A Comparison Between Two Spanish Sentiment Lexicons in the Twitter Sentiment Analysis Task

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Abstract. Sentiment analysis aims to determine people's opinions towards certain entities (e.g., products, movies, people, etc.). In this paper we describe experiments performed to determine sentiment polarity on tweets of the Spanish corpus used in the TASS workshop. We explore the use of two Spanish sentiment lexicons to find out the effect of these resources in the Twitter sentiment analysis task. Rule based and supervised classification methods were implemented and several variations over those approaches were performed. The results show that the information of both lexicons improve the accuracy when is provided as a feature to a Naïve Bayes classifier. Despite the simplicity of the proposed strategy, the supervised approach obtained better results than several participant teams of the TASS workshop and even the rule based approach overpass the accuracy of one team which used a supervised algorithm.

1 Introduction

Sentiment analysis can be tackled as a classification problem, where the classes are the polarity of the expressed opinions (i.e., positive or negative opinion). There are usually two approaches for sentiment analysis classification, the supervised and the unsupervised approach.

The unsupervised approach tries to determine the polarity of the sentiments without using prior knowledge of the data. Such methods are usually based on lexical resources like sentiment lexicons, which are a list of words with a sentimental attachment. In [1] dictionaries of words annotated with their semantic orientation or polarity were created and used for classifying the polarity of different user's reviews. Every word of the reviews was compared to the words on the dictionaries, in order to find a match; if they matched, the polarity of the words was used to determine the global sentiment polarity of the review.

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For English, numerous lexicons have been created over the years, for instance: SentiWordnet [2], the Harvard inquirer [3] and LIWC [4]. Many English lexicons have been translated to Spanish and have been used for sentiment analysis in Spanish.

On the other hand, most of the supervised approaches for sentiment analysis have used machine learning algorithms to train with data examples and then apply the learned model to unseen data. In [5] Naïve Bayes, Maximum Entropy and Support Vector Machine algorithms were used to classify sentiment polarity on a movie reviews English corpus. Even though the experiments obtained 82 % of accuracy, the authors point out that the applied algorithms were not able to achieve accuracies comparable to those reported for standard topic-based categorization, concluding that sentiment analysis is a more difficult problem than text categorization. There have been also some efforts to apply supervised methods to classify sentiment polarity for Spanish texts [6,7].

One of the most remarkable efforts for Spanish sentiment analysis is done in TASS (sentiment analysis workshop) organized by SEPLN (Spanish society for natural language processing). This workshop has created a general Corpus of Twitter posts [8], known as tweets, annotated with their global sentiment polarity. The workshop has been celebrated annually since 2012 and recurrently has included a task for determining the goblal polarity of every tweet in the corpus. The participants have tried different approaches for the task, from unsupervised [9,10] and supervised methods [11,12] to assembled systems [13].

In this paper we describe several experiments for classifying sentiment polarity on tweets performed on the Spanish corpus used in TASS workshop, in order to find out the contribution of the two selected lexicons. In the following sections we describe the resources we used (Sect. 2); the experiments performed and the results obtained (Sect. 3); and finally our conclusions and future work (Sect. 4).

2 Resources

The sentiment analysis task has attracted the scientific community attention during the last years. Thanks to the social networks, a lot of opinions are publicly available. Twitter is a social network in which users post messages (tweets) with a maximum length of 140 characters. Due to the importance of this social network and the difficulty to automatically determine the associated sentiment polarity of the tweets, we are interested in exploring different linguistic resources that could help in this task for Spanish.

Workshop
First of all, we have selected the general corpus used in TASS workshop. This corpus contains 68,017 tweets written in Spanish, posted between November 2011 and March 2012. The corpus is divided into a training set of 7,219 tweets (10 %) and a test set of 60,798 tweets (90 %). Every tweet is annotated with its global sentiment polarity at five levels: positive (P), strong positive (P+), negative (N), strong negative (N+), neutral (NEU) and an extra tag (NONE) for those tweets with no sentiment at all. Because we want to classify the tweets

according to their polarity instead of their intensity, we consider only 3 levels and NONE. The tweets from classes P and P+ are joined in a new positive class, and the same treatment is done to the tweets from classes N and N+, which are joined in a new negative class. Besides the difficulty related to the short length of the tweets, the corpus has the problem of being unbalanced. In Table 1 we show the frequency and the total number of tweets for every class in the training and testing sets.

