

AperTO - Archivio Istituzionale Open Access dell'Università di Torino

A survey on author profiling, deception, and irony detection for the Arabic language

This is the author's manuscript

Original Citation:

Availability:

This version is available <http://hdl.handle.net/2318/1837180> since 2022-01-31T01:32:58Z

Published version:

DOI:10.1111/lnc3.12275

Terms of use:

Open Access

Anyone can freely access the full text of works made available as "Open Access". Works made available under a Creative Commons license can be used according to the terms and conditions of said license. Use of all other works requires consent of the right holder (author or publisher) if not exempted from copyright protection by the applicable law.

(Article begins on next page)

Document downloaded from:

<http://hdl.handle.net/10251/146287>

This paper must be cited as:

Rosso, P.; Rangel-Pardo, FM.; Hernandez-Farias, DI.; Cagnina, L.; Zaghouani, W.; Charfi, A. (04-2). A survey on author profiling, deception, and irony detection for the Arabic language. *Language and Linguistics Compass*. 12(4):1-20.
<https://doi.org/10.1111/lnc3.12275>



The final publication is available at

<https://doi.org/10.1111/lnc3.12275>

Copyright Wiley

Additional Information

"This is the peer reviewed version of the following article: [FULL CITE], which has been published in final form at [Link to final article using the DOI]. This article may be used for non-commercial purposes in accordance with Wiley Terms and Conditions for Self-Archiving."

A Survey on Author Profiling, Deception and Irony Detection for the Arabic Language

Paolo Rosso¹, Francisco Rangel¹, Irazú Hernández Farías², Leticia Cagnina³, Wajdi Zaghouani⁴, Anis Charfi⁴

¹ Universitat Politècnica de València

² INAOE Puebla

³ Universidad Nacional de San Luis

⁴ Carnegie Mellon University Qatar

Abstract

The possibility of knowing people traits on the basis of what they write is a field of growing interest named author profiling. To infer a user's gender, age, native language, language variety or even when the user lies, simply by analyzing her texts, opens a wide range of possibilities from the point of view of security. In this paper, we review the state of the art about some of the main author profiling problems, as well as deception and irony detection, especially focusing on the Arabic language.

1. Introduction

Idiosyncrasy inherent to social media makes them a special environment of communication, due to its freedom of expression, informality and spontaneous generation of topics and trends. But also the possible anonymity of the users. In most cases, personal information is missing; in other cases, users lie. This lack of knowledge about who writes the contents contributes to the emergence of new security issues, such as threatening messages. For example, Magdy et al. (2015) collected a corpus of approximately 57 thousand tweeps, who authored nearly 123 million tweets. The tweets collected were mostly written in Arabic, and they are related to ISIS organization. To study the historical timeline of the users, Magdy et al. (2015) classified manually the tweets into anti-ISIS, and pro-ISIS, in other words ISIS supporter's vs ISIS opponents as they checked their historical timeline for the period before the creation of ISIS so they get insights into the antecedents of their support preference. Finally, a classifier was built using the collected data to predict eventually who is more likely will oppose or support the group.

To be able to determine the linguistic profile of a person who writes a "suspicious or threatening text" may provide valuable background information. For example, when analyzing a threatening text, we should know: *i*) the veracity of the threat, by detecting possible deception or irony in the message (since therefore does not represent a threat)¹ *ii*) the demographics of the author, such as age, and gender; *iii*) besides her cultural and social context (e.g. native language or/and dialect), with the

¹ Fake terroristic threat: two Irish were refused entry to the USA after tweeting that they were going to "destroy" America <http://abcnews.go.com/Blotter/pair-held-twitter-homeland-threat-mix-reports/story?id=15472918>

attempt of profiling potential terrorists (Russell and Miller, 1977). Recently, we started the Arabic Author Profiling project for Cyber-Security (ARAP) to address the lack of resources and tools for the author profiling task in Arabic.²

In this survey, we review the state of the art of some of the main author profiling areas in general and for the Arabic language in particular. We focused mainly on Arabic language, in order to stress the gap of what has been addressed in English and other languages as compared to the Arabic language. We start our survey with the age and gender identification task, the native language and language variety identification task. Later on, we present the work on the deception detection and the irony and sarcasm detection. Finally, we briefly discuss some of the challenges faced while processing the Arabic language in these tasks.

2. Age and Gender Identification

Author profiling is a research topic that is in vogue in the research community and several are the shared tasks organized on different demographic aspects during the last years. With respect to age and gender identification, a shared task has been organized at PAN³ at the Conference and Labs of the Evaluation Forum (CLEF)⁴ since 2013. The focus has been on age and gender identification, in different languages apart from English:

- In 2013 (Rangel et al., 2013), the aim was dealing with large datasets with high levels of noise, both in English and Spanish.
- In 2014 (Rangel et al., 2014), participants had to approach the task in multiple genres such as social media, blogs, Twitter and hotel reviews, for both English and Spanish.
- In 2015 (Rangel et al., 2015), age and gender identification problem was combined with personality recognition. In this case, the tweets were provided for Spanish, English, Italian and Dutch.
- In 2016 (Rangel et al., 2016b), the focus was on the cross-genre evaluation, that is, training in one genre (Twitter) and evaluating in another one (blogs, social media and reviews). This year data was provided for Spanish, English and Dutch.
- In 2017 (in progress), the goal is to identify the authors' gender as well as the specific variation of their native language.

Majority of approaches at PAN used combinations of style-based features such as frequency of punctuation marks, capital letters, quotations, and so on, together with parts-of-speech tags and content-based features such as bag of words, term frequency-inverse document frequency (TF-IDF), dictionary-based words, topic-based words, entropy-based words, or content-based features obtained with Latent Semantic Analysis (LSA). It should be highlighted this approach that obtained the overall best results for three years (López-Monroy et al., 2013; López-Monroy et al., 2014; Álvarez-Carmona et al., 2015) by using a second-order representation that relates documents with profiles (e.g. men, women, teenagers, etcetera) and subprofiles (e.g. videogamers, students, housewives, etc.). In another work (López-Monroy et al., 2015), the authors test their approach on Schler's collection (Schler et al., 2006) showing a significant improvement in

2 <http://arap.qatar.cmu.edu/>

3 <http://pan.webis.de>

4 <http://www.clef-initiative.eu>

accuracy up to 82.01% and 77.68% respectively for gender and age identification. On the English partition of the PAN-AP-13 dataset (Rangel et al., 2013), the authors in (Weren et al., 2014) show the contribution to the task of information retrieval features, obtaining accuracies of 62.1% and 68.2% respectively for gender and age identification. The authors in (Maharjan et al., 2014) approach the task with 3 million features processed with MapReduce, that allow them to obtain competitive results (higher than 61% for both gender and age identification in both English and Spanish datasets) with great reductions in time consumed. Finally, the EmoGraph graph-based approach (Rangel and Rosso, 2016) captures how users convey verbal emotions in the morphosyntactic structure of the discourse, obtaining competitive results with the best-performing systems at PAN 2013 and demonstrating its robustness against genres and languages on PAN-AP-14 corpus (Rangel and Rosso, 2015).

2.1 Age and Gender Identification in Arabic

The literature for age and gender identification in the Arabic language is scanty. The authors in (Estival et al., 2008) investigate the age and gender identification problem (besides the level of education or personality) in English and Arabic emails. For Arabic, they collect 8,028 emails from 1,030 native speakers of Egyptian Arabic. They built the Text Attribution Tool (TAT) by obtaining 518 features grouped as shown in Table 1, and test different machine learning algorithms such as support vector machines (SVM), k-nearest neighbors (KNN) or decision trees combined with chi-square or information gain. The accuracies reported are of 72.10% and 81.15% respectively for gender and age identification.

Feature Group	Description
ArabicNamedEntities	Language-independent named entities
ArabicChar	Character level features
ArabicMorphological	Morphological level features
ArabicLexical	Lexical level features

Table 1: Feature groups for the TAT system.

