Twitter Bot Behavior: How Twitter Bots Interact With People

Alic Szecsei
University of Iowa
alic-szecsei@uiowa.edu

Willem DeJong
University of Iowa
willem-dejong@uiowa.edu

ABSTRACT

Twitter bots are often cited as affecting the political process by manipulating the trending topics data; similar behavior is also cited on other social platforms, such as Facebook. We present our use of unsupervised machine learning, combined with Indiana University's *BotOrNot* service, to classify Twitter users as bots based on statistical analysis of their accounts, and then examine the ways in which they interact with other users. Determining how these bots interact with human users can help to focus bot-detection algorithms to target those bots that interact with human users in malicious ways.

1. INTRODUCTION

1.1 Background & Motivation

Social bots, also known as *sybil accounts*, are programs that automate interaction on social platforms. While some may simply be humorous or helpful accounts that don't attempt to hide their status as bots, others have more manipulative goals; they may flood a social network with spam, or attempt to more subtly influence the thoughts and behavior of the humans it interacts with. While social networks are extremely effective at causing social change and improving the quality of life of their users, they are also at risk of automated manipulation by bots.

Aral and Walker (2011) showed that social networks are highly effective at manipulating the public[1], and the automation of such behavior only increases this efficiency. In addition, Ratkiewicz (2011) showed that political bots actively manipulated the 2010 U.S. midterm elections[6].

1.2 Problem Statement

While there have been multiple approaches to bot detection[7][8][3], these have been restrained to simple detection. Very few have attempted to examine the ways that these fake accounts interact with real users. Our goal is to find a number of bot accounts and determine how they use social media to affect their target users. Determining which bots are attempting to manipulate social networks and which are providing services to human users is an import aspect of bot detection, and one we believe can be improved by examining how malicious bots interact with human users.

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1.3 Proposed Approach

In this paper, we use data from a bot-detection service run by Indiana University to determine whether or not users are bots. We then pull their latest tweets, as well as user data, and use the collected data in an unsupervised machine learning algorithm to cluster the users into 50 groups. We then take the data for each cluster and analyze common behavioral patterns.

1.4 Key Results

We found a general inverse trend between the *BotOrNot* score for a cluster and the number of retweets made by the cluster. In addition, a similar inverse trend exists for the number of links tweeted by users, and the number of mentions made by users.

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2. RELATED WORK

Davis (2016)[4] and Dickerson (2014)[5]. [TODO: Talk about cited papers, what their results were, how those results were relevant to our data] Lorem ipsum lorem ipsum.

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3. PROPOSED APPROACH

Many examinations of bot behavior on Twitter uses ground truths created by verified accounts. However, the social behavior of verified Twitter accounts is wildly different from that of the general public. Verified users often have a celebrity status, and so are less likely to retweet other users, and usually will not have a small number of followers.

In addition, verified Twitter accounts occasionally belong to people who exhibit bot-like behavior, advertising their services without much variety between tweets, and consistently linking to their personal websites. While these users may be verified, they are not guaranteed to be run by real people, and are often linked to other services to simply tweet links.

Instead, we chose to start with Twitter accounts we knew or who followed our personal accounts, and then attempt to provide a more detailed classification system to account for these "‘verified bots.”'

To retrieve a list of human and bot Twitter accounts, we compiled an initial list of 113 users with an approximately even split between humans and bots. We then retrieved data for their followers, and their followers' followers, leaving us with 9,025 Twitter users, which we then classified.

3.1 Clustering

BotOrNot analyzes a large amount of data retrieved from each user, including sentiment analysis and a temporal analysis to determine when users are likely to tweet. Using machine learning classifiers, it assigns a score to a user, with higher scores indicating a larger amount of bot-like behavior.

Testing *BotOrNot* lead us to discover a number of inconsistencies with the overall score. A Twitter bot owned by one of the authors was given a lower score than the personal account that the bot was attempting to imitate. Organizational accounts were often given a high *BotOrNot* score, which the official website discloses. One account was owned by the son of another user, who had only made 3 tweets and had a *BotOrNot* score of over 90

After discovering these issues, we determined that more information was required for automated analysis of Twitter accounts. Using unsupervised machine learning to cluster accounts let us successfully organize a large number of accounts into separate categories, which we manually classified and verified. As described by Bessi and Ferrera[2], we retrieved the most important descriptors of bots: whether they're using the default appearance, their retweet-to-tweet ratio, and others, in addition to the *BotOrNot* score and category scores. However, our best results were found when simply clustering based on the *BotOrNot* category scores.

