Identification of Twitter Bots Based on an Explainable Machine Learning Framework: The US 2020 Elections Case Study

Alexander Shevtsov, Christos Tzagkarakis, Despoina Antonakaki, Sotiris Ioannidis

Abstract

Twitter is one of the most popular social networks attracting millions of users, while a considerable proportion of online discourse is captured. It provides a simple usage framework with short messages and an efficient application programming interface (API) enabling the research community to study and analyze several aspects of this social network. However, the Twitter usage simplicity can lead to malicious handling by various bots. The malicious handling phenomenon expands in online discourse, especially during the electoral periods, where except the legitimate bots used for dissemination and communication purposes, the goal is to manipulate the public opinion and the electorate towards a certain direction, specific ideology, or political party.

This paper focuses on the design of a novel system for identifying Twitter bots based on labeled Twitter data. To this end, a supervised machine learning (ML) framework is adopted using an Extreme Gradient Boosting (XGBoost) algorithm, where the hyper-parameters are tuned via cross-validation. Our study also deploys Shapley Additive Explanations (SHAP) for explaining the ML model predictions by calculating feature importance, using the game theoretic-based Shapley values. Experimental evaluation on distinct Twitter datasets demonstrate the superiority of our approach, in terms of bot detection accuracy, when compared against a recent state-of-the-art Twitter bot detection method.

Introduction

Twitter is considered one of the most popular and widespread online social networks (OSNs) nowadays. It is used by millions of users and organizations to quickly share and discover information about a service, product, sports/social/political event etc. However, Twitter can be used as an intermediate system for malicious purposes, such as spreading fake news (Bovet and Makse 2019; Sharma et al. 2019) or manipulating public opinion (Badawy, Ferrara, and Lerman 2018).

Specifically, Twitter can be used to circulate propaganda (Neudert, Kollanyi, and Howard 2017; Jones 2019; Chatfield, Reddick, and Brajowidagda 2015), manipulate the public opinion (Bolsover and Howard 2019; Sco 2014), and influence the electorate towards a particular ideology or political party (Golovchenko et al. 2020; Howard, Kollanyi, and Woolley 2016). These tasks can be fully automated through a special organized group of agents, called bots, which are groups of sybil accounts that collectively seek to influence ordinary users. In particular, a botnet is a group of bots, i.e., automated programs programmed to run certain tasks. A sybil account in OSNs is a fake identity, not necessarily representing a real person or created by the real person it represents (impersonation technique) (Alsaleh et al. 2014).

It has been observed that Twitter bots can also be exploited to spread fake news, rumors and hate speech (Founta et al. 2018; Fortuna and Nunes 2018; Burnap and Williams 2015) by instantly republishing low credibility Twitter content (Shao et al. 2018) via popular users and Twitter mentions (Stella, Ferrara, and De Domenico 2018).

In this work, we aim to build a machine learning (ML) framework over a large collected dataset, to detect bot Twitter accounts. We identify and analyze Twitter bots during the US 2020 Elections period. The current study provides answers to the following questions:

• Is it possible to implement and fine-tune a ML-based bot detection model to efficiently apply it to the US 2020 Elections dataset?
• Which types of features can be extracted from the Twitter application programming interface (API) to promote high performance?
• Is it possible to examine the ML model’s generalization capability in terms of bot detection accuracy across several well-established datasets?
• Does the proposed ML model act as a black box or could the ML model’s mechanism be “unlocked” in order to investigate how it yields its predictions?

Our analysis can help the research community to better understand the bot detection task and how it can be performed in different types of datasets, or within diverse domains. The presented methodology achieves a high bot detection accuracy on the US 2020 Elections dataset, while attaining increased generalization performance in terms of bot identification when applied on additional, well-established Twitter datasets. The ML model’s outcome is also explained based on Shapley Additive Explanations (SHAP) method.

The rest of the paper is organized as follows: Background explores related past works. A detailed description of the
data collection process and the proposed methodology is given in [Methodology Experimental Results] evaluates the performance of our method, whilst [Conclusions and Future Work] summarizes the main outcomes and provides directions for future work.

**Background**

Twitter (social) bots can be used for malicious purposes spanning from junk news and fake news or rumor spreading ([Sharma et al. 2019], to propaganda and astroturfing ([Bovet and Makse 2019], [Howard et al. 2017], [Neudert, Kollanyi, and Howard 2017], [Howard et al. 2017b]). Specifically, an application is developed in [Hui et al. 2020] to track information spreading on Twitter and tweets and accounts associated with suspicious campaigns.

