RESEARCH

Studying Twitter User Accounts: Spotting Suspicious Social Bot Behavior

Marcelo J. Rovai

Correspondence: mrovair@udd.cl
Data Science Institute, Faculty of Engineering, Universidad del Desarrollo, Santiago, Chile
Full list of author information is available at the end of the article

Abstract

With a focus on the original tweets published during the first round of the 2017 Chilean presidential elections, this work aims to study the behavior of Twitter users by specific patterns retrieved from their tweets, such as the user's metadata, number of friends, followers, content, network, and time series. Each pattern is studied both individually and across different subsets of users, such as the number of tweets per account per day, newly created accounts, and so-called simple bots. Networking and timing related features proved to be critical in bot detection. Twitter users considered to "behave" like bots are compared with web applications (apps) used for bot detection. This work explores the visual analysis of groups of users with similar characteristics (clusters), suggesting that a bot behavior can be visually detected using dimensional reduction techniques such as Uniform Manifold Approximation and Projection (UMAP). The methodology used in this work can be applied to identify social bot behaviors in any set of tweets captured in a specific time frame.

Keywords: Social Bot; Twitter; Fake News; Cyborg; Botnet; Data Science; Visualization; UMAP

1 Introduction

In October 2019, massive protests took to the streets in Chile to protest against the highest inequality among OECD countries. Despite its legitimate demands, Chile's infrastructure had also suffered significant fires and destruction. Were these acts spontaneous? According to the U.S. State Department Acting Assistant Secretary Michael Kozak,"foreign actor" could have influenced protests in Chile once fake social media accounts pretending to be Chilean, was identified as emanating from Russia [1]. Are these true accusations? Could these fake accounts be called social bots? A year ago, in October 2018, Brazil elected as president Jair Bolsonaro who is a near-unknown and radical former army captain that served very poorly the Congress for nearly 30 years. Surprisingly, voters decided to migrate massively to the right side of the political spectrum after more than 24 years of center-left governments. Did social media and bots play a significant role in this presidential election [2]?

Many theories have emerged around the world, trying to explain these recent events both in Chile and Brazil. Furthermore, similar situations happened in Latin America (2017 Chilean presidential election [3], in Europe Brexit process [4]), and the U.S. (Trump election) with social bots being heavily used to spread low-credibility content and fake news [5].

Nowadays, we are observing a massive spread of digital fake news and misinformation, which constitutes a significant threat to modern democracies. This situation indicates that social bots play a disproportionate role in spreading articles from low-credibility sources on the so-called Social Media [6]. The phenomenon is, in fact, far broader than just social media. According to an independent survey conducted by Imperva [7] in 2016, bots (good and bad) drove nearly 51.8 % of internet traffic. In the 2018 survey [8], this number dropped to around 40 %, which may sound like good news; however, the reason behind is that bots are getting more sophisticated (nearly 75 % of bots are rated moderate or even sophisticated).

1.1 What are the Social Bots?

The term Social Bot is not well defined, and different scientific disciplines (and scholars) diverge on a standard definition. In order to detect if an account is a social bot or not, two tasks known as automation and orchestration can be used. Automation and orchestration workflow are the common methods used in creating the account's content, as shown in Figure 1 [9]. The orchestration is related to networking, where users (bots or humans) interact among themselves to increase content's spread.

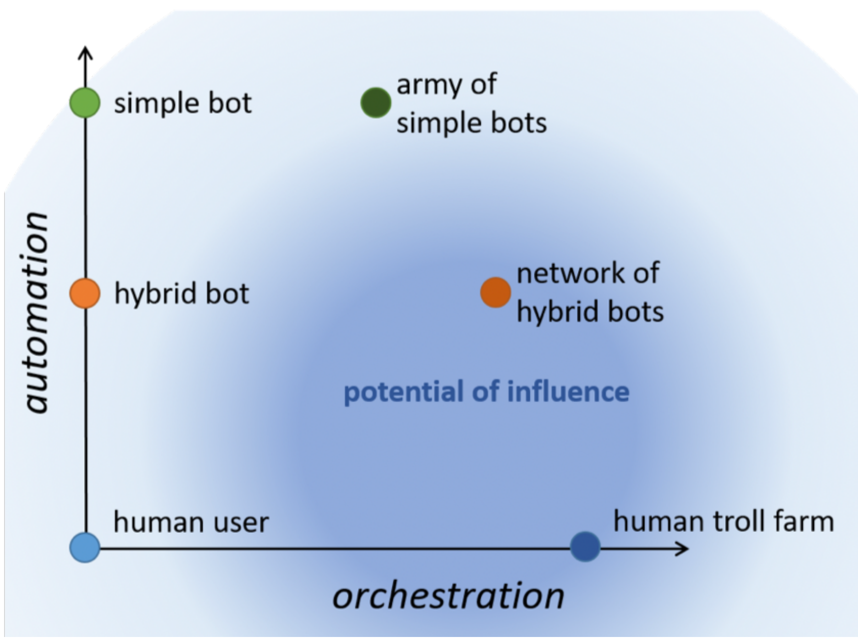


Figure 1: Social Bots - Automation and orchestration (GRIMME et al. 2017)

In terms of automation, a social bot can be classified from a simple bot to a human user, going through a hybrid or cyborg bot (fully automated account mixing with a human user). Simple bots (generically called bots) are automated user accounts that interact with the application through an API [10]. Regardless of its level of automation or orchestration, social bots can be programmed to perform tasks typically associated with human interaction, such as following other users, favoring tweets, sending direct messages, and, most importantly, posting content.

Additionally, social bots often retweet anything published by a specific set of users or promoting a specific hashtag. Many Twitter posts (bot generated or not) are used to perform essential functions, such as serving as part of an alert system which will post digital messages as seen in an earthquake event. However, in the case of a campaign (e.g. political or otherwise), bots are often used to generate high interest in specific content by spreading messages at speed not possible for human users [5].

Malicious social bots usually share low-credibility content, having as a target users with many followers, and using mainly original tweets and retweets with rare replies. However, a single account can generate posts with the same content hundreds and thousands of times [6].

Twitter is an important source for study because online interaction is part of day life of billions of people around the world, where social media users post their feelings, thoughts and opinions about every aspect of life [11]. This work aims to identify user accounts that could be potential bots based on their behavior. The data source of this study is an unstructured tweet dataset captured during the last Chilean presidential election (2017).

1.2 Different types of Social Bots

Bots can be [12] [13]:

- Fake Followers
- Retweet Frauds
- Hashtag Promotion
- URL Spamming

To spot a simple bot is not complicated, once its typical characteristics are [6]:

- Relatively recent account creation date
- Account name containing numbers
- More Retweets than generating original content
- Very high frequency on posting tweets
- A high number of tweets since account's start, but few followers
- Several different tweets with the same content
- Short replays
- Often No-Bio and No-Photo

According to [14], it is possible also to consider simple bots, accounts that have as characteristics:

- A high number of following accounts
- Tweet content with a high score in lexicon diversity (unique words per total words used)

And from [15]:

- A low number of mentions
- Few replays
- Username with long string of characters

In short, it is safe to say that meta-data extracted from tweets are considered to be among the most predictive and interpretive features. However, due to the low cost of creating a social bot [9], its constant evolution, sophistication and mixed human techniques (cyborgs), it is currently impossible to detect all types of social bots only by feature-based systems [15].

This work does not pretend to achieve a method or model to automatically spot a social bot, but to study accounts from a set of selected features, in order to find a "bot behavior". One promising technique explored is the grouping of accounts into a behavioral cluster. Clusters of users with similar behavior, suggests that a bot can be spotted visually [16], and for that, this work explores a novelty technique using Uniform Manifold Approximation and Projection (UMAP).

2 Related Work

Several different approaches are found in the literature regarding bot detection. The most common approach is the use of classification models based on supervised machine learning, but not necessarily with good results [17][18].

It is possible to find websites where a user account can be tested. The most important and cited project is Botometer [19], an online tool to classify Twitter accounts as human or bot. Botometer is part of the OSoMe (Observatory on Social Media) [20], which is a joint project of the Network Science Institute (IUNI), the Center for Complex Networks and Systems Research (CNetS) at SICE, and the Media School at Indiana University. The base of Botometer is a Random Forest classification model, using more than 1,000 features extracted from tweets metadata, interaction patterns, and content. Features are grouped into six main classes: Network, User, Friends, Temporal, Content, and Sentiment.

A not well known, but an attractive model still under development, is TweetBotOrNot [21]. It uses a machine-learning algorithm (Gradient Boosted) that was trained on thousands of real bot and non-bot Twitter accounts. Downloading the last 100 tweets from users, TweetBotOrNot extracts over one hundred different features from user-level attributes (such as bio, location, number of followers and friends), tweets-level (such as number of hashtags and mentions) and, text-based patterns (such as number of hashtags, mentions, and links, length of tweets, punctuation and word complexity).

In Brazil, researchers from ITS Rio (Institute for Technology and Society of Rio de Janeiro) [22] and the Institute of Equity & Technology, developed PEGABOT [23][24], a platform where is possible to check the activity of a Twitter account to discover the probability of a profile being a bot. PEGABOT is not a machine learning model trained from real accounts, but a kind of score calculator based on user account features. The bot score is weighted according to the importance of the feature and also to the context. Features are divided among User, Friend, Network, and Temporal, being the last two, the more weighted due to their importance on bot spotting.

Among other models cited in the literature to spot a bot exhibiting a novel behavior, but not available for testing, are:

- BotWalk, an unsupervised near-real-time adaptive Twitter exploration algorithm [17]
- DNA Inspired Model, a strikingly novel, simple, and practical approach to model online user behavior, where researches extract and analyze digital (DNA) sequences from online user actions, using Twitter as a benchmark to test the model [25]

3 Dataset

The dataset used on this work correspond to tweets posted during the 2017 Chilean presidential election [1]. The dataset covers 30 days (full November 2017) of tweets posted before and after the first round of 2017's elections (November 19, 2017).

3.1 Dataset General Exploration

The original raw dataset with a size of 7.5Gb is a text file imported in a JSON format. In general terms, the data set includes:

- Number of tweets: 1.6 million
- Number of unique user accounts: 91,500
- Average number of tweets per user: 17.5

The percentage of tweets that are:

- Retweets (RT): 31%
- Replies: 20%
- Plain Text: 26% (No RT or Mentions)

The percentage of tweets that includes:

- Hashtags (#): 28%
- Mentions (@): 74% (including RT)
- Mentions (@): 44% (not including RT)
- URLs (http or https): 37% (1/4 of them with two or more mentions)

Figure 2 shows the dataset split in its main categories.

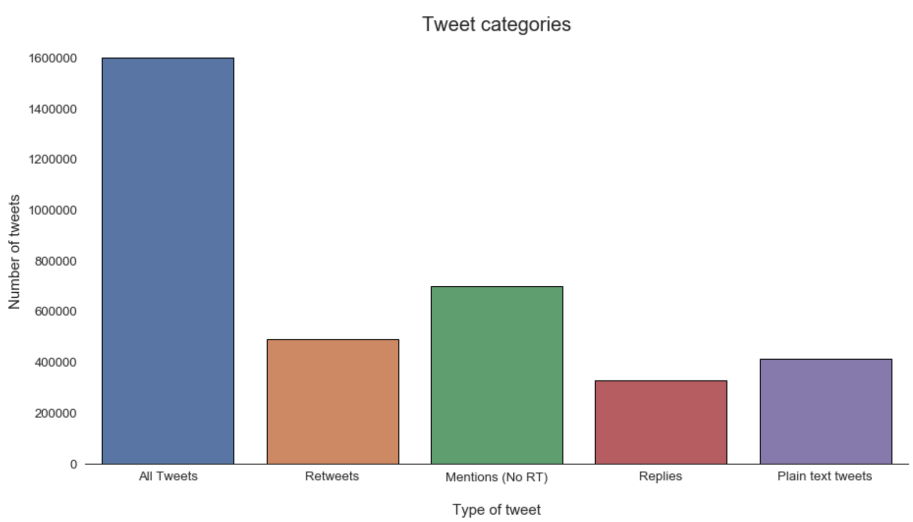


Figure 2: Tweets Summary Categories

It is possible to observe that mentioning an account (by its user screen-name, as @xxx) is a common practice on 75% of all tweets. This characteristic, when used by bots, increases the network and the effectivity of spreading fake news.

3.2 Timeline and devices

Regarding its timeline, tweets spread from November 1 to November 30, 2017. November 19 is the day with more posts, which coincides with the first round of

[1]Data collected by Eduardo Graells-Garrido (UDD and BSC)

elections. Also, it is noted that the number of tweets increased significantly after November 19, as shown in Figure 3.

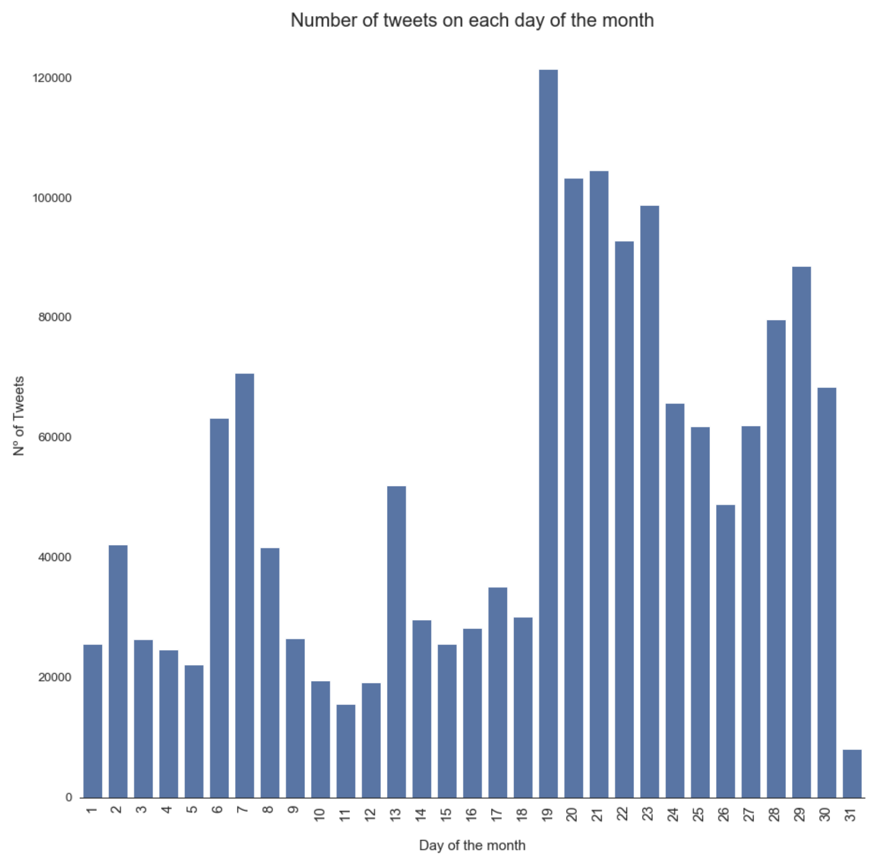


Figure 3: Tweets per Day

Figure 4 shows that around 1.1 million tweets (69% of total tweets) were generated by smartphones (Android or iPhone).

Also, some devices are classified officially by Twitter as "Bot" (1,330 tweets) from 89 unique user accounts. Looking deeper, only a few users generate more than 100 tweets during the month (4 users). One user that has the highest number of tweets (273) is @Ivonomas, a reporter that explicitly states on his profile that he retweets all tweets that mention him. Maybe this action could be done automatically, but it is not confirmed). Anyway this account is labeled officially as a bot by Twitter.

3.3 Dataset - Content

In terms of content, the tweets are heavily related with political subjects as shown in Figure 5. This is important because bots have more probability to be used on political events.

3.4 Deep diving on tweets main features

Table 1 describes the essential numerical features of tweets through their primary statistical data.

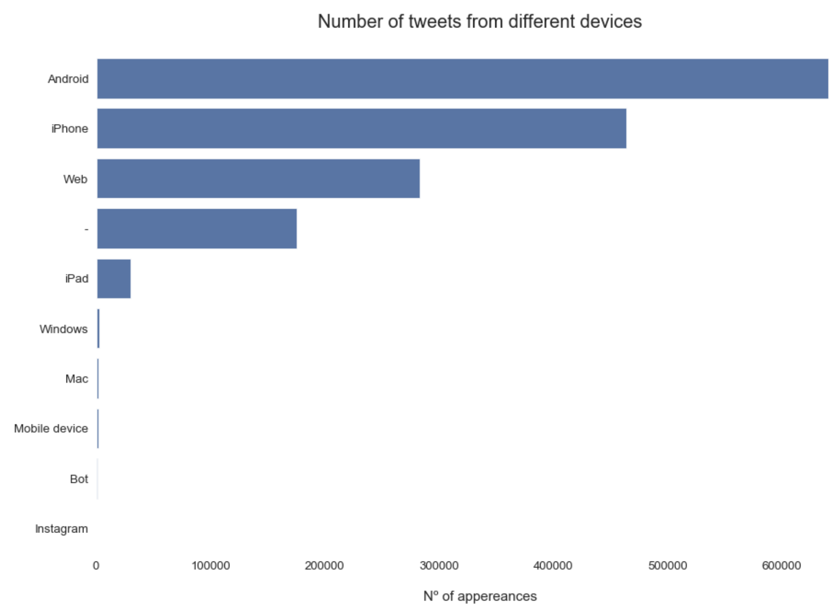


Figure 4: Tweets per Devices

Figure 5: Tweets Wordcloud

3.4.1 Text Length

Regarding text length, as expected, the average is 164 characters, being the median (50%) 139. Some tweets have more than 240 characters (15%), which seems rare, but this situation happens due to how Twitter applies its text limit (not exactly by the number of characters). For example, tweets with hundreds of characters were found, where dozens of mentions were posted with very few words. Even when mention to another account (@xxx) can be split into several characters, Twitter counts it more flexibly [26]. Bots could be who generate those rare tweets.

