphs, we compute the global Shapley Value of each node (Twitter account) using the Equations 1 and 2. In addition, having the URLs that are embedded in the tweets text as identifiers of the text and media material that has been diffused in the network, we collect the cascades which refer to those URLs which troll accounts have spread, either by posting an original root tweet or by retweeting. For simplicity, we call these URLs as URLs–troll.

In Figure 8(a) we plot the CCDF of the global Shapley Values, i.e., the contribution of each node/account on the overall diffusion of information. We have 27 out of 235 trolls and 161,513 out of 3.6 million authentic users with non–zero Shapley Value. Recall from Section 4.4 that, the “leaf” nodes of a flow graph always have zero Shapley Value since they do not transmit the information any further, i.e. their marginal contribution to any possible coalition is always zero. In other words, only 27 trolls have an effect on the diffusion of information that took place by the retweet cascades. Subsequently, based on the global Shapley Values, we get the global ranking, where the rank for the trolls is [27, 150, 181, 769, 1649, 1797, 2202, 3273, 3964, 4424, 10017, 12263, 12939, 22706, 23858, 38246, 58516, 58524, 64181, 90589, 114414, 124387, 139794, 142181, 146944, 1797, 2202, 3273, 3964, 4424, 10017, 12263, 12939, 22706, 23858, 38246, 58516, 58524, 64181, 90589, 114414, 124387, 139794, 142181, 146944, 158378, 158960]. Hence, only four troll accounts are in the top-100 and one of them in the top-1000 – the Shapley Values along with the Botometer CAP scores. For the sake of clarity in presentation, we plot only the users with CAP ≥ 0.2. Generally, the recommendation is that a score above 0.5 indicates a bot account (see [6]). Only 22 and 21 users have CAP(English) and CAP(universal) larger than 0.2, respectively. Only four users together with one user have CAP(English) ≥ 0.5 and CAP(universal) ≥ 0.5, respectively. This indicates that the larger portion of users in the top-k do not exhibit bot characteristics.

Finally, in Figure 8(b) we report the Shapley Values only for the retweet cascades of URLs–troll. We have 2,772 URLs which appear in 3,924 cascades consisting of 934K authentic users and 233 trolls, in total. The distribution for the trolls is the same with the global one, since the retweet cascades of URLs–troll are the only ones with troll accounts present. Regarding the authentic users, we recompute their total Shapley Value by the Equation 2 and only for the subset of retweet cascades that correspond to URLs–troll. Again, we reach a final ranking, where the ranking of trolls in the top-100 is [7, 28, 32, 125, 335, 361, 444, 697, 864, 981], namely, ten trolls appear in the top-100 and four of them in the top-1000.

How similar to bot accounts are the top-k users? In order to estimate this, we use the Botometer scores for the top-1000 users. In top-100, we identify 243 inactive accounts where the 24 of them are in the top-100. Although we are unable to report the reasons for their inactivity, still, this raises serious questions about their authenticity and practices. Figure 9 presents the scatter plots for the active accounts in top-100 – the Shapley Values along with the Botometer CAP scores. For the sake of clarity in presentation, we plot only the users with CAP ≥ 0.2. Generally, the recommendation is that a score above 0.5 indicates a bot account (see [6]). Only 22 and 21 users have CAP(English) and CAP(universal) larger than 0.2, respectively. Only four users together with one user have CAP(English) ≥ 0.5 and CAP(universal) ≥ 0.5, respectively. This indicates that the larger portion of users in the top-k do not exhibit bot characteristics.

Lastly, Table 4 shows the account information for the top-10 influential Twitter users based on the Shapley Value. We also present the corresponding rankings in terms of influence–degree and coreness along with the Botometer scores CAP(English, universal). We report the accounts information (user IDs, users screen–name) only for the active ones. Two accounts in top-10 are inactive, which raises serious doubts about the authenticity of these users. The top-10 users are part of the largest shell (854). Table 5 reports the account information of trolls in top-100 along with their rankings and coreness. All trolls are part of the largest 854–shell. Moreover, in retweet cascades initiated by them, more than 1.1% of the total number of retweets were from authentic users belonging to the top–1000 group.

