Contributions to the Detection of Unreliable Twitter Accounts through Analysis of Content and Behaviour

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Abstract: Misinformation propagation on social media has been significantly growing, reaching a major exposition in the 2016 United States Presidential Election. Since then, the scientific community and major tech companies have been working on the problem to avoid the propagation of misinformation. For this matter, research has been focused on three major sub-fields: the identification of fake news through the analysis of unreliable posts, the propagation patterns of posts in social media, and the detection of bots and spammers. However, few works have tried to identify the characteristics of a post that shares unreliable content and the associated behaviour of its account. This work presents four main contributions for this problem. First, we provide a methodology to build a large knowledge database with tweets who disseminate misinformation links. Then, we answer research questions on the data with the goal of bridging these problems to similar problem explored in the literature. Next, we focus on accounts which are constantly propagating misinformation links. Finally, based on the analysis conducted, we develop a model to detect social media accounts that spread unreliable content. Using Decision Trees, we achieved 96% in the F1-score metric, which provides reliability on our approach.

1 INTRODUCTION

The exponential growth of users in social networks such as Twitter and Facebook has contributed to their ascent as the number one medium for information distribution and propagation. A recent study has shown that, in 2017, 67% of adults consume some type of news in social media, with 20% of the respondents recurring often to social media for news consumption (Gottfried and Shearer, 2017).

The ease of sharing content via social networks combined with malicious users' intents, created conditions for the spread of misreported information and rumours. However, it was not until 2016, during the United States Presidential Elections that the term "fake news" became trending and a recurrent topic. In addition, it had provided a huge impact on the campaign, with several social media accounts deliberately disseminating false information via original posts or by sharing links to false news sites (Lazer et al., 2018).

Due to the major impact that fake news had, high reputation companies such as Google and Facebook started working to tackle the problem (Hern, 2017; Hern, 2018). The scientific community has also been active on the topic. As a matter of fact, Figure 1 shows the number of hits per year in Google Scholar regarding the term "fake news" where we can observe a constant growth on the number of publications on the topic (there is a slight decay in 2018 but this is probably due to a large number of works that are still being published). Particularly, in 2017, there was an increase of approximately 7000 publications in comparison with the previous year.

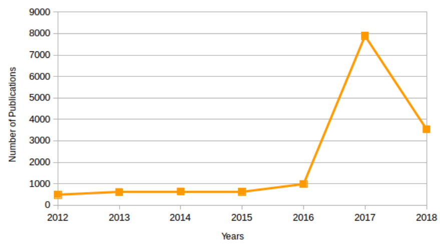

Figure 1: Number of hits per year in Google Scholar for the term "fake news".

Although "fake news" has become a familiar term after the 2016 elections and is normally associated with political news, there are other domains of misinformation that affect social media. Misinformation

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on health conditions or miraculous cures is also a concerning problem, since this type of content is shared more extensively than reliable information (Forster, 2018). Another example is extreme bias content which relies on out of context information or opinions distorted as facts (OpenSources, 2018). All these types of content are disseminated through social networks, influencing users beliefs and their perception of the truth. Therefore, not only is important to determine which content is false but also what accounts/sources to trust on social networks with respect to the large set of misinformation that exists.

In the next section, we cover the related work on fake news and misinformation. In Section 3, we present the methodology to extract unreliable posts. In Section 4 we perform an analysis on the content of unreliable posts and users that propagate them. Then, we create and evaluate a model to detect unreliable accounts, and finally, we draw some conclusions and provide some hypothesis for future work.

2 RELATED WORK

We divided the literature review into three subgroups: misinformation propagation, detection of fake content and spam/bot accounts detection.

2.1 Misinformation Propagation

We start by analyzing Shao's paper that describes a platform to track online misinformation (Shao et al., 2016). In this paper, the authors crawl posts from social networks that contained links from fake content and fact-checking websites. Then, they proceeded to an analysis of the popularity and activity of users that spread these URLs. One of the preliminary results achieved is that users who disseminate fake news are much more active and committed than the ones that spread the articles to refute them. In other words, there is a small set of top fake news accounts that generate a large number of tweets regarding the topic, while in the case of fact-checking it is more distributed across the network. This work presents some similarities with our approach. However, our goal is to detect unreliable accounts and not to analyse fact-checkers and users who disseminate fake news.