Table 1. Frequency and tweets of the general corpus.

Sentiment	Train		Test	
	Frequency	Tweets	Frequency	Tweets
Positive	39.94 %	2,884	36.57 %	22,233
Negative	30.22 %	2,182	26.06 %	15,844
None	20.54 %	1,483	35.22 %	21,416
Neutral	9.28 %	670	2.15 %	1,305

Lexicons

Sentiment lexicons are created for determining the attachment of a word to a sentiment or sentiments. For our research we have selected the Spanish Emotion Lexicon (SEL) [14] and LIWC [15] with a special list of Spanish words. SEL has already been used in [16] for Twitter sentiment analysis, while to our knowledge LIWC has been used for opinion mining in Spanish in [17], but not for Twitter sentiment analysis. Performance comparison with other lexicons such as those translated from other languages [2], [3] has been left as future research.

SEL is composed by 2,036 words. For every word SEL includes the probability factor for affective use (FPA for its acronym in Spanish). This value indicates how often a word is used to express some of the six different sentiments considered in the lexicon. Some words can be used to express more than one sentiment. In Table 2 we show the total number of words classified into every sentiment. Because this lexicon does not include an explicit reference to positive or negative sentiments, we have considered the words classified into the Joy and Surprise sentiments as positives, and the words classified into the rest of the sentiments as negatives.

Table 2. Sentiments and words of SEL.

Sentiment	Joy	Surprise	Anger	Fear	Disgust	Sadness
Words	668	175	382	211	209	391

LIWC is a lexicon composed by 12,656 words and stems. Words and stems are classified into four groups and every group is composed by several categories

Table 3. Groups and some categories of LIWC.

Group	Categories
Standard linguistic dimension	Personal pronouns, impersonal pronouns, articles, verbs, adverbs, prepositions, conjunctions, negations, quantifiers, numbers
Psychological process	Social process, **affective process**, cognitive process, perceptual process, biological process, relativity
Personal concerns	Work, achievement, leisure, home, money, religion, death
Spoken categories	Assent, nonfluencies, fillers

(a total of 464), some of them are shown in Table 3. This lexicon has a special category (marked in bold face) which indicates whether a word is used for a positive or negative sentiment.

3 Method

In order to measure the contribution of different lexicons and text characteristics, several experiments were ran. In this section we describe the performed experiments and the obtained results.

Rule based approach
Two experiments were carried out using the lexicons described in the previous section, following a rule based approach.

The algorithm to determine the sentiment polarity with the SEL lexicon uses the next steps for every tweet:

1. Tokenize
2. Lemmatize[1]
3. For every word in the tweet:
   (a) Compare the word with the words in the lexicon
   (b) Get the FPA value and the related sentiment (positive or negative) of the matched word in the lexicon
   (c) Accumulate the FPA value into its corresponding sentiment
4. Calculate the difference (df) between the positive and negative sentiment values
5. Get the overall sentiment polarity using the selected threshold shown in Table 7.

The algorithm used with LIWC follows the next steps:

1. Tokenize
2. Compare the word with the words in the lexicon
3. Count the words marked in the lexicon with the affective process category, according to its corresponding sentiment (positive or negative)
4. Calculate the difference (df) between the positive and negative counting

[1] All the words in the SEL lexicon are lemmatized.

5. Get the overall sentiment polarity using the selected threshold shown in Table 7

TASS corpus has extra information like date, user and topic. Topics has proved to be useful for polarity determination [18], but we did not take into account because Twitter does not include this information automatically (topics were manually annotated) and date and user seem irrevalevant for our task. For both algorithms the none class is assigned when no match is found between the words of the tweet and the words of the lexicon. For example the tweet *Medir las palabras en 140 caracteres:* http://t.co/s41kO7jt (Measure the words in 140 characters) has not any sentiment related word and therefore not of them would be found in the lexicons.

Supervised approach
We used a Multinomial Naïve Bayes classifier trained with the train set described in Table 1. Different features were used in order to find out the best performance. All the following representations used a lemmatized version of the corpus, except for the LIWC representation. Besides, for the first two representations a vocabulary of the full corpus is calculated.