Usually, a legitimate bots’ usage is adopted, to perform automated communication or administration during the electoral periods ([Howard, Woolley, and Calo 2018]). However, Twitter bots have been extensively used for opinion hijacking during the Russian elections ([Krebs 2017], [Shane 2017], [Lightfoot and Jacobs 2018], [Illing 2018], the 2017 French presidential election ([Ferrara et al. 2017], the US elections ([Howard, Woolley, and Calo 2018], [Byrnes 2016], [Rizoiu et al. 2018]), the Catalan independence referendum ([Stella, Ferrara, and De Domenico 2018], as well as in the Australian ([Vaugh et al. 2013], the Ukrainian ([Hegelich and Janetzko 2016] and the Brazilian electoral process ([Arnault 2017]). In ([Luceri et al. 2019], the authors study 245,000 accounts on Twitter during the US 2016 presidential election and 2018 midterm elections, and they detect approximately 31,000 bots. Forty-three million elections-related tweets of ongoing U.S. Congress investigation of Russian interference in the 2016 U.S. election campaigns are examined in ([Badawy, Ferrara, and Lerman 2018], where it is estimated that 4.9% and 6.2% of liberal and conservative users, respectively, were bots, with reported precision and recall scores above 90%. In ([Keller and Klinger 2019], the authors provide an analysis of the German parties’ posts on Twitter from before and during the 2017 electoral period, and they reveal an increased amount of social bots (7.1% to 9.9%).

Other studies focusing on Twitter bots analysis include ([Stukal et al. 2017] studying a specific consequential period in Russian politics (February 2014 to December 2015) and apply sentiment analysis or attempt to predict the results of the elections ([Ibrahim et al. 2015], [Antonakaki et al. 2017].

The authors in ([Garimella and Weber 2017] investigate the political polarization on Twitter between 2009 and 2016, with an increased polarization of 10% and 20% being reported. The impact of Twitter bots during the first U.S. presidential debate of 2016 is studied in ([Rizoiu et al. 2018], where a novel algorithm for estimating user influence from retweet cascades is introduced towards analyzing the role and user influence of bots versus humans. Moreover, a Twitter data analysis has been conducted in ([Fraiser et al. 2018] related to the 2017 French presidential campaign. The authors built a large and complex dataset of 22,853 active Twitter profiles during the campaign from November 2016 to May 2017. Analysis of political discourse on Twitter in elections dataset has been noted during the US 2016 presidential elections ([Yaqu et al. 2017]. Opinion hijacking has been observed not only in politics, but also in anti-vaccination promotion movements ([Broniatowski et al. 2018]. Thus, it is important to quantify the spread of fake news on Twitter ([Waugh et al. 2013] and the inherent variability ([Vosoughi, Roy, and Aral 2018], in order to distinguish bots from human agents and legitimate users ([Edwards et al. 2014].

It is evident that Twitter bot detection is a complex task, often requiring rigorous and solid treatment. Several ML-based solutions have been proposed. In particular, a real-time detection system dubbed as BotOrNot using a total amount of 1200 different features in combination with a Random Forest classifier is introduced in ([Davis et al. 2016]. An updated version of this system is described in ([Yang et al. 2019] named as Botometer, which requires Twitter API keys to collect user information during the real-time computations, thus it is not efficient to use real-time labeling tools in the case of big datasets. BotSentinel ([Sentinel 2021 (accessed April 19, 2021] on the other hand, is a non-real-time labeling tool, capable of processing large amounts of user accounts and storing the results in a database. BotSentinel’s offline labeling methodology is adopted whenever a user account is being suspended or removed, whereas real-time labeling does not provide any suspended account information. Moreover, the offline implementation allows us to increase the query rate limits, since it involves no labeling computational costs.

Since a fundamental part of the bot detection pipeline corresponds to the computation of features based on Twitter data, a plethora of different types of features have been proposed. Various features are based on content ([Ahmed and Abulaish 2013], [Gilani, Kochmar, and Crowcroft 2017], [Lee, Caverlee, and Webb 2010], [Davis et al. 2016], [Varol et al. 2017]), sentiment ([Loyola-González et al. 2019], [Dickerson, Kagan, and Subrahmanian 2014], [Ferrara et al. 2016], [Loyola-González et al. 2019]), account information ([Wald et al. 2013], [Chu et al. 2012], [Davis et al. 2016], [Lee, Caverlee, and Webb 2010], [Loyola-González et al. 2019]), usage ([Chu et al. 2012]), and network characteristics ([Feng et al. 2020], [Keller et al. 2017], [Cresci et al. 2017].

