Arabic Twitter User Profiling: Application to Cyber-security

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Abstract: In recent years, we witnessed a rapid growth of social media networking and micro-blogging sites such as Twitter. In these sites, users provide a variety of data such as their personal data, interests, and opinions. However, this data shared is not always true. Often, social media users hide behind a fake profile and may use it to spread rumors or threaten others. To address that, different methods and techniques were proposed for user profiling. In this article, we use machine learning for user profiling in order to predict the age and gender of a user's profile and we assess whether it is a dangerous profile using the users' tweets and features. Our approach uses several stylistic features such as characters based, words based and syntax based. Moreover, the topics of interest of a user are included in the profiling task. We obtained the best accuracy levels with SVM and these were respectively 73.49% for age, 83.7% for gender, and 88.7% for the dangerous profile detection.

1 INTRODUCTION

Social media networks allow users to share information, opinions and communicate with each other. Often, social media users choose not reveal their real identity such as name, age, and gender in order to express their ideas freely, without risking any retaliation. Some other users hide their real identity for dishonest and dangerous purposes such as threatening other social media users or spreading rumors and lies. Therefore, it has become very important to provide effective means for identity tracing in the cyberspace (Argamon et al., 2003).

Twitter is one of the most popular social media networks in the world and it has a large number of users who post a huge amounts of data in different languages. Posts cover a wide variety of topics such as politic, sport, and technology.

The volume and variety of Twitter data as well as the availability of APIs has attracted several researchers to use it including those who focus on user profiling (Feldman and Sanger, 2006).

Research in psychology (Frank and Witten, 1998) has revealed that the words used by an individual can project his or her mental and, physical health. With the advances in technology and computing, stylometry (Georgios, 2014) has been used to determine traits of the user's profile and personality based on what they write. Several stylometric features have been proposed to date, including features based on words, characters and punctuation.

In this article, we aim at profiling Twitter users, i.e., determining characteristics such as age and gender based on their tweets. This research is applicable in several fields, such as forensics and marketing.

The remainder of this paper is organized as follows. Section 2 reports on existing work on user profiling. Section 3 presents our approach and describes the features that could be considered as significant indicators of age and gender. Section 4

[1] https://developer.twitter.com/
[2] http://www.cs.cmu.edu/~ark/TweetNLP/
[3] https://emojipedia.org/
[4] https://dev.twitter.com/streaming/overview

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presents the corpus we used in this research. Section 5 presents the results we obtained and Section 6 concludes the paper with directions for future work.

2 RELATED WORK

Analyzing the user's' posts and their behavior on social networks has been the subject of numerous research works. Interest in this field of research has increased in recent years as several users misused the anonymity they could have on social media networks to spread threats, hate messages or false news.

By analyzing the contents produced by users, or the activities they perform, author-profiling researchers were able to determine several users' characteristics such as age, gender, mother tongue and level of education.

The shared task on Author Profiling at PAN 2013 focused on digital text forensics. Specifically, the purpose was to determine the age and gender of the authors of a large number of unidentified texts. In this context, (Argamon et al., 2005) determined experimentally that content features performed well for age and gender profiling.

In addition to that, (Peersman et al., 2011) worked on segments of blogs of the British National Corpus. They used features such as punctuation, average words, part of speech, sentence length, and word factor analysis to predict gender at an accuracy of 80%.

The detection of the author's profile consists of analyzing the way in which the linguistic characteristics vary according to the profile of the author (Koppel et al., 2014) used the SVM model trained on English, Spanish and Dutch Twitter data from unknown Twitter text to achieve 80% accuracy for gender prediction. The work focuses instead on punctuation, n-gram counts, sentence and word length, vocabulary richness, function words, out-of-vocabulary words, emoticons and part-of-speech.

In another study (Alwajeeh et al., 2014) the authors worked on blog segments using features such as speech analysis, punctuation, average word length, sentences, and word factors. They achieved a gender prediction rate of 72.2% (Tang et al., 2010).

In addition to that, (Estival et al., 2007) worked on Arabic emails and reported being able to predict the gender with a precision of 72.10%. They calculated 64 features describing psycholinguistic word categories (e.g. family, anger, death, wealth, family, etc.). Any feature describes the number of words detected in the similar category divided by all words in the text.

Although in (Mikros, 2012), the researchers worked on the automatic classification of blogs and emails, they obtained a precision of 81.5% of documents well classified for the dimension of gender and 72% for the dimension of age.