The TAT system includes several data repositories and a couple of components to derive the features and to build classifiers. The architecture is modular and it is organized around a chain of processing modules. This architecture allows a flexible experimentation with the different modules. As shown in Figure 1, The process is data-driven as the output of each processing module depends on its input (Estival et al., 2008).

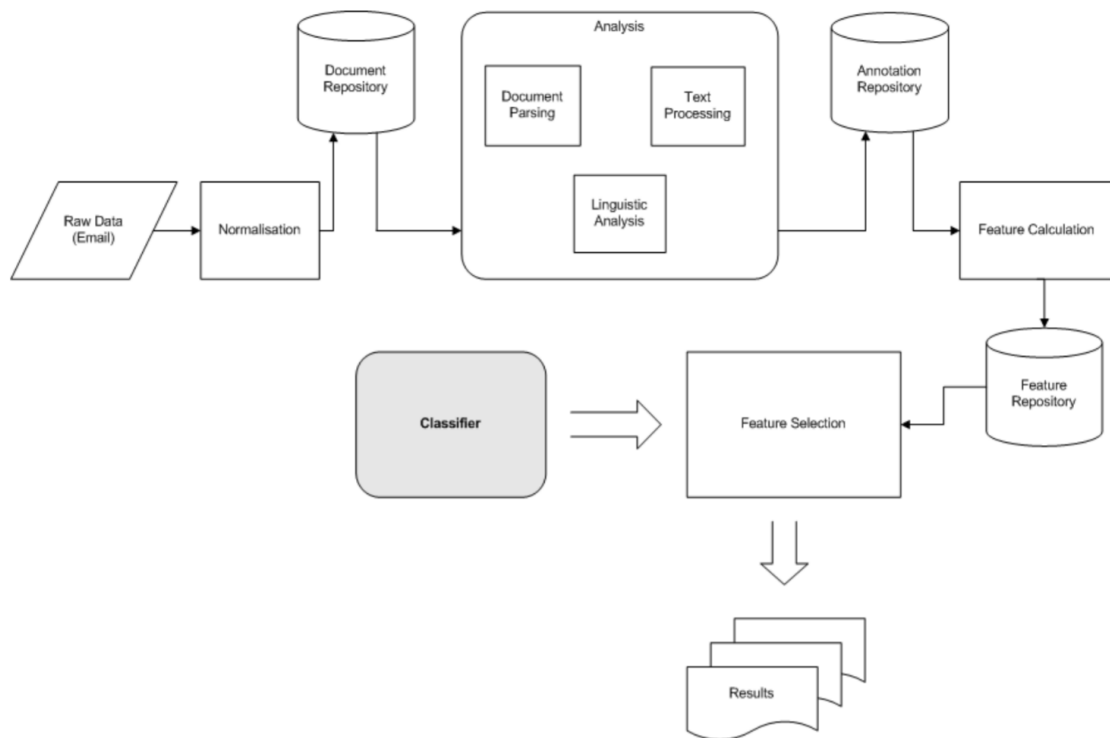


Figure 1: TAT System Diagram (Estival et al., 2008)

The authors in (Alsmearat et al., 2015) investigate gender identification in 500 articles collected from well-known Arabic newsletters. They collect articles from writers with similar academic profiles and with experience in journalistic writings and who write their articles in Modern Standard Arabic (MSA), from the Jordan and Palestine variations. They combine bag-of-words features with sentiments and emotions and explore different machine learning methods. In Table 2 their best results are shown. Subsequently, the authors (Alsmearat et al., 2014) extend their work to experiment with different machine learning algorithms, data-subsets and feature selection methods, reporting accuracies up to 94%.

Bag-of-words	86.4 %
Sentiments & emotions	61.9 %
Both	86.4 %

Table 2: Results for Alsmearat et al. (2015) in Arabic newsletters.

The authors in (AlSukhni and Alequr, 2016) collect 8,034 tweets from Jordanian dialects and label them manually with gender. They add to their bag-of-words approach the name of the authors of the tweets, reporting a great improvement in different evaluation metrics. They also add other features such as the number of words per tweet or the average word length. Several different machine learning algorithms are tested and the best results are shown in Table 3.

Approach Used	Results
---------------	---------

Bag-of-words	62.49%
Bag-of-words+ author's names	98.69%
Bag-of-words+ + number of words & average word length	99.50%

Table 3: Results for Alsukhni et al. (2016) in Twitter.

3. Native Language, Language Varieties, and Dialects Identification

Besides the language identification of a potentially threatening message, and especially with the rise of social media, there are new challenges to deal with such as the identification of the native language of its author or even the discrimination among varieties of the same language and dialects.

Native language identification consists of identifying the native language (L1) of an author who writes in another language (L2). This task is crucial for security because it allows contextualizing the author of a possible threat. For example, an author can be writing in Arabic albeit his native language may be Farsi or French, because he was born in France.

Several corpora have been built, mainly from academia where English is learned as a second language. For example, the two versions of the International Corpus of Learner English (ICLE & ICLEv2) (Granger et al., 2002), First Certificate in English (FCE) (Yannakoudakis et al., 2011), International Corpus Network of Asian Learners of English (ICNALE) (Ishikawa, 2011), Test of English as a Foreign Language (TOEFL) (Blanchard et al., 2013), International Corpus of Cross linguistic Interlanguage (ICCI) (Tono, 2012), National University of Singapore Corpus of Learner English (NUCLE) (Dahlmeier et al., 2013), Corpus of English Essays by Asian University Students (CEEAS) (Ishikawa, 2009). Similarly, Lang-8⁵ is a collaborative service where students from different languages can write essays to be corrected by native speakers.

Due to the interest in the field, the first shared task on native language identification was organized at the Innovative Use of NLP for Building Educational Applications (BEA-8) workshop at the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies NAACL-HT⁶ (Tetreault et al., 2013). There were 29 participants who had to discriminate among 11 languages of the TOEFL corpus. The most used features were character, word and POS *n*-grams, with support vector machine, maximum entropy and ensemble methods. The reported accuracies are approximately 84%.

On the other hand, the task of discriminating among similar languages such as Bosnian, Croatian and Serbian, or language varieties such as Portuguese from Brazil vs. Portugal, or Spanish from Spain vs. Argentina or Peru, steps up the difficulty of native language identification due both to the highest lexical, syntactical and semantic similarity of the texts, and the cultural idiosyncrasies of the writers.

This field has attracted the researcher's attention during the last years. There are several investigations with different languages such as English

5 <http://lang-8.com>

6 <https://sites.google.com/site/nlsharedtask2013>

(Lui and Cook, 2013), South-Slavic (Ljubescic et al., 2007), Chinese (Huang and Lee, 2008), Persian and Dari (Malmasi et al., 2015), or Malay and Indonesian (Bali, 2006), to mention just a few of them. For example, focusing on Portuguese the authors in (Zampieri and Gebre, 2012) collect 1,000 articles from well-known Brazilian⁷ and Portugal⁸ newsletters. They combine character and word n -grams and report accuracies of 99.6% with word unigrams, 91.2% with word bigrams and 99.8% with character 4-grams. With respect to Spanish, the authors in (Maier and Gómez-Rodríguez, 2014) investigate the identification among Argentinian, Chilean, Colombian, Mexican and Spanish on Twitter. They combine four types of features (n -grams and language models) and report accuracies of about 60-70%. The authors in (Rangel et al., 2016a) collect the HispaBlogs⁹ corpus by gathering posts from five Spanish varieties: Argentinian, Chilean, Mexican, Peruvian and Spanish. The authors ensure that training and test partitions do not share any author of instance between them, avoiding possible over-fitting. A low-dimensionality representation is proposed to reduce the number of features to only six per class, allowing to deal with big data environments such as social media. They report an accuracy of 71.1% in comparison to 72.2% and 70.8% that they obtain with Skip-grams and Sentence Vectors in (Franco-Salvador et al., 2015).

