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# Aggressive Language Identification in Social Media using Deep Learning

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## Abstract

1 The increasing influence from users in social media has made that Aggressive  
2 content propagates over the internet. In a way to control and tackle this problem,  
3 recent advances in Aggressive and offensive language detection have found out that  
4 Deep Learning techniques get good performance as well as the novel Bidirectional  
5 Encoder Representations from Transformer called BERT. This work presents an  
6 overview of Offensive language detection in English and the Aggressive content  
7 detection using this novel approach from Transformer for the case study of Mexican  
8 Spanish. Our preliminary results show that pre-trained multilingual model BERT  
9 also gets good performance compared with the recent approaches in Aggressive  
10 detection track at MEX-A3T.

## 11 1 Introduction

12 The exponential growth of social media such as Twitter and community forum has revolutionized  
13 the communication and content publishing, but it also increased explosively the propagation of the  
14 hate speech [1, 2, 3]. thus nowadays offensive language is pervasive in social media, this content  
15 which has profanity, abusive, aggressive or any kind of words that disparages person or a group is  
16 considered hate speech.

17 Social media platforms and technology companies have been investing heavily in ways to cope with  
18 this offensive language to prevent abusive behavior in social media [4] One of the first action for  
19 tackling this problem was the human control over those text content and due as a manual filtering  
20 is very time consuming and as it can cause post-traumatic stress disorder-like symptoms to human  
21 annotators, the most effective strategy is use computational methods to identify offense, aggression,  
22 and hate speech in user-generated content. This topic has attracted significant attention in recent  
23 years as evidenced in recent publications [5, 6, 7] and in order to improve the research efforts in  
24 Spanish Language, we propose to find out how deep learning in NLP techniques can contribute to  
25 improve to the identification of offensive and aggressive in Spanish.

## 26 2 Related work

27 the research of Offensive Language have been increasing in the last years [6, 8, 9]. the scientist have  
28 proposed various methods to get features, because on of the most interesting aspect to distinguish  
29 approaches is which features are used. Thus, one of the features most used with deep learning is  
30 the simple surface features such as *unigrams* and a larger *n-grams* [1, 10, 11] and find out that that  
31 character n-grams has better perform than tokens.

32 In contrast to features extractions, the classification methods for Offensive Language detection are  
33 predominantly supervised learning approaches [12]. The first scopes focus on manual features

34 engineering that are then consumed for a Machine learning algorithm such as SVM [2, 6, 11], Naive  
 35 Bayes [6], Logistic Regression [13, 4], On the other side, recent researches [10, 14, 8] works show  
 36 up that use deep learning paradigms which employs neural networks to automatically learn abstract  
 37 features representations has better performance. However, recently Word Embedding trained in neural  
 38 network have been show applied successfully [1, 7], while another approach appear this year using  
 39 Bidirectional Encoder Representation from Transformer called BERT [15], which give significant  
 40 improvements not only in this task if not in others. Although all of those techniques are applied to  
 41 the English language, recently IberEval and IberLEF for Iberian Languages Evaluation workshops  
 42 released the task with Aggressive identification task in 2017.<sup>1</sup> In order to develop this task, so far in  
 43 Spanish the main classifier used is SVM and recently approach in deep learning use CNN [16].

### 44 3 Preliminary Approach

45 In order to identify the Spanish Aggressive language in social media, we decided first re-implemented  
 46 the current work which achieved good performance in English Offensive Language as it shows in our  
 47 related work the Deep Learning classification methods CNN, SVM, BERT standing out. At first we  
 48 decided to apply those Deep Learning classification models in Mexican Spanish DataSet(MEX-A3T)  
 49 (see image 1), as we found that BERT classifier is highly effective in identifying offensive content  
 50 in English, then we implement multilingual BERT for Aggressive detection in Mexican Spanish.  
 51 Although the preliminary results show that *bert-base-multilingual-cased* has a good performance on  
 52 this Spanish task, there are still many things to accomplish and improve this model. We surprisingly  
 53 found that many words are not considered for instance: “hola” is not in the vocabulary, this is  
 54 because possibly the selection of vocabulary is data-driven, on the other hand, this method provides a  
 55 good balance between the characters and words delimited models and it is really good identifying  
 56 common words like: “si, no, contrario, excepto”, showing its effectiveness in understanding  
 57 the text context better than the previous pre-trained such as ELMo. Our preliminary accuracy is  
 58 shown in the table 1 below.

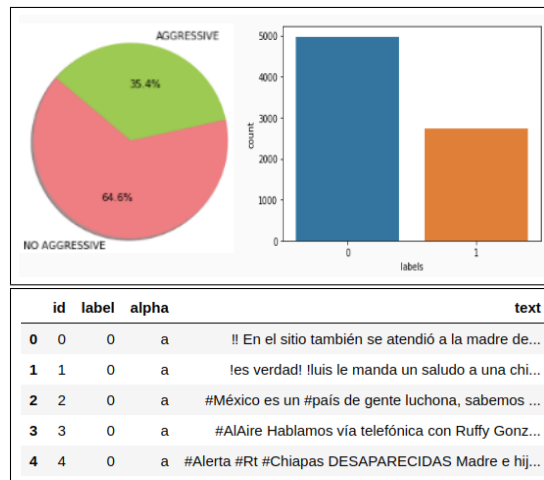


Figure 1: Left: MEX-A3T DataSet distribution 35.4% (green) AGGRESSIVE, 64.6 % NO AGGRESSIVE (pink) ,Right: Data labeled distribution. Below is the sample to feed in BERT

Table 1: Preliminary results for the aggressiveness identification

DATASET	Model	Accuracy
MEXT-A3T	SVM [17]	0.67
MEXT-A3T	DNN [18]	0.73
<b>MEXT-A3T</b>	<b>BERT</b>	<b>0.70</b>

<sup>1</sup>MEX-A3T: Authorship and aggressiveness analysis in Twitter case study in Mexican Spanish

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