Procesamiento del Lenguaje Natural, Revista nº 61, septiembre de 2018, pp. 117-124 recibido 04-04-2018 revisado 30-04-2018 aceptado 04-05-2018

Lexicon Adaptation for Spanish Emotion Mining

Adaptación de lexicones para la minería de emociones en Español

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Abstract: Emotion mining is an emerging task that is still at a first stage of research. Most of the existing works and resources focus on English, but there are other languages, such as Spanish, whose presence on the Internet is greater every day. In WASSA-2017 Shared Task on Emotion Intensity, it was found that the best systems included features from affect lexicons. This fact combined with the scarcity of resources in Spanish, led us to build a new Spanish lexicon that has been tested over the dataset released at SemEval 2018 Task 1. Moreover, it has been compared with the unique emotion intensity lexicon existing in Spanish, SEL lexicon, and it has shown the difficulty of the task and the importance of continuing working on the development of resources.
Keywords: emotion mining, emotion intensity, lexicon, iSAL, SEL

Resumen: La minería de emociones es una tarea emergente que todavía se encuentra en una primera etapa de investigación. La mayoría de los trabajos y recursos existentes se han realizado para textos en inglés, pero la presencia en Internet de otras lenguas, como el español, es cada vez mayor. En la tarea *Shared Task on Emotion Intensity* de la competición WASSA-2017 se llegó a la conclusión de que los sistemas que mejor realizaban la clasificación de intensidad de las emociones eran aquellos que incluían características de lexicones afectivos. Este hecho, combinado con la escasez de recursos en español, nos llevó a construir un nuevo lexicón para el español que ha sido probado sobre el conjunto de datos liberado en la tarea 1 de la competición SemEval 2018. Además, se ha comparado con el único lexicón de intensidades existente en español, el lexicón SEL, y se ha demostrado la dificultad de la tarea y la importancia de continuar trabajando en el desarrollo de recursos.
Palabras clave: minería de emociones, intensidad de la emoción, lexicón, iSAL, SEL

1 *Introduction*

Sentiment Analysis (SA) is an area of Natural Language Processing (NLP) that is focused on identifying, extracting, quantifying, and studying affective states and subjective information (Liu, 2015). SA includes the study of different tasks, from the simpler opinion detection to the more complex emotion mining (Cambria, 2016).

Although SA is a relative new discipline, an extensive number of research has been focused on some basic tasks in SA, such as polarity classification or subjectivity detection, even treating complex problems related to different languages or domains (Molina-González et al., 2015; Jiménez-Zafra et al., 2016; Montejo-Ráez et al., 2014). However, emotion mining in textual documents that studies emotional states such as “angry”, “sad”, and “happy”, is still in a first stage of research and it has a long way to proceed (Yadollahi, Shahraki, and Zaiane, 2017).

Some works are starting to explore the potential of emotion detection and emotion classification systems (Mohammad, 2017) but, as usual, most of the studies are oriented to treat English documents. However, it is necessary to adapt the systems in order

ISSN 1135-5948. DOI 10.26342/2018-61-13

to develop real emotion mining applications for a specific language. In this paper, we focus on the emotion mining task and specifically for Spanish documents. Unfortunately, one of the main problems to be resolved is the generation and integration of specific resources.

In the case of English there are some interesting resources that can be integrated into real systems such as WordNet-Affect (WNA) (Strapparava and Valitutti, 2004), Linguistic Inquiry and Word Count (LIWC) (Pennebaker, Booth, and Francis, 2007) or NRC word-emotion association lexicon (Mohammad and Turney, 2010). All these lexicons can be applied to develop English emotion recognition systems. However, when we move to other languages different from English, the first problem to be resolved is the lack of resources. Thus, in this paper, we focus on adapting the NRC English resource for emotion recognition in order to be used for Spanish emotion systems. We have applied several strategies combining automatic machine translation and manual revision in order to increase the recall and the precision.

In order to test the effectiveness of the resources generated, we have conducted several experiments over the Semeval 2018 corpora (Mohammad et al., 2018). Specifically we have focused on the EI-oc emotion intensity ordinal classification task.

The rest of the paper is organized as follows: Section 2 describes some related studies; dataset and lexicon adaptation for Spanish are presented in Section 3; Section 4 shows the results and discussion, and finally, our conclusions are presented in Section 5.

