# Tweeter Bots and Covid-19 Conspiracy Theories

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***Abstract*—The Covid-19 pandemic caused a previously unseen amount of misinformation spread on social media, sparking multiple pandemic related conspiracy theories. Previous studies have shown a substantial amount of social bots being active on social media, specifically amplifying the spread of dis-/misinformation. This study investigates just how large the bot population is for two of the most recent conspiracy theories, the VAIDS and the ClotShot conspiracy, on Twitter. The investigation consisted of gathering users from Twitter, then using the state-of-the-art bot detection tool called Botometer, calculating the bot-likelihood of the users. The study concludes that depending on the choice of complete automation probability, the amount of bots could exceed as much as 50% of the total amount of users gathered from both of the conspiracy theories.**

***Index Terms*—Covid-19, conspiracy theories, Twitter, bots, VAIDS, Clotshot**

## I. Introduction

### A. Motivation

The new strain of coronavirus disease, Covid-19, brought with it a considerable amount of unknowns regarding, amongst other things, origin, virulence and mortality rates [1]. The lack of available information led many people to social media platforms such as Twitter, in order to find answers [2]. Due to the nature of social media, misinformation is able to be rapidly spread throughout the network. The spread of misinformation, typically done through trending conspiracy theories, places a significant cost on society. The resulting mistrust of public health authorities during the pandemic has lead to unnecessary suffering [1].

Studies have shown an increase of the spread of misinformation and conspiracy theories during the Covid-19 pandemic [3]. One study found that as much as 33% of Americans had seen a large amount of false information regarding the virus on social media platforms [3]. Another study [4] claims that 38% of all Covid-19 information on Twitter is made up misinformation, and up to 60% of the information is recontextualized or refitted. However, it is not only humans spreading conspiracy theories. Shi et al. [5] estimate that as much as 10% of all Covid-19 conspiracy theories are spread by social bots. Two of the most recent major conspiracy theories are the Vaccine acquired immunodeficiency syndrome (VAIDS) and the ClotShot theories.

In this paper we aim to put numbers on the amount of social bots on Twitter that are interacting with the VAIDS and the ClotShot conspiracy. Interacting in this case means either retweeting posts regarding either conspiracy, or posting about either conspiracy. This was accomplished by gathering users through the Twitter API and the Twint API, and then using the Botometer API for bot classification and scoring.

While there has been a lot of similar research done for other Covid-19 related conspiracies (5G, Vaccine causes autism, etc), it is this paper's belief that nothing has been done on either VAIDS or ClotShot.

### B. Terminology

- Covid-19: The disease caused by severe acute respiratory syndrome coronavirus 2 (Sars-cov-2)
- VAIDS: Vaccine-acquired immunodeficiency syndrome
- Jab: Slang for taking a vaccine dose
- OSINT: Open-source intelligence
- Web scraping: Collecting publicly available information from the source code of websites visited by a bot/script.

### C. Research Questions

In this paper we will answer the following questions:

1) How much of the spread of the VAIDS conspiracy on Twitter is done by social bots?
2) How much of the spread of the Clotshot conspiracy on Twitter is done by social bots in comparison to the VAIDS conspiracy?

## II. Background

### A. Covid-19 Pandemic

In December of 2019, a new strain of the coronavirus (severe acute respiratory syndrome coronavirus 2) was detected in Wuhan, China. The virus spread like a wildfire across the globe, evolving into a pandemic. As of late March 2022, millions have died globally [6] and the pandemic is not yet over.

### B. Conspiracy theory

Uscinski and Parent [7] define a conspiracy theory as "an explanation of historical, ongoing, or future event that cites as a main causal factor [behind said event] a small group of powerful people [...] acting in secret for their own benefit against the common good" [7]. Although conspiracy theory is an umbrella term, it is often possible to identify certain shared ideas among most conspiracy theorists. For example, it's common to see a search for complex patterns linking arbitrary events and their causes to specific facts and moral beliefs [1].

### C. Vaccine-acquired immunodeficiency syndrome

VAIDS is a conspiracy theory that state that the different Covid-19 vaccines may cause AIDS. Although experts have found no such correlations, this idea began to spread on social media late 2021 [8].

### D. Clotshot

Clotshot is a conspiracy theory that refers to blood clotting. Similar to VAIDS, the clotshot theory promotes the idea that by taking the 'Covid-19 jab' you pose the risk of acquiring blood clots.