1. Bag of words (BOW). Every tweet is represented as a vector of lemmatized word frequency.
2. Binarized BOW (BBOW). Instead of the word frequency, the vector contains the values 1 or 0 depending on the existence of the word in the vocabulary.
3. FPA. The FPA values of the six sentiments (see Table 2) are obtained for every word in the tweet, and the FPA values are used in the vector of characteristics.
4. LIWC. The vector contains the frequency of every[2] category (see Table 3) marked in the lexicon for the words in tweet.

The following representations are combinations of the above described. For all the representations, the values are concatenated to each other, resulting in an augmented vector. The plus symbol (+) is used to indicate the concatenation.

5. BBOW + FPA.
6. BBOW + LIWC.
7. BBOW + FPA + LIWC.
8. BBOW + FPA + FPAG + LIWC. The new feature FPAG is obtained by accumulating the FPA values of the six sentiments and grouping them into positive and negative words, as it was done in the rule based approach.

Given the original tweet *Habia prometido responder a todos, pero me ha sido imposible. Y hoy no doy para mas. MUCHAS GRACIAS A TODOS* (sic) (I had promised to respond to everyone, but it has been impossible. And today I cannot give more. THANK YOU VERY MUCH TO ALL) the lemmatization process (using Freeling [19]) generates the following output *habia prometer responder a todo, pero me haber ser imposible. y hoy no dar para mas. mucho gracia a todo*

[2] Experimentally better results were achivied when using all the categories instead of using only the affective process category like in the rule based approach.

(i have promise to respond to everyone, but it have be impossible. and today i can not give more. thank you very much to all), after that the above mentioned variations operate over the obtained tokens (20 in the Spanish version) of the lemmatized tweet. In Table 4 we show the generated feature vectors.

Table 4. Variations on feature vector representation.

	BOW features					
	w_1	w_2	w_3	w_4	...	w_n
(1)	1	0	1	2	...	1
(2)	1	0	1	1	...	1
	FPA features					
	joy	anger	fear	disgust	surprise	sadness
(3)	0.597	0	0	0	0	0
	LIWC features					
	c_1	c_2	c_3	c_4	...	c_{464}
(4)	2	8	0	3	...	5
(5)	(2) + (3)					
(6)	(2) + (4)					
(7)	(2) + (3) + (4)					
(8)	(2) + (3) + FPAG + (4)					

4 Results and Discussion

Table 5 shows the accuracy obtained by all the performed experiments over the test set. As can be seen, the accuracy obtained on the rule based approach shows a little improvement when LIWC is used. We consider that this improvement occurs because LIWC lexicon has over 10,000 words more than SEL, so the probability to find a match is higher. In addition to that, LIWC provides a specific indicator for positive or negative words while SEL does not. Nevertheless, the idea of considering the Joy and Surprise categories as positive and the rest as negatives and the use of FPA values gives similar results than LIWC. Table 6 shows the best results obtained by the participants on the TASS 2015 workshop [8]. All systems used a supervised approach, so a fair comparison is not possible. Even though, our rule based algorithms obtained better results than the GAS-UCR team.

Results using the supervised approach were better than those obtained with the rule based experiments even though the simplicity of the features used. The improvement when using LIWC instead of SEL is preserved with this approach. Moreover, the best result is obtained when the information provided by both

Table 5. Experiments on TASS corpus with different lexicons and configurations.

Rule based experiments	Accuracy
SEL	0.529
LIWC	0.531
Supervised experiments	Accuracy
BOW	0.585
BBOW	0.586
FPA	0.425
LIWC	0.516
BBOW + FPA	0.596
BBOW + LIWC	0.599
BBOW + FPA + LIWC	0.605
BBOW + FPA + FPAG +LIWC	0.608

Table 6. Best results on TASS 2015.