2 Background

In the last decade, most of the work has focused on SA whose most important task is polarity classification. Pang and Lee (2008) give an excellent summary. However, one of the most complex areas that has not yet been studied in depth is Emotion Mining.

Emotion mining has been studied from many disciplines such as neuroscience, cognitive sciences, and psychology. However, only recently this area has attracted the attention in computer science perhaps due to the multiple and interesting applications (Yadollahi, Shahraki, and Zaiane, 2017). Gupta, Gilbert, and Fabbrizio (2013) describe a method that uses salient features to identify emotional emails in the customer care domain. In this way they improve contact center efficiency and the quality of the overall customer care experience. In Human Computer Interaction, the systems can monitor user's emotions to suggest suitable music or movies (Voeffray, 2011). In the field of psychology there are several works of great application. De Choudhury et al. (2013) detect if a patient is facing depression, stress or even is thinking about committing suicide. This fact is quite useful since the user can be referred to counseling services (Luyckx et al., 2012). Moreover, this area is becoming very popular, and some of the main conferences dealing with data mining and evaluation are currently including workshops and share tasks related to it. These include Semantic Evaluation (SemEval), Computational Approaches to Subjectivity and Sentiment Analysis (WASSA) and workshops on Computational Modeling of People's opinions, personality and emotions in Social Media (PEOPLE).

Emotion recognition is part of the broader area of Emotion Mining with aims to enable computers recognize and express emotions (Picard and others, 1995). Emotion mining techniques can be classified into two categories: lexicon based approaches and machine learning approaches (Cambria, 2016). The first one is based on lexical resources such as lexicons, bags of words or ontologies. Kim, Valitutti, and Calvo (2010) follow lexical-based approaches to evaluate the merit of the discrete emotion theory and the dimensional model using the WNA lexicon. The second one applies algorithms based on linguistic features. Luyckx et al. (2012) focus on a dataset of notes written by people who have committed suicide. The objective is to predict label(s) of a note among 15 possible emotions. First, they split all multi-labeled notes to single-labeled fragments manually. Then a Support Vector Machine (SVM) with Radial Basis Function is trained on these single-labeled data.

Almost all the emotion mining works focus on using and integrating different resources such as lexicons and corpora. Specifically, affect lexicons are very valuable because they provide prior information about the type and strength of emotion carried by each word of the text. Actually, in WASSA-2017 Shared Task on Emotion Intensity it was demonstrated that using features from affect lexicons is beneficial for emotion mining tasks (Mohammad and Bravo-Marquez, 2017).

However, the availability of resources in textual emotion mining is scarce and most of them are for English language. For example, WordNet-Affect (WNA) (Strapparava and Valitutti, 2004) is an emotional lexical resource based on the synsets of WordNet (Fellbaum, 1998) that has been applied in several studies. WNA contains a set of affective concepts correlated with affective words in English and one of its main problem is the low recall. Linguistic Inquiry and Word Count (LIWC) is another lexical resource that divides the words into different categories including emotional states (Pennebaker, Booth, and Francis, 2007). Finally, NRC word-emotion association lexicon (Mohammad and Turney, 2010) is a resource generated using a crowdsourcing annotation by Amazon's Mechanical Turk and provides real-valued affect intensity scores for four basic emotions (*anger*, *fear*, *sadness*, *joy*). This is one of the most popular emotion lexicons because it has been integrated in different systems combined with other resources or supporting machine learning approaches.

Regarding the availability of emotional resources in other languages different from English, we find that the number is very limited. Specifically, for Spanish we can metion the Spanish Emotional Lexicon (SEL) (Sidorov et al., 2012) although the obtained results in different experiments are not very promising.

In this work, we focus our attention on the relatively small amount of work in the generation of lexicons and on computational analysis of the emotional content of texts. We have adapted the NRC Affect intensity lexicon to Spanish, obtaining different versions that have been evaluated over the dataset released at SemEval 2018 Task 1: Affect in Tweets (Mohammad et al., 2018).

3 Resources

3.1 Dataset

To run our experiments, we used the Spanish dataset provided by the organizers in SemEval 2018 Task 1: Affect in Tweets (Mohammad et al., 2018). The dataset EI-oc is composed by a set of tweets that belong to an emotion E (*anger*, *fear*, *joy*, and *sadness*). Thus, separate datasets are provided for *anger*, *fear*, *joy*, and *sadness* emotions. The complete dataset is composed by 1,986 tweets for *anger*, 1,986 tweets for *fear*, 1,990 tweets for *joy* and 1,991 tweets for *sadness*. We trained our models on the train and dev sets, and tested the model on the test set. Table 1 shows the number of tweets for Spanish language used in our experiments.