There is a growing number of ML and data (statistical) analysis-based Twitter bot identification tools. The most popular can be considered the Stweeler tool ([Gilani et al. 2016], the Debott system ([Chavoshi, Hamooni, and Mueen 2016], which takes into account synchronous bots spreading content, the TSD Sybil Detector ([Alsaleh et al. 2014] that adopts a ML approach using 17 Twitter data-based features and the Retweet-Buster (RTbust) ([Mazza et al. 2019] which is an unsupervised learning tool combining feature extraction and clustering techniques. Moreover, sentiment analysis has been incorporated into the bot detection pipeline ([Dickerson, Kagan, and Subrahmanian 2014], [Loyola-González et al. 2019]. A set of sentiment features is also exploited by the BotOrNot tool in ([Varol et al. 2017]. The promising direction of ML-based Twitter bot detection can be reflected in DARPA competition, where six different research groups competed in performing bot identification, us-
Table 1: Most popular HTs in our dataset. Tweets may contain multiple HTs so that the sum of tweets is not equal to the number of tweets in our collection.

| Hashtag                                | Tweet Counts |
|----------------------------------------|--------------|
| #VOTE                                  | 3,044,999    |
| #Trump202                              | 2,403,586    |
| #Vote                                  | 2,200,954    |
| #Election2020                          | 1,906,959    |
| #Vote                                  | 1,838,645    |
| #Biden                                | 1,063,265    |
| #Debate2020                            | 839,717      |
| #BidenHarris2020                       | 781,697      |
| #VoteBlueToSaveAmerica                 | 746,896      |
| #Trump                                | 601,516      |

Table 2: The number of users during each phase of the labeling of our dataset (the symbol $M$ corresponds to million).

| Step            | Bot Users | Normal users | Total  |
|-----------------|-----------|--------------|--------|
| Before labeling | -         | -            | 1.3M   |
| BotSentinel     | 10,324    | 25,546       | 35,870 |
| Botometer       | 2,180     | 7,267        | 9,447  |
| Suspended       | 2,389     | 0            | 2,389  |
| Final           | 4,569     | 7,267        | 11,836 |

The acquired dataset does not contain explicit knowledge whether a user is a bot or not. Since the goal of the current study is to provide a supervised ML-based solution for Twitter bot detection, it is crucial to obtain a bot vs. normal users labeled dataset. Unfortunately, in the area of Twitter bot detection, it is not possible to collect accurate ground truth labels, without using third-party bot labeling tools. The classic solution of ground truth generation corresponds to a manual/crowd-sourcing analysis, which requires a thorough inspection of Twitter accounts, by human experts to identify the label of each account (via a majority voting rule). The manual labeling process is cumbersome when considering both the size of big datasets that contain millions of users (in our case the dataset contains 3.2 million users) and the sophistication level of bot accounts which has risen during the last years.

As a means of overcoming the inherent restrictions of manual labeling, we utilize off-the-shelf ML-based techniques, allowing us to scale up the labeling procedure. ML methods achieve higher accuracy, in terms of ground truth labeling, as compared with the manual/crowd-sourcing analysis, since they exploit Twitter data feature representations not evident to human experts. Here, we use the Botometer (project 2020 (accessed October 21, 2020), Varol et al. 2017) and BotSentinel (Sentinel 2021 (accessed April 19, 2021) online tools to obtain the user labeling information. To achieve highly confident results, we combine the set of labels provided as output by the Botometer and the BotSentinel tool, respectively. In particular, we compute the intersection of the two label sets. The intersection contains the labels that are equal in both label sets. The users identified as bots by one of the two tools are marked as unlabeled.

Both bot detection labeling tools yield an output score for each requested Twitter account. The Botometer score lies in the interval $[0, 5]$, while the BotSentinel score takes integer values in $\{0, \ldots, 100\}$. The higher the output score is, the higher the probability the requested account is a bot. A Twitter user is labeled as bot when the Botometer and BotSentinel’s output score is greater than 4.0 and 75, respectively. When the Botometer and BotSentinel’s output score is less than 1.0 and 25, respectively, the Twitter user is labeled as normal. As mentioned above, since none of the two tools guarantees 100% bot identification accuracy, we aim at combining the scores from both tools and take into consideration the labels that are (mutually) equal. When an account is already suspended, Botometer cannot query Twitter API, and thus we perform a Twitter API check to identify whether an account is suspended or not.

