
Advanced Transfer Learning Approach for Improving Sentiment Analysis on Different Dialects of Spanish

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Abstract

1 In the last years, innovative techniques like Transfer Learning have impacted
2 strongly in Natural Language Processing, increasing massively the state-of-the-
3 art in several challenging tasks. In particular, the Universal Language Model
4 Fine-Tuning (ULMFiT) and the Bidirectional Encoder Representations from Trans-
5 formers (BERT) algorithms have proven to have an impressive performance on
6 several English text classification tasks. In this paper, we aim at developing an
7 algorithm for Spanish Sentiment Analysis of short texts that is comparable to the
8 state-of-the-art. In order to do so, we have adapted the ULMFiT and BERT algo-
9 rithms to this setting. Experimental results on benchmark datasets (InterTASS 2017
10 and InterTASS 2018) show how this simple transfer learning approach performs
11 well when compared to fancy deep learning techniques.

12 1 Introduction

13 Spanish is the third language most used on the Internet¹. However, the development of Natural
14 Language Processing (NLP) techniques for this language did not follow the same trend. In particular,
15 this research gap can be observed in Spanish *sentiment analysis*. In this context, the main issue that
16 we aim to address is how to build a polarity detection system that can be interchangeably used across
17 several dialects of Spanish. It is challenging to have the same performance when classifying texts
18 written in Spanish from different dialects such as Peru, Argentina and so on. While there are a lot of
19 similarities among dialects, there are also several ways to express positive or negative sentiments.

20 2 Related Work

21 Since 2015, there have been several Deep Learning architectures used for Spanish Twitter Sentiment
22 Analysis, ranging from Multilayer Perceptron [4], Recurrent Neural Networks [2] and Convolutional
23 Neural Networks [9] and several combinations of them. We refer to [7] in order to get an in-depth
24 review of several deep Learning approaches for the Spanish language before 2018. Our proposal is
25 also based on deep learning but, unlike previous approaches, it plans to use a general language model
26 to improve the polarity detection task on different dialects of Spanish. This setup is novel for the
27 Spanish language.

¹<http://www.internetworldstats.com/stats7.htm>

28 3 Methodology

29 Our proposal is inspired by the success of transfer learning approaches in several text classification
30 tasks for the English language. In particular, we resort to ULMFit [3] and BERT [1] language models.
31 In this sense, it has been obtained interesting preliminary results using a modified ULMFit setup for
32 the Spanish language in [8] as described as follows:

- 33 (a) The language model (LM) is trained on a general domain corpus to capture general features
34 of the language in different layers. To do so, we have learned a LM for the Spanish language
35 using Wikipedia data.
- 36 (b) The full LM is fine-tuned on target task data using discriminative fine-tuning (Discr) and
37 slanted triangular learning rates (STLR) to learn task-specific features. In our case, the target
38 task is Spanish sentiment analysis from Tweets thus, fine-tuning of the LM is performed
39 using unlabeled Spanish Tweets.
- 40 (c) The classifier is fine-tuned on the target task using gradual unfreezing, Discr, and STLR to
41 preserve low-level representations and adapt high-level ones (shaded: unfreezing stages;
42 black: frozen). In our context, the sentiment analysis classifier is fine-tuned using labeled
43 Spanish tweets.

44 Currently, we are working for including attention mechanism, introduced in BERT, for improving the
45 pipeline presented above.

46 4 Experiments

47 A complete description about the hardware and software requirements for reproducing this paper are
48 described in the public repository of the project. In addition, we show some preliminary results.

49 4.1 Benchmark Datasets

50 In order to train our algorithms we are using benchmark datasets provided by the TASS competition
51 at SEPLN workshops [5, 6]. Those datasets comprise several collections of Spanish Tweets including
52 different dialects. In addition, those datasets will allow us to compare our approach against recent
53 Deep Learning approaches for Spanish sentiment analysis.

54 4.2 Preliminary Results

55 The results for InterTASS (Task1) Competition 2017 [6] were better than expected as shown in Table
56 1a, achieving the second best result, according to M-F1 metric (the ELiRF-UPV team reached a M-F1
57 score of 0.493).

58 Furthermore, results on InterTASS-PE (Task1 / Sub-task 2) Competition 2018 [5] are shown in Table
59 1b. While they weren't the best, they are within the best eight results of the competition.