The interest in the field is also reflected in the number of workshops and shared tasks organized:

- Defi Fouille de Textes (DEFT) 2010 shared task (Grouin et al., 2011) focused on language variety identification of French texts.
- LT4CloseLang workshop on Language Technology for Closely Related Languages and Language Variants (Nakov et al., 2014) organized in 2014 at the conference on Empirical Methods on Natural Language Processing (EMNLP)¹⁰.
- VarDial Workshop (Zampieri et al., 2014) on applying NLP Tools to Similar Languages, Varieties and Dialects, organized in 2014 at the International Conference on Computational Linguistics (COLING)¹¹, focused on thirteen languages divided into the following groups: Bosnian, Croatian, Serbian; Indonesian, Malay; Czech, Slovak; Brazilian Portuguese, European Portuguese; Peninsular Spanish, Argentinian Spanish; and American English, British English.
- LT4VarDial joint workshop on Language Technology for Closely Related Languages, Varieties and Dialects (Zampieri et al., 2015) organized in 2015 at RANLP¹², focused on thirteen languages divided into the following groups: Bulgarian, Macedonian; Bosnian, Croatian, Serbian; Czech, Slovak; Malay, Indonesian; Brazilian, European Portuguese; Argentinian, Peninsular Spanish; and a group with a variety of other languages.

7 <http://www.folha.uol.com.br>

8 <http://www.dn.pt>

9 <https://github.com/autoritas/RD-Lab/tree/master/data/HispaBlogs>

10 <http://alt.qcri.org/LT4CloseLang/index.html>

11 <http://corporavm.uni-koeln.de/wardial/sharedtask.html>

12 <http://ttg.uni-saarland.de/lt4vardial2015/dsl.html>

- Vardial workshop on NLP for Similar Languages, Varieties and Dialects (Malmasi et al., 2016) organized in 2016 at COLING¹³, with two subtasks: *i*) a more realistic DSL (Discriminating Similar Languages) task with new varieties such as Hexagonal vs. Canadian French, and the removal of very easy to discriminate languages such as Czech vs. Slovak and Bulgarian vs. Macedonian; and *ii*) a new subtask on discriminating Arabic dialects in speech transcripts (Ali et al., 2015) with Modern Standard Arabic and four dialects (Egyptian, Gulf, Levantine and North African), as described more in detail in Section 3.2.
- Author Profiling at PAN 2017, where together with gender identification, the aim is to detect the language variety of the authors. Four are the addressed languages with different variations: *i*) English (Australia, Canada, Great Britain, Ireland, New Zealand, United States); *ii*) Spanish (Argentina, Chile, Colombia, Mexico, Peru, Spain, Venezuela); *iii*) Portuguese (Brazil, Portugal); and *iv*) Arabic (Egypt, Gulf, Levantine, Maghrebi). For each variety, there are 1,000 authors (half per gender) with 100 tweets per author.

3.1 Arabic Native Language Identification

Few are the resources available for the Arabic language. It is worth to mention the BUiD Arab Learner Corpus (BALC) (Randall and Groom, 2009), a resource for studying the acquisition of English spelling. BUiD is a set of examination essays written by 16-year-old Arabic students with different proficiency levels in English. The corpus consists of 1,865 texts with 287,227-word tokens and 20,275-word types. The aim of this research project carried out in collaboration by the British University in Dubai, the United Arab Emirates, and the University of Birmingham in the UK, is to study the particular difficulties for Arab learners when spelling English. The authors draw some preliminary findings consistent with previous studies (Haggan, 1991; Sadhwani, 2005): Arab readers and writers have more problems with vowels than with consonants, reflecting the fact that Arabic is a consonantal script hence Arabs may pay more attention to consonants than to vowels (vowel blindness) (Hayes-Harb, 2006; Ryan and Meara, 1992).

Alfaifi et al. (2014) created the Arabic Learner Corpus (ALC), a large Arabic learner corpus (282K words) produced by native and non-native learners of Arabic from pre-university and university levels. Farwaneh and Tamimi (2012) built the Arabic Learners Written Corpus (ALWC).

The corpus of 51K words was produced by non-native Arabic speakers in various countries over a period of 15 years. The corpus covers three basic learner's levels (beginner, intermediate and advanced), and three text styles (descriptive, narrative and instructional). Abuhakema et al. (2008) created a corpus of 9K Arabic words written by native English speakers who learned Arabic as a foreign language while studying abroad. Hassan and Daud (2011) built the Malaysian Arabic Learners Corpus, they tried to investigate the usage of Arabic conjunctions among L2 learners. The corpus size is 240K words and it was written by Malaysian university students during their first and second year of Arabic major degree. Moreover, the corpus includes spontaneous essays produced using Microsoft Word.

¹³ <http://ttg.uni-saarland.de/vardial2016>

Zaghouani et al. (2015), within the scope of the Qatar Arabic Language Bank (QALB) project (Zaghouani et al. 2014), created a corpus of 2 million words of spelling errors for a variety of Arabic texts including (a) user comments on news websites, including dialectal Arabic (b) native speaker essays (c) non-native speaker essays, (d) machine translation output. The native student essays data is categorized by the student learning level (beginner, intermediate, advanced) and by the learner type (L2 vs. L1).

The goal of the automatic native language identification tool is to find the native language of the language learner using his writing. Most of the research in this area has been done on the native language of English learners. Recently, some efforts were made to identify the native language of text written in other languages such as Arabic. Malmasi and Dras (2014) built an SVM model using various features including function words, part-of-speech n-grams, and Context-Free Grammar (CFG) rules. Their system obtained an accuracy of 41% when it was evaluated using the Arabic learner corpus created by Alfaifi et al. (2014). More recently, Ionescu (2015) created a new distance measure for strings with the name, Local Rank Distance (LRD). His method was inspired by the rank distance method as it measures the local displacement of character n-grams among two strings. During the evaluation of the ALC corpus, Ionescu system outperformed Malmasi and Dras by 10 folds with an accuracy of 50.1%. Finally, Mechti et al. (2016), proposed a classification method using some statistical data generated from a corpus. It is considered a hybrid method combining surface analysis in the text with an automatic learning method.

3.2 Arabic Dialects Identification

The lack of language resources for dialectal Arabic well known, recently some researchers addressed this problem by creating lexicons, Wordnets, corpora, and treebanks. In (Zaidan and Callison-Burch, 2011) the authors collect the Arabic Online Commentary dataset (AOC), gathering 86.1K articles and 1.4M comments from three newspapers: *i)* Al-Ghad¹⁴ from Jordan; *ii)* Al-Riyadh¹⁵ from Arabia Saudi; and *iii)* Al-Youm Al-Sabe¹⁶ from Egypt. They use Amazon Mechanical Turk to manually label them with the corresponding dialect. With a smoothed word unigram model (Zaidan and Callison-Burch, 2014), they report accuracies of 87.2%, 83.3% and 87.9% respectively for Levantine, Gulf and Egyptian dialects. Also, in (Cotterell & Callison-Burch, 2014), a multi-genre dialectal corpus for Levantine, Gulf, North African, Iraqi and Egyptian dialects was described.

Graff et al. (2006), presented an Iraqi Arabic lexicon with words from recorded speech marked with morphology information, pronunciation, and part-of-speech. The annotation was done through a dedicated user interface. Boujelbane et al. (2013), built a Tunisian dialectal corpus in order to create a language model for a speech recognition system for a Tunisian Broadcast News company. Cavalli-Sforza et al. (2013) created an Iraqi Arabic WordNet using an English-Iraqi dictionary and the modern standard Arabic version of

14 <http://www.alghad.com>

15 <http://www.alriyadh.com>

16 <http://www.youm7.com>

WordNet as well as the English WordNet. Moreover, a Tunisian dialect WordNet was built in (Bouchlaghem & Elkhilifi, 2014) starting from a Tunisian corpus.