To minimize the time complexity of the labeling process, we separate our dataset into two parts. The first part contains data extracted during September 2020 and is utilized for user labeling, ML model fine-tuning, training, validation and testing purposes. The second part incorporates data from October 1st, 2020 until November 3rd, 2020 and is used to evaluate the generalization capability of the proposed ML-based Twitter bot identification system on unseen data.

The dataset separation allows us to reduce the labeling process (computational) time without significant information loss, since the accounts remain active throughout the whole period of September and October. The first part has 1.3 million users and more than 5 million tweets and retweets, while the second part consists of 2.6 million users.
and 10.6 million tweets and retweets. A subset of users remain active during both periods, therefore it is obvious to notice the overlap between the two parts.

Figure 1 shows the labeling pipeline. Our dataset has 1.3 million users during the BotSentinel labeling step. Then, the Botometer tool receives as input 35,870 users, i.e., 10,324 bot users and 25,546 normal users (see Table 2), and outputs 9,447 users (2,180) Twitter accounts labeled as bots and 7,267 Twitter accounts marked as normal accounts). As a parallel step, we query the Twitter API and the response provides a set of 2,389 users labeled as suspended. Therefore, the final labeled set has 4,569 bot users and 7,267 normal users. Note that the overall labeling procedure is initialized with BotSentinel, since it does not impose any daily query limitations, in contrast with the Botometer. In the case of a Botometer-based initialization step, the labeling outcome of the pipeline depicted in Figure 1 will be the same, but the processing time will grow dramatically and will require 650 days to terminate, due to the Botometer request limitations. So, starting with BotSentinel will require only 18 days.

We already mentioned that none of the existing labeling tools provide 100% accurate ground truth labels. To quantify the accuracy of our proposed labeling pipeline, we compare the labeling results of our pipeline against the Twitter bot detection algorithm after a period of six months. According to Twitter, the number of bot accounts is 4,569 (with 51% and 34% of the bot accounts being suspended and removed, respectively), while 7,267 Twitter accounts are identified as normal (with only 1.9% and 6.3% of the normal accounts being suspended and removed, respectively). Twitter’s labeling mechanism incorporates a lag time, and thus it cannot be efficiently used to compute our ground truth labels. Specifically, we manually confirmed that the lag time corresponds to about two months in the case of the US 2020 Elections.

Feature Extraction

Twitter API allows the collection of tweets, including information such as tweet text, tweet post time, as well as metadata such as HTs, URLs, and mentions. In this paper, we also include the user profile information by retrieving user objects, where all different types of the retrieved Twitter content are utilized, leading to a total amount of 335 computed features. The features can be divided into four categories, namely, user profile, user context, user time, and user interaction.

Profile Features

Twitter API retrieves user objects containing critical information to achieve accurate bot identification performance. The importance of user profile features is analyzed in various works (Chu et al. 2012; Wald et al. 2013; Gilani, Kochmar, and Crowcroft 2017; Yang et al. 2020). Typically, a user profile object includes user description, username, profile picture, and profile statistics (e.g., number of followers, friends, favourites, and listed). In this paper, bot vs. normal users distinction is promoted, by enriching the features set through the extraction of profile features. For this, the user profile description and the user/screen name digits are taken into consideration.

The computed user object-based features correspond to unedited parameters such as the number of followers, friends, favourites, listed lists, and description length. Flag type elements like location usage, account description, protected flag, geolocation usage, and background image usage, are also estimated. Additional parameters such as the Jaccard similarity of the user and the account screen name are pre-computed and included in the overall features set. Table 3 shows the list of the extracted feature set, where the feature names written in italics correspond to the statistical features described in Yang et al. 2020, and the feature names written in bold correspond to our proposed features leading to a 26-dimensional profile feature space.