Another work, which presents an approach on the network propagation of fake news, is described in (Tambuscio et al., 2015) where the interplay between believers of fake news and fact-checkers is analyzed. The presented model can be seen as a set of states and transitions similar to the spreading of a disease, where hoaxes (or fake news) are virus. The same model characterizes the users disseminating fake news as the infected patients, although they can "recover" when confronted with a fact-checking action. The main difference between the proposed approach and traditional SIS (Susceptible-Infected-Susceptible) and SIR (Susceptible-Infected-Recover) models is the existence of two sub-states in infected nodes: believers (the users that believe the hoax) and fact-checkers (the users who debunk the hoax). The authors test their approach in 3 different scenarios: a random network, a scale-free network, and a real social network (using Facebook). According to the authors, one of the main results of this work is that a minor activity regarding fact-checking can cancel a hoax, even when users believe it with a high probability.

2.2 Detection of Fake Content

In the study by Antoniadis (Antoniadis et al., 2015) the authors try to identify misinformation on Twitter during an event (hurricane Sandy). For that purpose, they labelled a set of tweets into credible and misinformation. Next, features were extracted from text and social feedback. The best result was achieved (F-measure = 78%) using a Bootstrap Aggregating Method. Two experiments are described in this paper. In the first, social feedback features (number of retweets, number of favourites...) were included. In the second, by removing these features, the results decay approximately 3%. The authors claim that the method is still efficient in real time.

In the work of Tacchini et al.(Tacchini et al., 2017) the authors state that "users who liked a post" is a feature of major importance for fake content detection and test their approach in two different models: Logistic Regression and an adaptation of a Boolean Label Crowdsourcing (BLC) algorithm to work with a training set. Using a small set of posts (15) for the training set, the authors achieved an accuracy near 80%. In addition, even with users liking fake (hoax) and true posts, the accuracy achieved can be higher than 90% using only 10% of the dataset for training.

2.3 Spammers/Bots Accounts Detection

The majority of works conducted have tried to detect spammers or bots in Twitter. The study in (Benevenuto et al., 2010) presents a model to detect spammers in Twitter. The authors relied on manual annotation to build a dataset of approximately 1000 entries of spammer and non-spammer users. Then, they developed attributes regarding content and user behaviour. The model built achieved 70% accuracy in detecting spammers and 96% in detecting non-spammers. Although a similar approach, spammers are more easily determined than unreliable accounts. According to the authors ”Tweet spammers are driven by several goals, such as to spread advertise to generate sales, disseminate pornography, viruses, phishing, or simply just to compromise system reputation”. Therefore, spammer accounts represent a subgroup of all unreliable accounts that we are trying to detect.

A similar work (Castillo et al., 2011) provides a model to detect credibility in Twitter events. The authors start by building and annotating a dataset of tweets (via Crowd-sourcing) regarding specific trending topics. Then, they use 4 different sets of features (Message, User, Topic, and Propagation) and a Decision Tree model to achieve an accuracy of 86% in a balanced dataset. Despite the fact this paper has tackled a different problem, some features presented may also have an impact on the detection of unreliable accounts.

Other works have also analyzed and tried to detect bot accounts. For example, the work in (Chu et al., 2012) presents an analysis of three different type of accounts: humans, bots, and cyborgs. The authors built a balanced dataset of 6000 users manually annotated. Next, they created a system for user classification with 4 different components (entropy measures, spam detection, account properties, and decision maker). This system achieves an average accuracy of 96% with the ”Human” class being the more correctly classified. In another work, (Dickerson et al., 2014) the authors present a framework to distinguish between human and bot accounts. In addition, the paper highlights the importance of sentiment features in such task.