Team	Accuracy
LIF	0.726
ELiRF	0.721
GTI-GRAD	0.695
GSI	0.690
LyS	0.664
DLSI	0.655
DT	0.625
SINAI_wd2v	0.619
INGEOTEC	0.613
UCSP	0.613
ITAINNOVA	0.610
Us Supervised	*0.608*
BittenPotato	0.602
CU	0.597
TID-spark	0.594
Us Rule based	*0.531*
GAS-UCR	0.446

lexicons is added to the feature vector. This suggests that each lexicon provides complementary information to the classifier allowing a better accuracy. In Table 6 we compare our results with other TASS workshop participants. Most of the participants used elaborated preprocessing steps [12,20,21] like spelling correction, emoticon handling and special treatment for Twitter elements (hashtags, URLs, users). Besides, the classifiers used like SVM and Logistic Regression are more complex and some participants used more than one [13]. Despite using only a lemmatizer during preprocessing and a Multinomial Naïve Bayes classifier with the information provided by both lexicons, the reached accuracy is better than the obtained by four participant teams.

4.1 Analysis of Results

(a) Threshold selection for rule based approach. Several experiments were run to determine suitable threshold values. The first experiment consider an initial range of 0.66 diference value to determine the neutral polarity, the following experiments decrease this range knowing that they are less frequent that other classes. We selected the threshold values of experiment 3 because no improvement was found when decreasing the range. In Table 7 we show the variations over the threshold values.

Table 7. Threshold values variations.

Experiments			
No.	*Sentiment polarity*	*Threshold*	*Accuracy*
1	Negative	$df < -0.33$	0.501
	Neutral	$-0.33 \leq df \leq 0.33$	
	Positive	$df > 0.33$	
2	Negative	$df < -0.23$	0.517
	Neutral	$-0.23 \leq df \leq 0.23$	
	Positive	$df > 0.23$	
3	Negative	$df < -0.1$	0.529
	Neutral	$-0.1 \leq df \leq 0.1$	
	Positive	$df > 0.1$	
4	Negative	$df < -0.05$	0.529
	Neutral	$-0.05 \leq df \leq 0.05$	
	Positive	$df > 0.05$	

(b) Confusion matrix. In order to identify the misclassification problems we show a confusion matrix in Table 8. None class is mostly confused with negative and positive class, while all the actual neutral tweets were misclassified. We consider that the unbalance in corpus and the few examples available for the neutral class generate these errors.

Table 8. Confusion matrix obtained in the experiment with best results in supervised approach.

Actual	Predicted	Total
N	P	1688
N	N	13959
N	NONE	192
N	NEU	5
NEU	N	940
NEU	P	362
NEU	NONE	3
NONE	P	8815
NONE	N	8337
NONE	NONE	4249
NONE	NEU	15
P	P	18756
P	N	2880
P	NONE	594
P	NEU	3

(c) Surprise as negative emotion. SEL lexicon does not include an explicit reference to positive or negative polarity, therefore we grouped the joy and surprise sentiments as positive while the rest of the sentiments listed in Table 2 were considered negative. Nevertheless some words marked in the corpus as surprise can be considered negative, for example *confuse* and *scare*. An additional experiment was run to determine if change of class would improve the performance, obtaining an accuracy 0.526. The result shows a decrease of 0.003 in comparison with the original experiment, leading us to think that the words related to surprise can have both positive and negative polarity.

4.2 Corpus Analysis

The results shown in Table 5 were obtained following the specifications of TASS workshop, which consider 10 % of the corpus for training and the remaining 90 % for testing. In order to explore how the learning rate is affected when the training size is increased, we run the experiments shown in Table 9 using the eighth variation from Table 4. For these experiments, we joined the training and testing corpora in a single new corpus and the tweets were shuffled. After that, we selected a fixed 20 % of the new corpus for testing and the remaining 80 % was left for training purposes. For the first experiment 1/8 part of the training corpus was used, for the second one the training corpus was incremented with other 1/8 (2/8 in total) and so on, until the eighth experiment that covers the whole training corpus. Our results show that for the first fourth experiments the

Table 9. Learning rate and vocabularies intersection.

