INGEOTEC at MEX-A3T: Author profiling and aggressiveness analysis in Twitter using μTC and EvoMSA

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Abstract. This paper describes our participation in the MEX-A3T challenge for Aggressiveness Detection and Author Profiling tasks for Mexican Spanish language. We used two approaches, μTC and EvoMSA systems. The first one is a minimalistic text categorization system, and the second one is a two-level architecture for Sentiment Analysis using information from different models on the current text analyzed to get a final prediction by a consensus view.

Keywords: emotion classification, text categorization, author profiling.

1 Introduction

Author profiling and aggressiveness detection are essential tasks for marketing, digital text forensics, cyber-bullying, security, among others. Aggressiveness detection allows us to identify offenses and misbehavior expressed in text and commonly shared in social networks. Author profiling is related to extract information from author's texts such as gender, age, and other kinds of personality traits. To increase the research in those areas, several international competitions have been organized to deal with them, such as PAN [14], SemEval [12], and TASS [11]. As part of this, recently, the MEX-A3T[5] [3] contest which is part of IBEREVAL'18[6] workshop has been launched on the research community. The purpose of MEX-A3T is deal with author profiling and aggressiveness detection in Spanish language focusing on Mexican Twitter users. MEX-A3T contest presents two tasks to classify Twitter text. The first one is aggressiveness detection task where systems have to determine whether a tweet is aggressive or not automatically. The second task is author profiling, where systems have to automatically determine the occupation and location (place of residence) of users from their tweets [3].

In the literature, several approaches have been proposed to tackle both author profiling and aggressiveness detection. Such is the case of [7] where a system based

[5] https://mexa3t.wixsite.com/home
[6] https://sites.google.com/view/ibereval-2018

on lexicon, fuzzy logic, and statistical approaches is proposed to detect aggressiveness in a text, or the proposed in [6] where a Lexical Syntactic Feature is used to detect offensive content and then be able to identify a potential offensive user in social media. Agrawal & Gonçalves [1] propose a combination of classifiers to identify gender associated with a set of texts. This propose includes TFIDF representation, and a dimension reduction of it, to finally employs Naive Bayes and Linear SVM as classifiers. In [4] several stylometric features are considered for identifying males from females in several age groups. Stylometric features are also used in [5] where tri-grams and complementary-weighted *Second Order Attributes* are employed.

In this work, we present the methodology proposed to deal with profiling and aggressiveness detection, which includes two approaches, μTC and EvoMSA systems. μTC is a minimalistic text categorization system, and EvoMSA is a two-level architecture for Sentiment Analysis using information from different models getting the final prediction by consensus. Both systems will be more detailed in following sections. The rest of the paper is organized as follows. Section 2 describes our system and the general approach to model the problem. Section 3 detail the experimental methodology and the achieved results. Finally, conclusions and future work are given in Section 4.

2 System Description

As commented, we use two systems to tackled the author profiling and the aggressiveness text detection tasks: μTC and EvoMSA, respectively. On the one hand, μTC is used mainly to evaluate author profiling task because in our experiments it obtained the best performance in this tasks. On the other hand, EvoMSA is used to evaluate aggressiveness task. In the following paragraphs, we describe these approaches.

2.1 EvoMSA

EvoMSA[7] has two stages. The first one, namely B4MSA [16], uses SVMs to predict their decision function values of a given text. On the second hand, EvoDAG [9, 10] is a classifier based on Genetic Programming with semantic operators which makes the final prediction through a combination of all the decision function values. Furthermore, EvoMSA is open to being fed with different models such as μTC, and lexicon-based models, and EvoDAG. It is an architecture of two phases to solve classification tasks, see Figure 1. In the first part, a set of different classifiers are trained with datasets provided by the contests and others as additional knowledge, i.e., whatever knowledge could be integrated into EvoMSA. In this case, we used tailor-made lexicons for the aggressiveness task: aggressiveness words and affective words (positive and negative), see Section 2.3. The precise configuration of our benchmarked system is described in Section 3.

2.2 μTC

μTC[8] (a.k.a. B4MSA) is a minimalistic system able to tackle general text classification tasks independently of domain and language. For complete details of the model see [17]. Roughly speaking, μTC creates text classifiers searching for the best models in given

[7] https://github.com/INGEOTEC/EvoMSA
[8] https://github.com/INGEOTEC/microTC

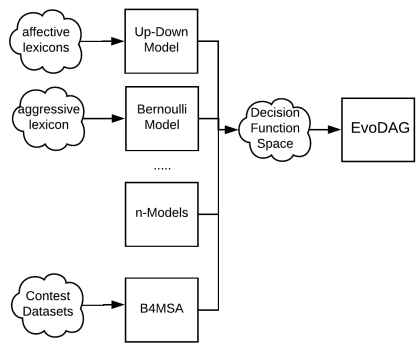

Fig. 1. Architecture of our EvoMSA framework

configuration space. A configuration consists of instructions to enable several preprocessing functions, a combination of tokenizers among the power set of several possible ones (character q-grams, n-word grams, and skip-grams), and a weighting scheme such as TF, TFIDF, or several distributional schemes. μTC uses an SVM classifier with a linear kernel. A text transformation feature could be binary (yes/no) or ternary (group/delete/none) option. Tokenizers denote how texts must be split after applying the process of each text transformation to texts. Tokenizers generate text chunks in a range of lengths, all tokens generated are part of the text representation. In Table 1, we can see details of text transformations used in our solution for detecting aggressiveness and profiling. For example, Tokenizers used for Profiling are unigrams, bigrams, trigrams of words, and q-grams of 1 and five characters length, and skip-grams of two words with a gap between them.