Duh & Kirchhoff (2006), built a Levantine lexicon using a transductive learning method through partially annotated text in order to perform sentiment analysis of social networks data using a dedicated lexicon for slang sentimental words and idioms was developed as described in (Hedar & Doss, 2013). Al-Sabbagh & Girju (2012b), described their initial work on building a corpus for Egyptian Arabic. The corpus was compiled from various data sources such as Twitter, Blogs and Forums. Also, Almeman & Lee (2013), used the web as a source to create a multi-dialect Arabic corpus for North African, Egyptian, Gulf and Levantine dialects.

Jarrar et al. (2014) presented his Palestinian Arabic corpus with 43K words and a parallel corpus for Algerian Arabic and MSA was proposed in (Harrat et al., 2014) for the purpose of machine translation. In (Elfardy and Diab, 2013) the authors investigate the discrimination between Egyptian and Modern Standard Arabic. They propose two set of features: *i*) core features such as token-based, perplexity, morphological-based, orthography, and similar; and *ii*) meta- features such as frequencies of punctuation signs, numbers, special characters, words in Roman script, words with character flooding, number of words, average word length, and so on. They report an accuracy of 85.5%.

The AOC dataset has been used in other investigations. For example, the authors in (Tillmann et al., 2014) discriminate between Egyptian dialect and Modern Standard Arabic by using a combination of character, word and part-of-speech *n*-grams with features obtained with the AIDA tool. They report an accuracy of 89.1%. In (Darwish et al., 2014), the authors combine the Egyptian part of the LDC2012T09 dataset (Zbib et al., 2012) with the Modern Standard Arabic dataset of the International Workshop on Arabic Language Translation¹⁷. They experiment with different combinations of machine learning features: *i*) word 1/3-grams with character 1/5-grams, reporting an accuracy of 84.7%; *ii*) morphological features, reporting accuracies between 89.3% and 90.1%; and *iii*) the use of a dialectal Egyptian lexicon, reporting accuracies of 93.6% by using 1,300 dialectal words, 94.6% by using 94K verbs and 94.4% by using 8K words with letter substitutions.

The authors in (Sadat et al., 2014) investigate machine learning techniques using Naïve Bayes classifiers and *n*-gram Markov language models for the automatic discrimination among 6 Arabic dialects: Egyptian, Iraqi, Gulf (including Bahrain, Emirates, Kuwait, Qatar, Oman and Saudi Arabia), Maghreb (including Algeria, Tunisia, Morocco, Libya and Mauritania), Levantine (including Jordan, Lebanon, Palestine and Syria), and Sudan. They use *n*-gram models and report accuracies close to 98%.

An interesting work is the one done on Algerian Arabic, Berber and Standard Arabic in (Adouane et al. 2017; Adouane et al. 2016a; Adouane et al. 2016b; Adouane et al. 2016c). The authors used hybrid methods combining dictionaries and supervised machine learning methods such as the Hidden

17 <https://wit3.fbk.eu/mt.php?release=2013-01>

Markov Model (HMM) and N-gram classification tagging to identify the dialects while Saâdane et al. (2017; Saâdane et al. 2015) used mainly a rule-based linguistic approach to detect the Arabic dialects.

The authors in (Shoufan and Al-Ameri, 2015) provided a comprehensive survey on natural language processing methods for Arabic, including a review of the dialect identification task. The increasing interest in Arabic dialects identification is attested by the eighteen teams participating in the Arabic subtask of the third DSL track (Ali et al., 2015). Its difficulty is backed up by the obtained accuracies of about 50%. A summary of the best approaches and their accuracies is shown in Table 4.

Approach	Accuracy
OPEN TRACK	
SVM, w/c n -grams	51.4%
Ensemble, w/c n -grams	51.2%
Multiple string kernels	50.9%
CLOSE TRACK	
SVM, char 5/6-grams	53.2%
Ensemble, w/c n -grams	49.1%

Table 4: Results for 2016 DSL Arabic subtask.

Recently, Habash et al. (2017),¹⁸ proposed MADAR, a large-scale project for dialectal Arabic covering 25 Arabic dialects from the main cities in the Arab region. Their dialectal identification tool is currently in progress.

4. Deception Detection

A deceptive opinion can be defined as a fictitious opinion written with the intention to sound authentic in order to mislead the reader. An opinion spam usually is a short text written by an unknown author using a not very well defined style. These characteristics make the problem of automatic detection of opinion spam very challenging (Rosso and Cagnina, 2017).

In the literature, the most research attends the problem of opinion spam detection for reviews written in English language. In (Fitzpatrick et al., 2015) the authors describe different behaviors indicative of deception such as physiological, gestural and verbal, considering the opinion spam detection among others problems. Several works approached the problem of the detection of deceptive opinions considering features based on the content of the reviews in a supervised way. In (Ott et al., 2011) the authors use the 80 dimensions of LIWC2007 (Pennebaker et al., 2007b), unigrams and bigrams as a set of features with an SVM classifier. In (Hernández Fusilier et al., 2015b; Hernández Fusilier et al., 2015a) the authors propose a PU-learning variant using two different representations: word n -grams and character n -grams. The best results are obtained with a Naïve Bayes classifier using character 4 and 5 grams as features (Hernández Fusilier et al., 2015b) and, the conjunction of word unigrams and bigrams in (Hernández Fusilier et al., 2015a). With those results, the authors conclude that PU-learning show to be appropriate for detecting opinion spam. Character n -grams in tokens, the sentiment score and LIWC linguistic features such as pronouns, articles, and

¹⁸ nlp.qatar.cmu.edu/madar

verbs (present, past and future tenses) were used in (Cagnina and Rosso, 2015) for the detection of opinion spam. The best results are obtained with a Naïve Bayes classifier and the combination of character 4-grams in tokens and LIWC features for the representation of the opinions.

4.1 Deception Detection in Arabic

The detection of spam in Arabic opinion reviews is a relatively new research field then, the bibliography is scarce in this area. In (Wahsheh et al., 2013b) the authors present one of the first systems to detect spam in Arabic opinions. The system named SPAR uses features as spam URLs (a blacklist with Arabic content/link spam web pages (Wahsheh et al., 2013a)), five or more consecutive numbers and, presence of the '@' symbol with letters around (e-mails address) for the classification of opinions like spam or not spam. The system also categorizes the spam opinions in 'high' or 'low' spam depending on the content of the review, using a special metric. At the same time, the non-spam reviews are labeled as 'positive', 'negative' or 'neutral' based on two language polarity dictionaries built by the authors, one with 2,800 words/phrases and other with 75 emoticons. SPAR is tested with a dataset of 3,090 opinions written in the Arabic language collected manually by the authors from Yahoo!-Maktoob News. An SVM classifier in Weka data mining tool is used to obtain the results. After performing a 10 fold cross-validation experiment, the accuracy reported is 97.50% and the error rate is 2.49%. The authors conclude that SPAR provides a reliable and trustworthy performance to distinguish spam from non-spam opinions.

In (Hammad and El-Halees, 2015) the authors propose a novel approach combining methods from data mining and text mining with machine learning techniques to detect spam in opinion reviews written in the Arabic language. Additionally, the approach uses methods to solve the class imbalance problem present in the dataset used. For the representation of the reviews, review content, meta-data about each reviewer and hotel information have been used as features. The authors build a dataset of 2,848 reviews from online Arabic websites such as Tripadvisor.com.es, Booking.com and Agoda.es. The classification is performed with Naïve Bayes (NB), SVM, ID3 and K-NN algorithms with a 10-fold cross-validation experiment. The best results are obtained with NB and over-sample method, that is 99.20% of accuracy, concluding in the effectiveness of this approach for identifying spam in Arabic reviews.