Tweets Numeric Features Description								
	count	mean	std	min	25%	50%	75%	max
followers	1,601,643	124,937.8	472,966.1	0	292	1,623	11,466	2,889,231
following	1,601,643	15,217.4	76,771.9	0	342	1,091	3,448	761,106
favourites	1,601,643	11,644.4	29,737.5	0	399	2,203	9,316	897,789
lists	1,601,643	423.4	1,538.8	0	2	13	72	10,641
tweets_cnt	1,601,643	62,869.6	132,104.9	1	3,350	14,351	56,741	1,397,706
lenght	1,601,643	164.3	85.5	13	127	139	189	1,017
retweet_cnt	1,601,643	86.0	298.6	0	0	0	30	4,629
favorite_cnt	1,601,643	101.5	394.8	0	0	0	29	6,618
num_hashtags	1,601,643	0.4	0.9	0	0	0	1	28
num_mentions	1,601,643	2.2	4.8	0	0	1	2	54
num_urls	1,601,643	0.4	0.6	0	0	0	1	4

Table 1: Tweets Numeric Features

3.4.2 Followers / Following

Sometimes metrics as Followers and Following can bring confusion, where some authors also use Friends, that can be found associated with one or another entity. This work uses when possible, the official Twitter definition [27] but Friends can also be used on some occasions but always as a synonymous of Following. Below some examples of using Following and Follower:

User A following a User B means:

- User A is subscribing to User B tweets as a follower
- User B updates appear in User A's home timeline
- User B can send User A Direct Messages

User A Followers are all users who receive User A tweets. If someone follows User A:

- They show up in User A followers list
- They see User A tweets in their home timeline whenever they log in to Twitter
- User A can start a private conversation with them

Table 1 shows that, on average, users are following fewer accounts (15,000) than are follow by others or be followers (125,000), what at first glance seems strange, because regular and ordinary people usually follow more people such as celebrities and politicians than are followed. This distortion can be explained by heavy users and also for bot behaviors that try to acquire as many followers is possible to gain popularity/influence and so evade detection by Twitter's defense [28]. When looking for specific accounts, the relation between those metrics is essential to spot a bot.

It is not possible to reach any conclusion about a user be a bot or not, only looking at the dataset from a tweet point of view because every tweet repeats its user metadata. Metrics other than text length should be acquired from a user point of view dataset.

4 Methodology

As explained in the Dataset General Exploration section, the original Tweet dataset ("Tweets") is a huge text file, where each of its instances (dataset's row) is a single tweet. From this dataset, a "User Data" dataset is constructed where each instance is a single user account, with its associated features. This User Data

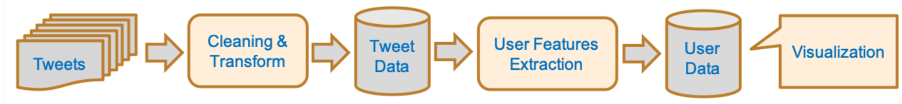
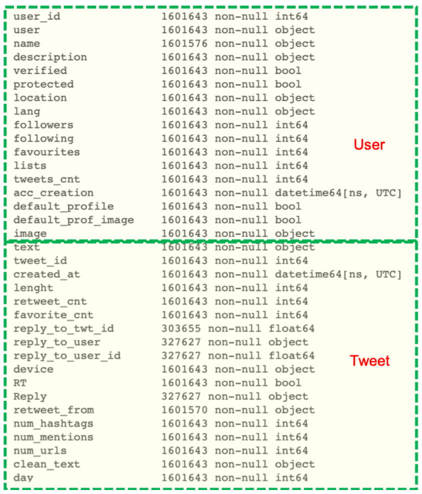
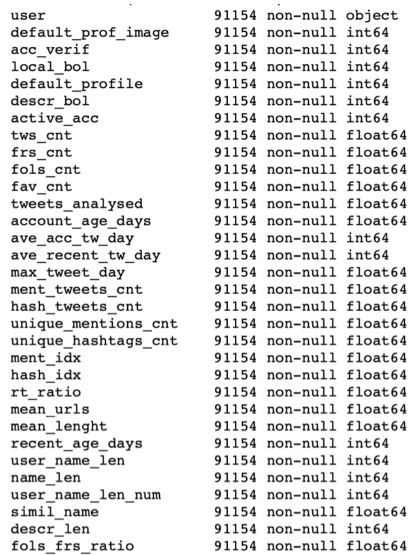


Figure 6: Steps from Twitter to User Dataset



user_id	1601643	non-null	int64	User
user	1601643	non-null	object	
name	1601576	non-null	object	
description	1601643	non-null	object	
verified	1601643	non-null	bool	
protected	1601643	non-null	bool	
location	1601643	non-null	object	
lang	1601643	non-null	object	
followers	1601643	non-null	int64	
following	1601643	non-null	int64	
favourites	1601643	non-null	int64	
lists	1601643	non-null	int64	
tweets_cnt	1601643	non-null	int64	
acc_creation	1601643	non-null	datetime64[ns, UTC]	
default_profile	1601643	non-null	bool	
default_prof_image	1601643	non-null	bool	
image	1601643	non-null	object	
text	1601643	non-null	object	Tweet
tweet_id	1601643	non-null	int64	
created_at	1601643	non-null	datetime64[ns, UTC]	
lenght	1601643	non-null	int64	
retweet_cnt	1601643	non-null	int64	
favorite_cnt	1601643	non-null	int64	
reply_to_twt_id	303655	non-null	float64	
reply_to_user	327627	non-null	object	
reply_to_user_id	327627	non-null	float64	
device	1601643	non-null	object	
RT	1601643	non-null	bool	
Reply	327627	non-null	object	
retweet_from	1601570	non-null	object	
num_hashtags	1601643	non-null	int64	
num_mentions	1601643	non-null	int64	
num_urls	1601643	non-null	int64	
clean_text	1601643	non-null	object	
day	1601643	non-null	int64	

Figure 7: Tweet and User Features



user	91154	non-null	object
default_prof_image	91154	non-null	int64
acc_verif	91154	non-null	int64
local_bol	91154	non-null	int64
default_profile	91154	non-null	int64
descr_bol	91154	non-null	int64
active_acc	91154	non-null	int64
tws_cnt	91154	non-null	float64
frs_cnt	91154	non-null	float64
fols_cnt	91154	non-null	float64
fav_cnt	91154	non-null	float64
tweets_analysed	91154	non-null	float64
account_age_days	91154	non-null	float64
ave_acc_tw_day	91154	non-null	int64
ave_recent_tw_day	91154	non-null	int64
max_tweet_day	91154	non-null	float64
ment_tweets_cnt	91154	non-null	float64
hash_tweets_cnt	91154	non-null	float64
unique_mentions_cnt	91154	non-null	float64
unique_hashtags_cnt	91154	non-null	float64
ment_idx	91154	non-null	float64
hash_idx	91154	non-null	float64
rt_ratio	91154	non-null	float64
mean_urls	91154	non-null	float64
mean_lenght	91154	non-null	float64
recent_age_days	91154	non-null	int64
user_name_len	91154	non-null	int64
name_len	91154	non-null	int64
user_name_len_num	91154	non-null	int64
simil_name	91154	non-null	float64
descr_len	91154	non-null	int64
fols_frs_ratio	91154	non-null	float64

Figure 8: User Dataset Features

dataset is used to analyze accounts, spotting Social Bot behavior as shown in Figure 6.

The numeric features extracted from User Data are studied individually and compared in different subsets of data, as high frequent tweet user versus low-frequency tweet users and different clusters obtained from applying Uniform Manifold Approximation and Projection (UMAP) technics. Clusters of users with similar behavior are spot visually using UMAP [29], which is a dimensional reduction technique that aims to preserve the essential high-dimensional structure and present it in a low-dimensional representation. The resultant analysis can be used to spot social bots' behavior from user accounts.

4.1 "Tweet Data" dataset

The starting point of this analysis is the posted-oriented Tweets dataset. Each one of the individuals tweets has numerous information embedded in it (tweet object), that are a long list of 'root-level' attributes, such as id, created_at, and text. Tweet objects are also the "parent" object to several child objects. Tweet child objects include user, entities, and extended_entities [30].

The clean tweet dataset (Tweet Data), shown in Figure 6, is generated and explored (some of the general metrics were already shown in the previous section). Figure 7 shows the tweet dataset columns where the vast majority of instances have 1.6M rows with the exceptions:

- Description and Location are information manually inserted by the user when Twitter's account is created. Usually, simple bots do not include that info once it is not mandatory, but if missed does not mean that the user is a bot. On dataset, non-description or non-location (NaN data) were replaced by a null string (“”).

- Coordinates are a small number because usually, users do not provide information about where the tweet is generated. This info is not considered on the user dataset.
- Replays related data off course is smaller, because not all tweets are replays.

4.2 “User Data“ dataset

User features are extracted from tweets. For starting, the tweets are grouped by user, and several metrics are generated from the grouped tweets of each user account. As explained before, the tweets database also includes user-specific metrics. So, for each account, the most updated account information is retrieved from the last tweet posted. For example, for a user that has posted during all November 2017 (from 1 to 30), account-specific metrics show his situation on November 30 (such as how many followers the user had, how many likes, his most current profile photo, and description and number of tweets).

New metrics are calculated (feature engineering) from the user grouped tweets such as maximum tweets per day, average tweets per month, number of unique hashtags, mention rate, and retweet rate.

Also, a test on Twitter is performed to verify if the account is still active in 2019. This test is used to verify if Twitter eliminated the account in the present day. Today, not valid accounts that have a very high frequency in tweets could be considered a serious candidate to be a bot back in 2017.

From literature, there are several different approaches to collect user-based features. More commonly, the features can be separated into six main categories, similar but not the same as used by [19] in their project Botometer as described:

User meta-data, such as:

- Id number
- User screen-name
- Number of numeric characters found on screen-name
- Full name
- Number of characters of the name
- The similarity between name and screen-name
- Account description
- Number of characters of the description
- Verified (if an account is verified or not)
- Location (input by the user)
- Number of followers
- Number of Following (Friends)
- Number of Favorites (Likes)
- Lists of tweets (since start)
- Account date creation
- Default profile image (True/False)
- Image (URL)

Timing, such as:

- The maximum number of tweets per day
- The time between consecutive tweets
- The time between consecutive retweets
- Number of tweets per hour and total
- Number of retweets per hour and total
- Number of replies per hour and total
- The average number of tweets (since start and recent)

Network:

- Number of nodes
- Number of Edges
- Clustering coefficient

Tweet specific metrics:

- Tweet id
- Tweet date creation
- Text length
- Retweet count
- Favorite count
- Reply to tweet Id
- Reply to user id
- Coordinates (very few data)
- Device (extract from "source")
- RT
- Reply
- Retweets ratio
- Unique Mentions and Hashtags index

Content-specific features

- Number of unique words used
- Lexical diversity
- Entropy of words
- Frequency and proportion of POS tags

Sentiment:

- Arousal
- Valence
- dominance
- happiness
- polarization & strength
- emotion

4.3 User Features

For this project, not all features used by [19] are extracted. The "User Data" dataset, having Twitter Screen Name and its related numeric features shown in Figure 8 and described by its essential numerical features in Table 2, is analyzed in details here:

default_prof_image - Integer variable [2] (1 or 0): where 1 means that a Twitter's default user image was used (sometimes known as Egg). Using Default Image was

[2] In fact, those features are Boolean, but was converted to integer (1 or 0) to be easier to get statistics data from them.

DF USER DESCRIPTION								
Feature	count	mean	std	min	25%	50%	75%	max
default_prof_image	91,154	0.1	0.3	0	0.0	0.0	0.0	1.0
acc_verif	91,154	0.0	0.0	0	0.0	0.0	0.0	1.0
local_bol	91,154	0.6	0.5	0	0.0	1.0	1.0	1.0
default_profile	91,154	0.5	0.5	0	0.0	1.0	1.0	1.0
descr_bol	91,154	0.7	0.5	0	0.0	1.0	1.0	1.0
active_acc	91,154	0.9	0.3	0	1.0	1.0	1.0	1.0
tws_cnt	91,154	9,198.7	28,376.3	1	231.0	1,406.0	6,627.5	1,386,920.0
frs_cnt	91,154	753.6	4,236.8	0	106.0	302.0	775.0	761,106.0
fols_cnt	91,154	1,599.4	29,394.8	0	33.0	141.0	499.8	2,882,527.0
fav_cnt	91,154	2,315.7	8,656.2	0	55.0	337.0	1,556.8	897,789.0
tweets_analysed	91,154	16.4	165.0	1	1.0	2.0	7.0	25,900.0
account_age_days	91,154	1,889.8	1,058.6	0	978.0	2,241.0	2,819.0	4,065.0
ave_acc_tw_day	91,154	5.0	22.4	0	0.0	1.0	3.0	1,246.0
ave_recent_tw_day	91,154	1.7	12.9	0	0.0	1.0	1.0	1,669.0
max_tweet_day	91,154	5.8	53.8	0	1.0	1.0	3.0	8,044.0
ment_tweets_cnt	91,154	12.4	96.0	0	1.0	2.0	6.0	15,603.0
hash_tweets_cnt	91,154	4.4	53.6	0	0.0	0.0	1.0	7,140.0
unique_mentions_cnt	91,154	10.2	28.6	0	1.0	3.0	8.0	1,342.0
unique_hashtags_cnt	91,154	1.7	5.5	0	0.0	0.0	1.0	220.0
ment_idx	91,154	1.6	1.5	0	1.0	1.2	2.0	49.0
hash_idx	91,154	0.5	0.7	0	0.0	0.0	1.0	16.0
rt_ratio	91,154	48.5	44.4	0	0.0	50.0	100.0	100.0
mean_urls	91,154	0.2	0.4	0	0.0	0.0	0.3	3.0
mean_lenght	91,154	134.9	45.4	14	116.0	132.0	140.0	987.0
recent_age_days	91,154	8.2	9.6	1	1.0	1.0	16.0	30.0
user_name_len	91,154	11.1	2.7	3	9.0	11.0	13.0	15.0
name_len	91,154	13.2	4.8	0	10.0	14.0	17.0	50.0
user_name_len_num	91,154	0.8	1.8	0	0.0	0.0	1.0	14.0
simil_name	91,154	63.1	27.6	0	41.7	63.6	88.9	100.0
descr_len	91,154	58.5	56.2	0	0.0	46.0	108.0	179.0
fols_frs_ratio	91,154	3.1	120.4	0	0.2	0.5	0.9	22,797.0

Table 2: User Dataset Statistical data

common with simple bots. Mean=0.1 means that the vast majority of the accounts do not use the default image.

acc_verif - Integer variable (1 or 0): If 1, means that Twitter has checked and considered the user, a legitimate one. Twitter usually verifies accounts that belong to celebrities and famous personalities who might be subject to identity theft on social networks. The vast majority of users are not verified. A verified account should not be considered a (bad) bot but could show a bot-like behavior (high-frequency tweets).

local_bol - Integer variable (1 or 0): If 1 means that the user introduced location. More than 50% of accounts have a location (it does not mean that they are a valid location). Simple bots may avoid this feature.

default_profile - Integer variable (1 or 0): where 1 means that a Twitter's default user profile was used. Half of the account uses a default profile.

descr_bol - Integer variable (1 or 0): If 1 means that user informed account description. The majority of accounts has some description. Simple bots usually are created without proper description.

active_acc - Integer variable (1 or 0): If 1 means that the account is currently active and not terminated by Twitter. Only a few accounts are not active in 2019 (If the account still exists but is blocked, this feature is 1).

tws_cnt: Number of tweets since the account was created. User accounts on this dataset are, on average, 5 years old, which leads to a high number of tweets (on average, 9,200 tweets).

frs_cnt: Number of Following users (Friends). 50% of accounts have less than 300 friends, 75% with less than 700, which is very common for normal humans' accounts. However, there are accounts with hundreds of thousands of friends. Those accounts should be analyzed with care because smart bots try to follow as many accounts is possible to increase network and avoid detection.

fols_cnt: Number of Followers that follow this account. Human accounts tend to have fewer followers than Friends. On this dataset, 75% of accounts have less than 140 followers (or almost half of their friends). Note that on average, followers are higher than friends (following), because of some outliers have a considerable number of followers. It could be celebrities (if the account is verified) or could be a bot.

fols_frs_ratio: Shows the relation between the number of followers that follow this account, divided by the following users (friends). Humans usually have this ratio low. 75% of users have this feature less than 0.9, but huge numbers can be found. Those are suspicious accounts.

fav_cnt: Number of times that a user favorites a tweet (gives a like). 75% of accounts have less than almost 1,600 likes. Those same accounts have less than 2,800 days of existence, which results in less than 2 likes a day, which seems reasonable. However, some accounts reach more than 900,000 likes, and no account has more than 4,100 days in age, which means that users give more hundreds of likes daily, which is very unlikely for humans. This situation should be analyzed.

tweets_analysed: This feature captures the number of tweets posted by a user during the timeline window of interest (November 2017).

max_tweet_day: Maximum number of tweets posted on a single day during November 2017. 75% of users posted less than three tweets /day, but around 356 non-verified users posted at least on a single day, more than 144 tweets. Those accounts are responsible for almost 25% of all tweets during November 2017. This feature is one of the essential metrics to spot a bot [31] [32].

account_age_days: Age in days, starting when the account was created until the last tweet posted. Looking Figure 9 is possible to observe two very marked group of accounts. One aged around 90 days and another with a little less than 3,000. Those accounts with less than 90 days should be analyzed because simple bots usually are created shortly to be used during the elections.

rt_ratio: Ratio in percentage between the number of tweets that are retweets and the total number of tweets during the period (November 2017). Looking at the statistics and based on this feature's mean, it seems that users usually retweet 50% of the times, but this is not true. Looking in more detail, Figure 10 shows that are two groups of very distinct users, the first with low rt_ratio, post new tweets, and the second around 100%, shows users that do not create new content and only retweet an existent tweet. Usually, simple bots tend to retweet.

ave_acc_tw_day: Average number of tweets per day. Take tweets posted since the account was created (tws_cnt) divided by account age in days (account_age_days). 75% of accounts post less than three tweets a day. The global average in the dataset is 5. It is because there are accounts that post a massive number of tweets a day (more than 1,000). Those accounts are most probably automated (bots).

