Using Facebook Reactions to Recognize Emotion in Political Domain

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***Abstract*—Opinion Mining and Emotion Mining are part of the Sentiment Analysis area, but they have different objectives. Opinion Mining is concerned with the study of opinions expressed in texts and its basic task is polarity detection, whereas Emotion Mining is related to the study of emotions and its basic task is emotion recognition. Polarity detection is usually a binary classification task with outputs such as *positive* vs. *negative* or *like* vs. *dislike*, while emotion recognition aims to enable computers recognize and express emotions. In this paper we focus on Spanish emotion classification. We first compile a corpus from Facebook using the reactions in comments and posts in order to label different emotions. Then we apply a basic machine-learning approach and two lexicon-based approaches, one using a Spanish version of the NRC Emotion Lexicon (Emolex) and another adapting WordNet-Affect to Spanish. The results demonstrate the difficulty of the task and show some interesting features in the lexicon approaches.**

***Index Terms*—Emotion Mining, Natural Language Processing, Social media, Facebook reactions, lexicon, machine learning, Emolex, WordNet-Affect**

I. Introduction

Emotion classification is a new task that combines several disciplines including Artificial Intelligence and Psychology, although Natural Language Processing is perhaps the most challenging area [1].

Recognize emotions in texts is becoming more and more important due to the fact that it can provide substantial benefits for different sectors [2], for instance detecting signs of depression [3], identifying cases of cyber-bullying [4] or contributing to improve student motivation and performance [5].

On the other hand, social media have changed the way people interact, as they allow the creation and exchange of user-generated content. Social networks are one of the main social media sites in which subjective information is published. Not only this social emotions are expressed in social media networks like Twitter or Facebook but also are said to have a high impact on public discourse and communication in society [6].

In this paper we focus on emotion recognition in Spanish over Facebook posts and comments for several reasons:

(i) Emotion mining is a difficult task and the current results are not as accurate as those of polarity classification due to its multi-label nature.

(ii) Most of the existing studies are focused on English, but the presence of other languages on the web is greater every day. Spanish is the second most spoken language in the world and in the two main social networks: Facebook and Twitter. [1].

(iii) There are few resources and corpora for emotion recognition in Spanish.

(iv) Facebook is currently the most popular social network. It has approximately 2,167 million of users according to a study of statista[2].

Therefore, in order to advance in emotion recognition in Spanish, we present a corpus of posts and comments in the political domain which was compiled from the Facebook page *DignidadyResponsabilidad*[3], a Spanish popular page about politics. We first propose a basic Machine Learning (ML) approach to classify emotions in Spanish using the Support Vector Machine (SVM). Then we compare the ML mehod with two lexicon-based approaches. The first one uses the Emolex Spanish lexicon [7] and the second one proposes adapting the well-known WordNet-Affect (WNA) resource [8] to Spanish.

The rest of the paper is organized as follows: Section 2 describes some related studies; Corpora, ML and lexicon-based approaches are presented in Section 3; Section 4 shows the results and discussion, and finally, our conclusions are presented in Section 5.

II. Background

Emotion recognition is becoming very popular, and some of the main conferences dealing with data and text mining and evaluation are currently including workshops and share tasks

[1] http://www.cervantes.es/sobre_instituto_cervantes/prensa/2017/noticias/Presentaci%C3%B3n-Anuario-2017.htm

[2] https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users

[3] https://www.facebook.com/DignidadyResponsabilidad/?ref=br_rs/

related to it. These include Semantic Evaluation (SemEval) [9], Computational Approaches to Subjectivity and Sentiment Analysis (WASSA)[4] and workshops on Computational Modeling of People's opinions, personality and emotions in Social Media (PEOPLE)[5].

