

What's All That Noise: Analysis and Detection of Propaganda on Twitter

Ansgar Kellner
TU Braunschweig

Christian Wressnegger
Karlsruhe Institute of Technology

Konrad Rieck
TU Braunschweig

ABSTRACT

For many, social networks have become the primary source of news, although the correctness of the provided information and its trustworthiness are often unclear. The investigations of the 2016 US presidential elections have brought the existence of external campaigns to light aiming at affecting the general political public opinion. In this paper, we investigate whether a similar influence on political elections can be observed in Europe as well. To this end, we use the past German federal election as an indicator and inspect the propaganda on Twitter, based on data from a period of 268 days. We find that 79 trolls from the US campaign have also acted upon the German federal election spreading right-wing views. Moreover, we develop a detector for finding automated behavior that enables us to identify 2,414 previously unknown suspicious accounts.

CCS CONCEPTS

• Security and privacy → Social aspects of security and privacy;

KEYWORDS

Twitter, Trolls, Bots, Propaganda, German Federal Election

ACM Reference Format:

Ansgar Kellner, Christian Wressnegger, and Konrad Rieck. 2020. What's All That Noise: Analysis and Detection of Propaganda on Twitter. In *13th European Workshop on Systems Security (EuroSec '20)*, April 27, 2020, Heraklion, Greece. ACM, New York, NY, USA, 6 pages. <https://doi.org/10.1145/3380786.3391399>

1 INTRODUCTION

The use of social media for propaganda purposes has become an integral part of cyber warfare [1]. Most prominently, in 2016 the US presidential elections have been targeted by a Russian interference campaign on Twitter [2]. However, the use of online propaganda is not an isolated phenomenon, but a global challenge [20, 24, 25]. The effect of political propaganda and fake news is further amplified by journalists that use Twitter to acquire “cutting-edge information” when chasing down trending topics for their next story [4, 5], and distribute them via traditional media.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

EuroSec '20, April 27, 2020, Heraklion, Greece

© 2020 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-1-4503-7523-8/20/04...\$15.00

<https://doi.org/10.1145/3380786.3391399>

In this paper, we investigate whether a similar influence on political elections can be observed in Europe as well and thus analyze the Twitter coverage of the German federal election (*Bundestagswahl*) to figure out to which extent the public opinion has been influenced. To this end, we have collected 9.5 million tweets related to the hashtags of all major German parties over 268 days, from January to September 2017. In contrast to earlier work on the influence on Twitter [3, 21, 31], we focus on basic features that can directly be derived from the tweets and their metadata, such as the number of retweets or quotes. The mere quantity of tweets is already sufficient to identify distinct events in time, that precede the election day, for instance, the presentation of the political manifestos of the individual parties or TV shows covering the election.

We start with the investigation of the influence of *troll accounts* of the Internet Research Agency (IRA), which have been disclosed in the context of the investigations of Russian interference in the 2016 US presidential elections [26, 27]. We find that 79 of these trolls have also been active for the German federal election, resulting in a total amount of 9,309 tweets in our dataset. Based on these first impressions we broaden our perspective to the entire political landscape looking for indicators of propaganda. In a detailed analysis, we survey specific topics and how these are related to political parties as well as individual users that have contributed to them. This allows conveying a feeling for the overall distribution of tweets per party and per political orientation, respectively. For instance, topics related to the controversial right-wing party *Alternative für Deutschland* (AfD) have been predominant during the election, including supporting as well as opposing positions.

Subsequently, we develop a detector that is able to rate automated behavior in order to identify *suspicious accounts* in our dataset, which have been identified for being a root cause for the amplification of propaganda [30]. Using this classifier we find 2,919 previously unknown accounts that exploit means of automated behavior, which represent 12.19% of all user accounts in our dataset. While this number seems surprisingly large, it is perfectly in line with previous research, which states that 9–15% of all active Twitter accounts are automated [28]. Since detecting automated behavior is difficult, our results should be rather seen as first indicators.

In summary, we make the following contributions:

- **Investigation of the Propaganda Landscape.** We collect and analyze the, to the best of our knowledge, largest Twitter dataset in the context of the German federal election.
- **Analysis of Known Actors.** We show that 79 of the IRA trolls accounts are still active during the German federal election, indicating an ongoing influence.
- **Detection of Automated Propaganda.** We detect 2,414 previously unknown automated Twitter accounts that are suspected to contribute as an amplifier for propaganda.