Dataset	train+dev	test	Total
anger	1,359	627	1,986
fear	1,368	618	1,986
joy	1,260	730	1,990
sadness	1,350	641	1,991
EI-oc	5,337	2,616	7,593

Table 1: Number of tweets per dataset

3.2 Lexicon generation

In a first instance we generated a parallel list of affect terms in Spanish from the affect lexicon in English (NRC Affect Intensity Lexicon) provided by Mohammad (2017). NRC is composed of 5,814 words (1,483 *anger* words, 1,765 *fear* words, 1,268 *joy* words and 1,248 *sadness* words). Each of them has an intensity score associated to one of the following basic emotions: *anger*, *fear*, *joy* and *sadness* and does not belong to any domain. The score ranges from 0 to 1, where 1 indicates that the word has a high association to the emotion and 0 that the word has a low association to the emotion. Our parallel list was generated by applying automatic machine translation techniques. Google translator was used for the automatic translation, taking into account the first translated word that this system returned for each original word from NRC. According to Google Translator, this first translated word is the most frequently used regardless of grammatical category. The new resource is called SAL (Spanish Affect Lexicon). Following, each translated word was written by using non capital letters. Thus, SAL is composed of 5,814 affect translations, with the same proportion of affect terms that the NRC list. During this process, we have found some issues that must be resolved. These issues are the following:

(i) 1,267 repeated Spanish terms

(ii) 110 English words untranslated

(iii) 45 English expression untranslated

(iv) 326 n-grams terms

The solution of each problem led us to the generation of new versions of the SAL list.

Below, we describe the improved SAL versions (iSAL) that we have generated automatically:

- **iSALv1a**: The first automatic version solves the issue related to the repetition of terms in general. We noticed that some English words shared the same first translation. For this reason, we decided to discard all of them from the SAL list in our first approach. The resulting list was called iSALv1a (improved SAL version 1 automatic) and it is composed of 2,338 unique affective Spanish terms with only one emotion associated.

- **iSALv2a**: The second automatic version improves the issue related to the repetition of terms. In this case, we considered that the repeated terms with intensity score associated in different emotions must be included. Thus, the new list is the sum of iSALv1a and 2,053 Spanish terms. In total, iSALv2a is composed of 4,391 Spanish terms. Table 2 shows some English words that shared the same first translation in different emotions.

English word	Spanish meaning	Emotion
abandonment	abandonando	anger, fear, sadness
hellish	infernal	anger, fear, sadness
unbeaten	invicto	sadness, joy
youth	juventud	anger, fear,joy
treat	tratar	anger, fear, joy, sadness

Table 2: Some English words that shared the same first translation in different emotions

- **iSALv3a**: The third automatic version improves the issue related to the repetition of terms too. In this case, we considered that the repeated terms with different intensity scores associated to the same emotion must be taken into account. The adopted solution was to compute the average of the intensities of each equal term in the same emotion and to include an unique term associated to that emotion with the average intensity. Thus, the new list is the sum of iSALv2a and 764 Spanish terms. In total, iSALv3a is composed of 5,155 Spanish terms. Table 3 shows some English words that shared the same first translation in the same emotion.

English words	Spanish meaning	Emotion
murderer, murderous, assassin, slayer, cut-throat	asesino	anger, fear
harass, harry, harassing	acosar	anger
cheerfull, jolly, joyful, glad, merry, cheery, rollicking	alegre	joy
dilapidated, bankrupt, blighted, ruined	arruinado	sadness
executioner, hangman	verdugo	fear

Table 3: Some English words that shared the same first translation in the same emotion

After resolving the issues related to the repeated terms in SAL, the next step in the process of the generation of an affect resource in Spanish was to solve manually the problems (ii), (iii) and (iv). We found many misspelled words or expressions in the NRC list, which should not be considered mistakes and could be improved manually. Therefore the new generated lexicons improved the previous versions.

These are the versions of improved SAL (iSAL) that were manually generated:

- **iSALv1m**: In the 2,338 terms of iSALv1a we found 110 English words and 45 expressions untranslated. It is important to note that all words did not have a properly assignment and therefore, they have been removed from the original list iSALv1a to generate the iSALv1m list. Then, from the 110 English words, only 33 had a manual assignment according to the Spanish language. From the 45 expressions, only 40 had a manual assignment according to the Spanish language. Tables 4 and 5 show some examples of this kind of words.