Scientific studies on classification of human emotions date back to 1960s. From a psychological perspective, an emotion is basic only if it does not contain another emotion; that is, if it represents an atomic, irreducible psychological construct [10]. Moreover, emotions can be recognized by humans all over the world regardless of their race, culture, and language. Many theorists have proposed sets of emotions that tend to be basic ones. While psychologists do not agree on what model describes more accurately the set of basic emotions, the most widely used in computer research is the one proposed by Ekman [11], with 6 emotions (anger, disgust, fear, joy, sadness and surprise) [12]. There are different works that use this model to create labeled emotions corpora or to identify emotions in the text. For example, Mohammad [13] created a corpus of emotional tweets from Twitter (TEC)[6]. He targeted the six basic emotions proposed by Ekman and chose six hashtags addressing these emotions to search for appropriate tweets. Another work is the one proposed by Strapparava and Mihalcea [14]. They describe the construction of a large data set annotated for six basic emotions and propose and evaluate several knowledge-based and corpus based methods for the automatic identification of these emotions in text.

Emotion mining techniques can be classified into two categories: lexicon based approaches and machine learning approaches [15]. The first one is based on lexical resources such as lexicons, bags of words or ontologies. The second approach applies ML algorithms based on linguistic features.

Several interesting studies have explored emotion recognition and most of them deal with English texts [16]. Many of these studies focus on evaluating information from social networks since they are appropriate places to share one's feelings easily and widely. Recognize automatically emotions in social media texts can provide the tools to researchers, and citizens in general, to monitor the pulse of the society towards specific topics of interest, a task traditionally accomplished only through opinion polls, which are costly and time consuming to conduct, and therefore frequently limited to small sample sizes. Most of the works have explored emotions from Twitter and different machine learning techniques [17]. For example, Purver and Battersby [18] exploit both emoticons and Twitter hashtags for emotion recognition, Mohammad and Kiritchenko [19] use hashtags to capture fine emotion categories from tweets and Bollen et al. [20] analyze emotions of all tweets in a specific time frame using a psychometric test, names "Profile of Mood States" (POMS).

[4]https://wt-public.emm4u.eu/wassa2018/
[5]https://peopleswksh.github.io/index.html
[6]http://saifmohammad.com/WebPages/lexicons.html.

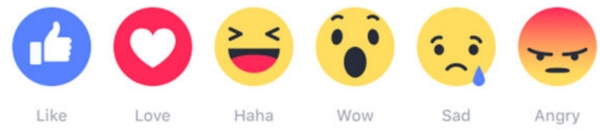

Fig. 1. Facebook reactions.

Regarding Facebook, there are few papers centered on emotion recognition, partly because it is difficult to get a labeled dataset for such a purpose. However, since February 2016 Facebook users have been able to express specific emotions in response to a given post or comment due to the newly introduced reaction feature. It has been observed that this new feature helps Facebook to know much more about its users and exploit this information for targeted advertising [21]. Krebs et al. [22] collected posts and their reactions from Facebook pages and constructed a dataset. They combine sentiment analysis and emotion mining techniques with neural network architectures in order to predict the distribution of reactions on Facebook posts. Moreover, they present a simple visualization environment. Pool and Nissim [23] take advantage of the Facebook reaction feature in a distant supervised fashion in order to train an SVM classifier for emotion detection, using several feature combinations and combining different Facebook pages. In our paper we follow the same idea to exploit the Facebook reaction feature, but applied to Spanish posts and comments.

III. Methodology

In this section, we describe the process for generating the corpora and the approaches applied.

A. Corpus generation

In February 2016, Facebook made a more explicit reaction feature available world-wide. *Reactions* is an extension of the *Like* button which gives people more ways to express themselves and share their reaction to a post or comment. The collection of reactions include *Like*, *Love*, *Haha*, *Wow*, *Sad* and *Angry* (Figure 1).

We collected Facebook comments and posts with their corresponding reactions from a public page using the Facebook graph API[7]. We chose the Facebook page DignidadyResponsabilidad[8]. It is a page that contains Spanish post and comments in the political domain. Currently it has 140,223 followers and 156,891 people like it. We downloaded the available posts and comments of this page from February 2016 to December 2017, recovering also the counts of reactions for each post and comment. The posts and comments are saved following a JSON structure. In the Figure 2 it can be seen an example.