The intended function of blood clotting (coagulation) is to prevent excessive blood loss when an injury has occurred [9]. This is essential for human survival, however in rare cases clots can incorrectly form inside veins causing restricted blood flow to the heart, which can be deadly. This is the type of clotting #Clotshot promotes as becoming more likely due to taking the Covid-19 vaccine.

### E. Twitter API

Twitter has an official API from which developers can access things like tweets, direct messages, spaces, lists, users, and more [10]. The most recent release is version V2. V2 has three access levels, all completely free, each with different level of privileges. These are:

- Essential
- Elevated
- Academic research

These access levels represent different limitations on the developer, where essential is the entry tier and what you get when you sign up. Developers may also apply for additional access through the developer portal, in which case they might be granted elevated or academic research privileges. Rate limits and access to certain endpoints are the main differences between the access levels.

### F. Twint

Twint is a free open-source Python Twitter scraping and OSINT tool that does not use Twitter's official API under the hood [11]. As a result, Twint serves as an alternative to the use of Twitter's own API since it can evade many of the limitations imposed by Twitter while still offering much of the provided functionality of the official API.

### G. Botometer

The Botometer API provides the functionality of estimating the likelihood that a specific Twitter account is a bot [12]. To accomplish this, Botometer uses machine learning algorithms to score user accounts on different metrics. These models have been trained by training sets publicly available on their website [13]. The API has the capability of providing an "overall score" which combines all known metrics to give the most accurate likelihood that the Twitter account is a bot. Botometer is currently able to score users in six different categories, these are:

- Astroturf
- Fake follower
- Financial
- Self declared
- Spammer
- Other

The scores are measured on a 0-5 scale, but API users can opt in to choose the 0-1 "raw" representation instead. A high score means it is likely a bot, and vice verse for a low score. [14]. The API also offers the complete automation probability (CAP) which asks "what are the chances that an account with a bot score higher than this account is human, or automated" [13]. This value represents the tool's approximate false positive rate.

Botometer is closed source, but as mentioned before, the machine learning training sets used to create the models are publicly available. OSoMe (The Observatory on Social Media) [15] currently offer three plans for the Botometer API, these are:

- Basic
- Pro
- Ultra

As they explain "The Basic plan is free. The Pro plan allows higher rate limits but requires a credit card. The Ultra plan allows ever higher rate limits." [12].

## III. Related Works

Several studies agree that social bots are actively discussing Covid-19 on Twitter [3], [16], [17]. Furthermore, several studies suggest the bots may be used to spread narratives. Ferrara et al. [16] examined 43.3 million Covid-19 related English tweets to investigate the presence of social bots for the Covid-19 discussions on Twitter, and if they amplify conspiracy theories & political narratives. To identify whether a user was a bot they used the machine learning through the Botometer tool (for which he is involved in developing) [14] as well as human validation. The study confirmed the presence of social bots, and suggested that the bots amplify the spread of misinformation and political & ideological narratives. Xu et al. [17] further confirmed Ferrara's study with regards to political narratives, finding that social bots amplify right-wing misinformation, particularly for anti-China-related topics. Furthermore, they suggested additional monitoring of social bots on Twitter due to the potential harm possible with these activities. Moffitt et al. [18] used a machine learning approach with BERT to classify tweets as either conspiracy theories or not, and looked at a wide range of hashtags. They found that social bots were more common in the conspiracy discussions compared to non-conspiracy discussions. Furthermore, they found that there was a credibility difference between users in conspiracy groups and non-conspiracy groups, where the former linked to mainly unreliable sources.

Moreover, several studies have studied to what extent bots are active, both in general conspiracy theories, and in specific conspiracy theories. Himelein-Wachowiak et al.'s [3] study looked at active currently known bots on Twitter and found that 66% (∼2000) of them were actively discussing Covid-19 conspiracy theories. Jamison et al. [19] studied the "vaccines causes autism" conspiracy and found that only 17% of the studied accounts were likely to be bots.

The main contributions of our work is to present to what extent bots are active in the spread of the VAIDS and Clotshot conspiracy theories.

## IV. Method

This project was divided into two parts, theoretical research and practical measurements.