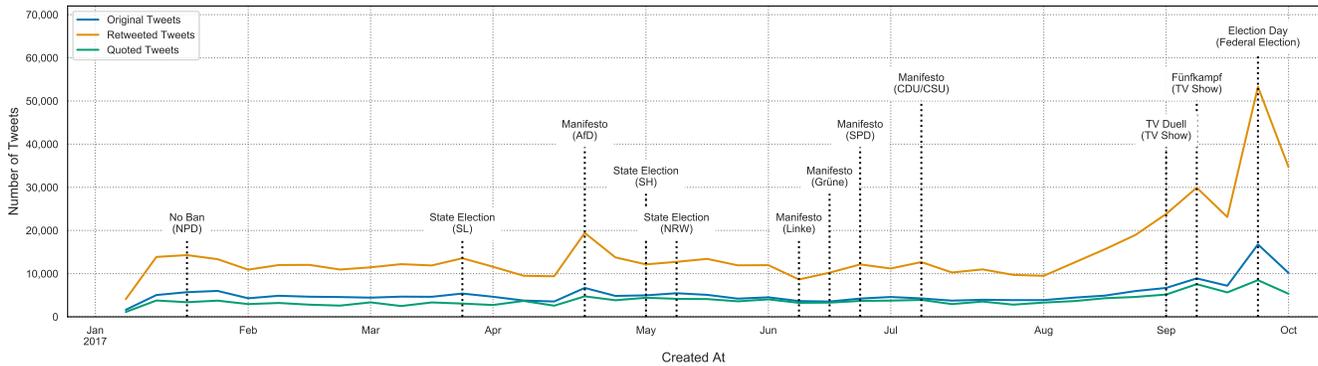


Figure 1: Development of tweet types over time.

The remainder of the paper is organized as follows: Section 2 discusses the basic properties of our dataset that has been recorded during and prior to the German federal election. In Section 3, we investigate the presence of known propaganda actors in this data, before we discuss the overall political landscape of the dataset regarding indicators of propaganda in Section 4. Subsequently, we describe and evaluate our bot detector in Section 5. Related work is discussed in Section 6, while Section 7 concludes the paper.

2 THE GERMAN FEDERAL ELECTION ON TWITTER

For our analysis, we consider 9.5 million tweets that have been published in the context of the German federal election (*Bundestagswahl*) and have been collected over 268 days, from January to September 2017. As we are relying on the publicly available Twitter Stream, we receive maximally 1% of all publicly available tweets. This limit, however, is only hit seldom. Due to random sampling, the subsequently reported numbers can be safely extrapolated and the drawn conclusions remain valid. To restrict our analysis to the German federal election, we apply the search terms shown in Table 1, that correspond to the abbreviations of the major German parties¹. For *Die Grünen* and *Die Linke* we use different common abbreviations, derived from the list of recognized parties by the Federal Electoral Committee [12], as these do not bear official acronyms.

Based on a manual plausibility examination of the collected data on a sample basis, we found an exceptionally high amount of tweets in Portuguese language matching the search term *fdp*. Further investigation revealed that *fdp* is a commonly used abbreviation for a Portuguese swearword that is tainting our dataset. Due to the fact that the language of the affected tweets is not correctly identified by Twitter, we cannot use this feature for filtering. Instead, we completely exclude all tweets that contain the search term *fdp*, which has accounted for 7.56% of the tweets. In the following, we focus on the 8,845,879 remaining tweets for further analysis.

¹We consider all parties that have cleared the 5% threshold in the previous federal election (2013) or in one of the previous state elections (2014 – 2016). We additionally consider the NPD that has closely failed the threshold (4.9%) in Saxony in 2014.

We proceed with the detection of known propaganda actors in our dataset. To this end, we have a closer look at troll accounts that have been involved in the 2016 US presidential elections and which have later been disclosed by Twitter.

3 KNOWN ACTORS

In the course of the investigations of Russian interference in the 2016 US presidential elections, Twitter has composed a list of accounts that are linked to the Internet Research Agency (IRA) [26] and had been identified to be influential during the US elections. An updated list was forwarded to the US Congress in June 2018 [27] and released to the public to foster further research on the behavior of those accounts [23].