[7]https://developers.facebook.com/docs/graph-api/
[8]https://www.facebook.com/DignidadyResponsabilidad/?ref=br_rs/

```
{
    {
    "status_id": "120857194649240_1259461114122170"
    "message": "REAL COMO LA VIDA MISMA Los Morancos y su particular versión sobre el juicio de Urmangarín."
    "status_published": "2017-03-12 08:31:59"
    "num_reactions": 88
    "num_comments": 3
    "num_shares": 32
    "num_likes: 74
    "num_loves": 4
    "num_wows": 0
    "num_hahas": 7
    "num_sads": 3
    "num_angrys": 0
    }
}
```


Fig. 2. Sample of resulting JSON file.

In order to assign the general emotion for the post or comment, we chose the majority reaction. In addition, we did not consider the reaction *Like* because it is the most generic that users tend to use and it would be biased. Finally, we obtained three different corpus: Post corpus (PC) with 1071 posts, Comment corpus (CC) that contains 1036 responses to the posts, and Post and comment corpus (PCC) with the union of the PC and CC, that is, 2107 samples in total. Statistics of Facebook reactions in these corpora can be observed in Table I. For the experimentation, we randomly partitioned the corpora into equally sized for training and testing (50% train and 50% test).

TABLE I
Number of different Facebook reactions in PC and CC

Facebook reaction	post	comment
Angry	747	171
Haha	225	359
Love	68	317
Wow	13	85
Sad	18	104
Total	1071	1036

B. Machine learning approach

In order to evaluate the ML method, we chose scikit learn package[9] of python and we applied as baseline 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 the linear. As has been mentioned before, 50% of the corpora was used for training and the remaining 50% for testing. Each document was represented as a vector of unigrams using the TF-IDF weighting scheme, but previously the following preprocessing step was carried out. The documents were tokenized using NLTK TweetTokenizer[10], stopwords were removed, stemming was performed using NLTK Snowball stemmer for Spanish [11] and all letters were converted to lower-case.

C. Lexicon-based approach

In order to evaluate the lexicon-based approach for emotion classification we followed two different methods. Firstly, we applied the NRC Spanish Emotion Lexicon [7] and secondly, we adapted the English WNA Lexicon [8] to Spanish.

The Emolex Spanish Emotion lexicon is a version of the NRC Emotion Lexicon (Emolex) [12] that was built by translating English emotional terms into Spanish using Google Translator. In order to classify emotions the documents were tokenized using NLTK TweetTokenizer, stopwords were removed, and all letters were converted to lower-case. The emotion labels (EL) of the terms present in the text are obtained by identifying the presence of these terms in the Emolex lexicon. We map these labels into Facebook reactions (Table II) and then assign 1 as confidence value (CV). Additionally, we identify the emojis present in the text using the faces of an emoji lexicon[13], we map them into Facebook reactions and we assign 1 as CV. Once the EL and CV of each word/emoji have been obtained, the general emotion is calculated in the following way: For each EL identified, we add the CV of the tokens that belong to it and we assign the EL with the highest sum to the text. In the case of two or more emotions having the same sum of CV or no EL being detected, we assign the most frequent EL, previously computed in the corresponding training corpus.

TABLE II
Mapping of the general emotion of Emolex to Facebook reactions

Facebook reaction	Emolex emotion
Sad	Sadness
Angry	Anger
Wow	Surprise
Love	
Haha	Joy

On the other hand, WNA is a linguistic resource that was built starting from WordNet Domains [24] through the selection and labeling of the synsets representing affective concepts. In particular, one or more affective labels are assigned to a number of WordNet synsets. This resource is focused on English, but we tackle Spanish texts. Therefore, we need to develop a method for obtaining affect labels for Spanish terms and obtaining their corresponding synsets with the aim of discovering the associated emotion in WNA. For this, we use the lexical disambiguator Babelfy[14] [25] to obtain the corresponding *BalbelNet synset id* for each term in the

[9] http://scikit-learn.org/stable/
[10] http://www.nltk.org/api/nltk.tokenize.html
[11] http://www.nltk.org/api/nltk.stem.html
[12] http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm
[13] https://github.com/erunion/emoji-lexicon
[14] Babelfy is based on the BabelNet multilingual semantic network and performs disambiguation and entity linking.

