
Overcoming Transformer Fine-Tuning process to improve Twitter Sentiment Analysis for Spanish Dialects

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Abstract

1 Is there an effective Spanish Sentiment Analysis algorithm? The aim of this paper
2 is to answer this question. The task is challenging because there are several dialects
3 for the Spanish Language. Thus, identically written words could have several
4 meanings and polarities regarding Spanish speaking countries. To tackle this
5 multidialect issue we rely on a transfer learning approach. To do so, we train
6 a BERT language model to “transfer” general features of the Spanish language.
7 Then, we fine-tune the language model to specific dialects. BERT is also used
8 to generate contextual data augmentation aimed to prevent overfitting. Finally,
9 we build the polarity classifier and propose a fine-tuning step using groups of
10 layers. Our design choices allow us to achieve state-of-the-art results regarding
11 multidialect benchmark datasets.

12 1 Introduction

13 Deriving an effective algorithm for Spanish Twitter sentiment analysis has been long pursued from
14 the research community in this language [3]. Nowadays, despite recent advances in algorithms (Deep
15 Learning [7]) and word embeddings [1]), the basic polarity detection task has not been completely
16 solved. Thus, whereas it is usually claimed that a transfer learning approach can smoothly solve any
17 classification tasks in NLP [4]; this is not usually the case when we applied it to Spanish. Moreover,
18 the task becomes harder when several language dialects are considered. In fact, low F1-macro values
19 were obtained on previous multi dialect benchmarks [5, 3].

20 2 Methodology

21 We propose a system to perform polarity classification in small datasets based on the high performance
22 Language Model (LM) called BERT [2]. In addition, by using a clever variation of this LM, we are
23 able to produce contextual data augmentation [6]. Finally, we build the polarity classifier and propose
24 a fine-tune process using groups of layers.

25 To build the classifier, we take the original pre-trained LM and fine-tune this using the target dataset
26 and using again the MLM task in order to enhance the semantic relationship to be extracted later
27 from this. Next, we put a single classification layer on top of the previous fine-tuned LM. Then, we
28 propose fine-tune this classifier using a novel grouped fine-tuning process that consists in freezing a
29 whole architecture and defrost not layer by layer but groups of layers at once and retrain the whole
30 model at each step on the target dataset. Moreover, with the aim of preventing overfitting, we use the
31 new enhanced dataset created before using the aforementioned data augmentation process. A general
32 view of our system is depicted in Figure 1.

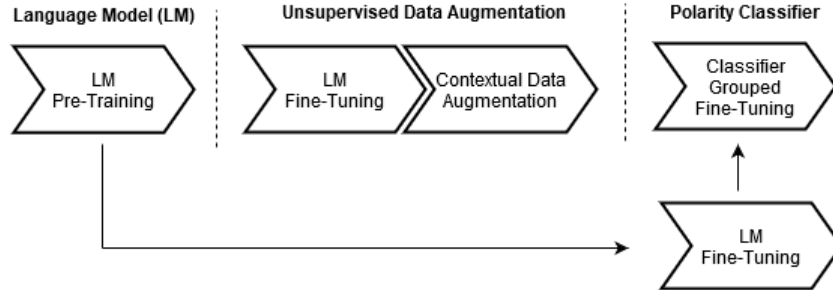


Figure 1: Overview of system pipeline. General pre-trained LM is used to build unsupervised data augmentation and a robust classifier system using two LM fine-tuning processes in the way. The final classifier is built using the previous steps and grouped fine-tuning technique.

3 Results

Our proposal was ranked 1st in all variants of Spanish presented in TASS 2019 competition among all submissions (F1-macro score) and boost the state-of-the-art in 4-labeled sentiment analysis in these dialects of Spanish adding a difference of even up to 4.6 percent with respect to the second place. A detailed report of results for **TASS 2019 Task 1 - Monovariant** is presented in Table 1.

Country	Team	F1-macro
CR	Our proposal	0.5529
	RETUYT-InCo	0.5120
	ELiRF-UPV	0.4960
ES	Our proposal	0.5409
	ELiRF-UPV	0.5070
	Atalaya	0.4840
MX	Our proposal	0.5143
	ELiRF-UPV	0.5010
	GTH-ETSIT-UPM	0.4870
PE	Our proposal	0.4862
	Atalaya	0.4540
	ELiRF-UPV	0.4470
UY	Our proposal	0.5609
	ELiRF-UPV	0.5150
	Atalaya	0.4990

Table 1: Top 3 results on TASS 2019.

Furthermore, in order to get a better understanding of these outstanding results, we perform ablation experiments removing every step of our pipeline at once and testing the performance of the remaining system. The outputs of these experiments are shown in Table 2 where we can observe the real impact of every step of our proposal. According to this, even when every fine-tuning process helps to increase the performance in similar way, it is our proposal of fine-tuning the classifier using unfreezing in groups of layer what was more relevant.

	CR	ES	MX	PE	UY
Our proposal					
All steps	0.5529	0.5409	0.5143	0.4862	0.5609
wo/ Unsupervised Data Augmentation	0.5293	0.5240	0.5166	0.4741	0.5333
wo/ Classifier: LM fine-tuning	0.5286	0.5371	0.4986	0.4741	0.5273
wo/ Classifier: grouped fine-tuning	0.5252	0.4523	0.4967	0.4329	0.5210

Table 2: Comparative analysis according to F1-macro metric on TASS 2019 Task 1 - Monovariant test dataset (F1-macro Score) removing one step at once. "wo/" denotes "without".

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