### A. Literature study

In order to write the related works section and to get a better understanding of the topics at hand, various articles relating to Twitter bots and conspiracy theories were read. These articles and papers were mainly found by searching LiU:s divaportal and the Google Scholar search engine [20] [21], however regular google searches were also used. Search results were sorted by relevance, not by date. Search terms included, but was not limited to, *Twitter bots conspiracy theories*, *VAIDS*, *Clotshot*. Due to the conspiracies in focus changing several times during the early stages of the project, some search terms included conspiracies such as *5G*, that were discarded later on.

### B. Practical measurements

In this study, the Botometer API was used to identify accounts on Twitter suspected of being bots [12]. The authors created a free RapidAPI account and then used the basic Botometer plan, whereas the supervisor had access to the ultra plan. To find tweets that used specific hashtags or words, the official Twitter API V2 and the Twint tool was used. To access the needed recent search endpoint, the authors applied for and received elevated access to the Twitter API.

The project was divided into several Python3 scripts. Furthermore, the data was split between queries using hashtags (for instance, '#VAIDS') and without hashtags (For instance, 'VAIDS'). One file called *log_tweets.py* was used to search for two specific hashtags, each corresponding to one of the conspiracies (i.e. #VAIDS and #Clotshot). Using the Python library called *requests*, the script constructed one of two predetermined queries (determined by a flag when starting the script) and then made a HTTP GET request to the recent search endpoint (*https://api.twitter.com/2/tweets/search/recent*). From the JSON response, the author id of each tweet was extracted. The script then looked if this particular user id had already been checked by Botometer. If yes, the script moved on to the next author id. If no, the script continued by adding the user id to the log file which kept track of accounts checked. It then called the *botometer.Botometer.check_account(user_id)* function to receive the bot scores of that particular user, which were extracted from its JSON response and then added to another log file. This script continued to run until either the recent search endpoint returned no more tweets using that query or the number of Botometer checks had exceeded it's daily max limit.

Another script, called *twint_search.py*, used the *twint.run.Search()* function to search for the same queries as the previously mentioned file did. The difference between these was that the twint query could specify tweets long before the past seven days, unlike the limited recent search endpoint (see chapter IV-C). The results were stored in temporary log files, one for each hashtag. A new script, *id_extraction.py*, retrieved the user ids from the temporary log files and created new log files to store these in. These files containing user ids from tweets collected by twint from 2022-01-01 to 2022-04-21, were sent to the project supervisor for analysis (see IV-C).

The *analyze_pickle.py* script extracted the bot scores from the files returned by the supervisor and added them to the ones extracted by *log_tweets.py*.

Finally, the *analyze_logs.py* script was used to calculate the results and graphs discussed in the next chapter. To create the graphs, a library called *matplotlib* was used in conjunction with the inbuilt *statistics* module.

### C. Limitations

Each library used had their own limitations, whether it be the rate limit (how many request / 15 min) or the number of requests per day. The main limitation of the Twitter API however, was that its recent search endpoint was limited to the past seven days (with elevated access). Chapter VI-E contains a discussion of the pros and cons of the Twitter API and Twint. One general limitation of looking far back is that it's more likely that accounts suspected of being bots have already been banned or had their tweets removed.

Botometer was another bottleneck of the project. The free version only allowed for 500 checks per day (together the authors could check 1000). This limitation was somewhat mitigated since the project supervisor had better access and could check more than enough accounts per day. Then there are the inherent limitations of Botometer's bot identification abilities. For example, Botometer is best calibrated to judge accounts that only write posts in English.

The chosen conspiracy theories in focus pose some limitations themselves, mainly that they are relatively unknown in comparison to other more established theories. In practice this means that there are relatively few people tweeting about them.

Lastly, the project was limited by the short time frame in which it was expected to be completed.

## V. Result

In total ∼15,000 unique users were gathered through the Twitter- and the Twint API. The Twitter API resulted in ∼2000 of the unique users. The VAIDS conspiracy resulted in ∼11,500 of the unique users, whilst the ClotShot conspiracy only resulted in ∼3200 unique users. Furthermore, out of the 11,500 users gathered with the VAIDS query, 2400 were found using the hashtag '#VAIDS', whilst the rest were found using 'VAIDS'. For the ClotShot conspiracy, 2300 was found using the hashtag '#ClotShot' whilst the rest were found using 'ClotShot'.

About 70% of the users posted the majority of their tweets in English. The final 30% wrote in a variety of languages ranging from Japanese to German to Portuguese.