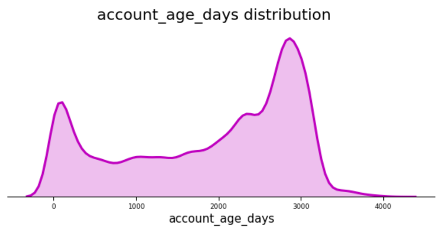


Figure 9: Account Age in days

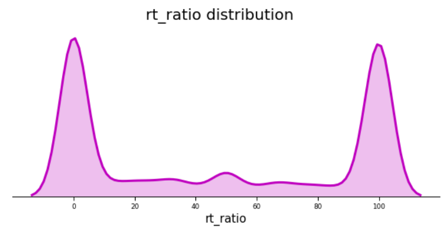


Figure 10: Retweet Ratio

ave_recent_tw_day: Average number of tweets per day, posted during the timeline window (November 2017). The calculation takes the number of tweets posted during November 2017 and divides by the number of days between first and last tweet posted. 75% of accounts post one tweet a day or none. Average in the dataset is 1.7, also because are accounts that post a massive number of tweets a day (more than 1,600). Those accounts are most probably automated (bots).

ment_tweets_cnt: Number of times that another user (screen-name) is included on a tweet. Half of the tweets include two or fewer mentions, which is typical for humans, but exceptions reach thousands of mentions and must be analyzed.

hash_tweets_cnt: Number of hashtags included on a tweet. 75% of users add at most one hashtag when posting. Exceptions of a hundred, even thousands of hashtags, are found. This anomaly can be related to automatized accounts.

unique_mentions_cnt: Total number of unique user scree-names (mentions) found on total tweets analyzed for that particular user at the timeline (November 2017). 75% of all users mention fewer than eight accounts.

unique_hashtags_cnt: Total number of unique hashtags found on total tweets analyzed for that particular user at the timeline (November 2017).

ment_idx: Total number of unique mentions (unique_mentions_cnt) divided by the total number of mentions (ment_tweets_cnt).

hash_idx: The total number of unique hashtags (unique_hashtags_cnt) divided by the total number of hashtags (hash_tweets_cnt).

mean_urls: The average number of URLs presents on each tweet. The majority of users do not include URLs on tweets. There is one group of users that includes URLs on all tweets and must be analyzed more deeply, as shown in Figure 11.

mean_lenght: Tweet's average number of characters. The average number of characters goes around 135 characters, which makes sense due to Twitter's historical rules. The surprise is the high number of outliers with hundreds of characters, that as discussed previously is do tweets with a large number of hashtags and mentions. Figure 12 shows this distribution.

recent_age_days: Number of days between the last tweet posted in November 2017 and the oldest ones in the same month. This feature is essential to calculate the ave_recent_tw_day feature. There is a distinguished group of users that post only during a short period of days, as shown in Figure 13, that should be analysed more carefully.

user_name_len: Number of characters present on screen-name. This feature varies from 3 to 15 characters. The average is 11 characters with a distinguished

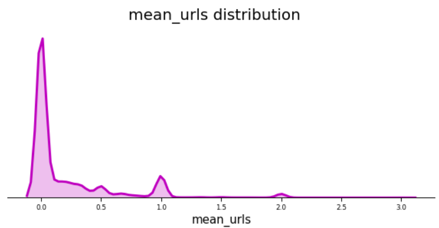


Figure 11: Average number of URLs

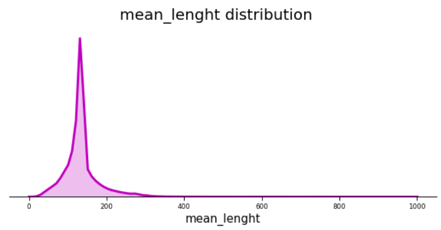


Figure 12: Average text length

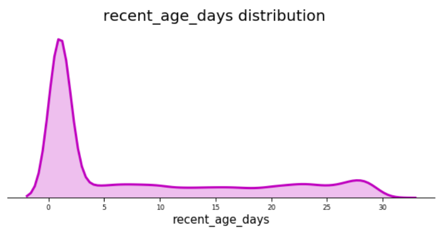


Figure 13: Recent Age Days

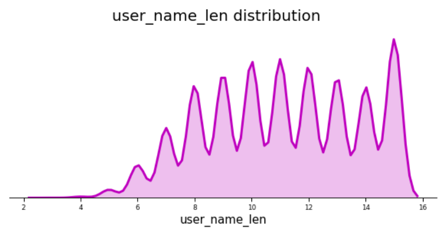


Figure 14: User-Name length

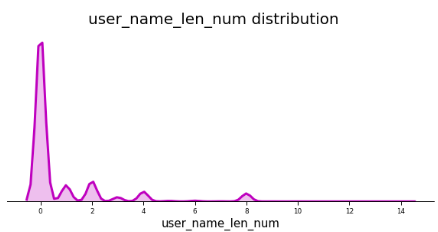


Figure 15: Numeric characters on User-Name

group that has 15 characters, as shown in Figure 14. Normal human users tend a keep it short, but it is possible to find large ones, but not with many numeric characters.

user_name_len_num: Screen-name's numeric characters. This feature shows how many of Screen-name's characters are numeric. Figure 15 and Table 2 show that 75% of users have one or less numeric characters on screen-name. Two or Four numeric characters are not uncommon, where age or year of birth can be added to scree-name by human users, but when several numbers are added, the screen-name became suspicious to be a bot.

name_len: Number of Characters present on the name that the user chooses to be identified. 75% of accounts present less than 17 characters, but some users have big names. Sometimes is due to the field for the name is used to include erroneously, descriptions.

simil_name: Shows the similarity between name and user name (screen-name), calculated by having Jaccard similarity between the set of letters of both features. A human user tends to have his screen-name (user_name) similar to his name and with few (or none) numeric characters. For example, with a name: Marcelo Rovai and a screen-name: @mjrovai, the Jaccard Similarity is 0.6, which is OK. Low

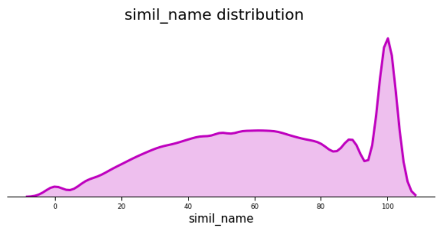


Figure 16: Jaccard Similarity Name and User-Name

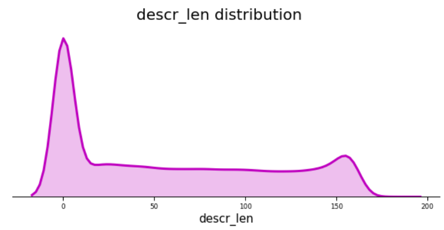


Figure 17: Account Description text length

values of Jaccard Similarity, like 0 or 10%, could be suspicious. Figure 16 shows the distribution.

descr_len: Number of characters found in the account description. Accounts with short or even no description can be suspicious to be a simple bot. Of course, a lack of description does not mean that the account is a bot but should be investigated. Figure 17 shows that a significant number of accounts lack description.

5 Studying Accounts per their frequency of posting

One critical metrics, when analyzing bot's behavior, is the frequency of tweets. By a study developed by Oxford University, accounts that post more than 50 tweets a day with the same specific hashtag is defined as having a high level of automation [2]. For DFRLab (Digital Forensic Research Lab) [31], accounts that post 72 tweets per day (one every ten minutes for twelve hours at a stretch) is suspicious to be a bot and over 144 tweets per day as highly suspicious. First Draft considers a minimum of 100 tweets a day as a general rule for flagging an account as suspicious of automation [32].

From the user dataset is possible to see that, from a total a range of 91,000 accounts, around 780 of them have at least one day during the month where more than 72 tweets were posted. This number of accounts is less than 0.09% of all accounts that posted at least one tweet during November 2017, but they are responsible for almost 42% of total tweets.

5.1 Filtering High and Low-Frequency Accounts

Selecting only the users that according to DFRLab that are highly suspicious of being a bot (maximum number of tweets a day higher than 144), and also, not considering the verified accounts, where celebrities could also behave as bots [33], the number of suspicious accounts can be reduced to only 356 users. However, this small number of suspicious accounts is responsible for posting an impressive number of 364,942 tweets; almost 25% of the total tweets posted during the analyzed period (November 2017). Let us call this group of accounts, high-frequency users.

On the other hand, filtering accounts with shallow activity (less than 50 tweets/day), we get almost 90,000 accounts, that are responsible for 775,000 tweets (52% of total). Let us call this group, low-frequency users.

From total accounts, around 300 accounts (responsible for almost 25% of total tweets) are considered "Gray Area", let us call them mid-frequency users.

Looking at its distribution, 75% of high-frequency users, posted as a maximum, between 145 and 470 tweets and the low-frequency users, less than three tweets a day.

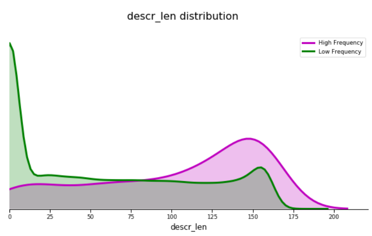


Figure 18: Account Description text length

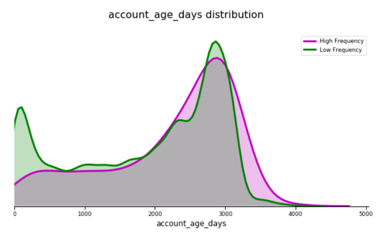


Figure 19: Account Age in days

5.2 Comparing select features

When exploring the user dataset in the previous section, some features presented a strange distribution such as desc_len , account_age_days, rt_ratio, recent_age_days. Here, those features are explored, assuming that those anomalies could be distinct, depending on how frequent a user posts.

desc_len: Low-frequency accounts description length shows a distinct group of users where short (or even NoN) descriptions are used. Instead, high-frequency users have a concentration in longer descriptions, as seen in Figure 18. The behavior shown is a surprise, once bots are expected to be more spotted among high-frequency accounts.

account_age_days: When splitting into low and high-frequency users, it is possible to realize that low-frequency users have younger accounts, as shown in Figure 19.

recent_age_days: This feature shows that high-frequency accounts usually posted all month (Figure 20).

rt_ratio: Analyzing Figure 21 is possible to see that low-frequency accounts present two distinct groups of ratios, low and high. However, high-frequency users retweet less. This feature is calculated, dividing rt_tweets_cnt per tweets_analyzed and multiplying the result by 100.

5.3 Comparing other basic features

High-frequency users post longer tweets (Figure 22) and attract more followers (Figure 23) at the same time that follows more users (Figure 24).

6 Possible approaches to Spot Suspicious Social Bot behaviors

Once account metrics are collected in a dataset of features, the first logical approach in the field of Data Science is to develop an algorithm (or model) to spot a bot account automatically. This approach is precisely the most common line of research found among academics, but while many of the metrics overlap, no two models are the same [34].

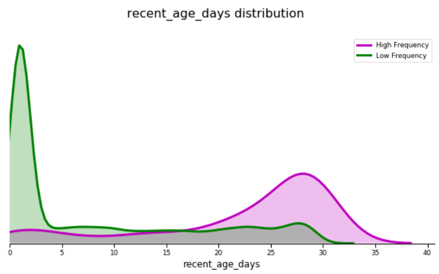


Figure 20: Recent Age Days

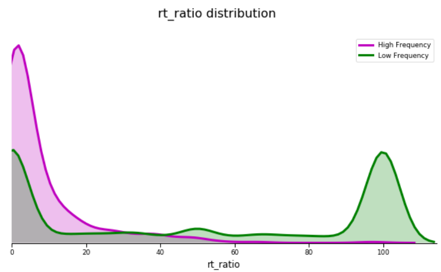


Figure 21: Retweet Ratio

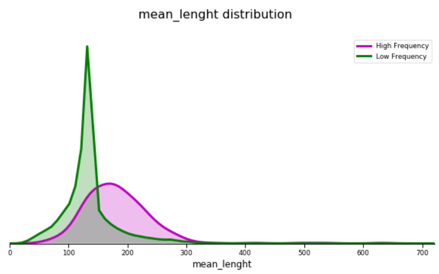


Figure 22: Average text length

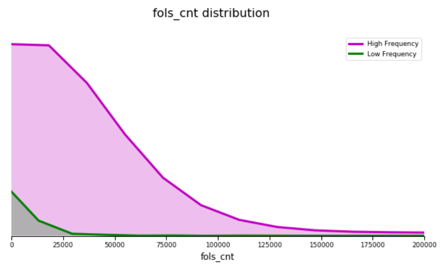


Figure 23: Number of Followers

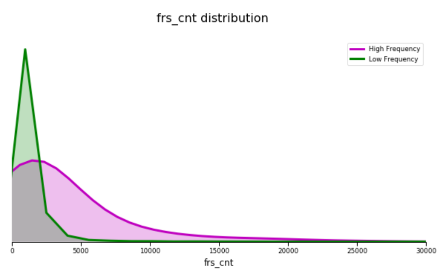


Figure 24: Number of Following (Friends)

To spot a bot, cyborg or a troll has much complexity due to the combination of human and machine. None of those features, if taken alone, are enough to say whether an account is a bot or not conclusively and could be seen as perfectly reasonable for some social media users, like celebrities (high-frequency post) or new users (lake of photo or description).

On the other hand, the more characteristics an account displays, the more likely it is to be automated (bot/cyborg) or coordinated (botnet). Even If a particular user shows several features that can spot it with a high probability of being a bot, this conclusion always depends on the circumstances and should be verified manually [32].

Botometer [35] and TweetBotOrNot [36] try to based on features, and with machine learning models to calculate the probability of an account to be a bot or not, while PEGABOT [24] gives to each feature a score, defining if an account is a bot or not based on the sum of such scores. From the tests done on this work, PEGABOT did a better job, confirming how difficult it is to spot a bot using machine learning algorithms.

So, the best way to spot a bot is to select a group of critical features and by filtering, to group suspicious users that share all of them, for in the sequence, to analyze each account individually and manually trying to confirm it.

Three groups are analyzed:

- Simple Bots
- High-Frequency users
- Younger Mid-Frequency accounts

6.1 Spotting Simple Bots

The first attempt to spot social bot behaviors is to select some accounts based on their features and printing them as a simple dashboard to manually decide if the account has a bot behavior or not. For example, classical simple bot behavior can be defined as:

- Account not verified
- Image Profile is the default
- Account description is missing
- 72 tweets posted in at least one day during the period

Filtering the User Dataset for users that math those parameters, three accounts were spotted:

- @fedoraletelier (Appendix A)
- @Aliciacarafipl3 (Appendix B)
- @Dolores09072598 (Appendix C)

@fedoraletelier: - Looking at the data from @fedoraletelier in detail, it is possible to realize that besides the standard features used for selection, this user is most probably a social bot due:

- Several tweets with the precisely same content.
- A high number of unique mentions
- A high number of historical tweets (161/day)
- A high number of likes (120/day)

Figure 25 shows its tweets and Figure 26 its actual page, where it is possible to realize that this account posted around 100,000 tweets/year from 2017 to 2019, increasing the number of both followers and friends significantly. For an almost "anonymous" account, those numbers make no sense. Once this account is still active is also possible to verify that Botometer [35] classifies it more like a human, with a 30% possibility of being a bot (or 1.5/5, as shown in Figure 27), what is far from reality (Note that Temporal: 2.3 and Network: 3.0 are the highest individual scores).

If we check with PEGABOT [24], the probability goes to 100%, confirming that this account behaves as a social bot, as shown in Figure 27. Note that User (Usuario: 100%), Frequency (Frequência:178%), and Network (Rede: 83%) are highlighted due to its high values. The bot behavior is also confirmed with TweetBotOrNot [36], with 99.3% probability, as shown in Figure 29.