5.3.2 Influence–degree. Now, we use the influence–degree as a measure to rank users and trolls according to the effect they have on the retweets cascade trees. Recall that the influence–degree of a given node i is the total number of nodes that have been directly influenced by i, in all cascade trees that i participates in, either as root of the tree or as intermediate node (for more details see Section 4.5).

Figure 10 reports the CCDF of non-zero influence values for users and trolls. In summary, we have 21 trolls and 118,960 users with non–zero influence. We found four troll accounts
Table 4: Top-10 influential accounts

| User ID       | Screen-name          | Ranking by Shapley | Ranking by Infl. Degree | Coreness | CAP(English)  | CAP(universal) |
|---------------|----------------------|--------------------|-------------------------|----------|--------------|---------------|
| 1339835893    | HillaryClinton       | 1                  | 1                       | 854      | 0.00148281   | 0.00193585    |
| 347627434     | LindaSuhler          | 2                  | 2                       | 854      | 0.00682617   | 0.0185992     |
| 25073877      |realDonaldTrump      | 3                  | 4                       | 854      | 0.00155435   | 0.00219844    |
| 729676086632656900 | TeamTrump       | 4                  | 5                       | 854      | 0.00141879   | 0.00186551    |
| 16589206      | wikileaks           | 5                  | 6                       | 854      | 0.00126169   | 0.00186551    |
| Inactive      | Inactive             | 6                  | 13                      | 854      | N/A          | N/A           |
| 18643437      | PrisonPlanet         | 7                  | 9                       | 854      | 0.0011786    | 0.00201394    |
| 1367531       | FoxNews              | 8                  | 7                       | 854      | 0.00281466   | 0.00257104    |
| Inactive      | Inactive             | 9                  | 11                      | 854      | N/A          | N/A           |
| 759251        | CNN                  | 10                 | 8                       | 854      | 0.00313413   | 0.00272963    |
| Inactive      | Inactive             | 11                 | 10                      | 854      | N/A          | N/A           |
| Inactive      | Inactive             | 13                 | 3                       | 96       | N/A          | N/A           |

Table 5: Troll accounts in top-1000

| User ID       | Screen-name          | Ranking by Shapley Value | Ranking by Infl. degree | Coreness | # Retweeted by top-1000 Users | # Retweeted by top-10 Users |
|---------------|----------------------|--------------------------|-------------------------|----------|-------------------------------|----------------------------|
| 4224729994    | TEN_GOP              | 27                       | 34                      | 854      | 1098 (1.11%)                  | 17                         |
| 4272870988    | Pamela_Moore13       | 150                      | 201                     | 854      | 372 (1.32%)                  | 4                          |
| 4218156466    | America_1st_        | 181                      | 241                     | 854      | 347 (1.34%)                  | 3                          |
| 3990577513    | tpartynews           | 769                      | 899                     | 854      | 63 (1.15%)                   | 2                          |

Figure 10: CCDF of the non-zero Influence-degree for troll and authentic user accounts.

In the top-1000 with rankings [34, 201, 241, 899] and one of them in the top-100 (see also Table 5). Finally, from Table 3 we observe that the influence-degree of trolls is more than 70 times larger than the users’ influence, on average; a similar result with the one for the Shapley Value.

Summary of Results: Four troll accounts were amongst the most influential users. Their tweets have been retweeted tens of times by top-1000 influential authentic users. In general, the top-1000 authentic users do not exhibit bot behavior. On the other hand, 24% of the accounts are now inactive something that raises questions about their authenticity and practices overall.

6 CONCLUSION

In this paper, we have extensively studied the influence that state-sponsored trolls had during the 2016 US presidential election by analyzing millions of tweets from that period. We first constructed the graph of interactions between trolls and authentic users which represent an approximation of the true social network and then we concentrate our analysis on the retweet cascades. Since the data provided by the Twitter API are not well-structured and all the retweets point to the original tweet, we estimate the retweet paths by constructing the retweet cascade trees. In order to measure the users’ impact on the diffusion of information, we introduce the notion of flow graph, where we apply a game theoretic–based centrality measure. In addition, we measure the direct influence that users had on the cascade trees. The results indicate that although the trolls initiated some viral cascades, their role was not a dominant one and the source
of influence was mainly the authentic users. At the same time, the average influence of trolls was roughly 70 times more than the influence of the authentic users. This indicates that, the strategies these trolls followed in order to attract and engage authentic users were sufficiently effective.

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