Context Features

The user profile feature set described in the previous section reflects the statistics of the user’s Twitter account, since the first day of the subscription to Twitter. However, the profile features lack semantic information regarding the actual content sent by the user. Thus, it is essential to incorporate contextual information such as user posts’ content, most important user tweeted/retweeted topics, popular user HTs and number of URLs usage per tweet. Table 4 summarizes the list of the estimated context features.

| Feature                        | Type       | Feature                        | Type       | Calculation                                                                 |
|--------------------------------|------------|--------------------------------|------------|-----------------------------------------------------------------------------|
| statuses_count                 | count      | screen_name_len                | count      |                                                                              |
| entities_count                 | count      | description_len                | count      |                                                                              |
| followers_count                | count      | screen_name_likelihood         | real-valued| likelihood of screen_name                                                   |
| friends_count                  | count      | name_screen_sim                | real-valued| name and screen_name similarity                                             |
| favourites_count                | count      | tweet_retweet_ratio            | real-valued| statuses_count / retweet_count                                              |
| listed_count                   | count      | name_digits                    | real-valued| number of digits in user name                                               |
| name_len                       | count      | screen_name_digits             | real-valued| number of digits in user screen_name                                        |
| geolocation                    | boolean    | tweets_by_age                  | real-valued| statuses_count / user_age                                                   |
| protected                      | boolean    | followers_by_age               | real-valued| followers_count / user_age                                                   |
| location                       | boolean    | friends_by_age                 | real-valued| friends_count / user_age                                                     |
| background_img                 | boolean    | favourites_by_age              | real-valued| favourites_count / user_age                                                  |
| default_profile                | boolean    | listed_by_age                  | real-valued| listed_count / user_age                                                      |
| verified                       | boolean    | followers_friends              | real-valued| followers_count / friends_count / users                                      |

Table 3: Profile features extracted from Twitter user objects.
| Feature                                      | Description                                                                 |
|----------------------------------------------|-----------------------------------------------------------------------------|
| $N_{tweet\_mentioned\_tfidf}$              | TF-IDF score of the 3 most popular user mentions contained in tweets        |
| $N_{tweet\_mentioned\_word}$               | The 3 most popular mentions in user tweets as word features                 |
| $N_{tweet\_hashtags\_tfidf}$                | TF-IDF score of the 3 most popular user HTs contained in tweets             |
| $N_{tweet\_hashtags\_word}$                | The 3 most popular HTs in user tweets as word features                      |
| $N_{retweet\_mentioned\_tfidf}$            | TF-IDF score of the 3 most popular user mentions contained in RTs           |
| $N_{retweet\_mentioned\_word}$             | The 3 most popular mentions in user RTs as word features                    |
| $N_{retweet\_hashtags\_tfidf}$              | TF-IDF score of the 3 most popular user HTs contained in RTs                |
| $N_{retweet\_hashtags\_word}$              | The 3 most popular HTs in user RTs as word features                        |
| $N_{tweet\_word}$                           | The 3 most popular words used by user in tweets as word features            |
| $N_{retweet\_word}$                         | The 3 most popular words used by user in RTs as word feature                |
| tweet $\_number\_of\_urls$                 | Number of URLs in tweets, computed as average and standard deviation        |
| retweet $\_number\_of\_urls$               | Number of URLs in RTs, computed as average and standard deviation           |
| tweet $\_number\_of\_hashtags$             | Number of HTs in tweets, computed as average and standard deviation         |
| retweet $\_number\_of\_hashtags$           | Number of HTs in RTs, computed as average and standard deviation            |
| tweet $\_number\_of\_mentions$             | Number of mentions in tweets, computed as average and standard deviation   |
| retweet $\_number\_of\_mentions$           | Number of mentions in RTs, computed as average and standard deviation      |

Table 4: Context features based on user tweets and RTs, crawled by Twitter API.

Tweet’s context characteristics provide a diverse range of uniqueness because each user operates in a different form of expression. To estimate the most frequent words and entities, we compute a subset of the context features such as the three most popular words, mentions and HTs per user (punctuation marks and stop words are removed since they do not provide important information). For each user, we discover the most frequent sentences (user mentions, hashtags, upper and lower words). User mentions and hashtags may provide unique information that highlights the characteristics of a particular user, thus we compute the term frequency-inverse document frequency (TF-IDF) (Rajaraman and Ullman 2011) on the collected dataset. This allows us to identify the importance level of the user’s hashtags and mentions. In particular, we compute the TF-IDF of the overall user mentions and hashtags and for each particular user, we identify the three most frequent mentions/hashtags. The final step is to compute the TF-IDF based on the overall frequency.

The next step is to use the word2vec algorithm (Church 2017) to learn the word embeddings from the obtained Twitter dataset, allowing us to transform text-based features into a 10-dimensional space. The most frequent words, mentions and HTs are transformed with the trained word2vec model. Note that the text-based features might differ between the user’s original tweets and RTs, since they are usually written by a different user. Thus, text-based features are computed separately for each user’s tweets and RTs.