@Aliciacarafipl3: - In the case of @Aliciacarafipl3, it is possible to highlight:

- Recent average tweets per day are not high (26/day), but historically was (69/day)

- Timeline.png

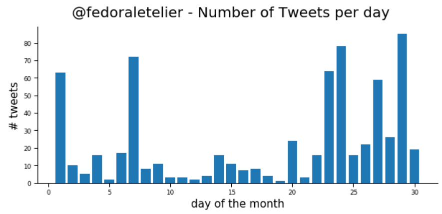


Figure 25: @fedoraletelier tweets/day

Figure 26: @fedoraletelier Twitter home page

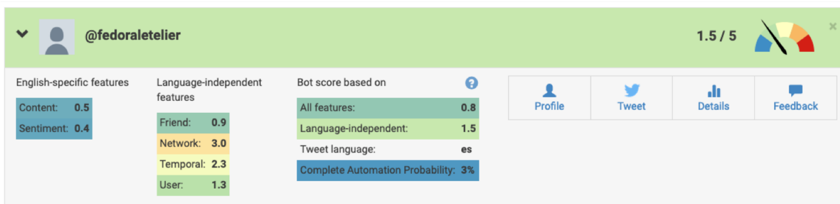


Figure 27: @fedoraletelier Botometer

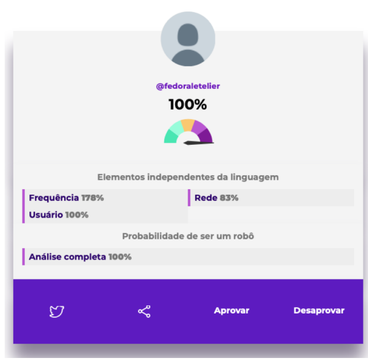


Figure 28: @fedoraletelier PEGABOT

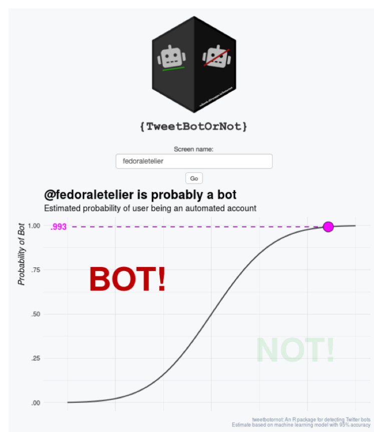


Figure 29: @fedoraletelier TweetBotOrNot

- Retweet Rate is very high (96%), which means that almost all posts are retweets
- 36 likes /day
- All tweets mention another account
- tweets repeated (similar text)

This account is still active, and it is possible to observe that in 2 years, the number of tweets jumped from 25,000 to 204,000, having the number of followers and friends also grown exponentially. So, on a simple analysis, this account most probably is a bot. This conclusion is also shared by PEGABOT (Figure 30) and TwitterBotOrNot (Figure 31), with respectively 100% and 99.7% probability of being a bot. Again, Botometer (Figure 32) does not consider this account a bot, indicating only a 25% probability score (1.3/5).

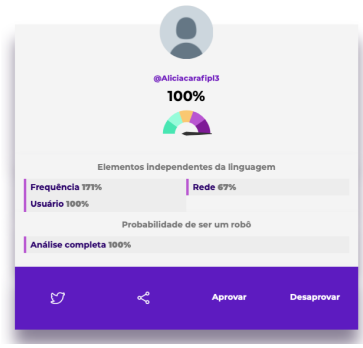


Figure 30: @Aliciacarafipl3 PEGABOT

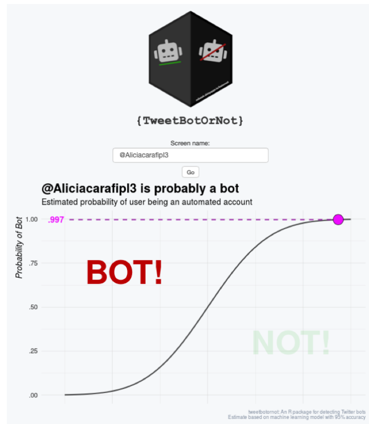


Figure 31: @Aliciacarafipl3 TweetBorOrNot

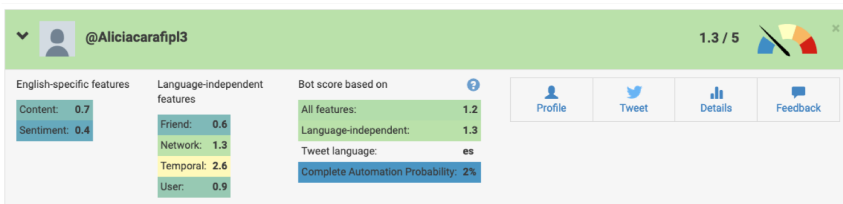


Figure 32: @Aliciacarafipl3 Botometer

@Dolores09072598:

- Recent average tweets per day are not high (113/day)
- Followers/Following_index very low (Following 100 per each follower)
- 100% of tweets are pure retweets
- All tweets mention another account

This account is still active but protected. In the last two years, this account posted 37,000 tweets, increasing by five times the number of friends, but not followers, keeping Followers/Following_index almost the same (from 0.09 to 0.12). Once it is protected, web applications can not be used to measure its probability of being a bot.

6.2 High-Frequency Users

Another manual attempt to select possible Social Bots is filtering high-frequency users and proceeding with a manual analysis as was done with simple bots.

Some results:

@AlbertoMayol: - (Appendix D): This is a cyborg account. The user is human, but its behavior sometimes is like a bot (mechanized), as we can see on his post's timeline during November 2017 (Figure 33). He has the maximum number of tweets on a single day among all users (5,163), posting only two times with a total of 6,930 posts. On each one of the days, a unique text content was posted. His recent activity at Twitter is very reasonable; what confirms that account is a cyborg. The web bot apps do not consider this account as a bot, being the scores: Botometer: 3%; PEGABOT: 30% and TweetBotOrNot: 10%.

@andres20ad - (Appendix F): In Figure 34, it is shown the timeline of @andres20ad, another active account that most certainly is handled by an human that sometimes has a bot behavior (cyborg). On November, 18, one day previous second round, this account posted 1,600 tweets, being the content split in only two different texts, as shown in Figure 35.

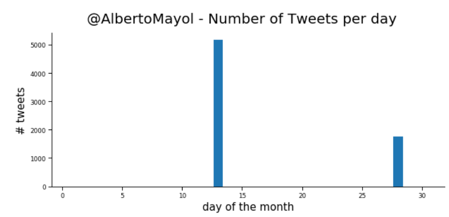


Figure 33: @AlbertoMayol tweets/day

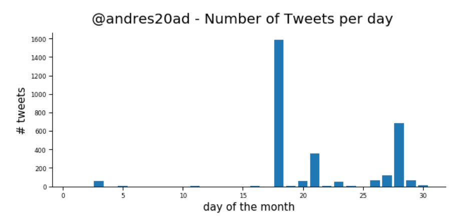


Figure 34: @andres20ad tweets/day

```
579503     En 1988 millones de chilenos se enfrentaron a ...
579527     En 1988 millones de chilenos se enfrentaron a ...
579556     En 1988 millones de chilenos se enfrentaron a ...
579579     El gobierno de Piñera fue el más corrupto de t...
579593     El gobierno de Piñera fue el más corrupto de t...
579597     El gobierno de Piñera fue el más corrupto de t...
579627     El gobierno de Piñera fue el más corrupto de t...
```

Figure 35: @andres20ad tweets on 11/19/17

@NelsonCL28 - (Appendix G): Figure 36 shows the timeline of another user with more than 1,600 on a single day. This account is still valid today, but its last post was this single one on November 19, 2017, day of Chilean Presidential election's 1st round. This account has very few followers (26), but this single tweet was retweeted 1,900 times and liked by 567 other users, which suggests that it must probably as part of a botnet of Fake-News. Figure 37 shows the actual post. Again, the web bot apps do not consider this account as a bot, being the scores: Botometer: 50%; PEGABOT: 27% and TweetBotOrNot: 18%. Interesting that in this case, Botometer shows the highest score among the users analyzed in this section. This result could probably be affected by a long time of inactivity of this account, which not means that a dormant user is a robot. A straightforward test was done with the user @ilzarovai, that it is not a bot, but has its account inactive by around one month. Botometer considers that this account has 69% of the probability of being a bot, a false positive. PEGABOT gives it 41% and TweetBotOrNot, 19%.

6.3 Young Mid-Frequency Accounts

In this group, accounts are filtered with not verified users posting more than 72 tweets/day and with less than 90 days since creation. Applying above filtering criteria resulted in 10 accounts spotted:

- **@EncuestaExpress** - (Appendix I) - [Bot] - On a single day (20/Nov), the user posted more than 700 tweets, having the great majority of them the same text. PEGABOT: 76%; Botometer: 78%

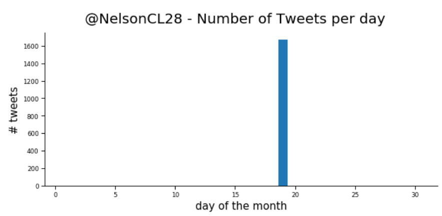


Figure 36: @NelsonCL28 tweets/day

Figure 37: Original single tweet

- **@RResponsablecl** - (Appendix J) - [Possible a Cyborg]: PEGABOT: 67%; Botometer: 20%
- **@cazadorandino90** - (Appendix X) - [Bot]: around 30,000 tweets in one year and no more tweets after October 2018. PEGABOT: 53%; Botometer: 24%
- **@Piagutierrezs** - (Appendix K) - [Bot]. Majority of tweets with the same text. This account is still active nowadays, with a high number of followers and friends. PEGABOT: 54%; Botometer: 18%
- **@NathalySeplved3** - (Appendix L) - [Possible a Cyborg]: Two days during the timeline window with more than 100 tweets (same text). Account is active nowadays, with high number of followers and friends. PEGABOT: 71%; Botometer: 8%
- **@ElCentinelaMPE** - (Appendix M) - [Could be human]:Only used during November 2017. Still active but not posting. PEGABOT: 45%; Botometer: 28%
- **@AShumman** - (Appendix O) - [Bot] Suspended Account
- **@PamelaSoler3** - (Appendix N) - [Bot] Not active nowadays
- **@Sumate_Guillier** - (Appendix P) - [Bot] Not active nowadays
- **@jav_ast**: [Bot] - (Appendix Q) - Single day with 104 same text tweets. Account still active but not posting. PEGABOT: 69%; Botometer: 78%

6.4 User Behavior - Manual spotting Results

Manually spotting and deciding if a user is a bot or cyborg is a tedious and time-consuming task but is the only way to define an account behavior. Many of the works that try to apply supervised machine learning techniques to identify if an account is a bot or not use humans (usually more than one to judge each account) before label it. With some of them, as Botometer, the result observed is not great.

7 Spotting User Behavior Clusters

This work experiments with an entirely new approach to spot a social bot behavior, exploring clusters of users with similar behavior visually, using a Uniform Manifold Approximation and Projection (UMAP).

UMAP is a dimension reduction technique that can be used for visualization similarly to t-SNE [37], but also for general non-linear dimension reduction. The algorithm is founded on three assumptions about the data:

- The data is uniformly distributed on a Riemannian manifold;
- The Riemannian metric is locally constant (or can be approximated as such);
- The manifold is locally connected.

From these assumptions, it is possible to model the manifold with a fuzzy topological structure. The embedding is found by searching for a low dimensional projection of the data that has the closest possible equivalent fuzzy topological structure.

The details for the underlying mathematics can be found in [29], McInnes, L, Healy, J, UMAP: Uniform Manifold Approximation, and Projection for Dimension Reduction.

To the user dataset, with its 32 features (user screen-name and 31 numeric metrics), was add a new feature named label. The idea is to label each of the users according to its frequency-post behavior, helping to spot users on the final UMAP visualization, but not to be used on calculations. Below how users are labeled:

- Low-Frequency: less than 50 tweets/day (89,959 users)
- Mid-Frequency: between 50 and 144 tweets/day (798 users)
- High-Frequency: More than 144 tweets/day (397 users)

As a model input, one Array with dimension (91154, 31) is created from the user dataset (the user that is the dataset index and the recently created label are taken out). The data was not normalized, once according to [29], this is one of the advantages of UMAP.

The three most essential hyper-Parameters of UMAP model [29] are:

- min_dist: In essence, this parameter determines how closely points can be packed together in the low dimensional representation. Low values on min_dist result in potentially densely packed regions, but will likely more faithfully represent the manifold structure. Increasing the value of min_dist forces the embedding to spread points out more, assisting visualization (and avoiding potential overplotting issues). This experience uses 0 for this parameter.
- n_components: The target embedding dimension such as 2 for 2D and 3 for 3D.
- n_neighbors: That represents some degree of trade-off between fine-grained and broad-scale manifold features. Smaller values ensure the detailed manifold structure is accurately captured (at a loss of the “big picture” view of the manifold), while larger values capture large scale manifold structures, but at a loss of fine detail structure which gets averaged out in the local approximations, as shown in Figure 38. A good compromise seems to be reached with n_neighbors = 30.

Figure 39 shows the same parameters variation, but using n_components=3. Each one of resultant visualization shown in both figures 38 is very fast to be computed, going from 1 to 4 minutes on a MacBook, 2.9GHz Core i7, 16GB RAM, where red Dots represent High-Frequency users; the blue: Mid-Frequency users and the Gray: Low-Frequency users.

7.1 Spotting known bots on UMAP

Analysis can be done with both, 2D or 3D projection, but the ideal on 3D is taken three 2D projections (x-y, y-z and x-z) and so, creating sub-groups for analyzing. Inspecting the results on both cases (n_component = 2 and 3), it seems that with n_neighbors = 30, we can find distinct regions with similar characteristics.

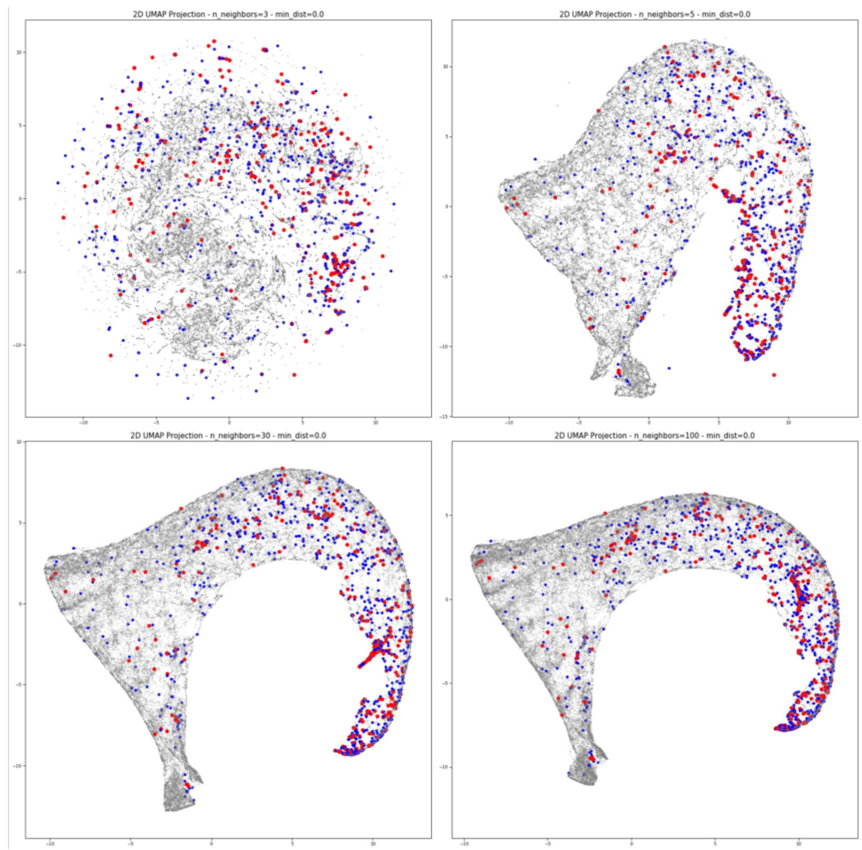


Figure 38: UMAP 2D User Dataset - Hyper Parameters selection

Taking the known bots spotted on previous sections and listed below:

- @fedoraletelier
- @Aliciacarafipl3
- @Dolores09072598
- @AlbertoMayol
- @Tomaskovacic
- @NelsonCL28
- @EncuestaExpress
- @RResponsablecl
- @cazadorandino90
- @Piagutierrezs
- @NathalySeplved3
- @ElCentinelaMPE
- @AShumman
- @PamelaSoler3
- @Sumate_Guillier
- @jav_ast

Figure 40 shows that such suspicious users are spread all over the 2D UMAP visualization (n_component = 2, n_neighbors = 30, and min_dist = 0) without be grouped on a clear area of bots.

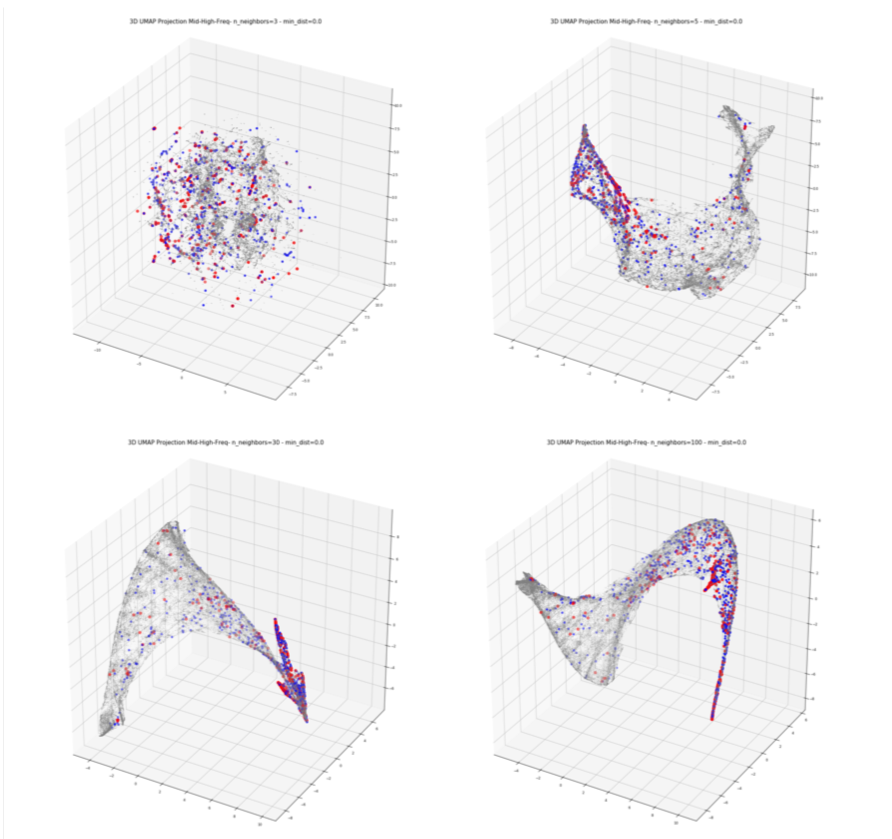


Figure 39: UMAP 3D User Dataset - Hyper Parameters selection

7.2 Creating clusters of users with similar behavior

Using as hyper-parameters: n_component = 2 (2D); n_neighbors = 30; and min_dist = 0, all 31 dimensions were reduced to only two, and used to plot the 2D figure. These two new dimensions "x" and "y" can be added to the original user dataset, and this way is possible to explore the regions of resultant visualization.