Finally, the last issue was related to the fact that the translation of an English word returned two or more words (n-grams). For these cases we assigned manually the best synonym (composed of only one term) for the translated word. In the iSALv1a list we found 266 n-grams but only 237 had a synonym composed of one term. Table 6 shows some examples of some manually reviewed translations. Thus, the new list iSALv1m is composed of 2,227 Spanish terms.

English word without translation	Spanish meaning
cantbreathe	asfixia
wracking	exprimiendo
sux	chupar
stoopid	estupido
grump	gruñón

Table 4: Some English words without translation

English expression	Spanish meaning
xoxo	bss
hee	eh
woohoo	viva
meh	bah
hohoho	jojojo

Table 5: Some English expressions without translation

English word	n-gram Spanish meaning	Spanish term
fuming	echando humo	encolerizar
makememad	me enfurece	enloquecerme
uphill	cuesta arriba	agotador
astray	por mal camino	descarriado

Table 6: Some Spanish n-grams found in iSALv1a

- **iSALv2m**: The second manually version improves the issue related to the n-grams. We found 45 n-grams in the 2,053 Spanish terms that were repeated in different emotions, but only 39 of them have been modified by only one synonym term. Table 7 shows some examples of this kind of words. Finally, iSALv2m are composed of iSALv1m and the 2,031 terms improved manually, in total 4,258 words.

English words	n-gram Spanish meaning	Spanish term
forcibly	a la fuerza	forzosamente
misconception	idea equivocada	malentendido
wince	contraerse de dolor	estremecerse
disreputable	de mala fama	desacreditado
landslide	deslizamiento de tierra	derrumbre

Table 7: Some Spanish n-grams found in iSALv2a

- **iSALv3m**: The third manually version improves the issue related to the n-grams, as well. We found 15 n-grams in the 764 Spanish terms that were repeated in the same emotion. Some of these n-grams have been modified by only one synonym term. Finally, iSALv3m is composed of iSALv2m and the 754 terms improved manually, in total 5,012 words.

4 Experiments and result analysis

In this section we describe the systems developed to test the different versions of iSAL lexicon in the SemEval's EI-oc task (Mohammad et al., 2018). Moreover, we analyze the results obtained.

4.1 Experiments

EI-oc is an emotion intensity ordinal classification task. Given a tweet and an emotion E, it consists of classifying the tweet into one of four ordinal classes of intensity of E that best represents the mental state of the tweeter. Separate datasets are provided for *anger*, *fear*, *joy*, and *sadness* emotions.

First, we preprocessed the corpus of tweets. We applied the following preprocessing steps: the documents were tokenized using NLTK TweetTokenizer[1], stemming was performed using NLTK Snowball stemmer[2] and all letters were converted to lower-case.

To solve this task we have used the following methodologies:

- **Heuristic 1 (H1)**. To perform the classification, we checked the presence of lexicon terms in the tweet and then we added the intensity value of these words grouping them by the emotional category (*anger*, *fear*, *sadness* and *joy*). The result is a vector of four values for each lexicon. Moreover, each tweet is represented as a vector of unigrams using the TF-IDF weighting scheme. The union of the lexicon vectors and the TF-IDF representation of the tweet are used as features for the classification using the SVM algorithm. We selected the SVM formulation, known as C-SVC, the value of the C parameter was 1.0 and the kernel chosen was linear.
- **Heuristic 2 (H2)**. In this case, we checked the presence of lexicon terms in the tweet and then we computed the sum, the average and the maximum of the intensity value of the words of the tweet grouping them by the emotional category (*anger*, *fear*, *sadness* and *joy*). The result is a vector of twelve values for each lexicon. The union of the lexicon vectors and the TF-IDF representation of the tweet are used as features for the classification using the SVM algorithm with the same configuration as that used in the first methodology.

For each version of iSAL we applied the two methodologies described above. The official competition metric to evaluate the systems in EI-oc subtask is the Pearson Correlation Coefficient (PCC) between semantic similarity scores of machine assigned and human judgments. The results of our experiments are shown in Tables 8, 9, 10, 11, 12 and 13.

On the other hand, we have also performed the experiments with the unique emotion intensity lexicon existing in Spanish, the SEL lexicon, to compare the results. The results are shown in Table 14.