**Time-Based Features** The automated bot accounts follow a non-uniform or highly uniform tweet posts time patterns. On the other hand, normal users’ tweets typically follow a diurnal pattern, which can be predictable for specific users. As mentioned in (Chu et al. 2010), the human activity follows a special pattern on Twitter since humans perform tweet posts at specific daily time intervals, while the activity appears to be lower during the weekends. Nevertheless, bots’ activity pattern is more unpredictable because it does not follow the same activity level per day. The automated behaviour of a bot accounts is constantly evolving, almost mimicking human users activity, making it a challenging task to detect bot accounts solely based on time-oriented features. However, due to the fact that not all automated behaviours are similar, we aim to compute and use time-based patterns as additional input to the proposed ML pipeline to enhance the bot vs. normal users detection accuracy.

In this paper, we extract multiple time-based features such as the RT time, as well as the hourly and daily activity. Regarding the RT times, we compute the difference between the original tweet and the RT time provided in the tweet object. We also measure the RT time distribution per user, where the minimum, maximum, average and standard deviation values of the RT time are included in the feature set. As an account activity metric, the daily percentage of tweets and RTs is computed (i.e., we can identify during which days the users appear to be more active). Similar metrics are estimated during the active days and hours, and thus we can identify the exact hourly intervals of the day in which the user is vigorously posting tweets or RTs. Table 5 presents the set of time-based features.

**Interaction Features** The final set of extracted features is based on the RT network graph which models user interactions. The RT graph is estimated based on the collected dataset, with the nodes representing users and the directed edges defining a RT action from user $i$ to user $j$. The edge weight indicates the number of RTs between the two users. The resulted graph represents the network of the RT con-
nections in our dataset. Finally, we use Gephi (Bastian, Heymann, and Jacomy 2009) to compute the node statistics such as in-degree and out-degree of each node.

**Experimental Results**

In this section, we examine the performance of our proposed system, with respect to the resulting bot vs. normal users detection accuracy.

### ML Framework

As a main step towards building a robust and accurate ML-based bot identification system, we perform a model selection procedure by examining the bot vs. normal users classification accuracy of several state-of-the-art ML algorithms. In particular, we evaluate the performance of Random Forest (Breiman 2001), Support Vector Machine (SVM) (Cortes and Vapnik 1995) and Extreme Gradient Boosting (XGBoost) (Chen and Guestrin 2016) algorithm.

Each ML method involves a different number of hyper-parameters, and thus it is of paramount importance to follow a hyper-parameter tuning procedure to identify the best (trained) version of each ML model and promote a fair models’ comparison. Figure 2 illustrates the ML model selection pipeline based on a combination of 80/20 train/test split (using random shuffle) and a 5-fold cross-validation scheme, i.e., the dataset is randomly shuffled, where 80% of the dataset is used for training/validation and the rest 20% (hold-out part) of the dataset is exploited for testing purposes. Each train/test split is performed in a stratified manner in order to have the same ratio of classes in both training and testing data. During the 5-fold cross-validation process, the synthetic minority oversampling technique (SMOTE) using Tomek links (Batista, Prati, and Monard 2004) is applied on the training folds to balance the two (bot vs. normal) distributions by oversampling the minority (bot) class distribution.

![Figure 2: ML model selection pipeline.](image)

| Feature | Description |
|---------|-------------|
| daily_rt | RT % each weekday |
| daily_tw | tweets % each weekday |
| daily_retweet_avg | average daily number of RTs |
| daily_tweet_avg | average daily number of tweets |
| hourly_rt | RTs % of daily hours |
| hourly_tw | tweets % of daily hours |
| hourly_retweet_avg | tweets/RTs % of daily hours |
| retweet_time | time difference between original tweet and user RT, computed as min/max/avg/std |

Table 5: Time-based features computed on user’s tweet/RT object. Min, max, avg and std correspond to minimum, maximum, average and standard deviation, respectively.

| Model       | F1   | PR-AUC | ROC-AUC |
|-------------|------|--------|---------|
| XGBoost     | 0.919| 0.967  | 0.979   |
| Random Forest | 0.908| 0.955  | 0.973   |
| SVM         | 0.889| 0.941  | 0.964   |

Table 6: Testing accuracy during the model selection phase.

Additionally, we employ feature selection based on three different methods, namely, Lasso (Tibshirani 1994), Random Forest feature selection and model feature importance. Among the three feature selection methods, the model feature importance provided the features having the highest predictive accuracy.