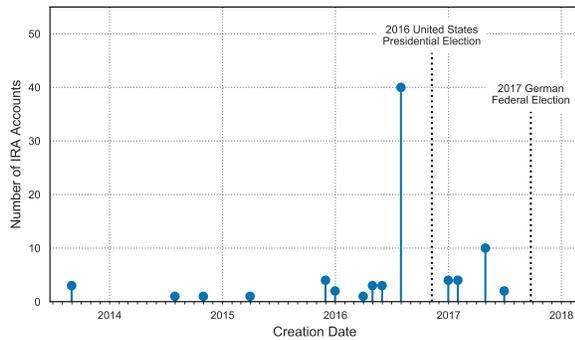
Based on the assumption that existing Twitter accounts are often reused for other purposes, we try to identify the same trolls in our dataset. To this end, we match the list of the 2,752 published IRA troll accounts to the user accounts from our dataset. Since the screen name of a user account can be freely changed, we first map the obtained screen names to their corresponding unique user IDs [32]. In doing so, we are able to detect 79 of the IRA troll accounts in our dataset which is 0.02% of the total number of users.

Table 1: Search terms used for the data acquisition.

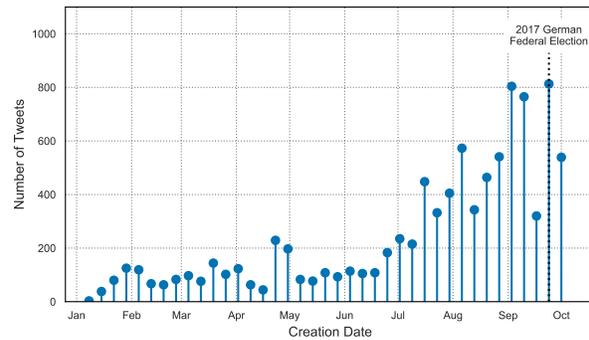
Party	Political Direction	Term
<i>Alternative für Deutschland (AfD)</i>	Right-wing to far-right	afd
<i>Christlich Demokratische Union (CDU)</i>	Christian-democratic, liberal-conservative	cdu
<i>Christlich-Soziale Union (CSU)</i>	Christian-democratic, conservative	csu
<i>Freie Demokratische Partei (FDP)</i>	(Classical) Liberal	fdp
<i>Bündnis 90/Die Grünen</i>	Green politics	gruene*
<i>Die Linke</i>	Democratic socialist	linke†
<i>Nationaldemokratische Partei Deutschlands (NPD)</i>	Ultra-nationalists	npd
<i>Sozialdemokratische Partei Deutschlands (SPD)</i>	Social-democratic	spd

*Additionally: grüne, diegrünen, diegrünen

†Additionally: dielinke



(a) Creation dates of IRA troll accounts.



(b) Tweets posted in the context of the German federal election.

Figure 2: Internet Research Agency (IRA) troll accounts.

Surprisingly, only one of the identified accounts has changed its screen name during this time. However, the identified accounts are only responsible for a total amount of 9,309 tweets that is 0.06% of the tweets from our dataset, rendering their potential direct influence comparably low. Interestingly, 79.75% of the identified accounts have tweeted less than 35 tweets over the entire period, while the top-3 troll accounts published more than 1,000 tweets each. Similarly, to the entire dataset, most of the trolls' tweets are actually retweets (4,341); however, there is also a vital amount of original tweets (3,520) and fewer quotes (1,448). Due to the fact that the list of IRA accounts was made publicly available a significant time ago, it is likely that the IRA has created new accounts that we are not aware of, yet.

Figure 2a shows the creation dates of the IRA accounts over the last few years. Most of the IRA accounts have been created before November 2016, the month of the US presidential elections, with a significant peak in July 2016. However, additional IRA accounts have been created between the beginning and mid-2017 which means right before the German federal election. Figure 2b shows the number of tweet contributions of the IRA accounts in the context of the 2017 German federal election. Unsurprisingly, there is a strong increase of tweets over the year 2017, with its highest peaks at the beginning of September, the month of the election, and particularly on the day of the election itself.

Finally, to examine the impact of the IRA accounts on other users, we verify if other accounts do interact with the IRA troll accounts, for instance, by retweeting their tweets. First of all 4,341 of the tweets posted by IRA accounts have been retweeted. Only 16 tweets originate from the known IRA accounts, leaving the large remainder to other users. Interestingly, the 1,448 quoted tweets from IRA accounts have all been quoted by other users, that are outside the peer group of known IRA accounts. Although the majority of the other users are likely regular user accounts, there seem to be a fraction of accounts that are unknown troll accounts, we are not aware of. We conclude that although the amount of IRA accounts and corresponding tweets is low, in comparison to the total amount of recorded users and tweets, there is a verifiable impact from the IRA accounts on other accounts of the dataset.