The CAP value distribution, as seen in figs. 1, 2 and 4 to 9 (appendix), was shown to be very similar for all of the queries, with around 20-25% of all the users scoring ∼0.8 (80%). The mean & median were very close for all of the queries as well, resulting in approximately 0.6 for the earlier and approximately 0.7 for the latter.

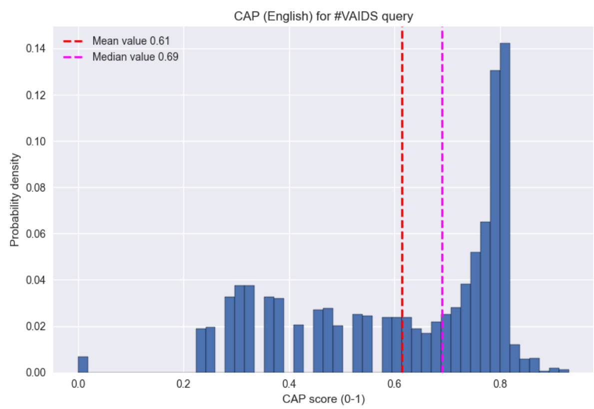


Fig. 1. CAP English score for #VAIDS query

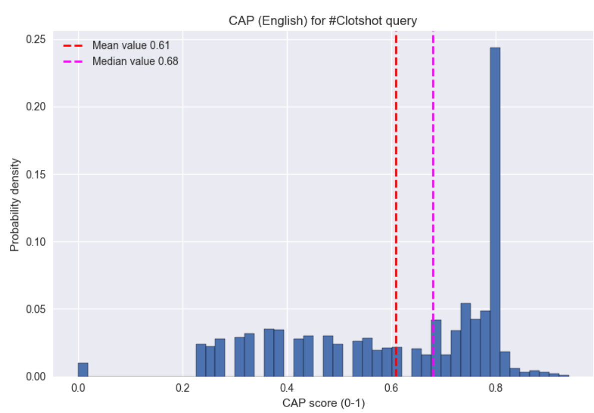


Fig. 2. CAP English score for #ClotShot query

For the Botometer category scores, similar patterns as for CAP was shown, where all of the values resulted in quite similar distributions regardless of the query (hashtag or not, Universal or English, VAIDS or ClotShot). The English values for VAIDS, as seen in figs. 3 and 10 to 15, show that the categories of Astroturf, Other, Overall and Fake Follower were the predominant factors, resulting in a mean value of 1.08, 1.22, 1.13 and 0.89 respectively. Meanwhile, Financial, Self declared and Spammer resulted in a mean of 0.11, 0.39 and 0.3 respectively. Similar patterns were found for all other queries. For more precise values, refer to tables I to IV.

| ClotShot | | |
|---|---|---|
| ClotShot | English (mean) | Universal (mean) |
| CAP | 0.60 | 0.66 |
| Astroturf | 1.27 | 1.29 |
| Fake Follower | 0.93 | 0.9 |
| Financial | 0.16 | 0.15 |
| Other | 1.24 | 1.4 |
| Overall | 1.22 | 1.35 |
| Self-Declared | 0.29 | 0.3 |
| Spammer | 0.30 | 0.37 |

TABLE I
CLOTSHOT CATEGORICAL MEAN VALUES.

| #ClotShot | | |
|---|---|---|
| #ClotShot | English (mean) | Universal (mean) |
| CAP | 0.61 | 0.66 |
| Astroturf | 1.38 | 1.4 |
| Fake Follower | 0.92 | 0.9 |
| Financial | 0.17 | 0.15 |
| Other | 1.24 | 1.38 |
| Overall | 1.24 | 1.38 |
| Self-Declared | 0.22 | 0.23 |
| Spammer | 0.29 | 0.35 |

TABLE II
#CLOTSHOT CATEGORICAL MEAN VALUES.

| VAIDS | | |
|---|---|---|
| VAIDS | English (mean) | Universal (mean) |
| CAP | 0.58 | 0.66 |
| Astroturf | 1.08 | 1.07 |
| Fake Follower | 0.89 | 0.87 |
| Financial | 0.11 | 0.11 |
| Other | 1.22 | 1.52 |
| Overall | 1.13 | 1.34 |
| Self-Declared | 0.39 | 0.42 |
| Spammer | 0.30 | 0.38 |

TABLE III
VAIDS CATEGORICAL MEAN VALUES.

| #VAIDS | | |
|---|---|---|
| #VAIDS | English (mean) | Universal (mean) |
| CAP | 0.61 | 0.69 |
| Astroturf | 1.27 | 1.25 |
| Fake Follower | 0.93 | 0.93 |
| Financial | 0.16 | 0.14 |
| Other | 1.23 | 1.49 |
| Overall | 1.25 | 1.45 |
| Self-Declared | 0.21 | 0.22 |
| Spammer | 0.31 | 0.38 |

TABLE IV
#VAIDS CATEGORICAL MEAN VALUES.