The authors in (Aloshban and Al-Dossari, 2016) present some preliminary ideas about a method for grouping spam detection in social media for the Arabic language. The proposal uses open source tools for the processing of the Arabic texts and consists of 4 phases: crawling (to collect tweets), preprocessing (to clean the texts), spamming activities detection and individual member's behavior scanning (to identify suspected spammers). The spam activities detection is based on the work of (Mukherjee et al., 2012) that aims to detect group members posting tweets on a particular entity for a short time (Group Time Window), check the similarity of a tweet content (Group Content Similarity) and detect if the members of a group post tweet on the entity at first (Group Early Time Frame). The authors

conclude that the research is at its early stage and a lot of work is still needed to finish this proposal.

5. Irony and Sarcasm Detection

A suspicious message may not be a threat when it is humoristic or ironic (Reyes et al., 2012). Irony and sarcasm represent an interesting way to communicate opinions toward a particular target in social media (Hernández Farías and Rosso, 2016). The most common definition of irony refers to the use of words for expressing the opposite meaning from what is literally said (Grice, 1975). When irony becomes offensive with a specific target to attack is considered as a form of sarcasm (Bowes and Katz, 2011). These figurative language devices represent a big challenge for natural language processing related tasks, especially for sentiment analysis (Bosco et al., 2013).

In recent years, several approaches have been proposed to deal with irony and sarcasm detection in social media. Irony (and sarcasm) detection has been addressed as a classification problem, where decision trees and support vector machine are among the classifiers that obtain the best results. The majority of research investigating irony and sarcasm detection has focused on Twitter. Surface features (such as punctuation marks and emoticons) together with textual markers to identify inconsistencies and incongruities in texts have been widely exploited (Reyes et al., 2013; Barbieri and Saggion, 2014; Hernández Farías et al., 2015; Joshi et al., 2015; Karoui et al., 2015). In (Barbieri et al., 2014; Sulis et al., 2016) the authors attempt to classify tweets labeled with #irony and #sarcasm. They use the same dataset achieving 0.62 and 0.69 in F-measure terms, respectively. Aiming to evaluate the performance of sentiment analysis systems in the presence of irony and sarcasm some evaluation campaigns have been organized in English (Ghosh et al., 2015) and in other languages such as Italian (Basile et al., 2014; Barbieri et al., 2016).

5.1 Irony and Sarcasm Detection in Arabic

With respect to works in Arabic, few are the attempts in which irony has been addressed in literature and mass media (Abuhajam, 2004; Alabban, 2014; Alharbi, 2015; Battish, 1983). There are no automatic approaches to detect irony and sarcasm. In (Sigar and Taha, 2012) the authors manually analyze the similarities and differences between ironic expressions in English and Arabic. They use data from books, articles and Internet (some images). A manual annotated Twitter dataset is instead described in (Refaee and Rieser, 2014). The authors asked two native speakers of Arabic to annotate polarity. Additionally, the presence of sarcasm has been annotated. Very recently a preliminary system for irony detection in Arabic in social media was presented in (Karoui et al., 2017). Several features have been taken into account: surface, sentiment, contextual, and shifter ones (e.g. false assertion, exaggeration). In the future, the authors plan to manually check the reliability of the hashtags they consider and include pragmatic features that should help to infer the context needed to understand further irony.

6. Challenges in Processing Arabic text

Processing the Arabic language for any NLP task can be sometimes challenging due to several peculiarities that we present in this section. First of all, Arabic morphology is relatively complex in that it uses prefixes, infixes and suffixes, not only for inflection but also to concatenate words. This various morphological variation can be dealt with by using hand-crafted rules, which enable to strip off possible prefixes and suffixes from the word stem before further processing. Furthermore, the spoken form of Arabic is quite different from the written form of the language as it is one of the few languages in the world with clear diglossia. For any native speaker of Arabic, there exist at least two forms of the language, the spoken form which is typically a specific dialect versus a formal written form, referred to as modern standard Arabic (MSA). Moreover, Arabic is different from English both morphologically and syntactically. Hence, Arabic is a challenging language to the existing NLP technology tailored to the nuances of the English language. From the morphological standpoint, Arabic exhibits rich morphology. Similar to English, Arabic verbs are marked explicitly for tense, voice and person, however, in addition, Arabic marks verbs with mood (subjunctive, indicative and jussive) information. Depending on the genre of the text at hand, not all of those features are explicitly marked in the naturally occurring text. Arabic writing is known for being underspecified for short vowels.

Developing NLP systems in a diglossic situation like Arabic could in indeed lead to some complication. For instance, it is very difficult for any single NLP application to process data from all the dialectal varieties of Arabic with their linguistic peculiarities (e.g. the loss of case distinctions) while they have some common properties. In order to successfully process a text with dialectal Arabic, the NLP application should be able to detect beforehand which variety it is aiming to address so the linguistic properties of the particular dialect can be applied. In order to tackle this issue, Habash et al. (2005) took the initiative to address the issue of Arabic dialects and made the assumption that is it much easier to develop natural language processing tools for the dialects by extracting and categorizing the grammatical features of a given dialect, making it to behave like Modern Standard Arabic (MSA) before applying MSA natural language processing tools to process a text. Currently, the MADAMIRA tool for the morphological analysis and disambiguation of Arabic is widely used and can be considered a state of the art tool to process Arabic (Arfath et al. 2014).

Conclusions

In this survey, we have reviewed the state of the art in the Arabic language of age, gender, native language and language variety identification, as well as of deception and irony detection. The main aim is to highlight what still needs to be done for the Arabic language for automatically profiling demographics or detecting deception and irony. The final aim will be to fill in these gaps and develop an author profiling system for cyber-security in Arabic.

References

- Abuhajam, M. (2004). *The irony of modern Algerian literature*. Algiers: Heritage Association.
- Abuhakema Ghazi, Reem Faraj, Anna Feldman, and Eileen Fitzpatrick. 2008. Annotating an Arabic Learner Corpus for Error. In *Proceedings of The sixth international conference on Language Resources and Evaluation, LREC 2008, Marrakech, Morocco*.
- Adouane Wafia, Simon Dobnik. (2017). Identification of Languages in Algerian Arabic Multilingual Documents. *Proceedings of The Third Arabic Natural Language Processing Workshop (WANLP)*, Valencia, Spain, April 3, 2017.
- Adouane Wafia, Nasredine Semmar, Richard Johansson. (2016a). Romanized Berber and Romanized Arabic Automatic Language Identification Using Machine Learning. *Proceedings of the Third Workshop on NLP for Similar Languages, Varieties and Dialects; COLING*, 53–61; December 12, 2016, Osaka, Japan.
- Adouane Wafia, Nasredine Semmar, Richard Johansson. (2016b). ASIREM Participation at the Discriminating Similar Languages Shared Task 2016. *Proceedings of the Third Workshop on NLP for Similar Languages, Varieties and Dialects; COLING*, 163–169; December 12; Osaka, Japan.
- Adouane Wafia, Nasredine Semmar, Richard Johansson, Victoria Bobicev. (2016c). Automatic Detection of Arabicized Berber and Arabic Varieties. *Proceedings of the Third Workshop on NLP for Similar Languages, Varieties and Dialects; COLING*, 63–72; December 12; Osaka, Japan.
- Al Sukhni, E., Alequr, Q. (2016). Investigating the use of machine learning algorithms in detecting gender of the Arabic tweet author. *International Journal of Advanced Computer Science & Applications*, 1(7):319–328.
- Alfaifi, A., Atwell, E., Hedaya, I.: Arabic learner corpus (ALC) v2: a new written and spoken corpus of Arabic learners. In: *Proceedings of the Learner Corpus Studies in Asia and the World*, May 2014
- Alharbi, K. (2015). *The irony volcano explodes black comedy*. 20 December 2015.
- Ali, A., Bell, P., Renals, S. (2015). Automatic dialect detection in Arabic broadcast speech. In *Interspeech Conference*.
- Alkanhal, Mohamed I, Al-Badrashiny, Mohamed A, Alghamdi, Mansour M, and Al-Qabbany, Abdulaziz O. (2012). Automatic Stochastic Arabic Spelling Correction with Emphasis on Space Insertions and Deletions. *IEEE Transactions on Audio, Speech, and Language Processing*, 20(7):2111–2122.
- Almeman, K., & Lee, M. (2013). Automatic building of Arabic multi dialect text corpora by bootstrapping dialect words. In *Communications, signal processing, and their applications (ICCSIPA), 2013 1st international conference on* (pp. 1–6).