Vocabulary size (considering types)					
V_{SEL}	V_{LIWC}	V_{test}			
1,891	12,552	41,173			
Intersections					
$V_{test} \cap V_{SEL}$		$V_{test} \cap V_{LIWC}$			
662		4466			
Experiments					
No.	Training size	Accuracy	V_{train}	$V_{train} \cap V_{SEL}$	$V_{train} \cap V_{LIWC}$
1	1/8	0.637	25,180	539	3,615
2	2/8	0.649	41,394	661	4,491
3	3/8	0.654	54,747	740	4,992
4	4/8	0.663	66,920	798	5,358
5	5/8	0.665	78,052	846	5,641
6	6/8	0.666	88,718	888	5,912
7	7/8	0.667	98,817	929	6,136
8	8/8	0.669	108,305	964	6,295

accuracy improve in 0.01, but from the fifth the improvement is around 0.001. We can conclude that using 50 % of the corpus for training is enough to improve the initial results. Another important information showed in Table 9 is the size of the intersection between the vocabulary of test corpus and the vocabulary of the lexicons as well as the size of the intersection between the vocabulary of training corpora and the vocabulary of the lexicons. Results show very low intersection between corpora's vocabulary (testing and training) and lexicons' vocabulary (SEL and LIWC). We consider that to improve the overall accuracy both aspects must be taken into account, therefore the size of the training corpus and the intersection between vocabularies need to be increased.

5 Conclusions and Future Work

Sentiment analysis is an interesting but difficult task, especially with the characteristics of tweets. A significant effort has been done for Spanish sentiment analysis and the TASS workshop has been an important platform. In this work two different Spanish lexicons were used with rule based and supervised approaches. To our knowledge the LIWC lexicon had not been used for determining the sentiment polarity of Spanish tweets, and according to our experimentation, this lexicon got better results than SEL lexicon. In addition to that, when the information of both lexicons was used with the Multinomial Naïve Bayes the best results were obtained. Despite the fact that our results are not the best when compared with the obtained by the participant teams on TASS 2015, the simple proposed strategy was able to overpass the results of four teams, which shows the potential of combining the information of the selected lexicons with a supervised approach. By doing a deeper analysis, we created a confusion matrix showing that the neutral and none classes has many misclassification issues, we think that this is because there are fewer examples of these classes in the training corpus and the classifier can not learn from them. In addition to that, several experiments were run to determine how the size of the training corpus and vocabularies intersection impact the performance. We conclude that when the size is increased to 50 % better results are obtained, but without an increment in vocabularies's intersection the following increments has no significant impact in the accuracy. For future work we would improve the preprocessing phase to increase the intersection between vocabularies as well as use other lexicons. More complex machine learning algorithms must be tried and other text representations can be explored.

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References

1. Taboada, M., Brooke, J., Tofiloski, M., Voll, K.D., Stede, M.: Lexicon-based methods for sentiment analysis. Comput. Linguist. **37**, 267–307 (2011)
2. Baccianella, S., Esuli, A., Sebastiani, F.: SentiWordNet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining. In: Calzolari, N., Choukri, K., Maegaard, B., Mariani, J., Odijk, J., Piperidis, S., Rosner, M., Tapias, D. (eds.) LREC. European Language Resources Association (2010)
3. Stone, P.J.: The General Inquirer: A Computer Approach to Content Analysis. The MIT Press, Cambridge (1966)
4. Tausczik, Y.R., Pennebaker, J.W.: The psychological meaning of words: LIWC and computerized text analysis methods. J. Lang. Soc. Psychol. **29**, 24–54 (2010)
5. Pang, B., Lee, L., Vaithyanathan, S.: Thumbs up? Sentiment classification using machine learning techniques. In: EMNLP 2002, Philadelphia, Pennsylvania pp. 79–86 (2002)
6. Urizar, X.S., Roncal, I.S.V.: Detecting sentiments in Spanish tweets. TASS 2012 Working Notes (2012)
7. Sidorov, G., et al.: Empirical study of machine learning based approach for opinion mining in tweets. In: Batyrshin, I., González Mendoza, M. (eds.) MICAI 2012, Part I. LNCS, vol. 7629, pp. 1–14. Springer, Heidelberg (2013)
8. Villena-Román, J., García-Morera, J., Cumbreras, M., Martínez-Cámara, E., Martín-Valdivia, M.T., López, L.A.U.: Overview of TASS 2015. In: Villena-Román, J., García-Morera, J., Cumbreras, M.Á.G., Martínez-Cámara, E., Martín-Valdivia, M.T., López, L.A.U. (eds.) TASS@SEPLN, CEUR Workshop Proceedings, vol. 1397, pp. 13–21 (2015)
9. Garcıa, D., Thelwall, M.: Political alignment and emotional expression in Spanish Tweets. In: Proceedings of the TASS Workshop at SEPLN, pp. 151–159 (2013)
10. Moreno-Ortiz, A., Pérez Hernández, C.: Lexicon-based sentiment analysis of twitter messages in Spanish. Procesamiento del Lenguaje Natural **50**, 93–100 (2013)

