Suicidal Profiles Detection in Twitter

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Abstract: About 800 000 people commit suicide every year and detecting suicidal people remains a challenging issue as mentioned in a number of suicide studies. With the increased use of social media, we witnessed that people talk about their suicide plans or attempts in public on these networks. This paper addresses the problem of suicide prevention by detecting suicidal profiles in social networks and specifically twitter. First, we analyse profiles from twitter and extract various features including account features that are related to the profile and features that are related to the tweets. Second, we introduce our method based on machine learning algorithms to detect suicidal profiles using Twitter data. Then, we use a profile data set consisting of people who have already committed suicide. Experimental results verify the effectiveness of our approachin terms of recall and precision to detect suicidal profiles. Finally, we present a Java based prototype of our work that shows the detection of suicidal profiles.

1 INTRODUCTION

Social media has changed the world. It has become an everyday part of our lives. Many people are nowadays active on several popular social networks such as Facebook, twitter, Instagram, etc. They share photos and posts on their daily life and experiences such as their food, their clothes, and their trips. Some people are more active on social networks, while others are less so.

On the other hand, social networks can reflect different social phenomena such as diseases, depression, suicide, etc. In particular, suicide is a complex and dangerous phenomenon that should be considered and studied in order to reduce mortality rates. A recent study[1]revealed that close to 800 000 people commit suicide every year, which means one person every 40 seconds. Thus, this growing phenomenon presents one of the biggest challenges the world is facing today. Understanding the symptoms related to suicidal tendencies is important to prevent such deaths.

[1]https://www.who.int/mental_health/prevention/suicide/suicideprevent/en/

In this respect, many studies on suicide prevention have become more prevalent in recent years. Indeed, one of the greatest things that characterize social networks is their use in extracting emotional thoughts and feelings of depression. For that reason, many researchers rely on social networks to study suicide. As an example, Twitter has become a very popular social network where millions of users share their opinions and feelings using short texts called tweets, which contains semantic expressions such as emoticons, hashtags, special characters, etc. Consequently, twitter provides a rich source of data for text mining.

Most suicidal people who are active in social networks give signals of their intentions. For example, they make statements such as "I want to kill myself," "I hate my life", "I have lived long enough "or “I’m so tired”. The best way to prevent their suicide is to catch these signals and predict other hidden signals behind their posting content in order to react to them and take appropriate actions.

Generally, a user in twitter is characterized by a profile and a set of tweets. The profile features describe his/her persona such as name, age, location, date of birth. On the other hand, tweets refer to the content shared by the user such as text, photos or videos. Some existing works (Jain et al., 2013) in this

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context utilize publicly shared attributes including name, gender, location, and other information to identify user profiles in social networks. However, due to the privacy settings, user's attributes are not available in many cases and this makes these existing works fragile. In addition, some researchers address the problem of suicide only through tweets (Kavuluru et al., 2016), (Colombo et al., 2015). However, even though tweets contain rich information that can identify users, they can miss some significant details that maybe available on the user profile public attributes and may contribute to a higher accuracy of suicide detection. Apart from these works, we utilize in our approach both user shared information that we call account features and tweets as an attempt to solve the problem of suicidal profiles detection. First, posted tweets pose important challenges to infer more information about users. The most relevant challenge is semantic features that are difficult to extract directly from user's posted tweets such as stylometry, writing style, sentiments, emojis, hashtags, n-grams, etc. Instead of many existing studies that ignore these features to identify users, we analyse tweets and extract as much as possible of semantic features. Second, adding account features to the user's posted tweets can help to improve the suicide detection task since they may reflect the habits and characteristics of users.

Although there are many studies (Sueki, 2014), (O'dea, 2018) that focused on the particular problem of suicidality detection in social networks, they do not take into account the profile itself. They only considered suicide related-communication with the aim of classifying text relating to suicide. However, the biggest challenge for the suicide task is how to detect users who want to commit suicide from their public profiles in social networks.