Table 1: Results over InterTASS Test datasets.

(a) InterTASS 2017.			(b) InterTASS-PE 2018.		
Team	M-F1	Acc.	Team	M-F1	Acc.
ELiRF-UPV-run1	0.493	0.607	retuyt-cnn-pe-1	0.472	0.494
Our proposal	0.481	0.567	atalaya-pe-lr-50-2	0.462	0.451
RETUYT-svm_cnn	0.471	0.596	retuyt-lstm-pe-2	0.443	0.488
ELiRF-UPV-run3	0.466	0.597	retuyt-svm-pe-2	0.441	0.471
ITAINNOVA-model4	0.461	0.476	ingeotec-run1	0.439	0.447
jacerong-run-2	0.460	0.602	elirf-intertass-pe-run-2	0.438	0.461
jacerong-run-1	0.459	0.608	atalaya-mlp-sentiment	0.437	0.520
INGEOTEC-evodag001	0.457	0.507	retuyt-svm-pe-1	0.437	0.474
RETUYT-svm	0.457	0.583	Our proposal	0.436	0.463
tecnolengua-sentonly	0.456	0.582	elirf-intertass-pe-run-1	0.435	0.440

60 **References**

- 61 [1] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018.
- 62
- 63 [2] M. Garcia-Vega, A. Montejo-Raez, M. C. Diaz-Galiano, and S. M. Jimenez-Zafra. Sinai in tass 2017: Tweet
64 polarity classification integrating user information. In *Proceedings of TASS 2017: Workshop on Sentiment
65 Analysis at SEPLN*, pages 91–96, 2017.
- 66 [3] Jeremy Howard and Sebastian Ruder. Universal language model fine-tuning for text classification. In
67 *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long
68 Papers)*, pages 328–339, Melbourne, Australia, July 2018. Association for Computational Linguistics.
- 69 [4] Lluís-F Hurtado, Ferran Pla, and Jose-Angel Gonzalez. Elirf-upv at tass 2017: Sentiment analysis in twitter
70 based on deep learning. In *Proceedings of TASS 2017: Workshop on Sentiment Analysis at SEPLN*, pages
71 29–34, 2017.
- 72 [5] Eugenio Martínez-Camara, Yudián Almeida-Cruz, Manuel Díaz-Galiano, Suilan Estévez-Velarde, M. Ángel
73 García-Cumbreras, Manuel García Vega, Yoan Gutiérrez, Arturo Montejo-Ráez, Andrés Montoyo,
74 Rafael Muñoz, Alejandro Piad-Morffis, and Julio Villena-Roman. Overview of tass 2018: Opinions, health
75 and emotions. In *Proceedings of TASS 2018: Workshop on Sentiment Analysis at SEPLN*, pages 13–27,
76 2018.
- 77 [6] Eugenio Martínez-Camara, Manuel Díaz-Galiano, M. Ángel García-Cumbreras, Manuel García-Vega, and
78 Julio Villena-Roman. Overview of tass 2017. In *Proceedings of TASS 2017: Workshop on Sentiment
79 Analysis at SEPLN*, pages 13–21, 2017.
- 80 [7] José Ochoa-Luna and Disraeli Ari. Deep neural network approaches for spanish sentiment analysis
81 of short texts. In Guillermo R. Simari, Eduardo Fermé, Flabio Gutiérrez Segura, and José Antonio
82 Rodríguez Melquiades, editors, *Advances in Artificial Intelligence - IBERAMIA 2018*, pages 430–441,
83 Cham, 2018. Springer International Publishing.
- 84 [8] Daniel Palomino and José Ochoa-Luna. Advanced transfer learning approach for improving spanish
85 sentiment analysis. In *To appear: 18TH MEXICAN INTERNATIONAL CONFERENCE ON ARTIFICIAL
86 INTELLIGENCE (MICAI 2019)*, 2019.
- 87 [9] Isabel Segura-Bedmar, Antonio Quiros, and Paloma Martínez. Exploring convolutional neural networks for
88 sentiment analysis of spanish tweets. In *Proceedings of the 15th Conference of the European Chapter of
89 the Association for Computational Linguistics: Volume 1, Long Papers*, pages 1014–1022. Association for
90 Computational Linguistics, 2017.