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Classification of Attitude Words for Opinion Mining

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ABSTRACT

This work details appraisal extraction from attitude expressions. Here, by attitude expressions, we refer to those single words that convey the evaluation of sentiments or emotional states, about human behaviors, objects, processes or people, according to the Appraisal Theory of language. The attitude words can be classified into affect, judgment, and appreciation; either positive or negative. Extraction of the attitude words has a significant range of applications from opinion extraction and summarization, up to temporal opinion analysis. To determine the attitude, we use two machine learning techniques; namely, Support Vector Machines and Random Forest. These algorithms classify a given word starting from a vector that represents the information from the context where the words tend to occur. On the other hand, we can observe the context of the words relying on a corpus of sentences from user generated contents, such as reviews, editorials and other online texts.

KEY WORDS: *Opinion Extraction, Appraisal Theory, Corpus Evaluation, Machine Learning.*

1 INTRODUCTION

Evaluation, according to Hunston and Thompson in 2000, "*is the broad cover term for the expression of the speaker or writer's attitude or* *stance towards, viewpoint, or feelings about the entities or propositions that he or she is talking about*" [1]. Appraisal Theory tries to explain the semantic option schemes that the language has to evaluate. It is actually focused on the linguistic expression of attitude, and it separates evaluation into three subsystems; namely, Attitude, Graduation and Engagement[1]. Attitude corresponds to the words that emit an evaluation or that invite to do it. Graduation considers the words that intensify, diminish, sharpen or blur the evaluation. Engagement corresponds to those words that indicate the posture that the issuer adopts with the statement.

The problem we try to solve in this paper (appraisal extraction from single words) is part of a more complex problem (appraisal extraction from phrases) which is our aim in future work. Therefore, here, we focus the Appraisal extraction only on Attitude from single words. When we will extend our work to phrases (word sequences), we will study the graduation and engagement components.

Appraisal Theory subdivides Attitude into affect (evaluation of sentiments or emotional states), judgment (evaluation of the human behavior), and appreciation (evaluation of objects, processes, or people when they are valued from an aesthetic viewpoint). Attitude, also, can be positive or negative.

We are mainly interested in recognizing appraisal on the Spanish language; since we have found few advances of Opinion Mining on this language. For this reason, we have prepared a word list of attitude; as well as a corpus of sentences in which is possible to observe the context of these words. Nevertheless, we consider that the assumptions in this paper can be applied to other languages. In Fig. 1, we can see some examples of the appraisal systems.

Extraction of the attitude words has a significant range of applications from opinion extraction and summarization [6], up to temporal opinion analysis [7]. Nowadays, many people express their sentiments, evaluations, or judgments online in a variety of sources, such as customer reviews, editorials, blogs, and others. Summarizing those opinions can be very helpful, but this requires the extraction of attitude key phrases that are cues of the opinions expressed in the text.

For example, in sentence (1) we can notice two subjective words, both with a positive polarity. We can infer that the polarity of the

1 Additional details about Appraisal Theory can be found in [2–5].

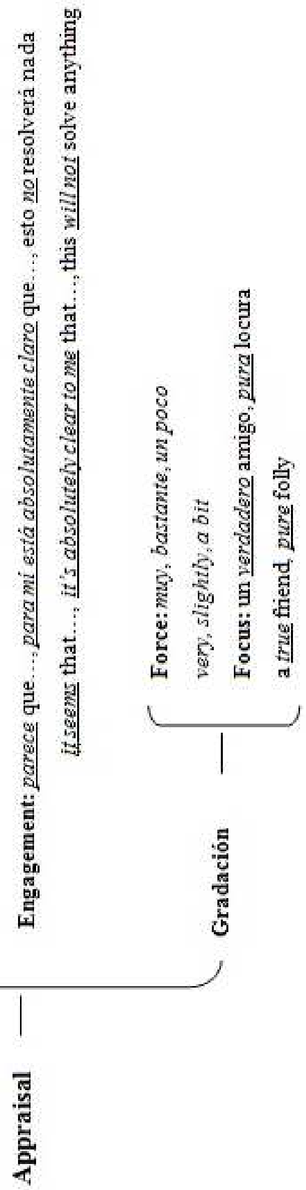

Fig. 1. Categories of Appraisal Theory and example words of Attitude system.

sentence is positive as well, by computing the amount of positive words[2].