In this paper, we consider the challenge of suicidal profiles detection in Twitter. We analyse posted tweets to extract semantic features including linguistic, emotional, stylometric, etc. These features allow us to distinguish between the writing styles of different users and thus to facilitate the final classification of users into suicidal or not suicidal. In particular, posted tweets contain temporal information that can indicate the real time of user's posting. Such information is very relevant to enrich the user identification and improve the suicide detection. We also use account features related to publicly shared information such as profile photo, location, biography, followees, etc. We exploit these features to infer other implicit ones and build a rich profile that can help us to predict suicidal users. We adopt different data mining tools and techniques for the extraction process. We also introduce a supervised machine learning model to learn the features identifying each user. Moreover, we adopt several classification techniques to classify profiles into suicidal and not suicidal. We apply our method to a data set collected from Twitter and including profiles whose owners committed suicide.

The rest of this paper is organized as follows: Section 2 discusses related work. Our method of suicidal profiles detection is explained in Section 3, which also presents the collection of data from twitter based on tweets and account features. Section 4reports on evaluation. Section 5 concludes the paper and outlines directions for future work.

2 RELATED WORK

Social media have become increasingly popular and the number of active users continues to increase. Several phenomena such as suicide are now visible on social media. To address suicide and reduce the related mortality rates, many studies were conducted on suicidality in social networks.

Kavuluru et al., 2016 conducted a suicide study by classifying text relating to suicide on Twitter. They built a set of account classifiers using lexical, structural, emotive and psychological features extracted from Twitter posts. Their aim was to distinguish between the more worrying content, such as suicidal ideation, and other suicide-related topics.

Other studies (Kavuluru et al., 2014) have focused on the writing styleusing the LIWC tool as a sampling technique to identify 'sad' Twitter posts that were subsequently classified using a machine learning classifier into levels of distress on an ordinal scale, with around 64% accuracy in the best-case. Additionally, (Birjali et al., 2017) based their work on WordNet to analyse semantically Twitter data. They address the lack of terminological resources related to suicide by constructing a vocabulary associated with suicide.

A case study (O'dea et al., 2015) used both human coders and a machine classifier to confirm that Twitter is used by individuals to express suicidality and that it is possible to distinguish the level of concern among suicide-related tweets.

In another work, (De Choudhury et al., 2016) considered online platforms such as Reddit and applied topic analysis and linguistic features to identify behavioural shifts and mental health issues such as suicidal ideation, thus highlighting the risks of supposedly helpful messages in such online forums. Furthermore, (Colombo et al., 2015) investigated the characteristics of the authors of Tweets containing suicidal thinking, through the analysis of their online social network relationships rather than focusing on the text of their posts.

More recently, (O'dea et al., 2018) used a dataset of suicide related posts to study how Twitter users respond to suicide-related content compared to non-suicide related content. They found that the rate of reply to the suicide-related posts was significantly faster than that one for non-suicide related posts, with the average reply occurring within 1 hour. Finally, (Braithwaite et al., 2016) classified text from Twitter users as suicidal or non-suicidal using affective markers and machine classification algorithms – stopping short of examining texts for other forms of suicidal communication.

Existing works on suicide prevention are mainly focused on identifying suicidal thinking or ideation and detecting suicidal posts. However, there are no significant research works that focused in particular on suicidal profile detection. Thus, our study aims to contribute to the literature on understanding communication on the topic of suicide in social networks by detecting suicidal profiles on Twitter.

3 SUICIDAL PROFILE DETECTION

In this work, we propose a method for detecting suicidal profiles. First, we analyse a number of profiles from the social network Twitter through exploiting the maximum of available data. Then, we adopt several features to distinguish between suicidal and not suicidal profiles. These features can be explicitly extracted from the user profile or implicitly inferred using different data mining tools and techniques. Here, we focus on emotional features and sentiment analysis, which gives indications about the psychological state of suicidal profiles. We further use account features to identify users through the shared information on their profiles. We finally present each user as a vector that integrates all the used features.

3.1 Data Preparation

Before proceeding to the analysis of the profiles and the extraction of features, it seemed necessary to us to clean and normalize the collected data. Generally, posted tweets are short and noisy. For instance, the language used is very informal, with Unicode characters, punctuation, poor spelling, acronyms, URLs, and abbreviations. Thus, to make the user's content look clearer and to improve the text analysis, we made a dictionary for the useless stop-words and created an R code that eliminates all noisy words from the original text.