Aloshban, N., Al-Dossari, H. (2016). A new approach for group spam detection in social media for Arabic language (AGSD). In: The International Conference on Latest Trends in Engineering and Technology (ICLTET'2016), pages 20–23.

Al-Sabbagh, R., & Girju, R. (2012). YADAC: Yet Another Dialectal Arabic Corpus. In international conference on Language Resources and Evaluation (LREC) (pp. 2882–2889).

Alsmearat, K., Al-Ayyoub, M., Al-Shalabi, R. (2014). An extensive study of the bag-of-words approach for gender identification of Arabic articles. In 2014 IEEE/ACS 11th International Conference on Computer Systems and Applications (AICCSA), pages 601–608. IEEE.

Alsmearat, K., Shehab, M., Al-Ayyoub, M., Al-Shalabi, R., Kanaan, G. (2015). Emotion analysis of Arabic articles and its impact on identifying the authors gender. In Computer Systems and Applications (AICCSA), 2015 IEEE/ACS 12th International Conference on.

Alvarez-Carmona, M.A., Lopez-Monroy, A.P., Montes-Y-Gomez, M., Villasenor-Pineda, L., Jair-Escalante, H. (2015). Inaoe's participation at PAN'15: author profiling task—notebook for PAN at CLEF 2015.

Arfath Pasha, Mohamed Al-Badrashiny, Mona Diab, Ahmed El Kholy, Ramy Eskander, Nizar Habash, Manoj Pooleery, Owen Rambow, and Ryan M. Roth. (2014). MADAMIRA: A Fast, Comprehensive Tool for Morphological Analysis and Disambiguation of Arabic. In Proceedings of LREC 2014.

Bali, R.M. (2006). Automatic identification of close languages—case study: Malay and Indonesian. ECTI Transaction on Computer and Information Technology, 2(2):126–133.

Barbieri, F., Basile, V., Croce, D., Nissim, M., Novielli, N., Patti, V. (2016). Overview of the Evalita 2016 Sentiment Polarity Classification Task. In Proceedings of Third Italian Conference on Computational Linguistics (CLiC-it 2016) & Fifth Evaluation Campaign of Natural Language Processing and Speech Tools for Italian. Final Workshop (EVALITA 2016). CEURWS.org, vol. 1749.

Barbieri, F., Saggion, H. 2014. Modelling irony in twitter. In Proceedings of the Student Research Workshop at the 14th Conference of the European Chapter of the Association for Computational Linguistics, pages 56–64.

Barbieri, F., Saggion, H., Ronzano, F. 2014. Modelling Sarcasm in Twitter, a novel approach. In Proceedings of the 5th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, pages 50–58, Baltimore, Maryland, USA, June. Association for Computational Linguistics.

Basile, V., Bolioli, A., Nissim, M., Patti, V., Rosso, P. (2014). Overview of the Evalita 2014 Sentiment Polarity Classification task. In Proceedings of the First Italian Conference on Computational Linguistics & the Fourth International Workshop EVALITA 2014, pages 50–57.

- Battish, S. (1983). *Humor and irony in Maroun Abboud's works*. Beirut: Dar Lana.
- Blanchard, D., Tetreault, J., Higgins, D., Cahill, A., Chodorow, M. (2013). *Toefi11: a corpus of non-native English*. ETS research report series, 2013(2):i-15.
- Bosco, C., Patti, V., Bolioli, A. (2013). Developing corpora for sentiment analysis: the case of irony and Senti-TUT. *IEEE Intelligent Systems*, 28(2):55-63.
- Boujelbane, R., BenAyed, S., & Belguith, L. H. (2013). Building bilingual lexicon to create dialect Tunisian corpora and adapt language model. *ACL 2013*
- Bowes, A., Katz, A. (2011). When sarcasm stings. *Discourse Processes: A Multidisciplinary Journal*, 48(4):215-236.
- Cagnina L., Rosso, P. (2015). Classification of deceptive opinions using a low dimensionality representation. In *Proceedings of the 6th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pages 58-66. Association for Computational Linguistics.
- Cavalli-Sforza, V., Saddiki, H., Bouzoubaa, K., Abouenour, L., Maamouri, M., & Goshey, E. (2013). Bootstrapping a Wordnet for an Arabic dialect from other Wordnets and dictionary resources. In *Computer systems and applications (AICCSA), 2013 ACS international conference on* (pp. 1-8).
- Cotterell, R., & Callison-Burch, C. (2014). A multi-dialect, multi-genre corpus of informal written Arabic. In *Proceedings of the language resources and evaluation conference (LREC)*
- Dahlmeier, D., Tou Ng, H., Mei Wu, S. (2013). Building a large annotated corpus of learner English: the NUS corpus of learner English. In *Proceedings of the 8th workshop on innovative use of NLP for building educational applications*, pages 22-31.
- Darwish Alabban, S. (2014). *Irony -> irony! :-)* theory and bringing down the Egyptian state. Cairo: Albawabah News daily.
- Darwish, K., Sajjad, H., Mubarak, H. (2014). Verifiably effective Arabic dialect identification. In *EMNLP*, pages 1465-1468.
- Duh, K., & Kirchhoff, K. (2006). Lexicon acquisition for dialectal Arabic using transductive learning. In *Proceedings of the 2006 conference on empirical methods in natural language processing* (pp. 399-407)
- Elfardy, E., Diab, M.T. (2013). Sentence level dialect identification in Arabic. In *ACL (2)*, pages 456-461.
- Estival, D., Gaustad, T., Hutchinson, B., Bao-Pham, S., Radford, W. (2008). Author profiling for English and Arabic emails.
- Farwaneh Samira and Mohammed Tamimi. 2012. *Arabic Learners Written Corpus: A Resource for Research and Learning*. The Center for Educational Resources in Culture, Language and Literacy

Fitzpatrick, E., Bachenko, J., Fornaciari, T. (2015). Automatic detection of verbal deception. *Synthesis Lectures on Human Language Technologies*. Morgan & Claypool Publishers.

Franco-Salvador, M., Rangel, F., Rosso, P., Taule, M., Marti, M.A. (2015). Language variety identification using distributed representations of words and documents. In *Experimental IR meets multilinguality, multimodality, and interaction*, pages 28–40. Springer.

Ghosh, A., Li, G., Veale, T., Rosso, P., Shutova, E., Barnden, J., Reyes, A. (2015). Semeval-2015 task 11: sentiment analysis of figurative language in twitter. In *Proceedings of the 9th International Workshop on Semantic Evaluation*, pages 470–478.

Graff, D., & Maamouri, M. (2012). Developing LMF-XML bilingual dictionaries for colloquial Arabic dialects. In *LREC* (pp. 269–274).

Granger, G., Dagneaux, E., Meunier, E. (2002). *The international corpus of learner English. handbook and CD-ROM*.

Grice, H.P. (1975). Logic and conversation. In P. Cole and J.L. Morgan, editors, *Syntax and Semantics: Vol. 3: Speech Acts*, pages 41–58. Academic Press, San Diego, CA.

Grouin, C., Forest, D., Paroubek, P., Zweigenbaum, P. (2011). Presentation et resultats du defi fouille de texte DEFT 2011 quand un article de presse a t-il ete ecrit? A quel article scientifique correspond ce resume? *Actes du septieme Defi Fouille de Textes*, page 3.

HABASH, N., OWEN, R., AND GEORGE, K. 2005. Morphological analysis and generation for Arabic dialects. In *Proceedings of the Association for Computational Linguistics (ACL'05)*.