(1) "*Viéndola, me doy cuenta de que si tanto me ha* *gustado*$^{+}$ *es porque la trama es* *comprensible*$^{+}$."

However, recognizing attitude in words (see sentence (2)) allows knowing the evaluation purpose of the sentence (sentiments, objects, or human behavior). Thus, sentences more relevant to a particular interest could be identified. For example, if the concerned item is the human behavior, you could be interested in summarize what anyone says about the capacity, or moral integrity of a given person, more than in its physical appearance or simple polarity.

(2) "*Viéndola, me doy cuenta de que si tanto me ha* [**affect**: *gustado*$^{+}$] *es porque la trama es* [**appreciation:** *comprensible*$^{+}$]."

On the other hand, the opinion usually tends to change on time, and the attitude extraction could be useful for monitoring or analyzing tendencies of public relations and marketing firms, opinions about products, people, organizations, etc.

Many words of an attitude system, according to the Appraisal Theory, have potential to express affect, judgment and appreciation when we consider them out of context, since affect is considered as the basic system of Attitude, whereas judgment and appreciation are derivations of this, manifesting institutionalized emotions. This situation has motivated us to use a corpus-based approach. This approach allows recognizing the evaluation of words considering the context where these tend to occur.

The present paper is structured as follows. In Section 2, we briefly explain the strategy to recognize appraisal in words. In Section 3, the structure and corpus composition are presented. In the last sections, we show the experimental results, as well as discussion and conclusions.

[2] Sentences that are shown as examples in this article are original sentences from the corpus we are working with, so we do not translate them here. Nevertheless, a translation for the sentence above is: *Seeing it, I realize that, if I liked it so much is because the plot is comprehensible.*

2 Recognizing Appraisal

Appraisal extraction is a Sentiment Analysis task; this is a novel research area. Some initial works date back to the late 1980's and early 1990's [8], [9]; Sentiment Analysis is conceived as Sentiment Classification, referring to the task of categorizing texts, or pieces of text, based on their subjectivity and orientation [10]. Others extend it to identify or classify appraisal targets, determining the source of an opinion in a text, and developing interactive and visual opinion mining methods [11]. Sentiment classification has been mainly focused in polarity classification; i.e., it determines if appraisal is positive, negative, neutral or if there is no appraisal in the text.

2.1 Related Works

Many previous works in sentiment classification have shown good performance using a lexicon-based approach. Starting by word lists manually annotated, they classify a larger piece of text, such as sentences [12] and paragraphs [13]. On the other hand, most of the works are focused on the English language; we have only found a few proposals for Spanish language that try to solve this problem generating a subjectivity-annotated corpus or dictionaries from translation of English subjective texts. (Banea et. al. 2008) propose to annotate (subjective and objective) sentences in Spanish and Romanian, by employing machine translation and leveraging on the resources and tools available for English like MPQA corpus and Opinion Finder system, respectively [14]. (Bautin et. al. 2008) determine entity sentiment scores on nine languages of news sources and five languages of a parallel corpus; i.e., they calculate the polarity (positive and negative) and subjectivity score (how much sentiment of any polarity the entity receives) for a given entity, by using the automatic English translation of this languages and Lydia system for Sentiment score calculation [15]. (Brooke et. al. 2009) intend the creation of Spanish dictionaries, making an analogy with adjective, noun, verb, adverb, and intensifiers dictionaries in English [16]. Each adjective, noun, verb, adverb dictionary in English is automatically translated to Spanish by means of the online bilingual dictionary Spanishdict and online Google translator, maintaining the polarity of words from English. Also for the bilingual dictionary and translator, the author proposed other method using a textual corpus in Spanish formed by 400 reviews about hotels, movies, music, phones, washing machines, books, cars, and computers. From this corpus, adjectives, nouns, verbs, adverbs, and intensifiers dictionaries were extracted, along the polarity for each word. That is a valid approach to cope with the problem of sentiment classification in Spanish. But, since the words “subjective sense”, as well as the intensity of this subjectivity, can be lost in the translation, we consider that a more detailed study has to be done, where the particularities of this language are taken into account, avoiding loss of generality, as far as possible. On the other hand, although lexicon-based approach has shown good performance in sentiment classification, we consider that the dictionaries are not exhaustive, and an automatic classification of words can be more useful because it allows finding new appraisal words.