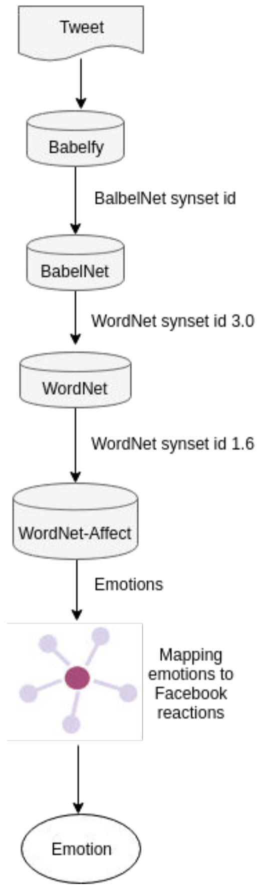

Fig. 3. Pipeline for adapting WNA to Spanish.

Spanish text. BalbelNet [26] [15] is a semantic network which is connected through synsets with WordNet. Using the BabelNet API we can obtain a correspondence between the *BalbelNet synset id* and the *WordNet synset id*. WNA includes a subset of appropriate synsets of WordNet 1.6 to represent affective concepts. However, the *WordNet synsets id* obtained with BabelNet API corresponds to the 3.0 version of WordNet. Therefore, we obtain the equivalent synset to the 3.0 version in the 1.6 version, and using the synset of the 1.6 version of WordNet we take the associated emotion and confident value from WNA. In Figure 3 it can be seen a diagram of the process described above.

WNA provides a set of emotional words organized in a tree. The leaf nodes represent specific emotions that are grouped into general categories (parent nodes). For example, *anger, hate* and *dislike* belong to the overall emotion *general-dislike*. However, WNA emotions are not the same as Facebook reactions. For this reason, each overall emotion of WNA has been mapped with Facebook reactions (Table III). The EL of the terms present in the text and their CV are obtained using WNAffect python package[16]. These EL are mapped into Facebook reactions following Table III. Moreover, we identify the emojis present in the text using the faces of an emoji lexicon, we map them into Facebook reactions and we assign 1 as CV. Once the EL and CV of each word/emoji have been obtained, the overall emotion is computed as follows: For each EL identified, we add the CV of the tokens that belong to it and we assign the EL with the highest sum to the whole text. In the case of two or more emotions having the same sum of CV or no EL being detected, we assign the most frequent EL, previously computed in the corresponding training corpus.

TABLE III
MAPPING OF THE GENERAL EMOTION OF WORDNET-AFFECT TO FACEBOOK REACTIONS

Facebook reaction	WNA emotion
Sad	apathy, neutral-unconcern, pensiveness, gravity, humility, compassion, despair, sadness
Angry	ambiguous-fear, ambiguous-expectation, ingratitude, shame, general-dislike
Wow	thing, ambiguous-agitation, surprise, positive-fear, positive-expectation, daze, anxiety, negative-fear
Love	gratitude, fearlessness, affection, self-pride, enthusiasm, positive-hope, calmness, love, liking
Haha	levity, joy

IV. Results and discussion

Table 2, 3 and 4 show the results obtained over the three datasets on the test sets (PC, CC and PCC). We can observe that the ML approach obtains better results as usual and expected. However, the results among the emotions are quite biased mainly due to the unbalance nature of the different corpora. Thus, it seems clear that we need to collect a corpus including enough samples for each emotion in order to our system can learn all of them.

Regarding the lexicon approaches, both methods achieve very low results. In addition, the majority emotion for each corpus determines the best result in this emotion because when our system does not recognize any emotion, we assign the majority one. For example, the *angry* emotion is the majority class in the PC and, thus, the results in this corpus are also biased to this emotion. For this reason, we performed other experiments, taking into account only the texts where our method recognizes one emotion, and neglecting the posts and comments with No-Emotion detected (WNA-NE and Emolex-NE). The results are very similar to the previous ones, but in this case it is interesting to note that WNA finds very few emotion words and, thus, the recall is very low, while with Emolex the texts detected with emotion almost reaches 80%. Specifically, WNA recognizes 67, 67 and 134 texts with emotions and Emolex

[15] BabelNet is a multilingual encyclopedic dictionary, with lexicographic and encyclopedic coverage of terms in 271 languages, and a semantic network which connects concepts and named entities, made up of more than 13 million entries

[16] https://github.com/clemtoy/WNAffect

500, 327 and 827 for the PC, CC and PCC, respectively. Taking into account that the total number of texts in each test corpus is 534, 516 and 1050, the texts classified with emotion represent 13%, 13% and 13% for WNA and 94%, 63% and 79% for Emolex, respectively.