Intuitively, it is possible to observe from figure 38 that bigger x and smaller y means more concentration of high/mid-frequency users and possible bots. The next approach is to select a few significant areas of the figure to analyzed them in more detail as shown in Figure 41.

The three areas marked in Figure 41 are possible clusters, and three sub-datasets were created to be analyzed.

7.3 Comparing user_cluster_1 with user_cluster_3

From Figure 42 it is possible to confirm that user_cluster_1 has a more significant concentration of High/Mid-frequency users, and user_cluster_3 almost is formed only with low-frequency users.

Regarding account description, user_cluster_3 is more populated with no or short description, as shown in Figure 43.

In terms of similarity of names, Figure 44 shows that user_cluster_3 is much more consistent with this feature over 60%, which is more typical in human accounts.

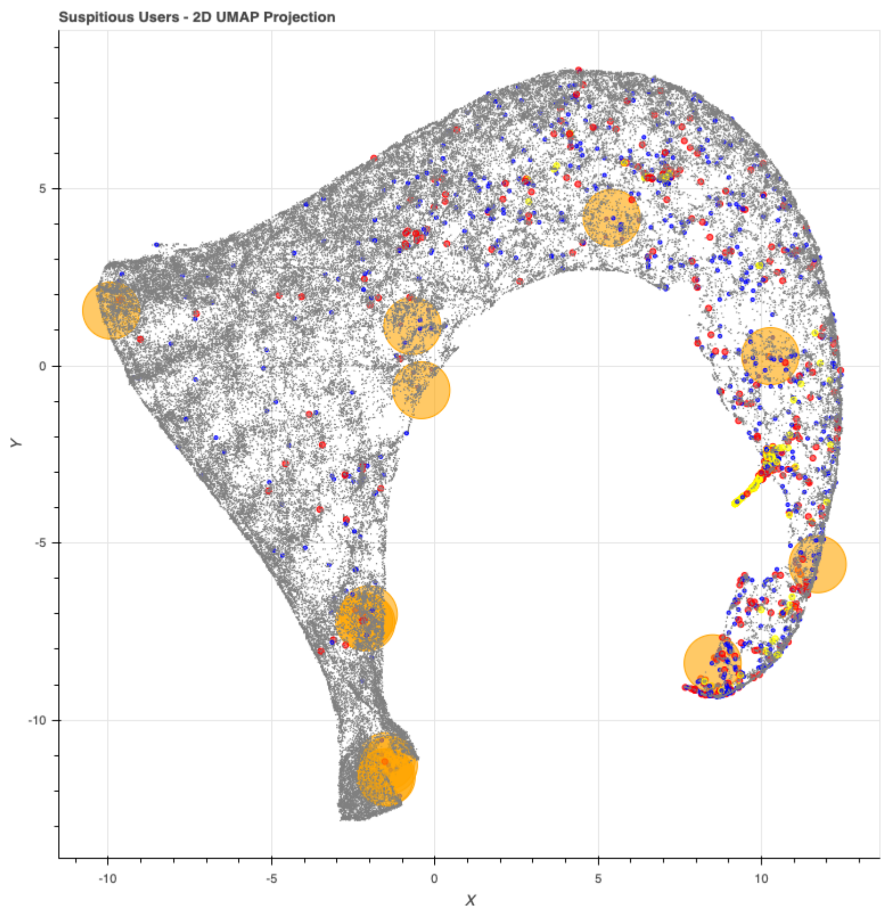


Figure 40: Suspicious Users

Figure 45 shows that username is shorter on user_cluster_1 and accounts on user_cluster_3 are younger than user_cluster_1, as shown in Figure 46 and accounts on user_cluster_1 retweet more than user_cluster_3, which is a good indication of social bots, as shown in Figure 47.

Only looking those metrics seems that accounts on user_cluster_1 (more to the right), tweet more frequently, are older, with higher retweet rate, have a full description and, do not have similarity on names (name and user-name could be inventions). At first sight, social bots could be concentrated on this area of graphics, however more work should be done here.

7.4 Filtering Mid/High-Frequency users

The next experiment is to apply UMAP to a filtered dataset, populated only with users that have posted more than 50 tweets/day in at least one occasion during the timeline window. In total, 1,195 accounts are considered, including verified users. From those, 798 accounts are Mid-Frequency (from 50 up to 144 tweets/day), and 397 are High-Frequency accounts (more than 144 tweets/day).

All users are colored in blue, except for verified users that are in yellow.

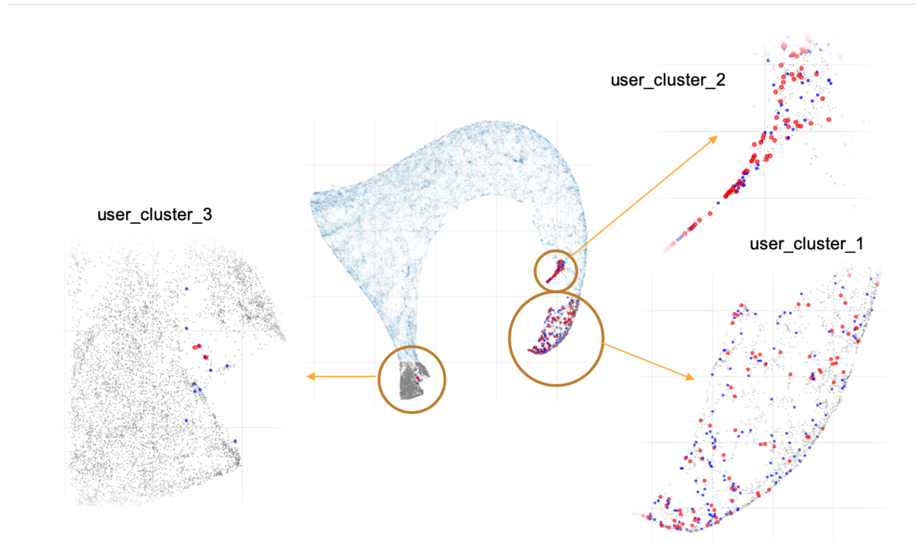


Figure 41: UMAP 2D - user selected clusters

In this case, testing with the same hyper-parameters as done with the complete dataset seems that several clusters can be defined using n_neighbors=5, as shown in Figure 48.

Now, taking the known bots spotted on previous sections and now colored in red, the result appears that the cluster formed with both x and y greater than 5, concentrate the majority of them and more precisely at its border. For reference, this area is called Cluster 0.

Using Bokeh [38], and doing zooming, it is possible to execute an exploration on the users that are part of the cluster 0 (49. Once capturing their user names, a manual analysis is done on their features in the same way that was done in previous sections.

When possible, the users are also tested with Botometer, PEGABOT, and TweetBotOrNot. Botometer missed almost all users, and PEGABOT is more assertive in finding bots. When working TweetBotOrNot seems better when compared with Botometer, but it is precarious and usually presented error.

On the sequence, selected users are listed with the main conclusion about their behavior.

@mrgrtgautier = BOT

- 100% RT
- 85% of all tweets have hashtags
- Almost all tweets (53/55) at a single day
- Young account: 12 days
- Active account - Last tweet dec/2017
- Pegabot: 8%
- Botometer: 22%

@ChristianPolo7 = BOT

- 87% RT
- 97% of all tweets have mentions

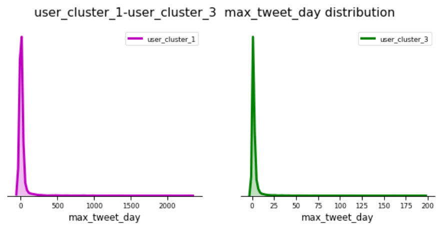


Figure 42: Max tweets/day by cluster

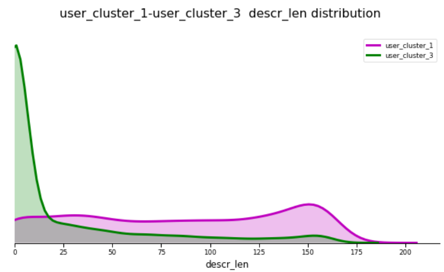


Figure 43: Descript. length by cluster

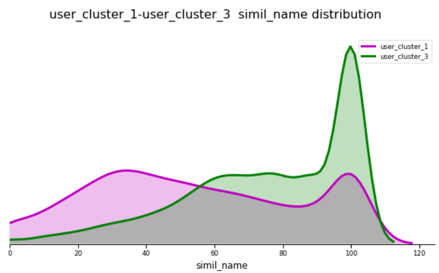


Figure 44: Similarity Name/User-Name by cluster

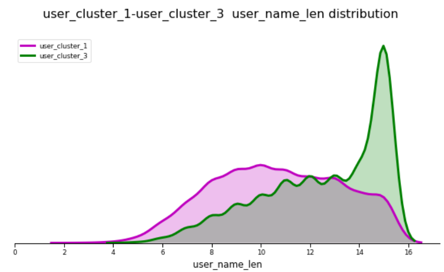


Figure 45: User-Name length by cluster

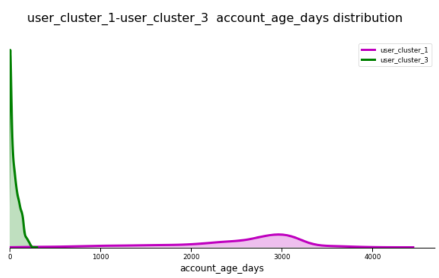


Figure 46: Account Age (days) by cluster

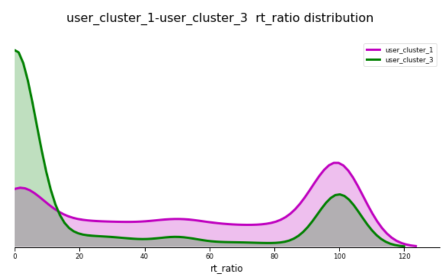


Figure 47: Retweet ratio by cluster

- Very active account during elections and few months after
- Young account: 15 days
- Active account - Last tweet march/2018
- Botometer: No (22%)
- PegaBot: 41% (Network: 85%)

@Conapro_jjcc = BOT

- 0% RT
- 85% of all tweets have a single mention (@Guillier)
- Only posting on 2 days same tweet/day
- Young account: 22 days
- Active account
- Last tweet march/2018
- Botometer: Bot (92%)
- PegaBot: No (16%)

@Atletadelgol32 = BOT

- 97% RT

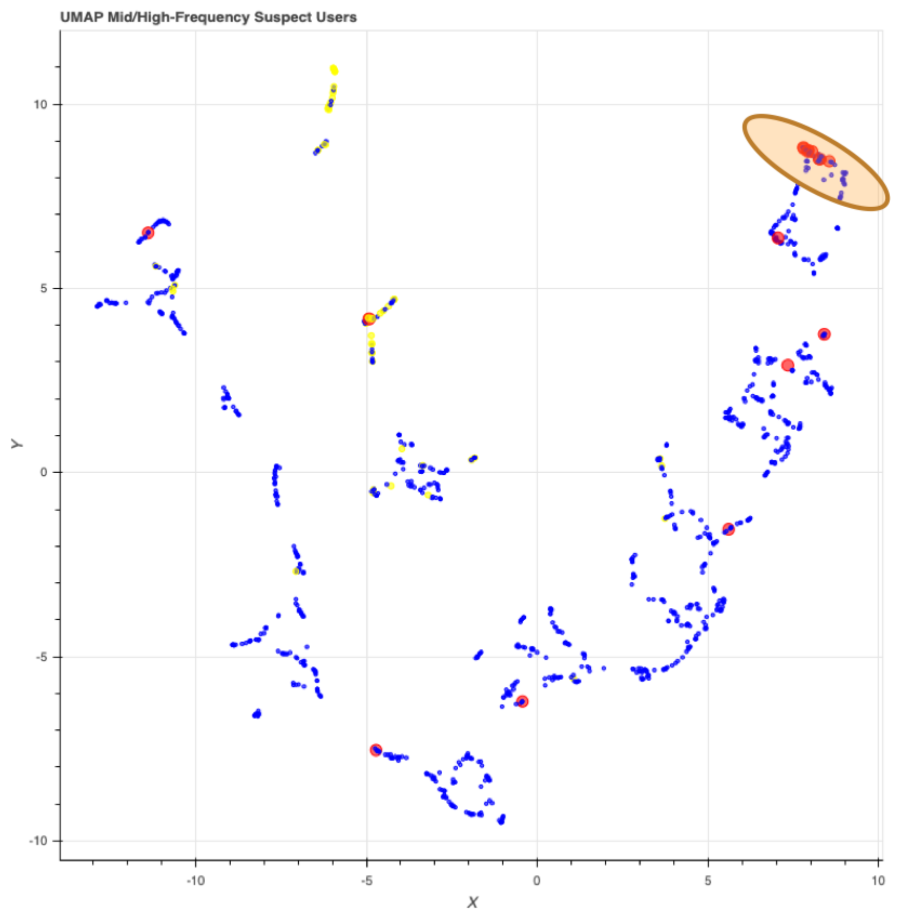


Figure 48: Suspect Users

- 100% of all tweets have mentions
- Only posting on 2 days
- Young account: 3 days
- Not Active account

@ElCentinelaMPE = BOT

- 1% RT
- almost 100% of all tweets have hashtags, being #Elecciones on 96 of them
- Only posting on 5 days (81% of all tweets (114 on the same day)
- Young account: created start of the month and did not post after nov/2017
- Active account
- Botometer: No (28%)
- Pegabot: No find

@JuanManuelCorn5 = BOT

- 1% RT
- 100% of all tweets have mentions: a lot of them!
- Average text length per tweet: 654 (@XXX)
- Only posting a few days after elections
- Young account: 92 days and do not post after dec/2017

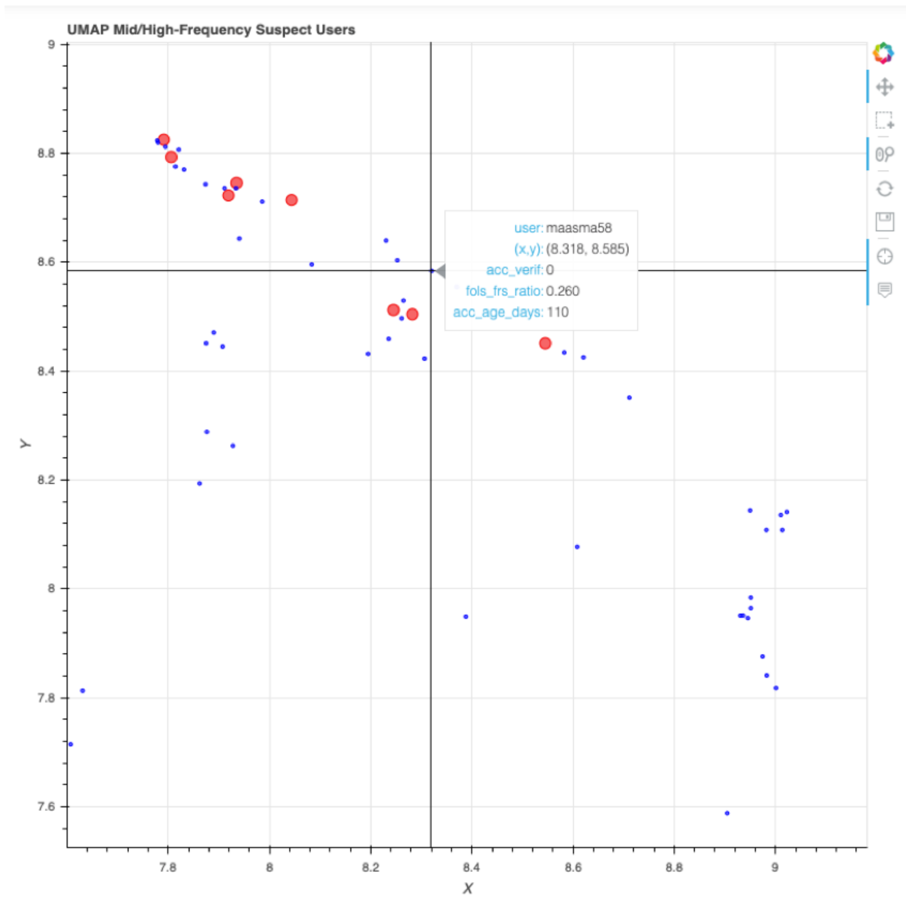


Figure 49: Cluster Exploration

- Active account
- Pegabot: 47% (Network 58%)
- Botometer: No (28%)

@Santiag87306226 = BOT

- 5% RT
- 99% of all tweets have mentions
- 89% have hashtags
- 70% of all tweets on the same day (6/nov), almost all with same text
- Young account: 44 days
- Blocked account

@SFelipeAlegreJ = Possible BOT or Cyborg

- 0% RT
- 100% of all tweets have mentions
- 88% have hashtags
- Almost all tweets on the same day (23/nov), almost all with same text
- Young account: 93 days
- Active account
- Botometer: no (34%)

- Pegabot: No found

@Trab_vXguillier = Possible BOT or Cyborg

- 1 day with the same tweet, having almost half of analyzed tweets

@Sumate_Guillier = BOT

- 3% RT
- 195 tweets on the same day (23/nov), almost all with two different texts
- Young account: created after 1st round election
- Not Active account

@viejofasho = Possible BOT or cyborg

- 0% RT
- 100% mentions, with multiples mentions on a single tweet
- Average text length per tweet: 344
- Young account: created end of October/17
- 5,725 in 9 months
- Active account, but w/o tweet since mid/18.
- PegaBot: 42% (77%:Network)
- Botometer: No (18%)
- TweetBotOrNot: Error

@RResponsablecl = Possible BOT or cyborg

- One day (26/nov) with 162 tweets, 2 different texts.
- young account, created same month (nov/17)
- still active, but seems normal nowadays
- Pegabot Yes (66%)
- Botometer: No (24%)

@BassaRiveros = Possible BOT or cyborg

- one day (26/nov) with 162 tweets, 2 different texts.
- young account, created same month (nov/17)
- still active, but seems normal nowadays
- Pegabot Yes (100%)
- Botometer: No (36%)

@arqmneira = Possible NOT BOT

- PegaBot: 81%
- Botometer: no (10%)
- TweetBotOrNot: Error

@Ignacio90415476 = Possible a cyborg

- Account created 90 days before the start of nov/17
- Today is active and posted 6,000 tweets/year since 2017
- Botometer: No
- PegaBot: Yes (76%)

@maasma58 = Possible bot

- Account created 90 days before the start of nov/17
- Today Blocked

@Aptimate = Possible cyborg

- Account created 10 days before the start of nov/17
- Today active
- Botometer: 14%

- PegaBot: 36%

@mas_estudiantil = Possible bot

- Few activities and one day with the same tweet repeated
- Today active but w/o post
- Botometer: Not find
- PegaBot: Not Find

7.5 User Behavior Clustering Results

Manually exploring each one of those accounts selected from cluster 0 proves that the vast majority of them have, in fact, a bot (or cyborg) behavior. When plotting those accounts on a Y/Z 3D UMAP visualization (complete user dataset), they also seem to be concentrate on one of its borders, as shown in Figure 50.