The work in (Juola, 2012) investigated the attribution and detection of the author's genre using Greek blogs. He chose this model of social networks because people can express their opinions on blogs. Juola focused on two types of features of text content. The first type includes classic stylometric features, which depend on vocabulary richness, word length, and word frequency. The second type of features depends on the bi-gram characters, and the n-gram of words. The results of their experiments showed an accuracy of gender identification of 82.6% with SVM (Maharjan et al., 2014).

The work in (Koppel et al., 2003) presented an application that detects various demographic characteristics such as name, age, gender, level of education. The authors used two corpora of e-mail for the Arabic and English languages. They used a questionnaire to check and examine the user's' profile including age, gender, and level of education. The authors used many machine-learning classifiers in their experiments such as SVM, KNN and decision trees. For gender detection, the best accuracy was achieved by SVM (Argamon et al., 2009).

Current author identification techniques go beyond stylometric analysis, which opens the way to profiling, attribution, and identification of authors. In addition, they explore data and use digital documents like graphics, emoticons, colors, layouts, etc. In this context, we cite a very recent work of 2015 in which a play "Double Falsehood" was identified as the work of William Shakespeare where the researchers were based on colors and graphics information for identification because each author or artist has his own style (Mechti et al., 2010).

The Arabic language is one of the most widely adopted languages with hundreds of millions of native talkers. Furthermore, it is used by more than 1.5 billion Muslims to practice their religion and spiritual ceremonies.

Authorship attribution is another field of related work that is concerned with the description and identification of the true author of an anonymous text. In the literature, authorship description is defined as a text categorization or text analysis and classification problem. The authorship has various potential applications in fields such as literature, program code authorship attribution, digital content forensics, law enforcement, crime prevention, etc. In the context of authorship attribution, stylometry has been used to determine the authenticity of the document. It is considered as the study of how people can judge others according to their writing style. Therefore, stylometry cannot only be used to identify a writing style but can also help identify the author's gender and age.

3 PROPOSED METHOD

The goal in this work is to analyze the profiles of anonymous authors and predict the author's age, gender, and whether the profile is a dangerous profiles. Our approach is purely statistical, i.e., it accepts input from any profiles written in Arabic and calculates the frequencies to identify age based differences (between young people and adults), gender based differences (between men and women), and profile risks (i.e., whether the profile is dangerous or not. We divided our work on author profiling into two parts: The first part focused on extracting relevant information from a user profile such as the number of friends, number of followers, number of retweets, etc. The second part focused on extracting information from the user's tweets based primarily on stylistic information (lexical, structural, syntactic) and semantic information.

3.1 Profiles Specific Features

User profiling allows determining the users' characteristics such as age and gender. In order to retrieve automatically the profile data and the users' tweets we used Twitter API [1]. Next, we explain which data was retrieved through the API (Peersman et al., 2011). The relevant Twitter terms for our work are the following:

- ReTweet: each user may republish on his profile a Tweet that was written by another user.
- Followers: users that receive and follow status updates of a given user.
- Friends: users that are followed by a given.
- Favorite accounts: a way to tag a tweet as a preference in order to see it easily later.
- Time of publications: for each author, her time of publication of tweet was retrieved. The chronology is mainly divided into four parts (from midnight to 6 am, from 6 am to noon, from noon to 6 pm and finally from 6 pm to midnight). Based on that, we can predict the user's favorite time to share their tweets.

We retrieved through the API the available profile data and examined the network formation resulting of users and their contacts with other users, e.g. by examining for a given user the number of followers, number of friends, number of favorite accounts, number of retweets and preferable time of publications. Then, we represented the user's profile as a normalized number vector with numbers corresponding to the profile features.

For each profile collected in our corpus, an expert in sociology helps us to identify and annotate the age, gender and whether the user has a dangerous profile.

3.2 Tweets Specific Features

What features allow to predict age, gender, and dangerous profiles is an open research question that several authors addressed in fields such as human psychology. Stylometry (i.e., the study of stylistics features shows that individuals can be classified and identified by their writing styles. The writing style of a person is defined by the selection of special characters, the terms used, and the composition of sentences...