It is important to mention that some of the context features are vectors provided by the pre-trained word2vec model. The word2vec model provides a 10-dimensional space representation of the text, but only a few out of the ten dimensions are informative for the model. For this, we keep only the informative dimensions through the feature selection process. An example is presented in Figure 2 where the feature “N1_retweet_hashtag_word,” represents the first most popular hashtag seen in the user retweets. According to the feature name, the seventh element of this particular word (embedding) vector corresponds to the most informative dimension.

Table 6 reports the F1 score and the two areas under the curve (AUC) scores, i.e., the precision-recall (PR) AUC value and the receiver operating characteristic (ROC) AUC value, averaged over ten repetitions. It can be seen that the XGBoost model achieves slightly better results on the testing data than SVM and Random Forest. Thus, we select XGBoost as the basic ML model applied in the next experimental evaluation phase.

### General Model Comparison

We evaluate the generalization capability of the XGBoost model, which is already fine-tuned on the US 2020 Elections dataset (see in section ML Framework), against a general model (Yang et al. 2020) applied to detect bots on various datasets. To perform this comparison, we collect the public datasets provided by (Yang et al. 2020) and we perform an experimental evaluation with similar specifications as described in ML Framework section. The authors in (Yang et al. 2020) utilize only the statistical features computed on the user objects, without exploiting any further knowledge related with user interactions, RT times, or contextual information of user tweets. As a result, we extract and use the same feature set in both XGBoost and general model implementation to promote a fair comparison.
Table 7: Publicly available labeled datasets used for bot detection performance evaluation in (Yang et al. 2020).

Table 8: Training dataset combinations and performance results between our XGBoost model and the method described in (Yang et al. 2020).

Table 9: Number of features extracted by each feature category from the US 2020 Elections dataset.

Statistical vs. Context Features

We compare the proposed XGBoost model with the model introduced in (Yang et al. 2020) in light of the statistical features set. The authors in (Yang et al. 2020) exploit only the statistical features set. To promote a fair models’ comparison we use the statistical features alone, including the number of followers, listed, favorites, and friends, as well as the computation of the growth rate, based on the user account age, the number of digits in the screen name and the account screen name likelihood. The extracted set of features do not contain semantic information related with the posts content. The rest of the feature types described in section Feature Extraction are utilized separately in our model, during the training and validation steps. Each feature category, presented in Table 9 is used separately and compared to each category’s performance against PR and ROC curves with the features described in (Yang et al. 2020), as well as the best features that were selected by our model. Figure 5 presents the precision vs. recall performance of those features, with separate information of F1-score of the hold-out dataset portion. Figure 6 illustrates the ROC-AUC curve and the corresponding AUC score for each feature set. According to the ROC-AUC performance model, utilizing a mixture
of multiple features with proper feature selection results in a better ROC-AUC performance model, since each feature set contains critical information for the model.

**Generalization Performance: US 2020 Elections Dataset**

The combination of multiple feature types provide the best bot identification accuracy as it is experimentally evaluated in section [Statistical vs. Context Features](#) where the number of multiple combined features is 228. We use this set of features to investigate the generalization capability of our XGBoost model on the US 2020 Elections dataset. In particular, we divide the US 2020 Elections dataset into two parts as mentioned in section [Twitter Users Labeling](#), i.e., the first part corresponds to the time interval between September 1st and September 30th, while the second part corresponds to the interval between October 1st and November 3rd. The experimental specification is the same as that adopted in section [ML Framework](#). The only difference is that the train/test split now is 70/30, where 70% of the September dataset is used for train/validation of the XGBoost model, while the rest 30% is used for testing with the F1 score equal to 0.916 and the ROC-AUC score is 0.98. A difference between these results and the ones depicted in Figure 3 due to the random data shuffling.

The second dataset (October 1st to November 3rd) is also used as testing data, to evaluate the bot identification performance of the already trained (on the 70% data of September) XGBoost model on unseen data that correspond to an extended time horizon. The XGBoost model achieves an average of 0.896 F1 score and 0.977 ROC-AUC. The aforementioned results, clearly indicate that our proposed ML model achieves impressive generalization capabilities by identifying bot accounts on future data, based on past training samples.