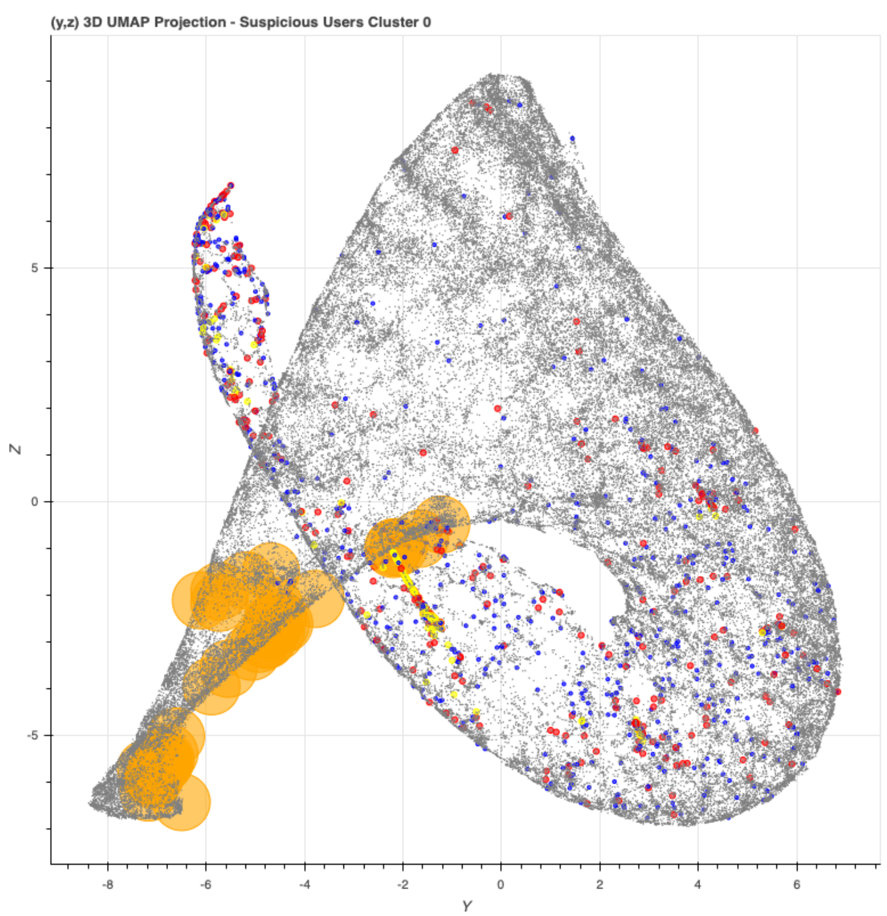


Figure 50: (y,z) plan of 3D UMAP Proj. - Cluster 0

This result is auspicious and is in line with [16], where the researches identify 10 distinct clusters, as shown in Figure 51. In that work, researchers create a 2-dimensional projection of users also obtained by a dimensionality reduction technique but using t-SNE [37] instead of UMAP. Varol et al. representation uses 100 features extracted from user accounts, which should be more representative than the 31 used on this work. From the 10 observed clusters, three of them, namely C0–C2, have high average bot scores, which was manually verified.

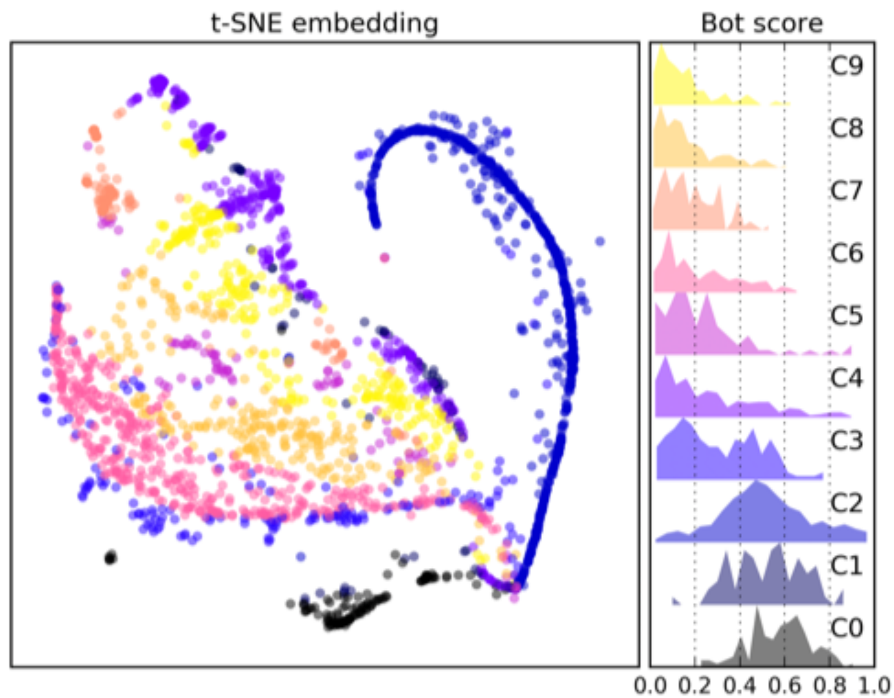


Figure 51: t-SNE Clusters - Varol et al. 2017

8 Future works

The similarity between users in this work is calculated based on their 31-dimensional representation in the feature space and is still challenging to spot a clear cluster of similar social bot behavior more automatically. Future work should capture more features, focusing on timing and network.

Once a significant part of the analysis is done manually, an API similar to [39] should be developed to explore suspicious accounts, extracting features from its more current tweets.

Also, the methodology developed in this study should be applied to different tweet datasets more significant and not biased, increasing the chance of finding suspicious social bot behavior.

9 Conclusion

Today, the traditional definition of fully automated bots acting on social media space, can not be applied as it, because it is more common having humans controlling such accounts, alternating its activities between "human" and "bot", the called "cyborgs", what difficult their detection. Simple bots are less and less found, and start studying the frequency of tweets seems the right path to follow.

In this work, a framework was presented, where no-structured data as text extracted from millions of tweets can be converted to a user-oriented dataset of engineered features to be studied using data science techniques. Applying dimension reduction techniques as UMAP leads to the conclusion that high-frequency accounts have several features in common, and it is worth to be explored deeply.

Acknowledgments
The analysis was performed in Python using Jupyter Notebooks, jointly with the Scikit-Learn, Pandas, Seaborn, Bokeh, Plotly, UMAP, Tweepy, and Botometer. It is essential to recognize the valuable advice, considerations, and share of experiences provided by Eduardo Graells-Garrido (UDD/BSC), Loreto Bravo (UDD), Leo Ferres (UDD), Maristela Rovai (SDSU), Ilza Rovai and Mauricio Pinto.

Source Code
Source code can be found at https://zenodo.org/record/3576148#.XfUbsi2ZNTY

Cite as
Rovai, Marcelo Jose. (2019, December 14). Studying Twitter User Accounts: Spotting Suspicious Social Bot Behavior (Version 2). Zenodo. http://doi.org/10.5281/zenodo.3576148

References
1. The Russians Are Meddling Again, this Time in Chile, Warns US Diplomat. https://www.rt.com/news/471945-russian-interference-chile-protests/ Accessed 2019-11-16
2. Bots in Brazil: The Activity of Social Media Bots in Brazilian Elections. https://www.wilsoncenter.org/blog-post/bots-brazil-the-activity-social-media-bots-brazilian-elections Accessed 2019-11-20
3. Santander, P., Elórtegui, C., González, C., Allende-Cid, H., Palma, W.: Redes sociales, inteligencia computacional y predicción electoral: el caso de las primarias presidenciales de chile 2017 **0**(41), 41–5656. doi:10.7764/cdi.41.1218. Accessed 2019-08-30
4. Study: Russian Twitter Bots Sent 45k Brexit Tweets Close to Vote. https://techcrunch.com/2017/11/15/study-russian-twitter-bots-sent-45k-brexit-tweets-close-to-vote/ Accessed 2019-11-20
5. Bots and Automation over Twitter During the U.S. Election. https://comprop.oii.ox.ac.uk/research/working-papers/bots-and-automation-over-twitter-during-the-u-s-election/ Accessed 2019-11-16
6. Shao, C., Ciampaglia, G.L., Varol, O., Yang, K.-C., Flammini, A., Menczer, F.: The spread of low-credibility content by social bots **9**(1), 4787. doi:10.1038/s41467-018-06930-7. Accessed 2019-06-13
7. Bot Traffic Report 2016. https://www.imperva.com/blog/bot-traffic-report-2016/ Accessed 2019-11-16
8. Bad Bot Report 2019: The Bot Arms Race Continues. https://www.imperva.com/resources/resource-library/reports/bad-bot-report-2019-the-bot-arms-race-continues/ Accessed 2019-11-16
9. Grimme, C., Preuss, M., Adam, L., Trautmann, H.: Social bots: Human-like by means of human control? Big Data **5** (2017). doi:10.1089/big.2017.0044
10. How to Spot a Twitter Bot. https://www.symantec.com/blogs/election-security/spot-twitter-bot Accessed 2019-11-16
11. Ahmed, W., Bath, P.A., Demartini, G.: Chapter 4: Using twitter as a data source: An overview of ethical, legal, and methodological challenges. In: Woodfield, K. (ed.) Advances in Research Ethics and Integrity vol. 2, pp. 79–107. Emerald Publishing Limited. doi:10.1108/S2398-601820180000002004. http://www.emeraldinsight.com/doi/10.1108/S2398-601820180000002004 Accessed 2019-10-10
12. The Follower Factory. https://www.nytimes.com/interactive/2018/01/27/technology/social-media-bots.html Accessed 2019-11-16
13. Platform Manipulation and Spam Policy. https://help.twitter.com/en/rules-and-policies/platform-manipulation Accessed 2019-11-16
14. Bot or Not: an End-to-end Data Analysis in Python. http://www.erinshellman.com/bot-or-not/ Accessed 2019-11-16
15. Ferrara, E., Varol, O., Davis, C., Menczer, F., Flammini, A.: The rise of social bots **59**(7), 96–104. doi:10.1145/2818717. 1407.5225. Accessed 2019-06-13
16. Varol, O., Ferrara, E., Davis, C.A., Menczer, F., Flammini, A.: Online human-bot interactions: Detection, estimation, and characterization. 1703.03107. Accessed 2019-06-13
17. Minnich, A., Chavoshi, N., Koutra, D., Mueen, A.: BotWalk: Efficient adaptive exploration of twitter bot networks. In: Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017 - ASONAM '17, pp. 467–474. ACM Press. doi:10.1145/3110025.3110163. http://dl.acm.org/citation.cfm?doid=3110025.3110163 Accessed 2019-07-06
18. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M.: The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In: Proceedings of the 26th International Conference on World Wide Web Companion - WWW '17 Companion, pp. 963–972. ACM Press. doi:10.1145/3041021.3055135. http://dl.acm.org/citation.cfm?doid=3041021.3055135 Accessed 2019-07-01
19. Davis, C.A., Varol, O., Ferrara, E., Flammini, A., Menczer, F.: Botornot: A system to evaluate social bots, 273–274. doi:10.1145/2872518.2889302. 1602.00975. Accessed 2019-06-13
20. Observatory on Social Media. https://osome.iuni.iu.edu/ Accessed 2019-11-20
21. Kearney, M.W.: tweetbotornot: Detecting Twitter bots (web app: https://mikewk.shinyapps.io/botornot/). Unpublished. type: dataset (2018). doi:10.13140/RG.2.2.10732.82562. http://rgdoi.net/10.13140/RG.2.2.10732.82562 Accessed 2019-11-20
22. The Institute for Technology Society of Rio. https://itsrio.org/en/en-home/ Accessed 2019-11-20

23. Spottingbot GitHub - Analyzing Profile on Twitter for Detect Behavior of a Spamming Bot. https://github.com/AppCivico/spottingbot Accessed 2019-11-20
24. PEGABOT. https://pegabot.com.br Accessed 2019-11-19
25. Cresci, S., Di Pietro, R., Petrocchi, M., Spognardi, A., Tesconi, M.: DNA-inspired online behavioral modeling and its application to spambot detection. 1602.00110. Accessed 2019-07-02
26. Counting Characters. https://developer.twitter.com/en/docs/basics/counting-characters Accessed 2019-11-16
27. Following FAQs. https://help.twitter.com/en/using-twitter/following-faqs Accessed 2019-11-16
28. Freitas, C.A., Benevenuto, F., Ghosh, S., Veloso, A.: Reverse engineering socialbot infiltration strategies in twitter. 1405.4927. Accessed 2019-11-12
29. McInnes, L., Healy, J., Melville, J.: UMAP: Uniform manifold approximation and projection for dimension reduction. 1802.03426. Accessed 2019-11-11
30. Tweet Object. https://developer.twitter.com/en/docs/tweets/data-dictionary/overview/tweet-object Accessed 2019-12-09
31. BotSpot: Twelve Ways to Spot a Bot. https://medium.com/dfrlab/botspot-twelve-ways-to-spot-a-bot-aedc7d9c110c Accessed 2019-11-16
32. How to Spot a Bot (or Not): The Main Indicators of Online Automation, Co-ordination and Inauthentic Activity. https://firstdraftnews.org/latest/how-to-spot-a-bot-or-not-the-main-indicators-of-online-automation-co-ordination-and-inauthentic-activity/ Accessed 2019-12-10
33. Gilani, Z., Farahbakhsh, R., Tyson, G., Wang, L., Crowcroft, J.: Of bots and humans (on twitter). In: Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017 - ASONAM '17, pp. 349–354. ACM Press. doi:10.1145/3110025.3110090. http://dl.acm.org/citation.cfm?doid=3110025.3110090 Accessed 2019-11-13
34. The Not-so-simple Science of Social Media 'bots'. https://firstdraftnews.org/latest/the-not-so-simple-science-of-social-media-bots/ Accessed 2019-12-09
35. Botometer An OSoMe Project (bot•o•meter). https://botometer.iuni.iu.edu/!/ Accessed 2019-11-19
36. TweetBotOrNot. https://mikewk.shinyapps.io/botornot/ Accessed 2019-11-19
37. T-distributed Stochastic Neighbor Embedding. https://en.wikipedia.org/wiki/T-distributed$_{s}tochastic_{n}eighbor_{e}mbeddingAccessed2019-11-16$
38. Bokeh. https://docs.bokeh.org/en/latest/ Accessed 2019-11-16
39. Udd SpotBot Producto de Datos. https://github.com/Mjrovai/UDD_Master_Data_Science/tree/master/PD_SpotBot_Final_Project Accessed 2019-12-14