Although the presented studies provide accurate systems to distinguish human accounts from bots and spammers, unreliable accounts are not guaranteed to be composed, in totality, of these two classes. In fact, human accounts may also spread unreliable posts due to their strong political beliefs or incapacity to distinguish reliable and unreliable content since that, on average, 50% of users who have seen a piece of fake content, prior to the U.S. 2016 election, believed it (Allcott and Gentzkow, 2017).

3 METHODOLOGY

In literature, misinformation, fake news, and rumours have being defined differently. Our main goal in this work is to explore characteristics that are common to unreliable content in general. We define unreliable content more loosely than the current literature, which focuses on more specific problems such as fake news or clickbait. In this work we consider content to be unreliable if, given a tweet with an external URL, one of the following statements is true:

- the content provided in the URL is verifiable to be false
- the content provided in the URL represents clear favouritism on one side of the political spectrum and/or disrespects the other using hate language
- the content provided in the URL is intended to generate web traffic to profit from advertising. For example, having an interesting but misleading headline or social media thumbnail.

With the goal of collecting a large number of tweets that propagate links from web pages that are known to publish unreliable content, we used OpenSources (OpenSources, 2018). OpenSources is a resource for assessing online information sources. Users can submit suggestions of websites to be inserted. However, submissions are carefully revised by the project researchers before inclusion. The classification for each site ranges from credible news sources to misleading and outright fake websites. For this study, we are interested in sites that are labelled as ”bias”,”fake”,”fake news”, ”hate”,”junksci”[1], ”rumour”,”conspiracy”,”clickbait”, and ”unreliable”. Table 1 presents the number of websites distributed by category at the time of the analysis (November 2017).

Table 1: Distribution of websites per dubious class.

Classification	Number of websites
Bias	133
Hate	29
JunkSci	32
Fake	236
Fake News	1
Clickbait	32
Unreliable	56
Total	**522**

For each web page on the previously mentioned categories, we used the URL as a query in the Twitter Search API. Consequently, the tweets returned include the URL (or sub-domains/pages) queried. For each URL, a maximum number of 100 tweets were extracted. This limit was established considering the API rate limit and the number of websites in OpenSources. However, in some websites, we have observed that this limit was not reached.

The extraction procedure is executed daily and the information retrieved is stored in a non-relational database built for the effect. All the information provi-

[1]”junksci” is an acronym for junk science

ded by the Search API is stored. In addition, sentiment analysis and named entity recognition (NER) is computed in each tweet. For sentiment analysis, we use Vader (Hutto and Gilbert, 2014) rule-based approach to determine the negative and positive sentiment values for each tweet. Regarding the NER component, we used NLTK (Loper and Bird, 2002) to detect 3 types of entities: location, organization, and persons.

In order to understand and identify common properties on tweets propagating unreliable content, an analysis on the retrieved data was conducted and is presented in the following section.

4 EXPLORATORY ANALYSIS

4.1 Content Analysis

In this analysis, we established a time window of approximately two months with tweets ranging from March, 15 to May, 4 of 2018. The total number of tweets retrieved in this period of time was 499530. Regarding the data characteristics, we formulate three research questions (RQ) that are important in order to establish useful indicators on unreliable tweets, with the ultimate goal of better detecting unreliable accounts.

- **RQ 1: Do Unreliable Tweets Follow Traditional Media Outlets in Terms of the Entities that they Mention?** The authors in (Vargo et al., 2017) have concluded that traditional online media outlets appear to be responsible for fake news agenda since the content of traditional media news make users more attentive to all content regarding that subject online. With this RQ we want to analyze if that is also the case on tweets. In addition, we also inspect the frequency of entities per post on both unreliable and traditional news media outlet tweets.
- **RQ 2: Which Hashtags are Used to Engage with Users?** Hashtags are commonly used by users to aggregate tweets regarding the same topic. We study which are the commonly used hashtags on unreliable tweets and how they differ from traditional news media.
- **RQ 3: Does the Sentiment Differ between Unreliable Tweets and Tweets from Reputed Sources?** One important factor suggested by the authors in (dos Reis et al., 2015) is that a news headline is more attractive if its sentiment is extreme. The same analysis was later conducted with "fake news" (Souppouris, 2016) with the conclusion that this type of content presents more negative sentiment than mainstream news outlets. Therefore, it is important to analyze if such behaviour is also noticed in unreliable tweets.