## VI. DISCUSSION

### A. *Complete automation probability*

When comparing the CAP thresholds chosen by different authors in published articles that cover the use of Botometer,

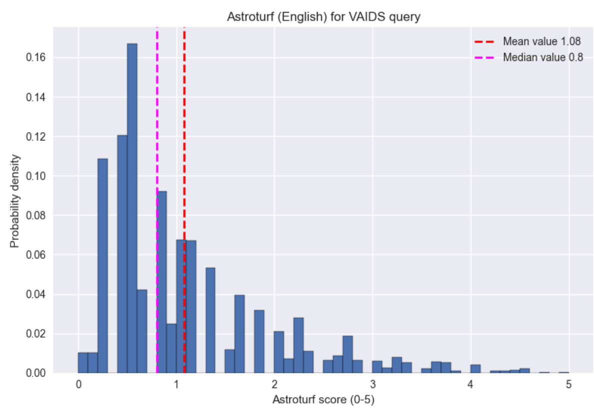


Fig. 3. Astroturf English score for VAIDS query

it's clear that defining a reasonable threshold is hard and subjective. For example, in Zhang et al's [22] study, a CAP value of 0.25 was chosen, which for our data set would result in 97.5% of the VAIDs tweeters being bots, and 96.7% of the ClotShot tweeters being bots.

Other examples include Xu et al's [17] and Keller et al's. [23] studies that used CAP values of 0.54 and 0.76 respectively. Applying these thresholds on our data results in 71% of VAIDS and 65% of Clotshot tweeters being bots according to Xu et al., and 47%, 37.9% according to Keller et al.

With a CAP value limit of 0.8 instead, significantly less bots are identified, with 11.3% of the VAIDS tweeters being likely bots, and just about 5.6% of ClotShot tweeters being likely bots. Similarly with a CAP value of 0.9, 0.6% of the VAIDS tweeters are classed as likely bots, and 0.4% of the ClotShot tweeters are classed as likely bots.

Choosing the highest CAP value threshold found in the reviewed related works, 0.76 from [23], the amount of likely bots found seem unreasonably high. Previous studies have shown much lower proportions of likely bot users. For example, Zhang et al. [22] found that less than 10% of sampled users were likely to be bots, using a 0.25 CAP as the threshold. Shi et al. [5] estimated that 10% of all users tweeting about Covid-19 conspiracy theories are likely to be bots. Varol et al. [24] (creators of Botornot, the precursor to Botometer) estimated 9-15% for Twitter accounts in general.

Looking at the CAP distributions of the different graphs, there is one common factor, namely a large spike at around 0.8. The reason behind this spike is unclear, although, one hypothesis could be that the Botometer tool is flawed and tend to put users in that bracket. Another hypothesis could be that the Botometer has correctly identified one particular type of bot, which is widely used and behaves similarly for every instance of it, and just happens to score in at 0.8.

### B. *Difficulties*

One difficulty with the project was to gather unique users, and the heavily skewed distribution created between users gathered from VAIDS compared to users gathered from ClotShot. One possible reason for this unbalanced distribution, except for the obvious one which is that VAIDS simply is a more popular theory and will thus be written more about, is that ClotShot isn't the unanimous hashtag used, and there exists multiple sub-branches of the conspiracy which wasn't detected in this study, compared to the VAIDS theory which seem more mainstream amongst the conspirators.

### C. *Choice of conspiracy theories*

The reason why #Clotshot and #VAIDS were chosen is because they were, at the time the project started, adequately large to warrant further investigation while still being new enough that no previous articles had mentioned them (at least from what we could find).