	H1	H2
anger	0.395	0.403
fear	0.54	0.524
sadness	0.500	0.493
joy	0.513	0.514
macro-avg	0.487	0.483

Table 8: Results of experiments using iSALv1a

	H1	H2
anger	0.403	0.399
fear	0.542	0.546
sadness	0.507	0.506
joy	0.516	0.517
macro-avg	0.492	0.492

Table 9: Results of experiments using iSALv1m

	H1	H2
anger	0.418	0.409
fear	0.528	0.534
sadness	0.504	0.492
joy	0.492	0.49
macro-avg	0.486	0.481

Table 10: Results of experiments using iSALv2a

	H1	H2
anger	0.418	0.405
fear	0.524	0.522
sadness	0.514	0.500
joy	0.514	0.510
macro-avg	0.493	0.484

Table 11: Results of experiments using iSALv2m

	H1	H2
anger	0.404	0.398
fear	0.519	0.520
sadness	0.499	0.499
joy	0.517	0.515
macro-avg	0.485	0.483

Table 12: Results of experiments using iSALv3a

4.2 Result analysis

If we take a look at the results it can be seen that the manual versions of the lexicons work better than the automatic ones. Specifically,

[1] http://www.nltk.org/api/nltk.tokenize.html

[2] http://www.nltk.org/_modules/nltk/stem/snowball.html

	H1	H2
anger	0.401	0.391
fear	0.521	0.519
sadness	0.496	0.500
joy	0.529	0.537
macro-avg	0.487	0.487

Table 13: Results of experiments using iSALv3m

	H1	H2
anger	0.402	0.395
fear	0.545	0.540
sadness	0.478	0.495
joy	0.489	0.502
macro-avg	0.479	0.483

Table 14: Results of experiments using SEL

iSALv2m is the best lexicon. There are expressions that are specific for each language and even they are used with different purposes and intensities, making the manual versions work better.

Focusing on the emotions, the lowest correlation has been obtained on *anger* emotion and the best correlation on *fear* emotion. On the contrary, in WASSA-2017 Shared Task on Emotion Intensity (Mohammad and Bravo-Marquez, 2017), most of the systems performed better on *anger* emotion and worse on *fear* and *sadness* emotions. In this competition, it was found that the best systems included features from affect lexicons. This fact combined with the scarcity of resources in Spanish encourage us to build a new Spanish lexicon.

In order to compare our results, we have accomplished experiments over the emotion intensity lexicon existing for Spanish, SEL (Sidorov et al., 2012). It can be seen that most of the results obtained with the proposed lexicons are better than those of the SEL lexicon, but they are only slightly better. This shows the difficulty of the task and the importance of continuing working on the development of resources for languages other than English. In addition, we have evaluated our results with the obtained in the SemEval's EI-oc task[3]. If we participated, we would be in sixth position in the ranking as can be seen in the summary Table 15.

[3] https://bit.ly/2Gj8Anm

(r) Team name	Pearson				
	macro-avg	anger	fear	joy	sadness
(1) AffectThor	0.664	0.606	0.706	0.667	0.667
(5) UWB	0.504	0.361	0.606	0.544	0.506
(6) AIT2018 Organizers	0.481	0.444	0.546	0.451	0.483
(15) AIT2018 Organizers	-0.022	0.011	-0.069	-0.005	-0.027

Table 15: Results of SemEval's EI-oc task in Spanish language

5 Conclusion

In this work, it has been presented the process performed to generate a new emotion intensity lexicon for Spanish. We have generated a parallel list to the NRC Affect Intensity Lexicon for English (Mohammad, 2017) by automatically translating the terms with Google translator. In the generated list (SAL list) we found some translation problems, such as repeated Spanish terms, English words untranslated and English expression untranslated. This led us to the generation of new versions of the SAL list using an automatic approach and a manual approach.

The different versions of the lexicon have been tested over the dataset released at SemEval 2018 Task 1 and iSALv2m has been the one that has provided the best results. Moreover, the generated lexicon has been compared with the unique emotion intensity lexicon existing for Spanish, SEL lexicon, and it has shown that emotion intensity is a difficult task that is still at a first stage of research and that is very important to continuing working on the development of resources.

Acknowledgements

This work has been partially supported by a grant from the Ministerio de Educación Cultura y Deporte (MECD - scholarship FPU014/00983), Fondo Europeo de Desarrollo Regional (FEDER) and REDES project (TIN2015-65136-C2-1-R) from the Spanish Government.

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