In addition, we also formulate an extra question regarding characteristics of unreliable accounts:

- **RQ 4: Can we Trust Verified Accounts?** Twitter has signalled with verified badges that a certain account of public interest is authentic. (Help, 2018). However, this does not directly imply that we can trust the content posted. In fact, there have been cases of verified accounts that propagated misinformation (Weisman, 2018). Therefore, it is important to analyze the percentage of verified accounts that spread unreliable news content, since they are likely to have more engagement and retweets.

Regarding **RQ 1** we compare the most mentioned entities in dubious tweets and in posts from traditional news media outlets. Consequently, we extract a dataset of tweets from the same interval used in unreliable tweets. We started by manually selecting a set of mainstream news outlets. We restrained our research to those who write in the English language and whose impact and popularity are relevant in the United States and the United Kingdom (since they are two of the most influential countries in the world (Haynie, 2015)). Therefore, we weighed on the number of followers of news accounts as well as how trustworthy they are for the general audience in the US (Nichols, 2016) and UK (BBC, 2015). The news media outlets selected are presented in Table 2:

Table 2: Selected News Media Outlets.

The Guardian	CNN	BBC
The Economist	Wall Street Journal	ABC
CBS News	Washington Post	NBC News
Reuters	Sky News	Fox News

Next, we extracted the top 50 entities for each category (persons, locations and organizations) for each dataset (reliable and unreliable tweets). The results achieved show that 36% of locations and persons identified and 42% of the organizations are the same in both datasets. This means that not only there are a lot of similar entities but also that these occur frequently on both datasets (since we are restraining our analysis to the top 50 entities of each category). In addition, on average, the number of entities of unreliable tweets is far superior than on news media outlets accounts. Table 3 illustrates the average entities per tweet on both datasets.

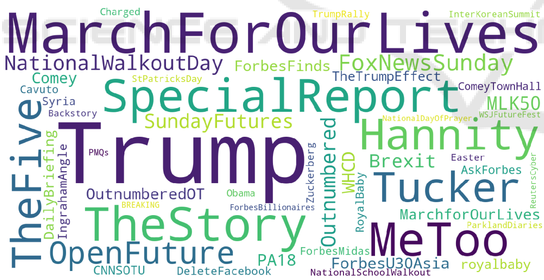
Therefore, the constant presence of entities in tweets must provide useful information regarding its

Table 3: Entities per tweet on unreliable and reliable data.

Entities	*Locations (per tweet)*	*Persons (per tweet)*	*Organizations (per tweet)*
Unreliable	**0.007**	**0.90**	**1.20**
Reliable	0.002	0.16	0.60
Difference	+ 0.005	+ 0.74	+ 0.6

reliability. However, it is also important to point out some limitations of these results. First, current state of the art systems have some difficulty to detect entities on short text and even more when they do not follow common syntax rules (such as the case of tweets). Therefore, although tweets from credible sources tend to be syntactically well written, tweets from common users are more free-form. Consequently, the detection of entities can result in a low accuracy when compared to larger text corpus.

(a) Hashtag wordcloud from unreliable tweets



(b) Hashtag wordcloud from news media outlet tweets

Figure 2: Hashtag Wordcloud for reliable and unreliable tweets.