Table 1. Example of set of configurations for text modeling

Text transformation	Aggressiveness	Profiling
remove diacritics	yes	yes
remove duplicates	yes	yes
remove punctuation	yes	false
emoticons	group	none
lowercase	yes	true
numbers	group	group
urls	group	group
users	group	delete
hashtags	none	none
entities	none	none

Text transformation	Aggressiveness	Profiling
Term weighting		
TF-IDF	yes	no
Entropy	no	yes
Tokenizers		
n-words	{1,2}	{1,2,3}
q-grams	{2,3,4}	{1,5}
skip-grams	—	(2,1)

2.3 Lexicon-based models

To introduce extra knowledge into our approach for aggressiveness task, we used two lexicon-based models. The first, Up-Down model produces a counting of affective words, i.e., for a given text, it is produced in two indexes one for positive words, and another for negative words. We created a positive-negative lexicon based on the several Spanish affective lexicons [2, 15, 13] and enriched with Spanish WordNet [8]. The other Bernoulli

Table 2. Results for Aggressiveness Detection

System	macro-F1	macro-Recall	Accuracy	F1-aggressiveness
EvoMSA+LexB+UpDown	**0.7941**	**0.8044**	**0.8061**	**0.7446**
EvoMSA+UpDown	0.7926	0.8023	0.8048	0.7421
EvoMSA+LexB	0.7888	0.7982	0.8014	0.7373
EvoMSA	0.7830	0.7866	0.7992	0.7238
μTC	0.7900	0.7915	0.8070	0.7304

model was created to predict aggressiveness using a lexicon with aggressive words. We created this lexicon gathering common aggressive words for Mexicans. These indexes and prediction along with B4MSA's (μTC) outputs are the input for EvoDAG system.

2.4 EvoDAG

EvoDAG[9] [9, 10] is a Genetic Programming system specifically tailored to tackle classification problems on very high dimensional vector spaces and large datasets. EvoDAG uses the principles of Darwinian evolution to create models represented as a directed acyclic graph (DAG). Due to lack of space, we refer the reader to [9] where EvoDAG is broadly described. It is important to mention that EvoDAG does not have information regarding whether input X_i comes from a particular class decision function, consequently from EvoDAG point of view all inputs are equivalent.

3 Results

As mentioned, we split the dataset provided by organizers into 70-30 partition for training and test. We run several configurations of our systems. In Table 2 and Table 3 results are shown. In the case of the aggressiveness task, Table 2, we use the F1-aggressiveness score to measure the performance. The basic configuration of EvoMSA is one model based on B4MSA's predictions using the training set provided by the competition. In case of EvoMSA, plus symbol indicates the model added to the EvoMSA basic configuration.

In our experiments, the best performance we obtained is the combination of basic EvoMSA along with a Lexicon-based Bernoulli model (LexB), and a counting model of affective words (UpDown). This configuration was used to evaluate on the gold standard that our approach obtained 0.4883 in F1-aggressiveness class, see Table 4, INGEOTEC team.

In the case of author profiling task, the best performance was μTC system for Occupation classes. Thus, we decided to apply the same approach to Location classes. Table 3 shows the results of author profiling in our experiments. Our best system was used to evaluate on the gold standard that our approach obtained 0.4470 of F1-score for Occupation, 0.8155 of F1-score for Location and 0.6312 of F1-score on average of both, see Table 5, INGEOTEC team .

Tables 4 and 5 list the top-final rankings for *aggressiveness detection* task and *user profiling* task, respectively, more details of all results of the contest see [3]. Our INGEOTEC team reached the first place in aggressiveness detection and the third place in the author profiling task.

[9] https://github.com/mgraffg/EvoDAG

Table 3. Results for Author Profiling

System	macro-F1	macro-Recall	Accuracy
	Occupation		
μTC	**0.4369**	**0.4018**	**0.7006**
EvoMSA	0.2946	0.3013	0.5758
	Location		
μTC	0.8086	0.7841	0.8522

Table 4. Final scores of the aggressiveness detection task

Rank	Team	F1-score (aggressive class)	F1-score (non-aggressive class)	Accuracy
1	INGEOTEC	0.4883	0.7535	0.6673
2	CGP	0.4500	0.7612	0.667
3	GeoInt-b4msa	0.434	0.7842	0.6876
4	aragon-lopez	0.4312	0.8069	0.7117
5	Trigrams (baseline)	0.4304	0.786	0.6888

Table 5. Final scores of the Author profiling task

Rank	Team	F1-score (Occupation)	F1-score (Location)	Average
1	MXAA	0.5122	0.8301	0.6711
2	aragon-lopez	0.4910	0.8388	0.6649
3	INGEOTEC	0.4470	0.8155	0.6312
4	CIC-GIL-run2	0.4894	0.7363	0.6128
5	CIC-GIL-run1	0.4727	0.7310	0.6018

4 Conclusions

In this paper was presented our solution for the MEX-A3T challenge. For Aggressiveness Detection task, we applied EvoMSA system which can integrate different models as additional knowledge as we have shown. Also, we applied our generic text classifier, μTC, for author profiling task. Both systems are designed to be multilingual, language and domain independent as much as possible. For the training step, we use extra knowledge coded into affective and aggressiveness lexicons our robust solution (EvoMSA) performs well for the aggressiveness task; however, there is room for further improvements in performance for author profiling task using another sort of knowledge such as semantic information into our architecture.

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