11. Urizar, J., San Vicente Roncal, I.: Elhuyar at TASS 2013. In: Proceedings of the TASS Workshop at SEPLN (2013)
12. Araque, O., Corcuera, I., Román, C., Iglesias, C.A., Sánchez-Rada, J.F.: Aspect based sentiment analysis of Spanish tweets. In: Villena-Román, J., García-Morera, J., Cumbreras, M.Á.G., Martínez-Cámara, E., Martín-Valdivia, M.T., López, L.A.U. (eds.): TASS@SEPLN, CEUR Workshop Proceedings, vol. 1397, pp. 29–34 (2015). CEUR-WS.org
13. Valverde, T.J., Tejada, C.J.: Comparing supervised learning methods for classifying Spanish tweets. In: Villena-Román, J., García-Morera, J., Cumbreras, M.Á.G., Martínez-Cámara, E., Martín-Valdivia, M.T., López, L.A.U. (eds.) TASS@SEPLN, CEUR Workshop Proceedings, vol. 1397, pp. 87–92 (2015). CEUR-WS.org
14. Rangel, I.D., Guerra, S.S., Sidorov, G.: Creación y evaluación de un diccionario marcado con emociones y ponderado para el español. Onomazein **29**, 31–46 (2014)
15. Pennebaker, J.W., Francis, M.E., Booth, R.J.: Linguistic Inquiry and Word Count. Lawerence Erlbaum Associates, Mahwah (2001)
16. Cámara, E.M., Cumbreras, M., Martín-Valdivia, M.T., López, L.A.U.: SINAI-EMMA: Vectores de Palabras para el Análisis de Opiniones en Twitter. In: Villena-Román, J., García-Morera, J., Cumbreras, M.Á.G., Martínez-Cámara, E., Martín-Valdivia, M.T., López, L.A.U. (eds.) TASS@SEPLN, CEUR Workshop Proceedings, vol. 1397, pp. 41–46 (2015). CEUR-WS.org
17. del Pilar Salas-Zárate, M., López-López, E., Valencia-García, R., Aussenac-Gilles, N., Almela, Á., Alor-Hernández, G.: A study on LIWC categories for opinion mining in Spanish reviews. J. Inf. Sci. **40**, 749–760 (2014)
18. Vázquez, S., Bel, N.: A classification of adjectives for polarity lexicons enhancement. In: Calzolari, N., Choukri, K., Declerck, T., Dogan, M.U., Maegaard, B., Mariani, J., Odijk, J., Piperidis, S. (eds.) LREC, pp. 3557–3561. European Language Resources Association (ELRA) (2012)
19. Padró, L., Stanilovsky, E.: FreeLing 3.0: towards wider multilinguality. In: Proceedings of the Language Resources and Evaluation Conference (LREC 2012). ELRA, Istanbul (2012)
20. Hurtado, L.F., Plà, F., Buscaldi, D.: ELiRF-UPV en TASS 2015: Análisis de Sentimientos en Twitter. In: Villena-Román, J., García-Morera, J., Cumbreras, M.Á.G., Martínez-Cámara, E., Martín-Valdivia, M.T., López, L.A.U. (eds.) TASS@SEPLN, CEUR Workshop Proceedings, vol. 1397, pp. 75–79 (2015). CEUR-WS.org
21. Álvarez-López, T., Juncal-Martínez, J., Gavilanes, M.F., Costa-Montenegro, E., González-Castaño, F.J., Cerezo-Costas, H., Celix-Salgado, D.: GTI-Gradiant at TASS 2015: a hybrid approach for sentiment analysis in twitter. In: Villena-Román, J., García-Morera, J., Cumbreras, M.Á.G., Martínez-Cámara, E., Martín-Valdivia, M.T., López, L.A.U. (eds.) TASS@SEPLN, CEUR Workshop Proceedings, vol. 1397, pp. 35–40 (2015). CEUR-WS.org