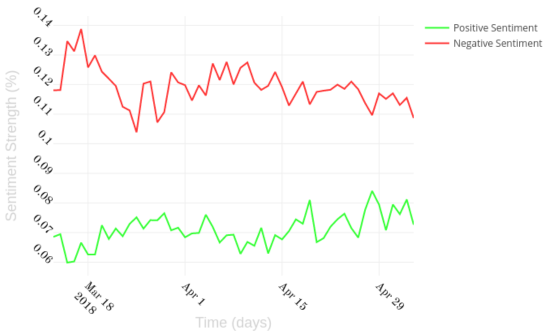
Regarding **RQ2** we inspected the 50 most used hashtags for each dataset (news media outlet tweets and unreliable tweets). Figure 2 represents each dataset wordcloud where the font size corresponds to the number of occurrences of the hashtag in the data (the larger the font, the larger the number of occurrences). Some interesting information is provided. First, in unreliable tweets, the majority of words can be associated with the political domain. Some examples include MAGA (acronym for the slogan "Make America Great Again"), TeaParty and Trump. Another interesting word is PJNET which stands for Patriot Journalist Network, Twitter group which was responsible for coordinating tweets and propagating false information through the network (Klein, 2017). There is also the mention of other Twitter groups such as TCOT and Red Nation Rising. In addition (and as expected) some hashtags refer to some topics that were trending in the news such as Trump, Syria, Skripal, Israel and Russia. Therefore, we can conclude that there is a mixture of hashtags regarding relevant topics, with Twitter-specific groups and propaganda. We can hypothesize that, in one hand, these hashtags lead to user engagement by using interesting and relevant topics and in other hand, try to associate the content with a specific group or page in an attempt to achieve a larger audience for those specific accounts.

The hashtag wordcloud for the news media outlet accounts has more emphasis on words corresponding to entities (such as Trump, Hannity, Syria and Comey) and topics associated with events or movements (MeToo, MarchForOurLives, NationalWalkoutDay). However, there is also the presence of self-reference hashtags (i.e. that promote the news media outlet where the tweets were extracted). For example CNNSOTU (a news program from CNN), TheFive, and The Story (both FoxNews shows). Hence, and similar to the unreliable tweets wordcloud, there is a mixture of news events related hashtags and self-promotion for news media outlets accounts.

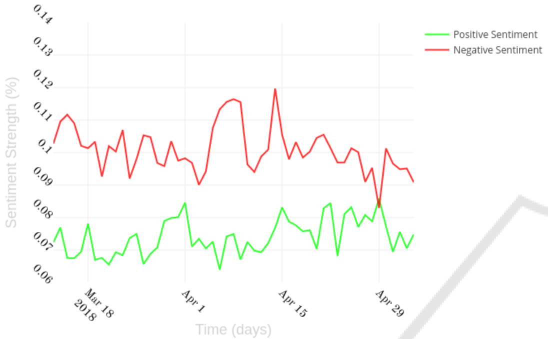
However, when comparing the frequency of hashtags per post, they largely differ. The average hashtag per tweet is 0.05 for the traditional news media outlets. This means that this type of tweets does not often contain hashtags. In another hand, the average hashtag per tweet in unreliable posts is 0.42 which means that, on average, there is a hashtag for every two tweets. This difference can provide effective indicators on the task of identifying unreliable accounts.

To answer **RQ3** once again we reuse the credible tweet news sources dataset used for RQ1 and RQ2.

Figure 3 presents the average sentiment strength of tweets by day on both reliable and unreliable sources. It is clear that negative sentiment is predominant across all the interval of time studied. Positive sentiment varies between 0.06 and 0.085, whether negative sentiment has its lowest value at approximately 0.105. In addition, the negative sentiment is stronger on unreliable tweets than on tweets from reliable sources. This pattern is observable across the majority of the days from the selected time period. Hence, sentiment analysis provides clear indicators that the text of tweets that share unreliable links follow the same principle for appealing users. Furthermore, in agreement with what was concluded in (Souppouris,



(a) Sentiment on unreliable tweets 1



(b) Sentiment on reliable tweets

Figure 3: Comparison of sentiment through time in reliable and unreliable tweets.

2016), the negative sentiment seems to have a small decay with time. This provides some enlightenment on the behaviour of this content. However, further analysis must be conducted to gain some confidence in these results.

Finally, **RQ 4** refers to the verification of accounts. More specifically to understand the ratio of verified accounts that spread misinformation (i.e. are unreliable). In order to do it, we sampled 72000 user accounts from the dataset and extract their verified status. The number of accounts that had tweeted unreliable links in this sample is 407 (0.6%) which is a significantly low percentage. This provides important insight that verified accounts are much less likely to diffuse unreliable information. Nevertheless, it is important to highlight that these type of accounts also represent a small percentage of all Twitter users, since only 226K of 330 million users (Statista, 2018) are verified (according to the official "Verified" account which follows all verified users (Twitter, 2018b)).