### D. *Botometer*

Accurately identifying Twitter accounts run by bots is not an easy feat and is outside of the scope of this study. For this study, a well known bot detection tool called Botometer was used. Botometer stands out from other bot detection tools in three main ways [25]. It has been around for a long time (7 years), it's easy to use and it has been extensively tested and used by various authors in different studies. These reasons solidify Botometer as the natural first choice for detecting bots on Twitter.

### E. *Twint vs Twitter API V2*

There are several reasons why a user could prefer the use of Twint instead of, or in addition to, the official API provided by Twitter themselves. The main difference between these is that the Twitter API queries the actual database for information relating to the endpoint used, whereas Twint is a web scraper that searches publicly available information and then filters it according to the user query.

Due to the nature of web scraping, Twint is able to bypass many of the limitations that are imposed upon the use of the official API endpoints. For instance, Twint is not affected by Twitter's defined rate limits. As mentioned in chapter II-E, Twitter separates privileges based upon each developer account's access level. Higher access level allows for higher rate limits and access to "premium" endpoints. For example, the recent search endpoint is limited to the past seven days unless you have access to *academic research*, in which case you can search the past 30 days. Twint on the other hand does not have different access levels, nor does it limit how far back you can search for tweets. Another benefit of Twint is that it requires less information about the user, only the bearer token, whereas the official API also requires an API key + secret and an access token + secret.

There are of course downsides to Twint and web scrapers in general. Mainly, it's not guaranteed that it will be able to find all the information available to Twitter's own API. Decreased accuracy and increased inconsistent results are also to be expected.

## VII. Conclusion

This paper has shown there is probable bot activity on Twitter surrounding the VAIDS and Clotshot conspiracy. Since the Botometer tool provides a CAP value as a likelihood in percent, the certainty of the extent of bots is debatable. Moreover, previous studies tend to use widely varying CAP values, making it difficult to give exact numbers. Using a CAP value of 0.76 as the threshold, as used in Keller et al.'s [23] study, approximately 40% of the users would be classified as likely to be bots. This is quite high in comparison to estimations made by previous studies, such as Shi et al. [5] estimating 10%. Despite this, 0.76 was by far the largest CAP found amongst the reviewed related works. Lower thresholds would have further increased the likelihood.

In conclusion, this study's best estimate is that 47% of the VAIDS and 37.9% of the Clotshot conspiracy theories are spread on Twitter by bots. Furthermore, this study found that both conspiracies lead to similar distributions in all of the Botometer subcategories, where the VAIDS query resulted in slightly higher average bot scores.

## VIII. Acknowledgments

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## IX. Declarations

The authors declare that they have no conflicts of interest.