Haggan, M. (1991). Spelling errors in native Arabic-speaking English majors: a comparison between remedial students and fourth year students. *System*, 19(1-2):45–61.

Hammad, A.A., El-Halees, A. (2015). An approach for detecting spam in Arabic opinion reviews. *Int. Arab Journal of Information Technology.*, 12(1):9–16.

Harrat, S., Meftouh, K., Abbas, M., & Smaili, K. (2014). Building resources for Algerian Arabic dialects. *Corpus (sentences)*, 4000(6415), 2415.

Hassan Haslina and Nuraihan Mat Daud. 2011. Corpus Analysis of Conjunctions: Arabic Learners Difficulties with Collocations. In *Proceedings of the Workshop on Arabic Corpus Linguistics (WACL)*, Lancaster, UK

Hayes-Harb, R. (2006). Native speakers of Arabic and ESL texts: evidence for the transfer of written word identification processes. *TESOL Quarterly*, pages 321–339.

Hernandez Farias, D.I., Benedi, J.M., Rosso, P. (2015). Applying basic features from sentiment analysis for automatic irony detection. In Roberto Paredes, Jaime S. Cardoso, and Xos M. Pardo, editors, *Pattern Recognition and Image*

Analysis, volume 9117 of LNCS, pages 337– 344. Springer International Publishing.

Hernandez Farias, D.I., Rosso, P. (2016). Irony, sarcasm, and sentiment analysis. Chapter7. In Federico A. Pozzi, Elisabetta Fersini, Enza Messina, and Bing Liu, editors, *Sentiment Analysis in Social Networks*, pages 113–127. Morgan Kaufmann.

Hernandez Fusilier, D., Montes-y-Gomez, M., Rosso, P., Guzman Cabrera, R. (2015a). Detecting positive and negative deceptive opinions using pu-learning. *Information Processing & Management*, 51(4):433 – 443.

Hernandez Fusilier, D., Montes-y-Gomez, M., Rosso, P., Guzman Cabrera, R. (2015b). Detection of opinion spam with character n-grams. In A. Gelbukh, editor, *Computational Linguistics and Intelligent Text Processing*, volume9042 of *Lecture Notes in Computer Science*, pages 285–294. Springer International Publishing.

Huang, C.H., Lee, L.H. (2008). Contrastive approach towards text source classification based on top-bag-of-word similarity. In *PACLIC*, pages 404–410.

Ishikawa, S. (2009). Vocabulary in inter language: a study on corpus of English essays written by Asian university students (CEEAS). *Phraseology, corpus linguistics and lexicography*, pages 87–100.

Ishikawa, S. (2011). A new horizon in learner corpus studies: the aim of the ICNALE project. *Korea*, 404:89–168.

Ionescu R.T. (2015) A Fast Algorithm for Local Rank Distance: Application to Arabic Native Language Identification. In: Arik S., Huang T., Lai W., Liu Q. (eds) *Neural Information Processing*. *Lecture Notes in Computer Science*, vol 9490. Springer.

Jarrar, M., Habash, N., Akra, D., & Zalmout, N. (2014). Building a corpus for Palestinian Arabic: a preliminary study. *ANLP 2014*, 18.

Joshi, A., Sharma, V., Bhattacharyya, P. (2015). Harnessing context incongruity for sarcasm detection. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 757–762, Beijing, China, July. Association for Computational Linguistics.

Jihen Karoui, Farah Benamara Zitoune and Véronique Moriceau. (2017). SOUKHRIA: Towards an Irony Detection System for Arabic in Social Media. *Third International Conference On Arabic Computational Linguistics, ACLing 2017*, November 5-6, 2017, Dubai, UAE

Karoui, J., Benamara, F., Moriceau, V., Aussenac-Gilles, N., Hadrich Belguith, L. (2015). Towards a contextual pragmatic model to detect irony in tweets. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 644–650, July.

Ljubescic, N., Mikelic, N., Boras, D. (2007). Language identification: how to distinguish similar languages. In 2007 29th International Conference on Information Technology Interfaces, pages 541–546. IEEE.

Lopez-Monroy, A.P., Montes-Y-Gomez, M., Jair-Escalante, H., Villasenor-Pineda, L. (2014). Using intra-profile information for author profiling—Notebook for PAN at CLEF 2014. In L. Cappellato, N. Ferro, M. Halvey, and W. Kraaij, editors, CLEF 2014 Evaluation Labs and Workshop –Working Notes Papers, 15-18 September, Sheffield, UK, September.

Lopez-Monroy, A.P., Montes-Y-Gomez, M., Jair-Escalante, H., Villasenor-Pineda, L., Stamatatos, E. (2015). Discriminative subprofile-specific representations for author profiling in social media. Knowledge-based systems, 89:134–147.

Lopez-Monroy, A.P., Montes-Y-Gomez, M., Jair-Escalante, H., Villasenor-Pineda, L., Villatoro-Tello, E. (2013). INAOE's participation at PAN'13: author profiling task—Notebook for PAN at CLEF 2013. In Pamela Forner, Roberto Navigli, and Dan Tufis, editors, CLEF 2013 Evaluation Labs and Workshop – Working Notes Papers, 23-26 September, Valencia, Spain, September.

Lui, M., Cook, P. (2013). Classifying English documents by national dialect. In Proceedings of the Australasian Language Technology Association Workshop, pages 5–15.

Magdy, W. K. Darwish, and I. Weber. #FailedRevolutions: Using Twitter to study the antecedents of ISIS support. First Monday, 21(2), 2016.

Maharjan, S., Shrestha, P., Solorio, T., Hasan, R. (2014). A straightforward author profiling approach in Mapreduce. In Advances in Artificial Intelligence. Iberamia, pages 95–107.

Maier, W., Gomez-Rodriguez, C. (2014). Language variety identification in Spanish tweets. LT4CloseLang 2014, page 25.

Malmasi, S., Dras, M. (2015). Automatic language identification for Persian and Dari texts. In Proceedings of PACLING, pages 59–64.

Malmasi, S., Dras, M. (2014). Arabic native language identification. In: Proceedings of the EMNLP 2014 Workshop on Arabic Natural Language Processing (ANLP), pp. 180–186, October 2014

Malmasi, S., Zampieri, M., Ljubescic, N., Nakov, P., Ali, A., Tiedemann, J. (2016). Discriminating between similar languages and Arabic dialect identification: a report on the third DSL shared task. VarDial 3, page 1.

Mehti, S., A. Abbassi, L. H. Belguith and R. Faiz, "An empirical method using features combination for Arabic native language identification," 2016 IEEE/ACS 13th International Conference of Computer Systems and Applications (AICCSA), Agadir, 2016, pp. 1-5.

Mukherjee, A., Liu, B., Glance, N. (2012). Spotting fake reviewer groups in consumer reviews. In Alain Mille, Fabien L. Gandon, Jacques Misselis, Michael Rabinovich, and Steffen Staab, editors, Proceedings of the 21st international conference on World Wide Web, pages 191–200. ACM.

Nakov, P., Osenova, P., Vertan, C. (2014). Proceedings of the EMNLP'2014 workshop on language technology for closely related languages and language variants. Association for computational linguistics, Doha, Qatar, October.

Ott, M., Choi, Y., Cardie, C., T. Hancock, J. (2011). Finding deceptive opinion spam by any stretch of the imagination. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 309–319. ACM.

Pennebaker, J.W., Chung, C.K., Ireland, M.E., Gonzales, A.L., Booth, R.J. (2007b). The development and psychometric properties of LIWC2007. In LIWC webpage. <http://www.liwc.net/LIWC2007LanguageManual.pdf>, pages 1–22. LIWC.net.

Randall M., Groom, N. (2009). The BUiD Arab learner corpus: a resource for studying the acquisition of L2 English spelling. In Proceedings of the corpus linguistics conference (CL).