4 PROPAGANDA LANDSCAPE

Based on our analysis of known propaganda actors, we broaden our perspective by taking the general political propaganda landscape into account. To this end, we proceed with an analysis of the total tweet corpus to verify if the same ratio of original tweets, retweets and quotes can be observed for all collected tweets and parties.

Figure 1 shows the temporal development for original tweets (blue), retweets (yellow), and quoted tweets (green). Notice that the amount of retweets significantly exceeds the other two tweet types. Consequently, these are a particularly strong factor of amplification when spreading opinions. Original or quoted tweets occur roughly 60–75% less frequently, each. However, the general trend leading up to the collection's highest value at election day, and the shape of the amount's development corresponds to all three types.

Throughout the recording, we observe local peaks that may be attributed to distinct events in time, which we briefly discuss in the following: In January the *Federal Constitutional Court* has ruled in favor of not banning the far-right, nationalists party *NPD*, which has been preceded and succeeded by heated debates. The state elections of *Schleswig-Holstein* (SH), *Saarland* (SL), and *North Rhine-Westphalia* (NRW), in turn, have only triggered mediocre response, whereas the presentation of the election manifestos for the German federal election partly receives significant attention. Particularly, the publication of the manifesto of the right-wing party *AfD* at the end of April is noteworthy at this point. Starting in August, we record a strong increase of tweets leading up to the federal election day on 24th of September. This rise is supported by several political talk shows, such as *TV Duell* and *Fünfkampf* at the beginning of September.

Hashtags. Among the ten most used hashtags we observe the acronyms of five political parties that have been up for election. Figure 3 shows a summary of the top 10 hashtags and their number of occurrences. Interestingly, the party that has triggered the largest peak in tweets when presenting their election manifesto, the *AfD*, also peaks in total as hashtag *#afd*, with 1,968,601 occurrences. Thereby, the *AfD* occurs three times more often than the second-placed *SPD* with 631,209 occurrences. The general hashtag for the German federal election, *#btw*, in turn, is only used in 442,457 tweets. On the

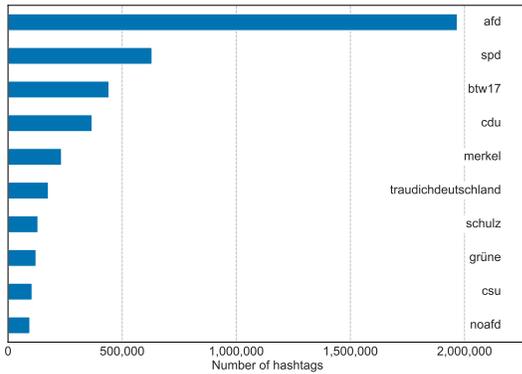


Figure 3: Top-10 individual hashtags.

sixth place, with the campaign *#traudichdeutschland*, the *AfD* takes a prominent position for a second time with 176,677 occurrences.

Moreover, we consider the most used combinations of hashtags and observe a similar dominance of the *AfD*. The hashtag *#afd* appears in four out of ten different combinations. In summary, the *Alternative für Deutschland (AfD)* seems to be particularly active on Twitter in comparison to other parties.

Quoted/Retweeted Users. As a measure of the popularity and influence of individual accounts, we also look at the most quoted and retweeted users on our recording. Interestingly, *@AfD_Bund*, and *@Beatrix_vStorch* are present in both rankings. The first is the official account of the *AfD* party, and the latter is an *AfD* politician, so are *@FraukePetry*, *@SteinbachErika*, *@lawyerberlin*, and *@Alice_Weidel*. Consequently, the list of the ten most retweeted users is largely dominated by one party. The remaining accounts, *@66Freedom66* and *@DoraBromberger*, advertise right-wing views and thus being also in line with the party.

Furthermore, three other political parties are rather prominently present: *@CDU*, *@CSU*, and *@SPD*. Especially the latter, the left-wing social democrats, have two politicians among the top 10 quoted user accounts (*@Ralf_Stegner* and *@MartinSchulz*). The remaining accounts mainly correspond to popular German news magazines: *@welt*, *@tagesschau*, *@wahlrecht_de*, and *@ZDFheute*.

5 DETECTING AUTOMATED PROPAGANDA

Based on our findings, we proceed with the identification of automatic account behavior, which holds responsible for being one of the root causes for the amplification of heavily discussed political topics [30]. To this end, we apply a supervised machine learning approach to detect suspicious accounts.