3.2 Features Extraction

Clearly, gathering rich information about users is crucial for providing a high quality of suicide risk detection. Moreover, several types of features can lead to more accurate suicidal detection. This allows us to decide which profile can be suicidal. Therefore, extracting features from twitter profiles is a necessary step for the classification process. To do so, we employed some data mining tools and techniques in order to infer implicit information that were not given explicitly by the user. We further used the Linguistic Inquiry and Word Count LIWC text analysis software (Pennebaker, 2001), to extract more relevant features associated with emotions. The great advantage of this tool is that it analyses text files on a word-by-word basis using an internal dictionary and computes the percentage of words in a text that are in each of these linguistic or psychological categories. Thus, it helped us to enrich the user's information especially on the emotional side, which is very important for the suicide topic. We considered in our work two types of features: account features and features based on tweets.

3.2.1 Account Features

In this type of features, we only consider information related to the profile. In other words, we do not consider tweets to identify users. Indeed, we use information that can be explicitly extracted from the profile. We consider three categories of account features according to their consistency.

Explicit Features.
Explicit features are those publicly shared by the user in his/her profile.

Table 1: Explicit features availability.

Twitter feature	Availability
Language	80%
Country	66%
Created profile	100%
Friend's number	100%
Profile description	90%
Profile photo	100%

They refer to the user's name, language, country, profile creation date, number of friends, profile description and profile photo. Some features are almost available while some others are sometimes missing.
Table 1 describes the availability of explicit attributes in the social network Twitter.

Facial Features.
The main limitation of twitter is the fact that some user's attributes are missing. In particular, age and gender, which are relevant information for identifying users, are not available in twitter. In order to deal with this issue, we used the picture profile to extract facial features such as gender and age. We used Microsoft Face API[2], a cloud-based service that provides the most advanced face algorithms (MAHESHWARI, 2017) to extract through a photo various facial attributes including gender, age, smile, facial Hair beard, facial Hair moustache, and facial Hair sideburns.

Followees.
Finding posts and profiles which the user follows may be a relevant indication to know which kind of profiles the user is interested in and to know about his/her interactions with other profiles. Consequently, if the user has suicidal ideations, normally she follows topics related to suicide. In addition, this information, allows us to know the degree of sociability of the user with people in the social network twitter. Thus, we collected posts with which the user interact with through likes, comments or retweets, and profiles who share these posts.

Table 2: Information extracted from followees.

Followees	Age ranges
	Histogram of photos
	Topics of Interest
	Sentiment analysis

Through the user's followees, we extract other information that describes more the profiles followed by the user to know if they really have an influence on his/her thoughts. For example, the histogram of photos allows us to know whether they use images with light colours or dark images. In particular, depressed people or those who have suicidal thoughts prefer to put dark images in their profiles. In addition, we extract the sentiment analysis and topics of interest from the tweets posted by the user's followees to identify the emotional state of these profiles. Also, the age ranges of the user's followees present relevant information. In other words, people with the same age or close in age have similar interests as a result of age-related life events.

3.2.2 Features based on Tweets

Linguistic Features.
Linguistic features are very important to distinguish between written styles of users. Indeed, many studies in suicidal ideation (Sueki, 2014), (BURNAP, 2017) focused on linguistic features to prevent suicide. It seems obvious that each user has a unique writing style. In social networks, some users may use similar writing style. For example, users that post emotional text generally use some particular characteristics such as elongation, adjectives, exclamations, etc. Therefore, extracting these features may highly increase the chances of detecting suicidal profiles. In this context, there are various writing styles that can be extracted from Twitter, and that contain different characteristics.

Table 3: Writing style description.

Writing style features	Description
LIWC features	e.g. adjectives, pronouns, adverbs, health, death, etc.
Special characters	Percentage of used special characters (e.g. $, %,&, (,), *, +, _, /, <, =, >, @, etc)
Frequent words	Number of frequent words repeated more than 5 times
N-grams	Number of frequent n-grams repeated more than 3 times (e.g. No More , want to kill, terrible times, don't want,etc)
Elongations	Percentage of used elongations(e.g. nooooo, ohhhhhhh, !!!!!!!!!, loooool, etc)
Sentences length	Average length of used sentences
Words length	Average length of used words
Writing language	Number of used languages
Htags	Percentage of used htags

We employed the LIWC tool to extract various linguistic features as described in table 3. For the other features, we implemented an R code that computes their values using the collected tweets.