Studies in literature (Guimaraes et al., 2017) show that there are no one-size-fits-all features set that is optimized and applicable to all people and to all domains. In fact, thousands of stylometric features have been proposed. Even though authors can consciously modify their own style, there will always be an unconscious use of certain stylistic features (Sara et al., 2014). For our work, we use the following features: (1) stylometric features (lexical, syntactic and structure) and (2) semantics and emotional features. Figure 1 shows the general process of our work for the extraction of features from tweets. The major steps of our method are as follows:

1. Pre-processing and Text Analysis: The process starts with data cleaning; the aim of this step is to lead to a cleaner representation of the tweets. For this purpose we have removed noisy data such as prefixes, suffixes, and URLs. We also transformed plural words to singular, and we applied lemmatization.
2. Calculating Features Vector: A feature vector is computed based on the profile data and the users' tweets. The extracted features are divided into two groups: training set and testing set. The training set is used to develop a classification model whereas the testing set is used to validate the developed model.
3. Classification: We train an SVM classifier using our training data from Step 2 to discriminate between various age groups, genders and dangerous profiles. More details on this step will be given in the next subsections.

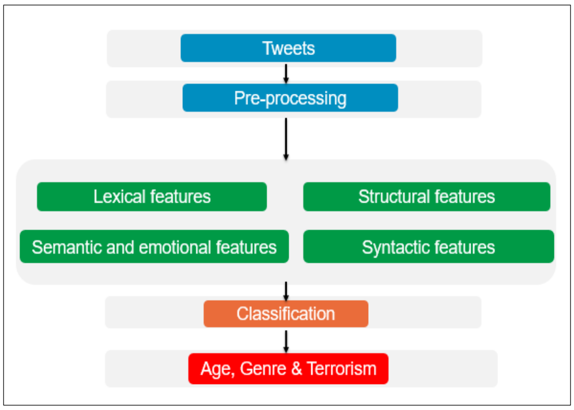

Figure 1: Architecture of our author profiling method.

3.2.1 Lexical Features

A tweet can be seen as a series of characters and word tokens grouped into sentences. A token can be a word, a punctuation mark or a number. Some studies on authorship attribution (Tan et al., 2009) were based on simple models such as sentence length and word length. The benefit of these features is that they can be used on any corpus in any language with no additional conditions except the availability of a tokenizer. Lexical features can be used to learn about the typical use of words and characters by a certain individual.

In the following, we discuss how we used in our work lexical features by considering different variations of the characters included within it.

First, we calculated the total number of characters, including all Arabic letters by Latin, digits (0-9), etc. The other stylometric analyzed in this part, as well as the total number of special characters, and white spaces were counted (Rangel et al., 2013).

Second, we analyzed words by applying 12 statistical measures including the total number of words, the average number of words, the total number of different words in a tweet, the total number of short words with three characters, the total number of long words with six or more characters, the total number of words with flooded characters (e.g. Heeeelloooo). All the characteristics of this approach were calculated with the ratio.

Vocabulary richness functions quantify the variety of the vocabulary of a tweet. Some models of this measure include the number of hapax legomena (words occurring once) and, the number of hapax dislegomena (words occurring twice). Various functions were proposed to achieve stability over text length, including Yule's K measure, Simpson's D measure, Sichel's S measure, and Honore's R measure (Tschuggnall et al., 2017).

3.2.2 Syntactic Features

Researchers discovered the effectiveness of syntactic elements in identifying an author (Hsieh et al., 2018). Syntactic features define the patterns used to form sentences (Potthast et al., 2016).

In informal writing, it is common to use multiple question exclamation marks to express better a feeling or a mood. Therefore, syntactic characteristics define the writing style of a writer. In this regard, we counted the total number of quotation marks, periods, semicolons, question marks, exclamation marks, multiple exclamation or question marks (???, !!!), and ellipses to determine the frequency with which authors use punctuation in their tweets.

One of the most important aspects of text classification is the word level that is used. N-grams based approaches are often used for text classification and they can be implemented on different levels, such as the word level. Furthermore, some researchers have used word n-grams to address authorship attribution. N-grams are tokens created by a contiguous sequence of n items. The unique and different n-grams constitute the most important feature for stylistic purposes. This demonstrates why word n-grams were used as input features for automatic methods of detecting and classifying authors with both promising results.

Another related approach is part of speech tagging (POS tag) which represents the tokens according to their function in the context. Basic POS [2] tags include the functional words in a sentence, (e.g., verbs, preposition, and pronouns) (Garciarena et al., 2015). Authors regardless of the topics use function words unconsciously and consistently and their use has a low probability of being deceived.

After we calculated the frequency of use of each grammatical category, we calculated the ratio between the number of verbs, pronouns, and the total number of words. Moreover, we calculated the ratio between the frequency of used dots, quotes and the total number of words. We also calculated the ratio between the unique, different grams and the total number of words. The same applied for the hashtags, which were represented as the ratio between the hashtags number and the total number of words (Pennebaker et al., 203). Table 1 represents the set used features.