In a previous work about automatic word classification, Turney and Littman intend to infer the polarity a word from extremely large corpora, considering its semantic association with other words, which they called "paradigms"[17], [18]. That is, they use two lists of words, called *positive paradigms* and *negative paradigms*, and calculated the association probabilities of a given word with the paradigms as the number of returned matching documents from AltaVista Advance Search, by means of hits (query), and using the NEAR operator. This method depends on the variations and availability of an online search system. Besides, the NEAR operator considers that two words are close when they are halfway at least ten words, but it does not distinguish if the words are in the same sentence, an aspect that we consider important to consider.

Other work closer to our study that intends to classify adjectives in affect, judgement and appreciation was proposed by Taboada & Grieve work in 2004 [19]. They, with similar approach to Turney and Littman, use the NEAR operator on AltaVista Advance Search. Nevertheless they associated the word with a “pronoun-copula” pair (¨I was¨ for affect, ¨he was¨ for judgement, and ¨it was¨ for appreciation) instead of paradigms. This is a first interesting approach to classify attitude using context; but, there are several examples that show that the three proposed combinations (I was (affect), He was (judgment), ¨It was¨ (appreciation)) are not enough and they even fail in some cases.

2.2 OUR PROPOSAL

We proposed a strategy to distinguish words that convey appraisal of an item from the rest, as well as to classify the evaluation polarity (positive or negative). In addition, relying on Appraisal Theory, we classified the evaluation words into affect, judgment, and appreciation. Both, polarity and attitude are recognized using a corpus-based approach. This approach allows recognizing the attitude and polarity of the words determined by the context where they tend to appear.

As we know, many words in the human language are ambiguous (they do not convey a single message) when they are studied out of context; i.e., the context strongly determines the word sense. The evaluative language is not an exception (e.g. it is difficult to know if *big* or *much* conveys a negative or positive evaluation). On the other hand, according to proponents of the Appraisal Theory, some words out of context can be ambiguous according to their attitude class (e.g. *aburrido* (boring), *cómodo* (pleasant), or *agradable* (nice)).

First, we assume that the sentences are the smallest units of coherent messages in texts. Therefore, we assume that the words that tend to co-occur in the same sentences are used with the intention of expressing similar or identical messages. We only focus on the appraisal that is indicated in an explicit and direct way. We describe a supervised strategy to learn sentiment classifiers of words.

Then, considering the previous assumptions, we also assume that words with a given polarity probably tend to occur in sentences of the same polarity. That probably does not happen in sentences with different polarity or without polarity. Therefore, if we start collecting a set of seed words and its polarity (positive, negative, and no-polarity), and if we represent them by a vector of words that occur in their sentences; then we hypothesize that it is possible to learn the context (words) of each polarity class, increasing our lexicon with new words of the same polarity. We have noted that in the current work, we are only interested in determining the positive and negative categories.