Additional Files

Appendices - User data sample

Appendix A

Data for Suspicious users.jpg

```
Info Data for @fedoraletelier

Name:                        fedoraletelier
Name Length:                 14
@user number Numeric Chars:  0
@user and name similarity:   0
User Id:                     2465345439
Default_Photo:               True
Photo URL:                   http://abs.twimg.com/sticky/default_profile_im
ages/default_profile_normal.png
Acc Verified:                False
Has Location:                False
Location:
default_profile:             True
Has Description:             False
Description:
Description length:          0
Account Active:              Active

Number of Tweets analyzed:          690
Last Tweet:                         2017-11-29T19:27:32.000000000
Older Tweet Analyzed:               2017-10-31T23:07:51.000000000
Account Active age (in days)        1,333.0
Average recent tweets per day:      24.64
Maximum Recent Tweets Per Day:      85 at day 29
Average tweets per day since start: 161.34
Total Tweets since start:           215,069
Followers_count:                    2,242
Friends_following_count             1,886
Followers/Following_index:          1.19
Favourites (Like) count:            156,764
Retweet_Like_index:                 0.0
Retweet Ratio:                      43%
unique mentions cnt:                325
Mention Ratio:                      70%
Mention index:                      0.16
unique hashtags cnt:                50
Hashtag Ratio:                      49%
Hashtag Index:                      0.1
Average URLs per tweet:             0.45
Average text length per tweet:      137.0

       [Tweets Sample at Peak Day]
 1429686    RT @Carmen_muller: @aldocardinali Guillier ha ...
1431240    RT @supernovaf_1000: #EstonoesPlazaItalia @Mov...
1433787    RT @Carmen_muller: @PadresPartSubv @mbachelet ...
1433812    RT @SoniaSHernandez: @PadresPartSubv @mbachele...
1435809    RT @Bella_DiGenaro: Extra! Extra! Me acaban de...
1435834    RT @klaudiaunik: @Bella_DiGenaro @guillier @je...
1435873    RT @Sirius4321: @Bella_DiGenaro @Makeka @guill...
1436465    RT @supernovaf_1000: #Cadem @guillier MIENTE N...
1439928    RT @alecabanast: @Commander_SB @anzunza @sebas...
1461708    RT @aeristac: @armandoredondo1 @aggrezgmailcom...
```

Appendix B

Data for Suspicious users-2.jpg

```
Info Data for @Aliciacarafipl3

Name:                         Aliciacarafiplanella
Name Length:                  20
@user number Numeric Chars:   1
@user and name similarity:    0
User Id:                      801131674402701312
Default_Photo:                True
Photo URL:                    http://abs.twimg.com/sticky/default_profile_im
ages/default_profile_normal.png
Acc Verified:                 False
Has Location:                 False
Location:
default_profile:              True
Has Description:              False
Description:
Description length:           0
Account Active:               Active

Number of Tweets analyzed:          747
Last Tweet:                         2017-11-30T22:22:11.000000000
Older Tweet Analyzed:               2017-11-01T21:52:14.000000000
Account Active age (in days)        373.0
Average recent tweets per day:      25.76
Maximum Recent Tweets Per Day:      78 at day 6
Average tweets per day since start: 69.12
Total Tweets since start:           25,781
Followers_count:                    200
Friends_following_count             113
Followers/Following_index:          1.77
Favourites (Like) count:            13,595
Retweet_Like_index:                 0.0
Retweet Ratio:                      96%
unique mentions cnt:                622
Mention Ratio:                      100%
Mention index:                      0.27
unique hashtags cnt:                96
Hashtag Ratio:                      19%
Hashtag Index:                      0.5
Average URLs per tweet:             0.15
Average text length per tweet:      140.0

       [Tweets Sample at Peak Day]
 144348    RT @LuisJValdivia: El problema de Guillier no ...
149179    RT @cla141966: #Tolerancia0 Guillier "estoy en...
149241    RT @pablolirar: Villegas se está paseando a Gu...
149269    RT @joseotero78: Guillier no tiene respaldo. E...
149374    RT @pablolirar: Jajajaja @Guillier dice que su...
149443    RT @joseotero78: Guillier dice que Chile crece...
149530    RT @pablolirar: .@Guillier:"Chile es el país n...
149716    RT @joseotero78: Mas de lo mismo! Guillier es ...
149776    RT @Regia_Pam: @Claunubed @guillier Esta noche...
149827    RT @joseantoniokast: .@guillier dice que soy u...
```

Appendix C

Data for Suspicious users-3.jpg

```
Info Data for @Dolores09072598

Name:                        Dolores Nunez
Name Length:                 13
@user number Numeric Chars: 8
@user and name similarity:  0
User Id:                     874119200205418497
Default_Photo:               True
Photo URL:                   http://abs.twimg.com/sticky/default_profile_im
ages/default_profile_normal.png
Acc Verified:                False
Has Location:                False
Location:
default_profile:             True
Has Description:             False
Description:
Description length:          0
Account Active:              Active

Number of Tweets analyzed:           431
Last Tweet:                          2017-11-30T18:54:12.000000000
Older Tweet Analyzed:                2017-11-03T04:13:46.000000000
Account Active age (in days)         171.0
Average recent tweets per day:       15.96
Maximum Recent Tweets Per Day:       113 at day 23
Average tweets per day since start: 0.56
Total Tweets since start:            96
Followers_count:                     28
Friends_following_count              300
Followers/Following_index:           0.09
Favourites (Like) count:             26
Retweet_Like_index:                  0.0
Retweet Ratio:                       100%
unique mentions cnt:                 384
Mention Ratio:                       100%
Mention index:                       0.44
unique hashtags cnt:                 79
Hashtag Ratio:                       28%
Hashtag Index:                       0.49
Average URLs per tweet:              0.14
Average text length per tweet:       129.0

       [Tweets Sample at Peak Day]
 1017117    RT @KiltroKaniechna: Quiero que gane Guillier,...
1017327    RT @pupi_oyanedel: Solo quiero a @guillier Pre...
1018146    RT @simonaxm: #LasCarasDeLaMoneda\n#GuillierGi...
1018208    RT @T13: 🔶 #LasCarasdelaMoneda | @guillier: "L...
1018312    RT @JovenesGuillier: Razones sobran, #SúmateAG...
1018366    RT @BelaAnjali: @aguilo_sergio @danieljadue @c...
1018399    RT @lufernavi: @sebasantanders @camila_vallejo...
1019101    RT @ChristianPolo7: #LasCarasDeLaMoneda Guilli...
1019631    RT @lorpalomita: @cron1411 @Coke92 Por 💌 a @mb...
1020345    RT @CARLOURREA: Vamos Alejandro Guillier. Todo...
```

Appendix D

Data for Suspicious users-4.jpg

```
Info Data for @AlbertoMayol

Name:                        Alberto Mayol
Name Length:                 13
@user number Numeric Chars: 0
@user and name similarity:  0
User Id:                     337542243
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/8927804748
29078530/4VeDYUuZ_normal.jpg
Acc Verified:                False
Has Location:                False
Location:
default_profile:             True
Has Description:             True
Description:                 Papá de Alessandro, esposo de Claudia, militan
te del Frente Amplio y de la U. Con el corazón a la izquierda.
Description length:          108
Account Active:              Active

Number of Tweets analyzed:          6930
Last Tweet:                         2017-11-28T15:55:56.000000000
Older Tweet Analyzed:               2017-11-13T01:51:06.000000000
Account Active age (in days)        2,325.0
Average recent tweets per day:      462.0
Maximum Recent Tweets Per Day:      5163 at day 13
Average tweets per day since start: 2.26
Total Tweets since start:           5,265
Followers_count:                    168,523
Friends_following_count             479
Followers/Following_index:          351.82
Favourites (Like) count:            443
Retweet_Like_index:                 0.0
Retweet Ratio:                      0%
unique mentions cnt:                6
Mention Ratio:                      75%
Mention index:                      0.0
unique hashtags cnt:                2
Hashtag Ratio:                      20%
Hashtag Index:                      0.0
Average URLs per tweet:             0.0
Average text length per tweet:      185.0

       [Tweets Sample at Peak Day]
 403036    Impresionante que @sebastianpinera sea incapaz...
403061    Impresionante que @sebastianpinera sea incapaz...
403075    Impresionante que @sebastianpinera sea incapaz...
403078    Impresionante que @sebastianpinera sea incapaz...
403083    Impresionante que @sebastianpinera sea incapaz...
403085    Impresionante que @sebastianpinera sea incapaz...
403095    Impresionante que @sebastianpinera sea incapaz...
403097    Impresionante que @sebastianpinera sea incapaz...
403098    Impresionante que @sebastianpinera sea incapaz...
403100    Impresionante que @sebastianpinera sea incapaz...
```

Appendix E

Data for Suspicious users-5.jpg

```
Info Data for @Tomaskovacic

Name:                       Tomas Iturbe Covacic
Name Length:                20
@user number Numeric Chars: 0
@user and name similarity:  0
User Id:                    94687772
Default_Photo:              False
Photo URL:                  http://pbs.twimg.com/profile_images/8925741438
40796672/j37U6wrm_normal.jpg
Acc Verified:               False
Has Location:               True
Location:                   Viña del Mar
default_profile:            False
Has Description:            True
Description:                Ingeniero Comercial | Economista en formación
| Coordinador Nacional de @LaBrujulaCL | Viñamarino y Cruzado
Description length:         107
Account Active:             Active

Number of Tweets analyzed:          2062
Last Tweet:                         2017-11-30T16:06:34.000000000
Older Tweet Analyzed:               2017-11-01T15:58:23.000000000
Account Active age (in days)        2,917.0
Average recent tweets per day:      71.1
Maximum Recent Tweets Per Day:      1962 at day 21
Average tweets per day since start: 19.98
Total Tweets since start:           58,284
Followers_count:                    2,302
Friends_following_count             510
Followers/Following_index:          4.51
Favourites (Like) count:            619
Retweet_Like_index:                 0.0
Retweet Ratio:                      1%
unique mentions cnt:                58
Mention Ratio:                      5%
Mention index:                      0.32
unique hashtags cnt:                13
Hashtag Ratio:                      1%
Hashtag Index:                      0.31
Average URLs per tweet:             0.0
Average text length per tweet:      243.0

       [Tweets Sample at Peak Day]
 819662    @HalunkeValnor Compa, Bitar lleva más de dos m...
839341    RT @betojandro: De verdad un saco de wea tuite...
842770    RT @BeaSanchezYTu: “Yo no quiero un gobierno d...
851582    RT @RedGuillier: "El país habló fuerte y claro...
854504    @olivares3891 @NuevaMayoriacl @guillier Te fal...
875591    Ya, lean los cambios del comando nacional de G...
895915    1988: “Si gana el NO seremos Cuba”\n1989: “Si ...
896126    1988: “Si gana el NO seremos Cuba”\n1989: “Si ...
896135    1988: “Si gana el NO seremos Cuba”\n1989: “Si ...
```

Appendix F

Data for Suspicious users-6.jpg

```
Info Data for @andres20ad

Name:                        Andrés
Name Length:                 6
@user number Numeric Chars:  2
@user and name similarity:   0
User Id:                     762803779737616384
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/7628061062
84515328/y4AvLMUb_normal.jpg
Acc Verified:                False
Has Location:                False
Location:
default_profile:             True
Has Description:             True
Description:                 Uno de muchos, que luchan por mejorar este mun
do, con mayor justicia, solidaridad e igualdad
Description length:          92
Account Active:              Active

Number of Tweets analyzed:           3060
Last Tweet:                          2017-11-30T23:43:09.000000000
Older Tweet Analyzed:                2017-11-03T02:54:41.000000000
Account Active age (in days)         478.0
Average recent tweets per day:       113.33
Maximum Recent Tweets Per Day:       1583 at day 18
Average tweets per day since start:  18.93
Total Tweets since start:            9,049
Followers_count:                     6,464
Friends_following_count              6,208
Followers/Following_index:           1.04
Favourites (Like) count:             8,939
Retweet_Like_index:                  0.0
Retweet Ratio:                       0%
unique mentions cnt:                 69
Mention Ratio:                       5%
Mention index:                       0.27
unique hashtags cnt:                 10
Hashtag Ratio:                       75%
Hashtag Index:                       0.0
Average URLs per tweet:              0.09
Average text length per tweet:       271.0

       [Tweets Sample at Peak Day]
 579384    En 1988 millones de chilenos se enfrentaron a ...
579419    En 1988 millones de chilenos se enfrentaron a ...
579476    En 1988 millones de chilenos se enfrentaron a ...
579478    En 1988 millones de chilenos se enfrentaron a ...
579492    En 1988 millones de chilenos se enfrentaron a ...
579503    En 1988 millones de chilenos se enfrentaron a ...
579527    En 1988 millones de chilenos se enfrentaron a ...
579556    En 1988 millones de chilenos se enfrentaron a ...
579579    El gobierno de Piñera fue el más corrupto de t...
579593    El gobierno de Piñera fue el más corrupto de t...
```

Appendix G

Data for Suspicious users-7.jpg

```
Info Data for @NelsonCL28

Name:                        Nelson Sánchez G.
Name Length:                 17
@user number Numeric Chars:  2
@user and name similarity:   0
User Id:                     175420136
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/9323402979
16387328/uUSFt7NI_normal.jpg
Acc Verified:                False
Has Location:                True
Location:                    Valparaíso, Chile
default_profile:             False
Has Description:             True
Description:                 Praise Kek!
Description length:          11
Account Active:              Active

Number of Tweets analyzed:          1669
Last Tweet:                         2017-11-19T20:20:33.000000000
Older Tweet Analyzed:               2017-11-19T20:20:33.000000000
Account Active age (in days)        2,662.0
Average recent tweets per day:      inf
Maximum Recent Tweets Per Day:      1669 at day 19
Average tweets per day since start: 0.02
Total Tweets since start:           50
Followers_count:                    26
Friends_following_count             22
Followers/Following_index:          1.18
Favourites (Like) count:            36
Retweet_Like_index:                 0.0
Retweet Ratio:                      0%
unique mentions cnt:                0
Mention Ratio:                      0%
Mention index:                      0.0
unique hashtags cnt:                4
Hashtag Ratio:                      100%
Hashtag Index:                      0.0
Average URLs per tweet:             1.0
Average text length per tweet:      279.0

       [Tweets Sample at Peak Day]
 663850    Impresentable suplantación de identidad! Concu...
663892    Impresentable suplantación de identidad! Concu...
663919    Impresentable suplantación de identidad! Concu...
664029    Impresentable suplantación de identidad! Concu...
664114    Impresentable suplantación de identidad! Concu...
664266    Impresentable suplantación de identidad! Concu...
664318    Impresentable suplantación de identidad! Concu...
664340    Impresentable suplantación de identidad! Concu...
664422    Impresentable suplantación de identidad! Concu...
664528    Impresentable suplantación de identidad! Concu...
```

Appendix H

Data for Suspicious users-8.jpg

```
Info Data for @Ivonomas

Name:                        Ivo Barrientos
Name Length:                 14
@user number Numeric Chars:  0
@user and name similarity:   0
User Id:                     1677545442
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/3788000003
11704613/57dba5d1d296053000c81f1acbf9cd60_normal.jpeg
Acc Verified:                False
Has Location:                False
Location:
default_profile:             True
Has Description:             True
Description:                 periodista sin título que busca solamente dese
nmascarar la demagogia que abunda en este espacio. Si me mencionas te hago
RT.
Description length:          124
Account Active:              Active

Number of Tweets analyzed:          299
Last Tweet:                         2017-11-30T21:03:14.000000000
Older Tweet Analyzed:               2017-11-01T07:09:21.000000000
Account Active age (in days)        1,566.0
Average recent tweets per day:      10.31
Maximum Recent Tweets Per Day:      40 at day 30
Average tweets per day since start: 4.86
Total Tweets since start:           7,618
Followers_count:                    2,149
Friends_following_count             3,254
Followers/Following_index:          0.66
Favourites (Like) count:            528
Retweet_Like_index:                 0.0
Retweet Ratio:                      1%
unique mentions cnt:                3
Mention Ratio:                      1%
Mention index:                      1.0
unique hashtags cnt:                9
Hashtag Ratio:                      14%
Hashtag Index:                      0.21
Average URLs per tweet:             0.9
Average text length per tweet:      137.0

       [Tweets Sample at Peak Day]
 1515720    Ex ministro de Piñera compartió Photoshop de M...
1528400    .PamJiles por eventual apoyo del FA a Guillier...
1528401    Felipe Kast hace llamado a Alejandro Guillier ...
1528420    RD no se sumará a campaña de Guillier: "Querem...
1533205    VIDEO | Guillier: "El Frente Amplio quiere no ...
1536375    "Cuánta hipocresía en una foto": la imagen que...
1538726    Luis Mesina pide a Alejandro Guillier aclarar ...
1540992    Pamela Jiles, diputada electa del Frente Ampli...
1543988    "No+AFP" se moviliza en la Alameda antes de cr...
```

Appendix I

Data for Suspicious users-9.jpg

```
Info Data for @EncuestaExpress

Name:                        #EncuestaExpressCL
Name Length:                 18
@user number Numeric Chars: 0
@user and name similarity:  0
User Id:                     921483211514970114
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/9240128801
64540417/cLUUNNEv_normal.jpg
Acc Verified:                False
Has Location:                True
Location:                    Chile
default_profile:             False
Has Description:             True
Description:                 Medio Independiente.
#NoTeQuedesSinVoz!!
Si no votas ¿Con qué cara pides cambios en la sociedad?
#ElPoderEstaEnTuVoto
Description length:          117
Account Active:              Active

Number of Tweets analyzed:          1314
Last Tweet:                         2017-11-26T16:50:34.000000000
Older Tweet Analyzed:               2017-11-01T00:19:55.000000000
Account Active age (in days)        36.0
Average recent tweets per day:      52.56
Maximum Recent Tweets Per Day:      748 at day 20
Average tweets per day since start: 9.61
Total Tweets since start:           346
Followers_count:                    32
Friends_following_count             45
Followers/Following_index:          0.71
Favourites (Like) count:            83
Retweet_Like_index:                 0.0
Retweet Ratio:                      3%
unique mentions cnt:                43
Mention Ratio:                      90%
Mention index:                      0.02
unique hashtags cnt:                34
Hashtag Ratio:                      81%
Hashtag Index:                      0.02
Average URLs per tweet:             0.08
Average text length per tweet:      138.0

       [Tweets Sample at Pick Day]
 761035    Esta elección se define en Segunda:\n\n¿POR QU...
761110    Esta elección se define en Segunda:\n\n¿POR QU...
761414    [ACARREO DE VOTOS]\n¿Cuántos de los votos de @...
761415    Esta elección se define en Segunda:\n\n¿POR QU...
761460    [ACARREO DE VOTOS]\n¿Cuántos de los votos de @...
761466    Esta elección se define en Segunda:\n\n¿POR QU...
761493    Esta elección se define en Segunda:\n\n¿POR QU...
761516    Esta elección se define en Segunda:\n\n¿POR QU...
```