Table 1: Set of used features.

Lexical Features

Word-based Features
Total number of words (M)
Average word length
Number of long word (than 6 characters) /M
Number of short (1-3 characters) word/M
Number of word elongation word /M
Different words frequency/M
Hapaxlegomena (unique word)
Hapaxdisplegomena
Yule's K measures
Simpson's D measures
Honore's R measure
Entropy measure
Entropy lines measure

Character-based Features
Number of Arabic characters by Latin /M
Number of letters /M
Number of digital characters /M
Number of white /M
Number of special characters (22 features) /M

Syntactic Features

Number Frequency of punctuations/ M {“'”, “.”, “:”, “;”, “ ? ”, “! “,“ " ” ,“???” , “!!!”, “…”}
Number of different n-grams
Number of unique n-grams
Number of Hashtags/M

POS tagging
Number of adjective/M
Number of adverbs/M
Number of abbreviations/M
Number of conjunctions/M
Number of gender-specific word/M
Number of interjections/M
Number of names/M
Number of particles/M
Number of prepositions/M
Number of pronouns/M
Number of proper names/M
Number of verbs/M

Structural Features

Average phrases
Average number of words per sentence
Average words length
Average sentences length
Number of lines /M
Number of blank lines /M
Number of paragraphs /M

Semantics and Emotional Features

Emotion
Number of angry word/M
Number of disappointed word/M
Number of disgusted word/M
Number of gleeful word/M
Number of happy word/M
Number of romantic word/M
Number of sad word/M
Number of satisfied word/M
Number of surprised word/M

Topic
Number of sports word/M
Number of political word/M
Number of military and weapons word/M
Number of family and friends word/M
Number of economic, money, work and social word/M
Number of death and religion word/M
Number of body and sexual word/M

Profiles Features

Number of friends
Number of followers
Number of retweet
Number of favourite is accounts
Time of publication

3.2.3 Structural Features

Structural features (or structure-based features) are about the organization and format of a text.

They assess the overall impression of the document's writing style. These features can be define at the paragraph-level, message-level or according to the technical construction of the document. Rendering a large number of features does not necessarily produce excellent results, as some features give very little information. Nevertheless, in the authorship verification of computer-mediated online information such as tweets and blogs the structural features seem to be encouraging (Modak et al., 2014).

In this context, the structural features describe the process an author follows to create a tweet. People have different habits when creating a publication. This is even more important in the context of online texts, which have limited content

Frequently, structural features include the length of the paragraph from a tweet, separators used in sentences like lank lines, length of a sentence, word length, length of words per sentence, the layout of the whole document.

3.2.4 Semantical and Emotional Features

Sentiment analysis has become one of the most active areas of research in natural language processing. It is also generally, used in the domains of data mining and document extraction. Sentiment analysis aims to predict or extract the antithesis of people opinions in specific fields. It is regarded as a challenging task for feeling analysis. Most current approaches in the research distinguish two main types of attributes that can be used to predict the author's profile: the stylistic and the content based of their tweets.

The basic types of features that can be used for content-based authorship profiling are the emotional and semantic features. We looked for the similarities that can group a set of terms in the same class. The corpus of the Arabic text is much larger. Therefore, we manually grouped the terms belonging to the same class of attributes. We identified nine classes of emotion and emoticons [3] namely: surprise, satisfaction, joy, romance, sadness, anger, pleasure, disgust and disappointment. The use of emoticons aims at making the text messages more expressive.

For the semantic features, we manually collected seven dictionaries of the following domains: sports, politics, army and arms, family and friends, economic and social, death and religion, body and sexuality.

In total, we built 8000+ terms, explicitly conveying 16 classes (sports, political, angry…). Moreover, we obtained the root for each word and then calculated the probability factor (ratio) of using words in the tweets for each class. For example, a user talks about sport in 80% of his/her tweets and about politics in 20% of her tweets.

4 DATASET

In each authorship classification problem, there exists a collection of authors, a set of users profiles of known authors (training dataset), and a collection of user profiles of unknown authorship (test dataset). For each user profile, we retrieved the first 200 tweets that were written in Arabic, as well as the maximum number of words up to 140 words. In total, we collected about 32032 tweets from 422 users.