V. Conclusion

In conclusion, emotion classification is a hard task that needs not only a deeper study but also specific linguistic resources in order to tackle the problem. Our next study will focus on collecting a larger and more balanced emotion corpus including others domains and studying the combination of different resources in order to generate a quality lexicon. In addition, we will compare the results obtained with English and Spanish corpora. Also, we plan to continue working on emotion recognition in Spanish because we have observed that the work in this language is very scarce, although it is the second most spoken language in the world and in the two main social networks: Facebook and Twitter.

It could be interesting to explore more affect lexicons 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 [17].

Finally, this system could be used to measure the satisfaction of citizens with politicians that could be very useful, for example, to predict results in a political campaign based on the emotions transmitted by users in posts and comments of the Facebook page *DignidadyResponsabilidad*[17].

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TABLE IV
Results on the test set of PC

	angry			haha			love			wow			sad		
Approach	prec	rec	f	prec	rec	f	prec	rec	f	prec	rec	f	prec	rec	f
SVM	0.71	0.97	0.81	0.35	0.05	0.09	0	0	0	0	0	0	0	0	0
WNA	0.7	0.9	0.79	0.25	0.02	0.03	0.1	0.06	0.07	0.07	0.17	0.1	0	0	0
Emolex	0.67	0.67	0.67	0.16	0.07	0.1	0	0	0	0	0	0	0	0	0
WNA-NE	0.6	0.2	0.3	0.25	0.17	0.2	0.1	0.33	0.15	0.07	0.05	0.12	0	0	0
Emolex-NE	0.7	0.66	0.68	0.16	0.08	0.11	0	0	0	0	0	0	0	0	0

TABLE V
Results on the test set of CC

	angry			haha			love			wow			sad		
Approach	prec	rec	f	prec	rec	f	prec	rec	f	prec	rec	f	prec	rec	f
SVM	0.3	0.21	0.25	0.38	0.46	0.42	0.38	0.51	0.43	0	0	0	0.08	0.02	0.03
WNA	0.24	0.06	0.1	0.36	0.91	0.51	0.37	0.03	0.05	0	0	0	0.13	0.04	0.06
Emolex	0.16	0.21	0.18	0.4	0.71	0.51	0	0	0	0	0	0	0.16	0.25	0.2
WNA-NE	0.24	0.45	0.31	0.29	0.11	0.15	0.36	0.15	0.21	0	0	0	0.13	0.29	0.18
Emolex-NE	0.16	0.35	0.22	0.36	0.46	0.40	0	0	0	0	0	0	0.16	0.34	0.22

TABLE VI
Results on the test set of PCC

	angry			haha			love			wow			sad		
Approach	prec	rec	f	prec	rec	f	prec	rec	f	prec	rec	f	prec	rec	f
SVM	0.55	0.78	0.65	0.4	0.35	0.37	0.31	0.21	0.25	0	0	0	0	0	0
WNA	0.43	0.91	0.59	0.27	0.01	0.03	0.17	0.03	0.05	0.04	0.02	0.03	0.09	0.03	0.05
Emolex	0.43	0.66	0.52	0.27	0.13	0.18	0	0	0	0	0	0	0.07	0.21	0.10
WNA-NE	0.37	0.25	0.3	0.27	0.13	0.17	0.17	0.15	0.16	0.04	0.2	0.06	0.09	0.22	0.13
Emolex-NE	0.54	0.63	0.58	0.27	0.2	0.23	0	0	0	0	0	0	0.07	0.28	0.11

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