Subsequently, the attitude class of words is related to its sense and to the item (sentiment, human behavior, or object) target of the evaluation. We had assumed that in a single sentence, the evaluation of a single item prevails. Therefore, we start from the hypothesis that the words that tend to co-occur in the same sentence are being used with the intention of expressing the same kind of attitude. In a previous work, we represent the words of attitude by a vector of dimension n, where n was the corpus size (sentences), assuming that sentences can be adequate to discriminate the attitude class of words [20]. That is, given a word, the i-entry of the associated vector was 1 if the word was in the i-th sentence, and 0, otherwise. But, the resultant matrix of word by sentence was very sparse. Thus, in this work we decided to represent an attitude word by means of the vector of words used in the same sentences, and similarly for polarity. This allows us to obtain a more condensed matrix that preserved the same assumptions.

Finally, taking into account the overlap of the classes inherent to the Appraisal Theory, which we also found in polarity as well, but to a lesser extent than in affect, appreciation, and judgment (see next section), we consider that some words may potentially be in more than one of these classes. Therefore, we do not treat either polarity or attitude classification as a multi-classification problem. But, we provide a binary classifier for each polarity and attitude class. For example, for affect, we take as positive examples all word vectors labeled as affect, and as negative examples the remaining vectors labeled as appreciation and judgment.

3 CORPUS STRUCTURE

We assume that words attitude can be determined by the context (the vocabulary) where they tend to appear. We use a Spanish corpus of sentences to study a word context. Since these sentences are in Spanish, we do not use any translation tool to obtain them. Besides of the corpus, we gathered a manually annotated word list in Spanish for each attitude class. The words were classified according to the context where they were actually observed in the corpus. That is, a given word was only manually classified with an attitude if it was observed in any sentence belonging to this attitude type. But, these lists did not have enough words; therefore, we increased them by adding new words used by Turney and Littman, available in the General Inquirer lexicon, which we translated using Power Translator system. We removed words resulting erroneous (i.e. non appraisal word or phrases) and we did not preserve their polarity from English. Thus, all words (previous and new) were annotated considering all its possible uses, without taking into account the corpus. That increased the overlap among the compiled lists (see Table 1). We actually got an overlap of 45.2% for affect, 68.9% for appreciation, 63.6% for judgment, 7.6% for negative, and 10.25 for positive class. We took this lexicon of words manually classified as a reference of "*good-classification*" to compare the results automatically obtained by Support Vector Machine and Random Forest classifiers.

Table 1. Statistics for previous and current data collections.

List	Previous	Current
Affect	352	672
Judgment	287	1 806
Appreciation	788	1 758
Positive	573	1 268
Negative	389	1 702
Corpus		
No. sentences	1 408	56 970
No. words	32 920	1 358 727

For corpus construction, we manually extracted sentences selected from movie reviews in Spanish, gathered from the website *ciao.es*. Sentences that were considered as containing words expressing some attitude class were selected from each review, these sentences are referred as “attitudinal sentences”. This website contains reviews about many items; namely, movies, books, cars, cookware, phones, hotels, music, computers, and others. We decided to select movie reviews given that a great variety of appraisal expressions can be observed.

In addition, we included editorials (or opinion articles). These texts are elaborated by communication specialist, such as journalists and editors. Thus, an editorial shows a more elaborated writing style than that in reviews, allowing other elaborations of appraisal expressions. On the other hand, these texts present a novel topic of public interest, which are usually related to politics, economy, society, art, and sport. That helps to increase the number of judgment expressions. We selected editorials of *excelsior.com.mx*, corresponding to the years 1998, and 1999[3].

Finally, we completed the corpus with sentences that were automatically extracted, containing any word from the translation that we did to increase the lexicon. These new sentences were obtained from online texts of an audible book Hispanic library, with 3200 freely available books. We selected 20 texts of stories and poems. Besides, we added letters from a book collection in Spanish, taken from the Project Gutenberg EBook. Both source are freely available.[4,5] These latter texts

3 http://www.exonline.com.mx/home/.
4 http://leemp3.com/

present a more formal style of writing than movie reviews, also different from the editorials style. The editorials are opinions from a personal and critic author viewpoint, whereas stories, poems and letters usually describe sentiments that exemplify emotional states. Our aim was to increase the affect expressions in the corpus.