To classify each cluster, we set up a basic Python script using Selenium that displayed a sample set of Twitter feeds, and allowed a user to submit a category for the user. Based on the categories reported for the cluster, we could determine what type of Twitter account a user was likely to be. We then manually categorized approximately [TODO: Number] 750 of these accounts, split evenly among each cluster.

3.2 Tweet Analysis

We determined how bots could engage with human users on the Twitter platform, determining that these vectors consisted of:

- Mentioning a user in a tweet
- Retweeting a user
- Using a popular hashtag or phrase
- Following a user
- Favoriting another user's tweet

We collected data about how many accounts each account was following, how many accounts followed them, and how many tweets each account had favorited. This user data let us analyze how many accounts each cluster was following, and helped manually classify certain users as bots.

In addition to retrieving this user data, the latest tweets made by each account, with a total of over 1 million tweets. We could then determine whether the tweet had been retweeted from another user, contained links, mentioned other users, and which hashtags were used.

Using these social behaviors, we were able to determine how each cluster and category of user tended to interact with other users. Focusing bot detection on these interactions could result in improved efficiency for spam removal services or other bot-related studies.

4. RESULTS & DISCUSSION

Examining the correctness of *BotOrNot* scoring was the first part of analysis we performed. Manually determining whether a number of accounts were bots, humans, or indeterminate, we found that the majority of accounts with a *BotOrNot* score over 50% we were unable to determine if the account was automated, or the account was clearly a bot. Likewise, the majority of accounts with a score less than 50% were clearly human users, as seen in Figures 1 and 2.

We next examined how *BotOrNot*'s category subscores aligned with its overall account score.

Figure 1: Manual identification of accounts

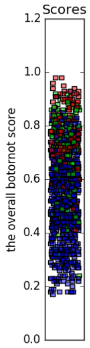


Figure 2: Manual identification of accounts

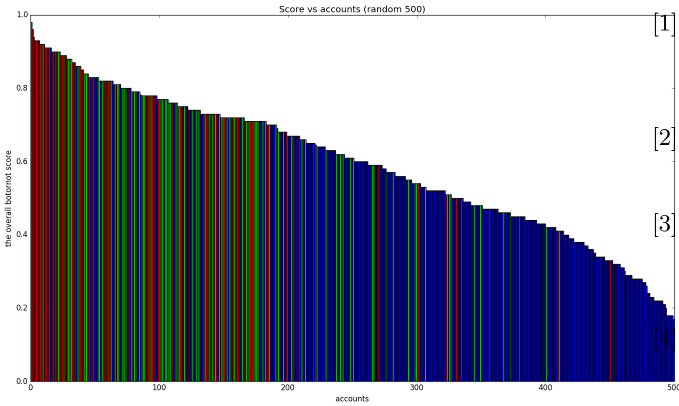
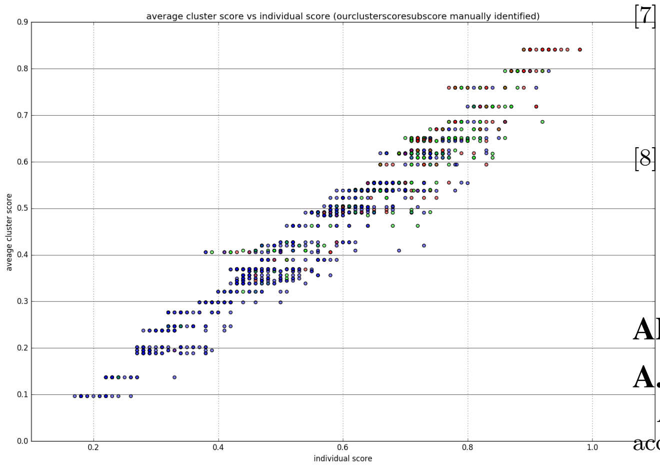


Figure 3: *BotOrNot* Scores vs Category Subscores



5. CONCLUSION

Our study focused on analyzing interaction between human and bot Twitter users. We used *BotOrNot*, combined with unsupervised machine learning, to cluster users and determine how bots gain visibility with their target audience. We determined that bots are unlikely to engage with human users beyond simply following them.

5.1 Further Work

Although we were able to manually identify advertising links, when we retrieved data on individual Tweets we did not expand Twitter's shortened URL format. This made media, such as photos, appear identical to other links, since Twitter represents media as URLs. In addition, the sample size for manual classification was small by necessity; setting up a web service such as Mechanical Turk to crowdsource this account classification would improve analysis and clustering.

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APPENDIX

A. CONTRIBUTIONS

Alic Szecsei provided data retrieval methods for Twitter accounts, programmed the unsupervised machine learning, and wrote the data analysis.

Willem DeJong programmed BotOrNot score retrieval, retrieved data for Twitter accounts to store in SQL databases, and created many of the graphs and charts.