Emotional Features.
Most suicidal users suffer from mental health problems due to psychiatric disorder, social problems, substance abuse, etc. Therefore, their posted tweets are generally associated with depression terms such as

[2]https://docs.microsoft.com/en-us/azure/cognitive-services/face/quickstarts/csharp

death, mad, killing, lonely, etc. However, the frequent occurrence of these terms in their posted texts may increase the risk of suicidal ideation. Therefore, extracting this type of features has helped so far to reveal suicidal users. In our work, we focused on two main emotional features: sentiment analysis and emojis.

Sentiment Analysis.

Sentiment analysis works best on text that has a subjective context such as suicide. In this context, many studies (Pestian, 2012), (BIRJALI, 2017) used sentiment analysis to target the problem of suicide since emotions are closely related to sentiment. Typically, they classify feelings according to their polarities: either positive, negative or neutral. Having the same aim, we adopt Open NLP[3] as a machine learning based toolkit for processing natural language, which understands the language used in a text and uncovers the sentiment behind it. We also added two significant attributes associated with sentiment named positive terms and negatives ones. To that end, we prepared a rich dictionary that contains positive and negative terms collected from differentsites. We also added a dictionary vocabulary of words called opinion lexicon[4], which includes around 6800 negative and positive English words. The sentiment analysis features are shown in Table4.

Table 4: Sentiment analysis features description.

Sentiment analysis features	Description
Positive sentiment	Percentage of positive used sentences
Negative sentiment	Percentage of negative used sentences
Neutral sentiment	Percentage of neutral used sentences
Positive terms	Number of positive used terms (e.g. happy, enjoy, well, wonderful, well, etc)
Negative terms	Number of negative terms (e.g. sad, suffer, depression, mad, etc)

Emojis.

Emojis or emoticons are often used to show various types of emotions. However, using typical emojis such as the happy and sad emojis may not give detailed emotional state of users. Clearly, the more we specify the type of emojis the more we get precise recognition of emotions. Based on(Parrott, 2001), we employ six primary emotions including love, joy, surprise, anger, sadness, and fear. Emojis features are described in Table 5.

Table 5: Emojis features description.

Emojis features	Examples
Love	:-* :* <3 ♥ □ □ □
Joy	xD :-) :) :D :o) :] :3 :c) :> =] 8) ;-) :-P XP
Surprise	:-O :O :-o : o :-0 8-0
Anger	:-J >:(>:O
Sadness	:-(:(:'(:'-(
Fear	%-) %) v.v

Some emojis include simple characters that are typically used in text while others include Unicode characters that are difficult to explicitly extract. To deal with that, we exploit recent emoticons and smiley faces existing in some sentiment sites with unicode.

Temporal Features.

Collecting data from Twitter provides us temporal information that indicates the real time of a user's posting.

Table 6: Timeline features description.

Temporal features	Description
Posting at night	Percentage of posting tweets 20:00 to 04:00
Posting at morning	Percentage of posting tweets 04:01 to 12:00
Posting at afternoon	Percentage of posting tweets 12:01 to 20:00
Posting in ordinary day	Percentage of posting tweets all the week-day except Saturday and Sunday
Posting in weekend	Percentage of posting tweets on Saturday and Sunday
Posting in winter	Percentage of posting in winter
Posting in summer	Percentage of posting in summer
Posting in spring	Percentage of posting in spring
Posting in autumn	Percentage of posting in autumn
Posting per day	Percentage of posting per day
Posting per week	Percentage of posting per week
Posting per month	Percentage of posting per month

According to (Xiangnan, 2013), a user usually posts his/her content on different social networks at similar time slots. Such temporal information is very relevant for user identification. For example, some users like to post their content at night, while other users share their posts in the morning. Also, there are users who are very active on the weekend unlike other users who share posts frequently on ordinary days. Thus, for each user, we can extract the exact time of his/her publicly posted tweets. Through this information, we collect 12 types of temporal features as described in Table 6.

[3]https://cran.rproject.org/web/packages/openNLP/index.html

[4]https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html

4 EVALUATION

4.1 Dataset

We spent 2months to collect twitter profiles whose owners committed suicide. We referred to the TWEET HEREAFTER[5] site, which contains some users that uttered a final word on their profiles a few time prior their suicide. We also searched for popular persons that committed suicide worldwide and checked if they had twitter profiles. Our final dataset consisted of 115 suicidal profiles and 172 not suicidal profiles. Statistics on this set are provided in Table7.

Table 7: Statistical information of dataset.