Although the topic of bot detection is well-known, the detection of automated political accounts, in particular, is still an open challenge, as indicated in related work [e.g., 9, 13]. On the one hand, this is due to its diverse characteristics, involving the political direction and target audience, and, on the other hand, due to the constant evolution of automated accounts that are approaching a more human-like behavior by imitating common usage patterns [13, 19].

For the implementation of our classifier, we make use of the insights gained from the identified IRA trolls and saliences found in our in-depth analysis of the political landscape.

Labeling. As the dataset has been just recorded for this purpose, there are no existing labels of automated and non-automated accounts, respectively, available that are required to train a supervised machine learning model. We therefore manually attribute Twitter accounts for both classes using a set of simple heuristics. These include a test for repetitive behavior of the same tweeting pattern, a frequently posting of tweets without adhering sleep breaks at least every 48 h or tweeting of multiple hashtags from the trending topics combined with a URL, etc. Even for trained experts, the distinction between both account types remains a difficult challenge. To avoid wrongly labeled training samples, we concentrate on those accounts for which we could identify the class with high confidence. As a result, we gathered 505 automated and 874 non-automated accounts in total for the training of the classifier.

Features. Based on the heuristics that were used to manually label the training data, we proceed with the engineering of additional features to improve the detection rate of automatic accounts by exploring the available tweet and user profile information from our dataset. We engineered 44 unique features that are covering the four main categories of metadata-based, text-based, time-based and user-based features. The *metadata-based* features include features such as the average number of tweets per day, the number of different clients used or the retweet-to-tweet ratio. In contrast, the *text-based* features comprise, for instance, the average tweet length, the vocabulary diversity or the URL ratio. Furthermore, the *time-based* features involve the longest average break within 48 h the median time between a retweet, the original tweet, etc. Finally, the *user-based* features imply, e.g., the number of followers, the account verification status or the voluntary disclosure of being a bot.

Models. We train and evaluate seven different machine learning algorithms for the classification of bots and humans. This includes the statistical-based *LogisticRegression* model, the non-parametric *KNeighbors* model as well as the decision tree models *RandomForest*, *AdaBoost* and *GradientBoosting*. Apart from that the two support vector machine learning variants *LinearSVC* and *SVC* are applied and evaluated for their aptitude.

We proceed with the application of our classifier in two experiments: a controlled experiment and an extrapolation of our findings. While the first controlled experiment targets the validation of our classifier on the previously labeled training data and comparison to Botometer [11] as a baseline, the second extrapolates our findings by applying the classifier on the remainder of our unlabeled dataset as an indicator of the degree of automation ratio within the entire dataset.

5.1 Controlled Experiment

Next, we apply the selected machine learning models to our training data by making use of 10-fold cross-validation and repeating the experiments 100 times, followed by averaging the result metrics. We identify the best parameter combination per classifier, by employing a grid search, optimizing for the metric of best average *Area Under Curve (AUC)*. Table 2 shows the examined classifiers with the best parameters found for each classifier type, sorted by the average AUC overall repetitions in descending order. We further compute the *F1-Score* for a single value comparison that considers both

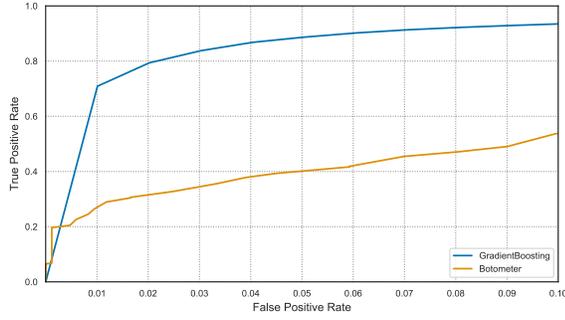


Figure 4: Receiver Operating Characteristics (ROC) of GradientBoosting vs. Botometer with FPR bound to 10 %.

the precision and the recall likewise. The best performance for each metric is shown in the table. The best performing classifier, regarding the average AUC, is the *GradientBoosting* classifier with an AUC of 0.972 and 0.1-bounded AUC with 0.907.

Baseline. As a baseline, we compare our results to the predictions of Botometer, formerly known as BotOrNot [11], a popular bot classifier that is publicly available on the Internet. To this end, we query the Botometer API for each of the previously labeled Twitter accounts from the training dataset to obtain a corresponding bot score. The Botometer classifier yields an AUC of 0.802 and a value of 0.679 if the false positive rate is bound to 0.1, that is, a false alarm rate of 10%. Figure 4 shows the two ROC curves of Botometer and our improved *GradientBoosting* classifier. Our novel classifier outperforms the mature Botometer classifier on our dataset by providing significantly better results.