**Model Explainability**

One of the ultimate goals of the current paper is to “unlock” the proposed ML model mechanism in order to better understand how the model yields its predictions. We use SHapley Additive exPlanations (SHAP) values proposed in [Lundberg and Lee (2017)](https://shap.readthedocs.io/) since they present several advantageous characteristics. First and most importantly, SHAP values are model-agnostic, i.e., they are not bound to any particular type of ML model. Secondly, SHAP values present properties of local accuracy, consistency, and missingness, which are not found simultaneously in other methods. Lastly, SHAP implementation is actively supported by an open-source community, it is well documented and straightforward to use.

Before proceeding to the SHAP values explanation, let us first, provide a description of the concept of Shapley value. More specifically, Shapley introduced a game-theoretic approach for assigning fair payouts to players depending on their contribution to the total gain (Shapley 1953). Within a predictive modeling task, this translates to assigning an importance numerical value to features that depend on their contribution to a prediction. Thus, in the predictive ML context, a Shapley value can be defined as the average marginal contribution of a feature value across all possible feature coalitions. Based on this definition, a Shapley value for a given feature can be interpreted as the difference between the mean prediction for the whole dataset and the actual prediction.

The Shapley values are represented as a linear model of feature coalitions by the SHAP method [Lundberg and Lee (2017)](https://shap.readthedocs.io/). SHAP values exploit the game theory’s Shapley interaction index, which allows allocating payouts, i.e., importance, not just to individual players, i.e., features, but also among all pairs of them. As a result, SHAP values can ex-
plain the modeling of local interaction effects, and allow the possibility of providing new insights into the ML model’s features.

Figure 5 shows the summary plot for SHAP values related with the features extracted from the US 2020 Elections dataset. The top twenty features with the highest impact at the XGBoost model’s output are depicted. For each feature, one point corresponds to a single Twitter user. A point’s position along the x-axis (i.e., the actual SHAP value) represents the impact that feature had on the model’s output for that specific Twitter user. Mathematically, this corresponds to the malicious behaviour risk relative across Twitter users (i.e., a Twitter user with a higher SHAP value has a higher risk being malicious relative to a Twitter user with a lower SHAP value). Features are arranged along the y-axis based on their importance, which is given by the mean of their absolute Shapley values. The higher the feature is positioned in the plot, the more important it is for the XGBoost model.

A further analysis of the results in Figure 5 indicates that the top twenty features with the highest impact on the XGBoost model’s output correspond to statistical, time and graph-based features. In particular, features such as Twitter lists and average number of mentions in user tweets appear to have a high impact in XGBoost model’s output. We expect that a combination of features with the highest output impact could provide the best possible bot identification performance. This statement can be confirmed by the results mentioned in section Generalization Performance: US 2020 Elections Dataset.

Based on the SHAP values summary plot depicted in Figure 5, it is obvious that “listed_count” corresponds to the feature with the highest impact at XGBoost model’s bot vs. normal user detection. As shown in Figure 5, bot users tend to not belong to Twitter lists, whereas normal users could be members of more than one list. We can also deduce that bot users have lower values of “favourites_by_age” (also known as likes), which means that bot users tend to ignore the like button of other users’ posts. This could be explained by the complexity of bot account implementation. Finally, we notice that bot users have high values of “friends_by_age” feature, which means that they tend to connect to more accounts within a short period of time. This activity is obvious since bot accounts try to gain high visibility and expand to larger parts of the Twitter network. Presented explanations confirm our initial intuitive explanations regarding the difference between normal and bot accounts activity.

Conclusions and Future Work

This paper introduces a novel methodology based on a supervised machine learning (ML) framework for identifying bot vs. normal Twitter users using a wide range of extracted features. Specifically, the proposed system incorporates the extraction and labeling of multiple features, with the ground truth labels estimated through the combination of two online bot detection tools’ output. A thorough ML analysis involving train/validation/test split, feature selection, oversampling and hyper-parameters tuning, establishes the Extreme Gradient Boosting (XGBoost) algorithm as the best ML model along with a specific set of features. The selected XGBoost model when trained on a wide range of combined features spanning from profile and context features to time-based and interaction features achieves the highest bot detection accuracy.

The generalization capability of the proposed ML system is extensively examined through an experimental evaluation process, and compared with a recently introduced general model (Yang et al. 2020). Finally, the obtained explanations revealed meaningful insights from a Twitter data analysis point of view about the reasoning process behind the XGBoost model’s decisions. Future work concerns the extension of the proposed methodology by performing text analysis on the tweet corpus posted by the bot users, to identify the shared type of content during the US 2020 Elections period.

The code and the employed datasets are available at the following link in GitHub repository: [Code repository 2021]

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