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# Appendix

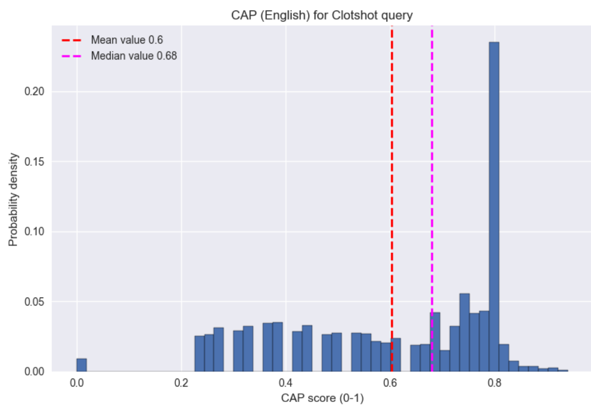


Fig. 4. CAP English score for ClotShot query

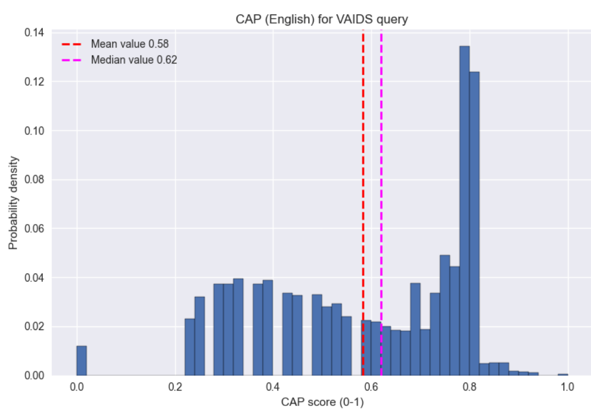


Fig. 5. CAP English score for VAIDS query

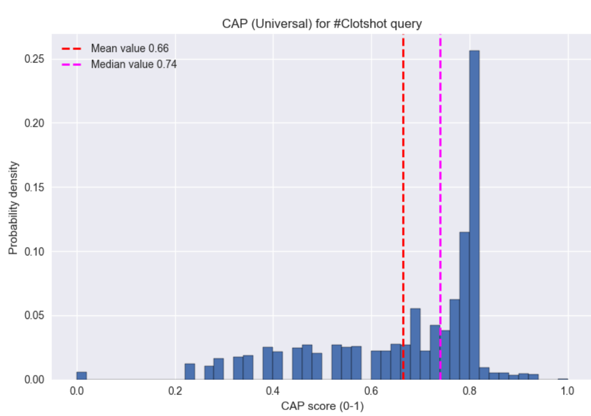


Fig. 6. CAP universal score for #ClotShot query

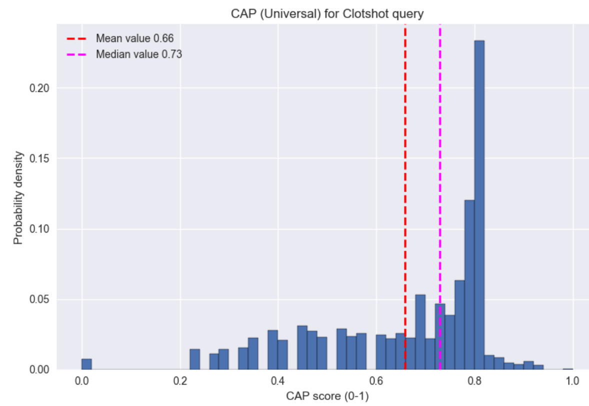


Fig. 7. CAP universal score for ClotShot query

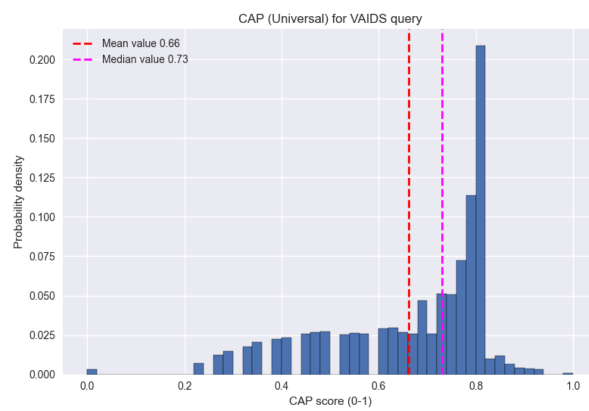


Fig. 8. CAP universal score for VAIDS query

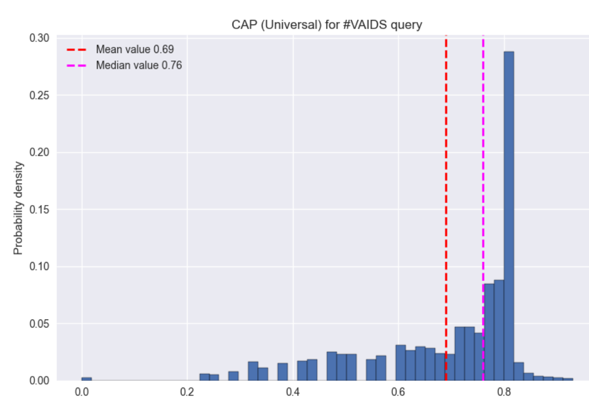


Fig. 9. CAP universal score for #VAIDS query