5.2 Extrapolated Findings

As an indicator of the degree of automation ratio within our entire dataset, we apply the best performing classifier (*GradientBoosting*) on the remainder of our extracted user dataset. We focus on the 23,949 potentially interesting users that have published at least 30 tweets during the collection period. Using our classifier we obtained predictions for 20,157 non-automated and 2,414 automated accounts. In total, that means in combination with the previously manually labeled accounts, we can identify 21,030 non-automated (87.81 %) and 2,919 potentially automated (12.19 %) accounts within the interesting Twitter accounts. Though we do not have labels for the complete user dataset to verify our predictions, our results seem consistent with the recent study of Varol et al. [28], who claim that between 9 % and 15 % of active Twitter accounts are likely to be operated automatically.

Table 2: Results of the tested classifiers.

Classifier	Avg. F1-Score	Avg. AUC
GradientBoosting	0.891 ± 0.033	0.976 ± 0.011
RandomForest	0.861 ± 0.039	0.972 ± 0.013
AdaBoost	0.885 ± 0.035	0.971 ± 0.013
SVC	0.851 ± 0.038	0.949 ± 0.021
LogisticRegression	0.841 ± 0.043	0.946 ± 0.021
LinearSVC	0.821 ± 0.040	0.934 ± 0.025
KNeighbors	0.704 ± 0.060	0.871 ± 0.034

6 RELATED WORK

In the past, a plethora of research on various aspects of social media and Twitter has been conducted; its contact points we discuss here:

Analyses of Political Elections. The first line of research deals with the analysis of political elections on Twitter. For instance, Franco-Riquelme et al. [14] as well as Prati and Said-Hung [18] investigate the 2015 and 2016 general elections in Spain. While Franco-Riquelme et al. [14] measure the regional support of political parties on Twitter during the electoral periods in 2015 and 2016, Prati and Said-Hung [18] focus on the two trending topics #24M and #Elecciones2015 on the election day in 2015 and build a predictive model to infer the ideological orientation of tweets. Also, the US 2016 presidential elections on Twitter are a topic of ongoing research: For instance, Sainudiin et al. [22] characterize the Twitter networks of the major presidential candidates, Donald Trump and Hillary Clinton, with various American hate groups defined by the US Southern Poverty Law Center (SPLC), while Caetano et al. [6] analyze the political homophily of users on Twitter during the 2016 US presidential elections using sentiment analysis.

Furthermore, there are recent works on the 2017 German federal election: Gimpel et al. [15] collect a representative dataset on the German federal election and conduct a cluster analysis to derive eleven emergent roles from the most active users, while Morstatter et al. [17] try to discover communities and their corresponding themes during the German federal election. Subsequently, they analyze how content is generated by those communities and how the communities interact with each other.

Bot Detection. The second line of research deals with the detection of bots on Twitter. Most recent works include Chavoshi et al. [8] who present a correlation finder to identify colluding user accounts using la-sensitive hashing. This has the advantage that no labels are required as for supervised approaches. In contrast, Cresci et al. [10] study the phenomenon of social spambots on Twitter and provide quantitative evidence for a paradigm-shift in spambot design. The authors claim that the new generation of bots imitates human behavior, thus making them harder to detect.

Walt and Eloff [29] try to detect fake accounts that have been created by humans. To this end, a corpus of human account profiles was enriched with engineered features that had previously been used to detect fake accounts by bots. The tested supervised machine learning algorithms, could only detect the fake accounts with an F1 score of 49.75 %, showing that human-created fake accounts are much harder to detect than bot created accounts.

Kudugunta and Ferrara [16] use a deep neural network based on contextual long short-term memory (LSTM) to detect bots at the tweet level. Using synthetic minority oversampling, a large dataset is generated that is required to train the model. As a result, an AUC of 0.99 is achieved. Recently, Castillo et al. [7] study the use of bots in the 2017 presidential elections in Chile. They manually derive labels for the training data and then build a classifier for detecting bots. Though the model reached good results in the training stage, the testing results were not as good as they hoped.

In comparison to the above-mentioned classifiers, our detector makes use of features from multiple categories of different domains i.e., metadata, text, time and user-profile, to cover all aspects of modern automated account behavior.