Appendix J

Data for Suspicious users-10.jpg

```
Info Data for @RResponsablecl

Name:                         Reg Responsable Cl
Name Length:                  18
@user number Numeric Chars: 0
@user and name similarity:  0
User Id:                      924982201434898433
Default_Photo:                False
Photo URL:                    http://pbs.twimg.com/profile_images/9249862491
43836674/DKYiJprG_normal.jpg
Acc Verified:                 False
Has Location:                 False
Location:
default_profile:              False
Has Description:              True
Description:                  Buscamos transformar la política de drogas de
Chile para regular democráticamente las vías de acceso al Cannabis medicin
al y para el uso adulto.
Description length:           144
Account Active:               Active

Number of Tweets analyzed:          422
Last Tweet:                         2017-11-26T12:57:43.000000000
Older Tweet Analyzed:               2017-11-01T01:06:03.000000000
Account Active age (in days)        27.0
Average recent tweets per day:      16.88
Maximum Recent Tweets Per Day:      162 at day 26
Average tweets per day since start: 1.37
Total Tweets since start:           37
Followers_count:                    34
Friends_following_count             345
Followers/Following_index:          0.1
Favourites (Like) count:            2
Retweet_Like_index:                 0.0
Retweet Ratio:                      3%
unique mentions cnt:                51
Mention Ratio:                      72%
Mention index:                      0.06
unique hashtags cnt:                24
Hashtag Ratio:                      53%
Hashtag Index:                      0.04
Average URLs per tweet:             1.27
Average text length per tweet:      223.0

       [Tweets Sample at Pick Day]
 1251424    El Candidato Alejandro Guillier reafirma su co...
1251944    Alejandro @Guillier reafirma su compromiso por...
1253536    Alejandro @Guillier reafirma su compromiso por...
1253544    Alejandro @Guillier reafirma su compromiso por...
1253608    Alejandro @Guillier reafirma su compromiso por...
1253681    Alejandro @Guillier reafirma su compromiso por...
1253699    Alejandro @Guillier reafirma su compromiso por...
1253717    Alejandro @Guillier reafirma su compromiso por...
1253839    Alejandro @Guillier reafirma su compromiso por...
```

Appendix K

Data for Suspicious users-11.jpg

```
Info Data for @Piagutierrezs

Name:                        Pilar Gutierrez Soto
Name Length:                 20
@user number Numeric Chars: 0
@user and name similarity:  0
User Id:                     903026378903343110
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/9121626151
61495553/JvaFizmK_normal.jpg
Acc Verified:                False
Has Location:                True
Location:                    Puerto Varas, Chile
default_profile:             True
Has Description:             True
Description:                 Dirigente social
Description length:          16
Account Active:              Active

Number of Tweets analyzed:          419
Last Tweet:                         2017-11-28T22:36:15.000000000
Older Tweet Analyzed:               2017-11-01T03:08:48.000000000
Account Active age (in days)        89.0
Average recent tweets per day:      15.52
Maximum Recent Tweets Per Day:      131 at day 1
Average tweets per day since start: 19.24
Total Tweets since start:           1,712
Followers_count:                    1,030
Friends_following_count             2,539
Followers/Following_index:          0.41
Favourites (Like) count:            1,829
Retweet_Like_index:                 0.0
Retweet Ratio:                      5%
unique mentions cnt:                57
Mention Ratio:                      66%
Mention index:                      0.08
unique hashtags cnt:                6
Hashtag Ratio:                      7%
Hashtag Index:                      0.15
Average URLs per tweet:             0.9
Average text length per tweet:      154.0

       [Tweets Sample at Pick Day]
 6201    Piñera miente el país no se cae a pedazos GRAN...
6251    Piñera miente el país no se cae a pedazos GRAN...
6272    Piñera miente el país no se cae a pedazos GRAN...
6629    Piñera miente el país no se cae a pedazos GRAN...
6746    Piñera miente el país no se cae a pedazos GRAN...
6781    Piñera miente el país no se cae a pedazos GRAN...
6833    Piñera miente el país no se cae a pedazos GRAN...
6868    Piñera miente el país no se cae a pedazos GRAN...
6946    Piñera miente el país no se cae a pedazos GRAN...
7055    Piñera miente el país no se cae a pedazos GRAN...
```

Appendix L

Data for Suspicious users-12.jpg

```
Info Data for @NathalySeplved3

Name:                       Sepúlveda Natha
Name Length:                15
@user number Numeric Chars: 1
@user and name similarity:  0
User Id:                    922302808791150592
Default_Photo:              False
Photo URL:                  http://pbs.twimg.com/profile_images/9223118740
74509313/GO9ffztI_normal.jpg
Acc Verified:               False
Has Location:               True
Location:                   Metropolitana de Santiago, Chi
default_profile:            True
Has Description:            True
Description:                Más zurda que ayer!!!

Mi otra cuenta @nathalyseplved2   está sin funcionar,. nos leemos por acá.
Description length:         97
Account Active:             Active

Number of Tweets analyzed:          634
Last Tweet:                         2017-11-30T21:14:41.000000000
Older Tweet Analyzed:               2017-11-01T17:44:05.000000000
Account Active age (in days)        38.0
Average recent tweets per day:      21.86
Maximum Recent Tweets Per Day:      165 at day 20
Average tweets per day since start: 14.61
Total Tweets since start:           555
Followers_count:                    294
Friends_following_count             520
Followers/Following_index:          0.57
Favourites (Like) count:            315
Retweet_Like_index:                 0.0
Retweet Ratio:                      10%
unique mentions cnt:                94
Mention Ratio:                      87%
Mention index:                      0.13
unique hashtags cnt:                53
Hashtag Ratio:                      84%
Hashtag Index:                      0.06
Average URLs per tweet:             0.2
Average text length per tweet:      176.0

       [Tweets Sample at Pick Day]
 729046    RT @mtnancyts: @guillier @BeaSanchezYTu @marco...
730568    Los Zurdos de verdad deben unirse y dar el eje...
731302    Los Zurdos de verdad deben unirse y dar el eje...
732178    Los Zurdos de verdad deben unirse y dar el eje...
734723    Los Zurdos de verdad deben unirse y dar el eje...
734861    Los Zurdos de verdad deben unirse y dar el eje...
735795    Los Zurdos de verdad deben unirse y dar el eje...
735890    Los Zurdos de verdad deben unirse y dar el eje...
736092    Los Zurdos de verdad deben unirse y dar el eje...
```

Appendix M

Data for Suspicious users-13.jpg

```
Info Data for @ElCentinelaMPE

Name:                         El Centinela
Name Length:                  12
@user number Numeric Chars: 0
@user and name similarity:  0
User Id:                      921445622678478848
Default_Photo:                False
Photo URL:                    http://pbs.twimg.com/profile_images/9214464398
46383616/VJVnqA3F_normal.jpg
Acc Verified:                 False
Has Location:                 True
Location:                     Santiago, Chile
default_profile:              False
Has Description:              True
Description:                  Noticias y actualidad desde el Magíster en Per
iodismo UC-El Mercurio.
Description length:           69
Account Active:               Active

Number of Tweets analyzed:          141
Last Tweet:                         2017-11-20T00:44:21.000000000
Older Tweet Analyzed:               2017-11-02T17:00:04.000000000
Account Active age (in days)        30.0
Average recent tweets per day:      8.29
Maximum Recent Tweets Per Day:      114 at day 19
Average tweets per day since start: 0.47
Total Tweets since start:           14
Followers_count:                    9
Friends_following_count             25
Followers/Following_index:          0.36
Favourites (Like) count:            1
Retweet_Like_index:                 0.0
Retweet Ratio:                      1%
unique mentions cnt:                13
Mention Ratio:                      30%
Mention index:                      0.15
unique hashtags cnt:                13
Hashtag Ratio:                      90%
Hashtag Index:                      0.08
Average URLs per tweet:             0.74
Average text length per tweet:      166.0

       [Tweets Sample at Pick Day]
 620134    En las mesas de China y Hong Kong:\nPiñera 88 ...
624504    Rodeado de prensa y adherentes, Sebastián Piñe...
626233    Piñera sale resguardado tras votar. Afuera de ...
626646    En Viña del Mar, a esta hora vota el senador F...
626815    En Viña del Mar, a esta hora vota el senador F...
626863    En Viña del Mar, a esta hora vota el senador F...
626997    En Viña del Mar, a esta hora vota el senador F...
627004    En Viña del Mar, a esta hora vota el senador F...
627317    En Antofagasta, acaba de votar Alejandro Guill...
627339    En Viña del Mar, a esta hora vota el senador F...
```

Appendix N

Data for Suspicious users-14.jpg

```
Info Data for @PamelaSoler3

Name:                        gitanilla andaluza
Name Length:                 18
@user number Numeric Chars:  1
@user and name similarity:   0
User Id:                     909141300221501443
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/9264312552
89266177/CWlqixNW_normal.jpg
Acc Verified:                False
Has Location:                False
Location:
default_profile:             True
Has Description:             True
Description:                 chilena , mamá y esposa ,feliz con mi vida , l
ibre pensante ..aprendiz de bruja y por sobre todo de IZQUIERDA y este es
el medio que comparto mis ideas!
Description length:          152
Account Active:              Not Active

Number of Tweets analyzed:         136
Last Tweet:                        2017-11-30T22:36:22.000000000
Older Tweet Analyzed:              2017-11-07T01:43:58.000000000
Account Active age (in days)       75.0
Average recent tweets per day:     5.91
Maximum Recent Tweets Per Day:     82 at day 23
Average tweets per day since start: 8.33
Total Tweets since start:          625
Followers_count:                   354
Friends_following_count            353
Followers/Following_index:         1.0
Favourites (Like) count:           2,131
Retweet_Like_index:                0.0
Retweet Ratio:                     1%
unique mentions cnt:               31
Mention Ratio:                     65%
Mention index:                     0.14
unique hashtags cnt:               7
Hashtag Ratio:                     59%
Hashtag Index:                     0.08
Average URLs per tweet:            0.17
Average text length per tweet:     194.0

       [Tweets Sample at Pick Day]
 1060250    Que diferencia entre una familia que se ama po...
1060439    Que diferencia entre una familia que se ama po...
1061100    Que diferencia entre una familia que se ama po...
1061219    Que diferencia entre una familia que se ama po...
1061342    Que diferencia entre una familia que se ama po...
1061622    Que diferencia entre una familia que se ama po...
1061640    Que diferencia entre una familia que se ama po...
1062502    Que diferencia entre una familia que se ama po...
1062644    Que diferencia entre una familia que se ama po...
```

Appendix O

Data for Suspicious users-15.jpg

```
Info Data for @AShumman

Name:                        Alexander Shumman
Name Length:                 17
@user number Numeric Chars:  0
@user and name similarity:   0
User Id:                     914950957712146432
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/9150016574
06173185/XHQaAxZ0_normal.jpg
Acc Verified:                False
Has Location:                True
Location:                    ogazparan
default_profile:             True
Has Description:             True
Description:                 autodidacta
Description length:          11
Account Active:              Active

Number of Tweets analyzed:          371
Last Tweet:                         2017-11-30T03:46:18.000000000
Older Tweet Analyzed:               2017-11-02T19:51:44.000000000
Account Active age (in days)        58.0
Average recent tweets per day:      13.74
Maximum Recent Tweets Per Day:      122 at day 23
Average tweets per day since start: 115.31
Total Tweets since start:           6,688
Followers_count:                    308
Friends_following_count             4,164
Followers/Following_index:          0.07
Favourites (Like) count:            6,407
Retweet_Like_index:                 0.0
Retweet Ratio:                      99%
unique mentions cnt:                276
Mention Ratio:                      100%
Mention index:                      0.41
unique hashtags cnt:                63
Hashtag Ratio:                      41%
Hashtag Index:                      0.3
Average URLs per tweet:             0.17
Average text length per tweet:      127.0

        [Tweets Sample at Pick Day]
 1017505    RT @Tinnnto: Acá esperando a que empiece #LasC...
1017565    RT @JParadaHoyl: A punto de partir #LasCarasDe...
1017574    RT @JMAS_Region: ¡En breve! Nuestro candidato ...
1017597    RT @MPialfaro: Esperando la entrevista de nues...
1017630    RT @pellegrini_jj: #LasCarasDeLaMoneda esta fo...
1017653    RT @Sumate_Guillier: Hoy 22.30 hrs! El candida...
1017669    RT @_Garrettt_: #LasCarasDeLaMoneda lo únicos ...
1018664    RT @canal13: Amigos recuerden, hoy después de ...
1018998    RT @CiudadanosxG: #Ahora #ElPresidenteDeLaGent...
1019105    RT @Sumate_Guillier: 🔃 Hoy 22:30 !!!!! El cand...
```

Appendix P

Data for Suspicious users-16.jpg

```
Info Data for @Sumate_Guillier

Name:                         #SúmateAGuillier
Name Length:                  16
@user number Numeric Chars: 0
@user and name similarity:  0
User Id:                      933384768804110336
Default_Photo:                False
Photo URL:                    http://pbs.twimg.com/profile_images/9333854407
94632192/MwSY39xo_normal.jpg
Acc Verified:                 False
Has Location:                 True
Location:                     Chile
default_profile:              True
Has Description:              True
Description:                  Súmate a apoyar la candidatura del próximo Pre
sidente de Chile, Alejandro Guillier.
Description length:           83
Account Active:               Not Active

Number of Tweets analyzed:          530
Last Tweet:                         2017-11-29T13:47:07.000000000
Older Tweet Analyzed:               2017-11-22T18:17:45.000000000
Account Active age (in days)        6.0
Average recent tweets per day:      88.33
Maximum Recent Tweets Per Day:      195 at day 23
Average tweets per day since start: 0.33
Total Tweets since start:           2
Followers_count:                    18
Friends_following_count             32
Followers/Following_index:          0.56
Favourites (Like) count:            1
Retweet_Like_index:                 17.0
Retweet Ratio:                      3%
unique mentions cnt:                15
Mention Ratio:                      53%
Mention index:                      0.03
unique hashtags cnt:                11
Hashtag Ratio:                      79%
Hashtag Index:                      0.02
Average URLs per tweet:             0.55
Average text length per tweet:      159.0

       [Tweets Sample at Pick Day]
 1011443    Hoy 22.30 hrs! El candidato de la gente @guill...
1011591    Hoy 22.30 hrs! El candidato de la gente @guill...
1011640    Hoy 22.30 hrs! El candidato de la gente @guill...
1011706    Hoy 22.30 hrs! El candidato de la gente @guill...
1012063    Hoy 22.30 hrs! El candidato de la gente @guill...
1012223    Hoy 22.30 hrs! El candidato de la gente @guill...
1012258    Hoy 22.30 hrs! El candidato de la gente @guill...
1012924    Hoy 22.30 hrs! El candidato de la gente @guill...
1013534    Hoy 22.30 hrs! El candidato de la gente @guill...
1013561    Hoy 22.30 hrs! El candidato de la gente @guill...
```

Appendix Q

Data for Suspicious users-17.jpg

```
Info Data for @jav_ast

Name:                        Javier Astudillo
Name Length:                 16
@user number Numeric Chars: 0
@user and name similarity:  0
User Id:                     934771590583279616
Default_Photo:               False
Photo URL:                   http://pbs.twimg.com/profile_images/9347807861
58592000/dj9mU4xY_normal.jpg
Acc Verified:                False
Has Location:                False
Location:
default_profile:             True
Has Description:             True
Description:                 Estudiante de Medicina UCH - Salud Artes y Cul
tura Comida Política y Gobierno
Description length:          77
Account Active:              Active

Number of Tweets analyzed:          104
Last Tweet:                         2017-11-27T12:03:15.000000000
Older Tweet Analyzed:               2017-11-27T11:38:45.000000000
Account Active age (in days)        0.0
Average recent tweets per day:      inf
Maximum Recent Tweets Per Day:      104 at day 27
Average tweets per day since start: inf
Total Tweets since start:           7
Followers_count:                    42
Friends_following_count             104
Followers/Following_index:          0.4
Favourites (Like) count:            0
Retweet_Like_index:                 0
Retweet Ratio:                      2%
unique mentions cnt:                7
Mention Ratio:                      100%
Mention index:                      0.04
unique hashtags cnt:                3
Hashtag Ratio:                      98%
Hashtag Index:                      0.01
Average URLs per tweet:             0.0
Average text length per tweet:      155.0

       [Tweets Sample at Pick Day]
 1309981    RT @kitaalarcon: @sebastianpinera Porque mejor...
1310246    #ESPUCh analiza las propuestas de los candidat...
1310282    #ESPUCh analiza las propuestas de los candidat...
1310294    #ESPUCh analiza las propuestas de los candidat...
1310321    #ESPUCh analiza las propuestas de los candidat...
1310331    #ESPUCh analiza las propuestas de los candidat...
1310349    #ESPUCh analiza las propuestas de los candidat...
1310354    #ESPUCh analiza las propuestas de los candidat...
1310380    #ESPUCh analiza las propuestas de los candidat...
1310467    #ESPUCh analiza las propuestas de los candidat...
```