We used cross-validation with the 422 profiles for training. Then, we used another 232 user profiles to test in order to evaluate the finished model. The data was balanced by gender and dangerous v.s non-dangerous. However, it was not balanced with respect to age. The distribution of the number of user's profiles per dataset is shown in Table 2.

For each profile we calculate a numerical vector, whose elements represents all extracted features from the profile and the respective tweets, which help us discriminate the relevant classes.

Table 1: Data size for each classification task.

Classes	Attributes	Number of profiles for learning	Number of profiles for the test
Age	Adult	136	88
	Young	147	84
Gender	Women	89	52
	Man	89	52
Terrorist	Terrorist	31	11
	Not Terrorist	31	11

5 RESULTS

The step of selection classes was important and became a great influence on the results. We computed the ratio of all characteristics used and then we normalized all used features. In total, we made use of the 143 attributes.

In this research, we applied classifiers to select the relevant attributes and to predict the performance for age, gender and dangerous profiles of a Twitter profile. As shown in Table 3, the SVM [4] classifier outperforms the other two classifiers multilayer perceptron and random forest. SVM provides the highest accuracy with 73.49% for age, 83.70% for gender and 88.70% for dangerous profiles.

Table 3: Classification accuracy using 10-fold cross-validation with the training partition.

Classes	SVM	Multilayer Perceptron	Random Forest
Age	**73.49** %	70.31 %	66.07 %
Gender	**83.70** %	76.40 %	74.71 %
Terrorist	**88.70** %	82.25 %	80.64 %

Based on our results, the style features that prove most useful for age discrimination are the use of joyful and happy emotion in the writing of young people. While adults use more 'angry' emotions, long words, prepositions with a high entropy measurement (the more the words of a Tweet are varied the higher the entropy is).

The features that prove to be most useful for gender discrimination are military terms and weapons, a high measure of tweets diversity with the use of multiple question marks (markers of male writer). In counterparts, the markers of female writers are a large number of followed accounts, in addition to the use of the first personal pronoun.

The most discriminating style features indicate that dangerous profiles tend to write their Tweets after midnight with more emotions of satisfaction. They also tend, to use two different grams and to write their publications with a large number of semi-colons. Moreover, they usually have a large number of friends. Concerning non-dangerous profiles, we can notice that their posts are enriched with adverbs and adjectives. Moreover, they are interested in using more sports terms with long, unique words. In addition, non-dangerous accounts often use in their posts syntactic characters such as double quotes, multiple question marks, and seedling-colonists.

Table 4 shows the results obtained with the test data set for the three classes. Our dataset contains 232 new Twitter user profiles that not be seen from before. As shown in that table, the Random Forest classifiers outperforms other classifiers with 80.81% for age and 75.00% for gender both accuracy. On the other hand, SVM classifier gave the better accuracy of 81.81% for detecting dangerous profiles.

Table 4: Supplied test set classification accuracy.

Classes	SVM	Multilayer perceptron	Random Forest
Age	69.18 %	72.03 %	**80.81** %
Gender	73.07 %	74.03 %	**75.00** %
Terrorist	**81.81** %	68.18 %	54.54 %

6 CONCLUSIONS

In this paper, we tackled the problem of automatically determining the age, the gender of users on the Twitter social network, and the detection of terrorist profiles, focusing mainly on Arab profiles that have not occupied research, the place they deserve.

We used our own body of user profiles, we started by extracting Tweets from these profiles by proposing a set of characteristics that allow us to predict the three classes considered, namely (age, gender, danger). We considered three families of characteristics: the stylistic family (syntactic, lexical and structural characteristics), the semantic family where we collected several dictionaries manually to characterize different available themes and the family of information about the profiles themselves. Finally, we have shown how the right combination of stylometric characteristics and automatic learning methods allows an automated system to effectively determine the desired aspects of an anonymous author.

The results show the stylometric characteristics were more efficient and accurate, according to what is accepted and believed in the literature. To be more precise, the best performance obtained on our database was 73.49% for age detection and was obtained using the SVM classifier. On the other hand, the best performance in terms of gender detection was 83.70% and was obtained using the SVM classifier as well. Finally, the best performance for detecting terrorists was 88.70% and it was still obtained using the SVM classifier.

After analyzing the experimental results, we found that the SVMs seem to be the best classifier among those tested for the identification of the three classes of profiles adopted.

In the future, our goal is to explore new multilingual author profile detection techniques by adopting more sophisticated features such as those based on the user's geographic location, for example. Similarly, we are considering increasing the size of the dictionaries used to predict the feelings and different themes considered.

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