7 CONCLUSION

We have analyzed a total of 9.5 million tweets to investigate the dissemination of propaganda in the context of the German federal election. We find that 79 of the trolls of Internet Research Agency (IRA) that have already been influencing the US presidential elections in 2016 have also been active a year later in Germany.

Based on these findings and the knowledge about the significance of retweets and quoted tweets for propaganda purposes, we have then broadened our analysis to the general political landscape. In this scope, we have particularly inspected the most tweeted hashtags as well as the involved users. Our evaluation shows that especially the right-wing party *AfD* has played a prominent role in several controversial discussions. The hashtag *#afd*, for instance, dominates the top-10 ranking of hashtag combinations and also the most retweeted users are *all* involved with this right-wing party. Given the partly significant influence on the public discourse on Twitter, it remains an open question whether this influence is driven by automated efforts and bots. The detector we have developed has enabled us to identify 2,919 previously unknown automated accounts, which account for 12.19% of all user accounts.

The large proportion of automated accounts highlights the potential danger when used for propaganda purposes. While it has been inconclusive whether the propaganda efforts observed in our dataset is mainly attributable to bot accounts, our study of the German federal election clearly shows that the political landscape heavily relies on propaganda on social media. Particularly troublesome is the amount of right-wing positions featured in the data.

REFERENCES

- Jessikka Aro. 2016. The cyberspace war: propaganda and trolling as warfare tools. *European View* 15, 1 (2016), 121–132.
- Adam Badawy, Emilio Ferrara, and Kristina Lerman. 2018. Analyzing the Digital Traces of Political Manipulation: The 2016 Russian Interference Twitter Campaign. In *Proc. of IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*. 258–265.
- Eytan Bakshy, Jake M Hofman, Winter A Mason, and Duncan J Watts. 2011. Everyone's an influencer: quantifying influence on twitter. In *Proc. of the international conference on Web search and data mining*. ACM, 65–74.
- Alexandre Bovet and Hernán A Makse. 2019. Influence of fake news in Twitter during the 2016 US presidential election. *Nature communications* 10, 1 (2019), 7.
- Marcel Broersma and Todd Graham. 2012. Social media as beat: Tweets as a news source during the 2010 British and Dutch elections. *Journalism Practice* 6, 3 (2012), 403–419.
- Josemar A Caetano, Hélder S Lima, Mateus F Santos, and Humberto T Marques-Neto. 2018. Using sentiment analysis to define twitter political users' classes and their homophily during the 2016 American presidential election. *Journal of Internet Services and Applications* 9, 1 (2018), 18.
- Samara Castillo, Héctor Allende-Cid, Wenceslao Palma, Rodrigo Alfaro, Heitor S Ramos, Cristian Gonzalez, Claudio Elortegui, and Pedro Santander. 2019. Detection of Bots and Cyborgs in Twitter: A Study on the Chilean Presidential Election in 2017. In *International Conference on Human-Computer Interaction*. Springer, 311–323.
- Nikan Chavoshi, Hossein Hamooni, and Abdullah Mueen. 2016. DeBot: Twitter Bot Detection via Warped Correlation. In *Proc. of the IEEE International Conference on Data Mining (ICDM)*. IEEE, 817–822.
- Zi Chu, Steven Gianvecchio, Haining Wang, and Sushil Jajodia. 2012. Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Transactions on Dependable and Secure Computing* 9, 6 (2012), 811–824.
- Stefano Cresci, Roberto Di Pietro, Marinella Petrocchi, Angelo Spognardi, and Maurizio Tesconi. 2017. The paradigm-shift of social spambots: Evidence, theories, and tools for the arms race. In *Proc. of the International Conference on World Wide Web Companion (WWW Companion)*. International World Wide Web Conferences Steering Committee, 963–972.
- Clayton Allen Davis, Onur Varol, Emilio Ferrara, Alessandro Flammini, and Filippo Menczer. 2016. BotOrNot: A System to Evaluate Social Bots. In *Proc. of the International Conference Companion on World Wide Web*. International World Wide Web Conferences Steering Committee, 273–274.
- Federal Returning Officer. 2017. 48 parties may participate in the 2017 Bundestag Election. https://www.bundeswahlleiter.de/en/info/presse/mitteilungen/bundestagswahl-2017/05_17_parteien_teilnahme.html. visited September, 2019.