4.2 Unreliable Users Analysis

Not only is important to have an overview analysis of tweets that propagate dubious content, but also to make an in-depth analysis of accounts that more frequently propagate it. Thus, and considering the previously mentioned interval of time, we plot the number of tweets that propagate dubious content per account. However, to avoid a very long tail plot, we only included accounts that posted more than 200 dubious tweets. Figure 4 presents the accounts ordered by number of tweets. There is some important information to retain from this analysis. First, in the course of 50 days, there are accounts who have posted more than 1500 tweets with dubious websites that were captured by our extraction methodology. It is important to emphasize that this number can be higher since the Twitter Search API only captures a small percentage of the total number of tweets matching the query parameters (Twitter, 2018a). This means that, on average, there are accounts that post over 30 tweets a day containing dubious links. In addition, there are 28 accounts that tweeted more than 500 times with the most frequent account to post a total of (at least) 2154 tweets.

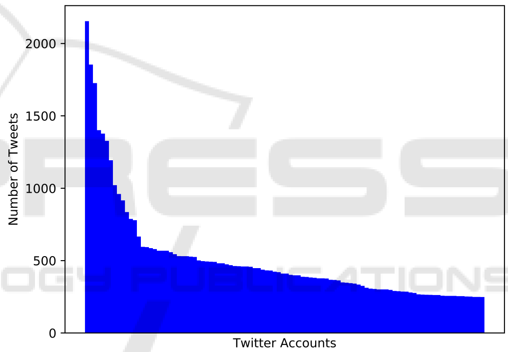


Figure 4: Number of dubious tweets per account.

To make a more detailed study of the users that are continuously propagating dubious content, we proceed to extract the last tweets for each one of the ten more frequent accounts. Consequently, for each user, we extracted the more recent tweets from their timeline. For each account, at least 3200 tweets were retrieved (the maximum allowed by the API). However, before the extraction procedure began, one user account has been suspended, which restrain our analysis to 9 users.

First, we conducted an analysis of the post frequency of the top users to understand if there is a common pattern. Figure 5 presents the "tweeting" distribution of the last 3200 tweets for each account per day. In other words, for a day x we divide the total number of posts for each accounts by the total number of posts for that day.

The main conclusion is that post frequency is not similar in these accounts. For example, account 7 posted the last 3200 tweets at a low rate across 5 months.

This is illustrated by the 100% presence on the most distant dates. In another hand, the 3241 more recent tweets from account 3 were posted in a 2 day period (consequently, it appears with a large distribution at the end of the plot) . Thus, pattern frequency in the latest posts is on both ends with accounts presenting a constant number of posts per day and others presenting a difference of approximately 500 tweets between two days (account 3). In addition, through a more detail analysis, we conclude that account 4,5, and 7 are with a great probability associated with websites used for the extraction methodology since they share very similar names.

The second analysis refers to the extended network of mentions in each tweet. Analyzing each mentioned user (on the latest tweets for the top accounts) we can figure out if they had already spread dubious content (by performing a query in our database). Unlike the current state of the art, the goal is not to study the neighbour accounts by the following/follow metric but according to the number of ”mentions” of unreliable accounts. Figure 6 illustrates the connection between top users and other users through tweet mentions. Duplicate mentions are removed. The nodes represented in blue are the top users (2 users did not have any mention to other users on their tweets). Nodes in orange are the accounts which no information was present in the database and whose accounts are not verified. Nodes in red are users that have already post dubious links where the larger the node, the more dubious tweets were found on the database. The verified accounts were excluded since they are not likely to disseminate dubious content (as it was analyzed in RQ4).

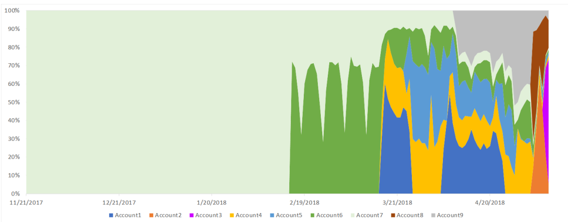


Figure 5: Last tweets of the most frequent accounts.