Twitter	Suicidal profiles	Non suicidal profiles
Profile numbers	115	172
Male numbers	41	81
Female numbers	74	91
Average number of tweets per user	84	102

4.2 Learning Process

In order to demonstrate the effectiveness of our work in detecting suicidal profiles, we need to compare it with prior works. However, such comparisons are not evident because prior works did not target the profile, but rather focused on detecting suicidal text. On the other hand, feature descriptions are different and not all works use the same features. Therefore, we made a comparison of methods using another way. We conducted two types of experiments to show the effectiveness of our work. First, we used only features based on tweets to detect suicidal profiles. Then, we added account features and presented the difference between the results.

We used the collected profiles in order to train and test a number of machine classifiers to classify profiles into suicidal and not suicidal. We adopted a supervised machine learning approach based on various features as described in Section 3. We used Weka[6] as a data mining tool to extract all useful information for the classification of suicidal profiles according to the machine learning algorithms implemented in Weka. We selected five classifiers including BayesNet, Adaboost, J48, SMO and Random Forest. Experiments were carried out with 10-fold cross validation on the training data.

In order to evaluate further of our method in identifying suicidal profiles, we implemented a web based java application that shows if a given profile is suicidal or not. Given a twitter screen name, the application extracts all features related to the targeted profile and then returns the prediction result. Figure 1 shows the suicide prediction result of a profile related to a user who committed suicide recently.

Figure 1: Suicidal profile detection exemple.

4.3 Experiments and Results

4.3.1 Using Only Tweet based Features

Table 8 presents the precision, recall, and F-measure of our model in identifying suicidal profiles when we use only features based on tweets. The experiments were run with a 10-fold cross validation. As shown in table 8, the best reached F-Measure is 77% with the random forest classifier. The precision of the SMO classifier with a PolyKernel function was74%.

Table 8: Classification results using features based on tweets.

Classifiers	Precision	Recall	F-measure
Bayes Net	70%	70%	70%
Adaboost	71%	71%	71%
SMO	74%	74%	74%
J48	70%	70%	70%
Random Forest	77%	77%	77%

4.3.2 Using All Features

Then, we tested our method with all the features including account features and features based on

[5] http://thetweethereafter.com/?page=2&s=death_desc&fbclid=IwAR34cC1kZFiCzt0Mapn_lX4MuAGdhyVGNfinkZRlHJE5VVZfompbCXz3sD4

[6] https://www.cs.waikato.ac.nz/~ml/weka/

tweets. The experiments were run with a 10-fold cross validation. Table 9 shows the obtained results.

Table 9: Classification results using all features.

Classifiers	Precision	Recall	F-mesure
Bayes Net	73%	74%	73%
Adaboost	78%	78%	78%
SMO	79%	79%	78%
J48	80%	81%	81%
Random Forest	83%	83%	83%

The results show that the best performing classifier in terms of precision is Random Forest yielding a value of 83%. When using all features, the results improved with all classifiers. In particular, J48 classifier increased to 80% in terms of precision instead of 70% when using only tweet based features.

Furthermore, we test our method with a testing set including 10 suicidal profiles and 10 not suicidal ones as shown in Table 10.

Table 10: Classification results using testing test.

Classifiers	Precision	Recall	F-measure
Bayes Net	72%	80%	76%
Adaboost	81%	90%	85%
SMO	72%	80%	76%
J48	72%	80%	76%
Random Forest	81%	90%	85%

The results show that our method performed well on the profiles of the testing set. As shown in Table 10, we were able to a reach a recall of 90% with the classifiers Random Forest and Adaboost, which means that we could correctly classify 9 profiles out of 10. This proves the effectiveness of our method to identify suicidal profiles.

5 CONCLUSIONS

In this paper, we worked on detecting user profiles that are at risk of suicide. We worked on twitter and defined a detection model using a set of rich features including linguistic, emotional, facial, timeline as well as public features to identify twitter profiles. We used several machine learning methods (mainly classifiers) for the suicidal detection. Moreover, we implemented a Java based tool to detect suicidal profiles. To evaluate our work, we conducted a series of experiments using a data set of profiles that committed suicide. Results were promising with an average recall of 86%.

As future work, we aim at improving the results of the suicidal profiles detection by determining more precisely their degree of suicidality. Furthermore, we would like to target other social media platforms such as Facebook and Instagram.

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