- Emilio Ferrara, Onur Varol, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2016. The rise of social bots. *Commun. ACM* 59, 7 (2016), 96–104.
- José N. Franco-Riquelme, Antonio Bello-García, and Joaquín B. Ordieres Meré. 2019. Indicator Proposal for Measuring Regional Political Support for the Electoral Process on Twitter: The Case of Spain's 2015 and 2016 General Elections. *IEEE Access* 7 (2019), 62545–62560.
- Henner Gimpel, Florian Haamann, Manfred Schoch, and Marcel Wittich. 2018. User Roles in Online Political Discussions: a Typology based on Twitter Data from the German Federal Election 2017. In *Proc. of the European Conference on Information Systems (ECIS)*. 8.
- Sneha Kudugunta and Emilio Ferrara. 2018. Deep Neural Networks for Bot Detection. *Information Sciences* 467 (2018), 312–322.
- Fred Morstatter, Yunqiu Shao, Aram Galstyan, and Shanika Karunasekera. 2018. From *Alt-Right* to *Alt-Rechts*: Twitter Analysis of the 2017 German Federal Election. In *Proc. of the Companion of the The Web Conference (WWW)*. 621–628.
- Ronaldo Cristiano Prati and Elias Said-Hung. 2019. Predicting the ideological orientation during the Spanish 24M elections in Twitter using machine learning. *AI & SOCIETY* 34, 3 (2019), 589–598.
- SiHua Qi, Lulwah AlKulaib, and David A Broniatowski. 2018. Detecting and characterizing bot-like behavior on Twitter. In *International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction and Behavior Representation in Modeling and Simulation*. Springer, 228–232.
- Marina Ramos-Serrano, Jorge David Fernández Gómez, and Antonio Pineda. 2018. Follow the closing of the campaign on streaming: The use of Twitter by Spanish political parties during the 2014 European elections. *new media & society* 20, 1 (2018), 122–140.
- Fabián Riquelme and Pablo González-Cantergiani. 2016. Measuring user influence on Twitter: A survey. *Information Processing & Management* 52, 5 (2016), 949–975.
- Raazesh Sainudiin, Kumar Yogeewaran, Kyle Nash, and Rania Sahioun. 2019. Characterizing the Twitter network of prominent politicians and SPLC-defined hate groups in the 2016 US presidential election. *Social Network Analysis and Mining* 9, 1 (2019), 34.
- Adam Schiff. 2018. Schiff Statement on Release of Twitter Ads, Accounts and Data. <https://intelligence.house.gov/news/documentsingle.aspx?DocumentID=396>. visited September, 2019.
- Jieun Shin, Lian Jian, Kevin Driscoll, and François Bar. 2017. Political rumoring on Twitter during the 2012 US presidential election: Rumor diffusion and correction. *new media & society* 19, 8 (2017), 1214–1235.
- Sebastian Stier, Armim Bleier, Haiko Lietz, and Markus Strohmaier. 2018. Election campaigning on social media: Politicians, audiences, and the mediation of political communication on Facebook and Twitter. *Political Communication* 35, 1 (2018), 50–74.
- Twitter, Inc. 2017. List of IRA Accounts as passed to the US Congress. https://democrats-intelligence.house.gov/uploadedfiles/exhibit_b.pdf. visited September, 2019.
- Twitter, Inc. 2018. Extended list of IRA Accounts as passed to the US Congress. https://democrats-intelligence.house.gov/uploadedfiles/ira_handles_june_2018.pdf. visited September, 2019.
- Onur Varol, Emilio Ferrara, Clayton A. Davis, Filippo Menczer, and Alessandro Flammini. 2017. Online Human-Bot Interactions: Detection, Estimation, and Characterization. In *Proc. of the International AAAI Conference on Web and Social Media*. AAAI, 280–289.
- Estée Van Der Walt and Jan Eloff. 2018. Using Machine Learning to Detect Fake Identities: Bots vs Humans. *IEEE Access* 6 (2018), 6540–6549.
- Samuel C Woolley and Philip N Howard. 2016. Automation, algorithms, and politics| political communication, computational propaganda, and autonomous agents—Introduction. *International Journal of Communication* 10 (2016), 9.
- Shaozhi Ye and S Felix Wu. 2010. Measuring message propagation and social influence on Twitter.com. In *Proc. of the international conference on social informatics*. Springer, 216–231.
- Savvas Zannettou, Tristan Caulfield, Emiliano De Cristofaro, Michael Sirivianos, Gianluca Stringhini, and Jeremy Blackburn. 2018. Disinformation Warfare: Understanding State-Sponsored Trolls on Twitter and Their Influence on the Web. In *Proc. of the Workshop on Computational Methods in Online Misbehavior (Cyber-Safety) (WWW Companion)*.