Two of the accounts mention a slightly larger number of unknown users while the others mention, in their majority, users already flagged in our database. The number of mentions also differs significantly. In the last 3200 tweets, some top users had over 200 mentions while other only 2. Curiously, the accounts that are associated with websites from OpenSources also behave differently since one of the accounts does not have user mentions in the latest tweets while the other is the one that has the most. However, almost all nodes (except one which only mentions two users) are linked to dubious users.

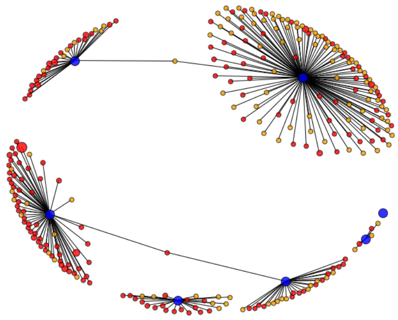


Figure 6: Graph representing mentions from top accounts.

5 MODEL CREATION

There are two components which play an important role in building a high accuracy model in machine learning: the learning data (i.e. ground-truth) and features extracted from it. Regarding the assessment of establishing a ground truth and build a scalable dataset without human annotation, we consider the top 200 accounts who spread unreliable links from our database. It is important to mention that we are no longer restricted to the subset used for data analysis but to all the database (from 22 February 2018 to 18 of May 2018). Regarding the reliable class and considering the negligible percentage of verified accounts that was captured in our analysis (RQ 4), we can assume with a certain degree of confidence that these accounts are reliable. In addition, since our main goal is to detect reliable and unreliable accounts, only using news media outlet accounts (like the ones in Section 4) would probably skew the learning step of our models. Thus, we argue that verified accounts capture a larger set of different accounts, ranging from celebrities, companies to news media outlets. Consequently, this would allow the model to better discriminate unreliable accounts from all others.

Therefore, we extract 200 verified accounts randomly selected from the Twitter Verified account (Twitter, 2018b).

With respect to the features, there were some constraints due to the limitations of our dataset. First, since the goal of our model is not being able to distinguish between unreliable and verified accounts, this type of meta-data can’t be used. In addition, the number of followers and following is also an important discriminating characteristic between verified accounts and others since verified accounts are normally accounts of public interest (Help, 2018). Hence, we focus on determining posting patterns and the characteristics of the content of the posts where verified accounts behaviour is more likely to the common user. The set of features extracted were:

- **Posting Patterns:** we extracted features based on the frequency of tweets posted by day. Due to the analysis conducted, unreliable accounts post in a higher frequency and unusual patterns, while the majority of users "tweet" less than one time a day (Sysmonos, 2009). Thus we computed the average and standard deviation of posts by day for each user.

- **Sentiment Patterns:** The difference of sentiment between unreliable and news media accounts (studied in the previous section) is the basis for these features. In addition, sentiment features have also provided significant importance in related tasks (Dickerson et al., 2014). Therefore, we extracted the average positive and negative sentiment for the tweets of each account using Vader sentiment system (Hutto and Gilbert, 2014).

- **Hashtags and Mentions Patterns:** The number of hashtags and mentions have already been pointed out as a differentiating factor from normal user accounts and spammers (McCord and Chuah, 2011; Benevenuto et al., 2010). Accordingly, we complemented our feature set with this indicator since spammers are a subgroup and fit our definition of unreliable accounts. We also do not differentiate mentions that have been verified and that are present in our database (unreliable) since we are using this principle to determine our ground-truth. For this reason, the inclusion of such features would skew our analysis.

- **Entities Pattern:** It is our assumption that entities are an important factor for building a model capable of detecting unreliable accounts, since a large portion of posts on social media are regarding irrelevant information and chat between users (Figueira et al., 2016; Castillo et al., 2011). In addition, the analysis conducted in RQ1 provided evidence on the different number of entities in traditional news outlets and unreliable tweets. Consequently, the frequency of the different type of entities may present decisive indicators for differentiating unreliable accounts from all others. Thus, we built 3 numeric features regarding the average of entities detected by tweet in 3 different categories: persons, locations and organizations.