Rangel, F., Rosso, P. (2015). On the multilingual and genre robustness of Emographs for author profiling in social media. In 6th international conference of CLEF on experimental IR meets multilinguality, multimodality, and interaction, pages 274–280. Springer-Verlag, LNCS (9283).

Rangel, F., Rosso, P. (2016). On the impact of emotions on author profiling. *Information processing & management*, 52(1):73–92.

Rangel, F., Rosso, P., Chugur, I., Potthast, M., Trenkmann, M., Stein, B., Verhoeven, B., Daelemans, W. (2014). Overview of the 2nd author profiling task at PAN 2014. In Cappellato L., Ferro N., Halvey M., Kraaij W. (Eds.) CLEF 2014 labs and workshops, notebook papers. CEURWS.org, vol. 1180.

Rangel, F., Rosso, P., Franco-Salvador, M. (2016a). A low dimensionality representation for language variety identification. In 17th International Conference on Intelligent Text Processing and Computational Linguistics, CILing. Springer-Verlag, LNCS.

Rangel, F., Rosso, P., Koppel, M., Stamatatos, E., Inches, G. (2013). Overview of the author profiling task at PAN 2013. In Forner P., Navigli R., Tufis D. (Eds.), CLEF 2013 labs and workshops, notebook papers. CEURWS.org, vol. 1179.

Rangel, F., Rosso, P., Potthast, M., Stein, B., Daelemans, W. (2015). Overview of the 3rd author profiling task at PAN 2015. In Cappellato L., Ferro N., Jones G., San Juan E. (Eds.) CLEF 2015 labs and workshops, notebook papers. CEUR Workshop Proceedings. CEURWS.org, vol. 1391.

Rangel, F., Rosso, P., Verhoeven, B., Daelemans, W., Potthast, M., Stein, B. (2016b). Overview of the 4th author profiling task at PAN 2016: cross-genre evaluations. In Working Notes Papers of the CLEF 2016 Evaluation Labs, CEUR Workshop Proceedings. CLEF and CEURWS.org, September.

Refaee, E. Rieser, V. (2014). An Arabic twitter corpus for subjectivity and sentiment analysis. In LREC, pages 2268–2273.

- Reyes, A., Rosso, P., Buscaldi, D. (2012). From humour recognition to irony detection: the figurative language of social media. *Data & Knowledge Engineering*, 74:1–12.
- Reyes, A., Rosso, P., Veale, T. (2013). A multidimensional approach for detecting irony in twitter. *Language Resources and Evaluation*, 47(1):239–268.
- Rosso P., Cagnina L. (2017). Deception Detection and Opinion Spam. In: *A Practical Guide to Sentiment Analysis, Socio-Affective Computing*, vol. 5, E.Cambria, D. Das, S. Bandyopadhyay, S. Feraco (Eds.), Springer-Verlag, pp. 155-171
- Russell, C., Miller, B.H. (1977). Profile of a terrorist. *Studies in Conflict & Terrorism*, 1(1):17–34. Saâdane Houda, Damien Nouvel, Hosni Seffih, Christian Fluhr. (2017). Une approche linguistique pour la détection des dialectes arabes. *Actes de TALN 2017*.
- Saadane Houda. (2015) *TRAITEMENT AUTOMATIQUE DE L'ARABE DIALECTALISE: ASPECTS METHODOLOGIQUES ET ALGORITHMIQUES*. Thèse de doctorat en Sciences du langage, Université Grenoble Alpes, 2015.
- Sadat, F., Kazemi, F., Farzindar, A. (2014). Automatic identification of Arabic language varieties and dialects in social media. *Proceedings of SocialNLP*, page 22.
- Sadhwani, P. (2005). Phonological and orthographic knowledge: An Arab-Emirati perspective.
- Schler, J., Koppel, M., Argamon, S., Pennebaker, J.W. (2006). Effects of age and gender on blogging. In *AAAI Spring Symposium: Computational Approaches to Analyzing Weblogs*, pages 199–205. AAAI.
- Shoufan, A., Al-Ameri, S. (2015). Natural language processing for dialectal Arabic: a survey. In *ANLP Workshop 2015*, page 36.
- Sigar, A., Taha, Z. (2012). A contrastive study of ironic expressions in English and Arabic. *College of Basic Education Researchers Journal*, 12(2):795– 817.
- Sulis, E., Hernandez Farias, D.I., Rosso, P., Patti, V., Ruffo, G. (2016). Figurative messages and affect in twitter: differences between #irony, #sarcasm and #not. *Knowledge-Based Systems*, 108:132 – 143.
- Tetreault, J., Blanchard, D., Cahill, A. (2013). A report on the first native language identification shared task. In *Proceedings of the 8th workshop on innovative use of NLP for building educational applications*, pages 48–57.
- Tillmann, C., Mansour, S., Al Onaizan, Y. (2014). Improved sentence-level Arabic dialect classification. In *Proceedings of the VarDial Workshop*, pages 110–119.
- Tono, Y. (2012). International corpus of crosslinguistic interlanguage: project overview and a case study on the acquisition of new verb co-occurrence patterns. *Developmental and crosslinguistic perspectives in learner corpus research*, pages 27–46.

Wahsheh, H.A., Al-kabi, M.N., Alsmadi, I.M. (2013a). A link and content hybrid approach for Arabic web spam detection. In *International Journal of Intelligent Systems and Applications (IJISA)*, pages 30–43.

Wahsheh, H.A., Al-Kabi, M.N., Alsmadi, I.M. (2013b). SPAR: A system to detect spam in Arabic opinions. In *2013 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT)*, pages 1–6, Dec.

Weren, E., Kauer, A., Mizusaki, L., Moreira, V., Oliveira, P., Wives, L. (2014). Examining multiple features for author profiling. In *Journal of Information and Data Management*, pages 266–279.

Zaghouani, W., Habash, N., Bouamor, H., Rozovskaya, A., Mohit, B., Heider, A., and Oflazer, K. (2015). Correction annotation for non-native Arabic texts: Guidelines and corpus. In *Proceedings of the Association for Computational Linguistics, Fourth Linguistic Annotation Workshop*, pages 129–139.

Zaghouani Wajdi, Behrang Mohit, Nizar Habash, Ossama Obeid, Nadi Tomeh, Alla Rozovskaya, Noura Farra, Sarah Alkuhlani, and Kemal Oflazer. 2014. Large Scale Arabic Error Annotation: Guidelines and Framework. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)*, Reykjavik, Iceland, May 2014.

Zaidan, O.F., Callison-Burch, C. (2011). The Arabic online commentary dataset: an annotated dataset of informal Arabic with high dialectal content. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: short papers -Volume 2*, pages 37–41. Association for Computational Linguistics.

Zaidan, O.F., Callison-Burch, C. 2014. Arabic dialect identification. *Computational Linguistics*, 40(1):171–202.

Zampieri, M., Gebre, B.G. (2012). Automatic identification of language varieties: the case of Portuguese. In *The 11th conference on natural language processing (KONVENS)*, pages 233–237. Österreichischen Gesellschaft für Artificial Intelligende (OGAI).

Zampieri, M., Tan, L., Ljubescic, N., Tiedemann, J. (2014). A report on the DSL shared task 2014. In *Proceedings of the First Workshop on Applying NLP Tools to Similar Languages, Varieties and Dialects*, pages 58–67.

Zampieri, M., Tan, L., Ljubescic, N., Tiedemann, J., Nakov, P. (2015). Overview of the DSL shared task 2015. In *Joint Workshop on Language Technology for Closely Related Languages, Varieties and Dialects*, page 1.

Zbib, R., Malchiodi, E., Devlin, J., Stallard, D., Matsoukas, S., Schwartz, R., Makhoul, J., Zaidan, O.F., Callison Burch, C. (2012). Machine translation of Arabic dialects. In *Proceedings of the 2012 conference of the north American chapter of the Association for Computational Linguistics: Human language technologies*, pages 49–59. Association for Computational Linguistics.