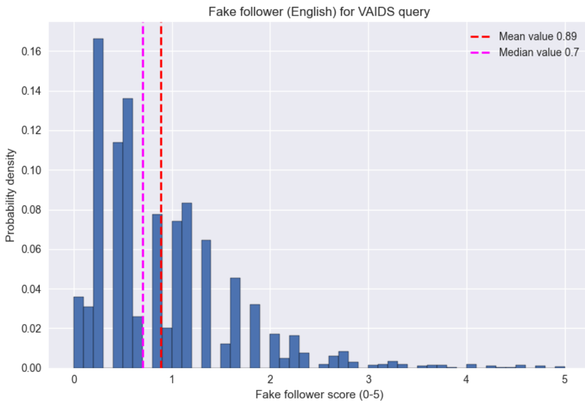


Fig. 10. Fake Follower English score for VAIDS query

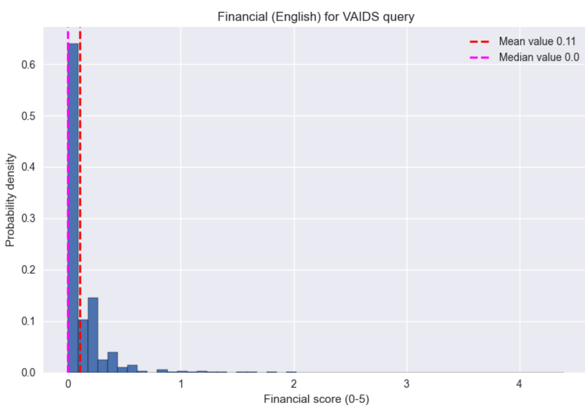


Fig. 11. Financial English score for VAIDS query

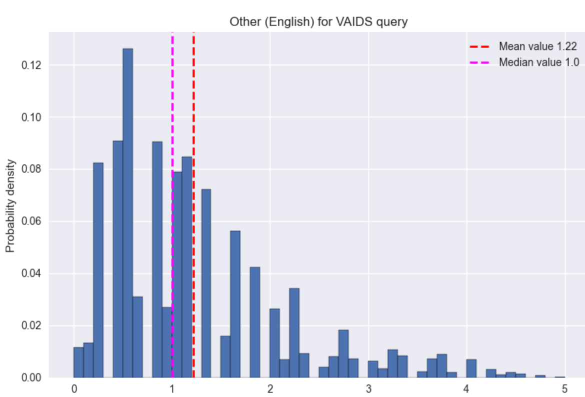


Fig. 12. Other English score for VAIDS query

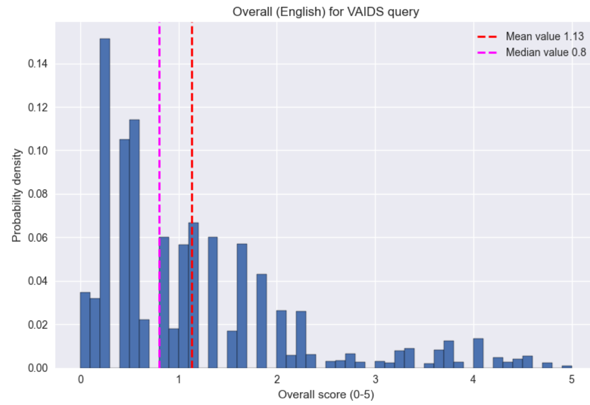


Fig. 13. Overall English score for VAIDS query

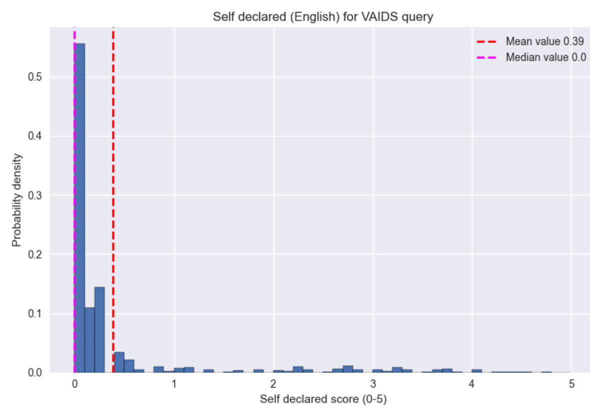


Fig. 14. Self-Declared English score for VAIDS query

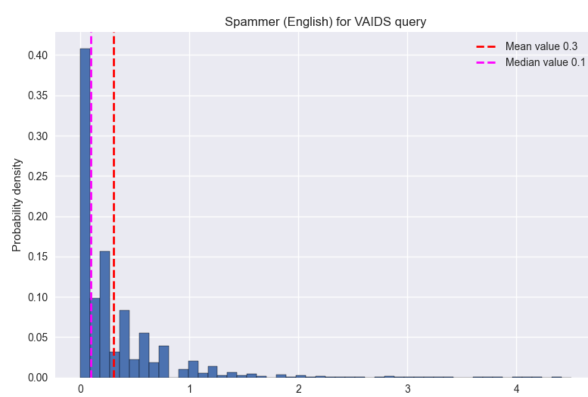


Fig. 15. Spammer English score for VAIDS query