To extract the set of features we repeated the process from Section 4.2 and extract the most recent tweets for each account of our dataset.

5.1 Evaluation

We split our data into train and test sets in an 80% and 20% ratio, respectively. We used three machine learning algorithms to perform our experimental evaluation: Decision Trees (J48), Naive-Bayes and Support Vector Machines (SVM). Decision Trees used a confidence factor of 25%. The kernel chosen for the SVM was a radial basis function (RBF) with a gamma value of 0.083 and a cost of 1.0. The tests were conducted using WEKA (Hall et al., 2009). Regarding the evaluation metrics, we focused on the weighted precision, recall, and F1-measure. The results are presented in Table 4

Table 4: Performance of the models evaluated.

Model	*Precision (%)*	*Recall (%)*	*F1-Measure (%)*
Naive Bayes	91.2	91.1	91.1
Decision Tree	**96.2**	**96.2**	**96.2**
SVM	93.5	92.4	92.4

The results achieved in the evaluation procedure provide some reliability on our approach to the problem. Decision trees accomplish the best result (96.2% in F1-measure) while Naive Bayes has the lowest performance of the three models tested. When analyzing the performance on individual classes, Decision Trees maintain the highest F1-measure score (96.4 % in the reliable accounts class and 96.0% in the unreliable).

There are some limitations that must be mentioned. First, the automatic annotation may not represent the totality of Twitter users. However, due to the analysis conducted in Section 4 and the information provided in (Help, 2018), this type of accounts seems like a good ground-truth data for users that do not spread unreliable content and has the advantage of scaling the dataset without human intervention. In addition, the manual annotation of Twitter accounts would be an exhaustive and enduring task, since annotators would have to analyze content post by post and verify its veracity. Second, the size of the dataset is also not ideal. However, we wanted in a first stage to capture characteristics of accounts which are frequently spreading unreliable content. Therefore, we strict our number of accounts to the top 200 of our database, since we do not want to capture accounts which spread dubious links in a very small quantity. Nonetheless, since our methodology is constantly updating and populating our database, the number of users with significantly large tweets will increase and in future work we explore how a large number of entries influence these results.

6 CONCLUSION AND FUTURE WORK

In this work, we tackled the problem of detecting unreliable accounts in Twitter. In order to do it, we designed an extraction methodology that retrieved tweets in large quantities based on OpenSources.

With the data retrieved, we performed a content and behaviour analysis to understand characteristics of tweets and accounts that spread unreliable information. The main findings are 1) the different strength in negative sentiment and the contrasting inclusion of hashtags and entities in unreliable and reliable posts 2) the negligible number of verified accounts that are spreading unreliable tweets and 3) high variations on the number of posts per day in unreliable accounts.

Based on the analysis, we built a small dataset to determine the effectiveness of a supervised model to detect unreliable accounts. However, since we do not want to differentiate traditional news media outlet accounts from unreliable ones, we used verified accounts as our ground truth for the ”reliable” class since 1) the large majority does not include unreliable content and 2) they capture a larger set of different accounts (for example celebrities, politicians, companies and news outlets).

Combining the data with some features derived from the analysis and related literature, we built three different models. The performance obtained is above 90 % on all metrics considered, with Decision Trees achieving the best results. This provides some confidence on the method proposed and that unreliable accounts can be distinguished based on the pattern and content published.

However, there are still some limitations in the current study that we propose for future work. First, extend our list of features (with the remaining data from Section 4), without skewing the model. We intend to use Crowdsourcing platforms to facilitate the task of building a human-annotated dataset. Then, with a significantly larger dataset of reliable and unreliable accounts, we can use features such as the verified status and number of followers/following.

With a new dataset, we can also include features derived from our database without incurring into building a skewed model. For example, if the account had tweets with unreliable content captured by our methodology. In addition, we also wish to analyze how the performance varies over time. I.e., to evaluate if the used features become more important as the size of the database grows.

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