Corpora are resources very often used in text processing tasks that are approached with machine learning. The corpus composition can influence the quality of learning and therefore the result might not be as expected. On the other hand, elaborating a customized corpus usually becomes a hard work considering the human effort and time required to achieve it, and even so these efforts could not guarantee a 100% quality. However, we can compute some features of our corpora, which can provide indication that we can achieve the desired results. Thereby, we have used The Watermarking On-line Corpus System (WaCOS) [21]. This tool provides a supervised (corpus and gold standard are required) and unsupervised (only the corpus are required) measure set to evaluate features like domain broadness, shortness, stylometry, class imbalance, and structure. We only used the first two.

The domain broadness of a given corpus is measured by the semantic relation among the categories of the texts that form the corpus. These relationships determine whether the corpus domain is narrow (closely related) or wide (unconnected). In this work, we calculated the domain broadness with the Unsupervised Vocabulary-Based (UVB) measure, which is based on vocabulary dimensionality. Let C be a corpus of n sentences, UVB assumes that if the sentences of C share the maximum number of unique term, then the domain of C is narrow.

$$UVB = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{|V(o_i)| - |(V(C))|}{|C|}\right)^2}\ , \qquad \textbf{(1)}$$

where $V(C)$ is the corpus vocabulary and $V(o_i)$ is the vocabulary of the i-th sentence, and $|C|$, $|V(o_i)|$ and $|(V(C))|$ are the cardinalities of C, $V(o_i)$ and $V(C)$ respectively.

The average vocabulary and text length of this corpus are used to approximate the shortness degree. This is calculated using the Shortness-based measure, VDR.

We work with sentences and we know that they are short texts; we also select texts from different source, i.e. reviews, editorial, stories,

5 http://www.gutenberg.org

poems, and letters. We were also interested in knowing the complexity of the selected sentences, i.e., the rate of the average vocabulary for sentence by average sentence size, Vocabulary vs. Document cardinality Ratios (VDR),

$$VDR = \frac{\log\left(\frac{1}{n}\sum_{i=1}^{n}|V(o_i)|\right)}{\log\left(\frac{1}{n}\sum_{i=1}^{n}|o_i|\right)}, \quad (2)$$

where $V(o_i)$ is the vocabulary of the i-th sentence, and $|V(o_i)|$ and $|o_i|$ are the cardinality of $V(o_i)$ and o_i, respectively.

In addition, we evaluated these measures on two others corpora used in Sentiment Classification task; the SFU Review Corpus[6] of movie, book, and consumer product reviews and Pang & Lee´s[7] corpus of 5000 subjective and 5000 objective processed sentences. The statistical properties for these two corpora are taken as reference to compare our results; and they are displayed in Table 2. In this table, we observe that the three corpora have similar properties, considering domain broadness and shortness, but varying in size.

Table 2. Statistical properties of SFU, Pang & Lee, and our corpus.

Corpus	*UVB*	*VDR*	Total Terms	Corpus Vocabulary Size
SFU	12.19	0.96	95 184	14 801
Pang & Lee	11.70	0.96	231 001	23 926
Ours	21.45	0.95	1 603 234	118 552

When we observed UVB results in Fig. 2, we noted that our corpus has a narrow domain. It show that word senses are constrained to its use in the corpus domain, therefore the automatic classification of some words can lead to results that we do not desire, considering that it was manually classified, estimating many of its possible uses. On the other hand, if the domain is narrow then the vocabulary will be limited, which could complicate the classification of new words.

[6] http://www.sfu.ca/~mtaboada/research/SFU_Review_Corpus.html
[7] http://www.cs.cornell.edu/people/pabo/movie-review-data/

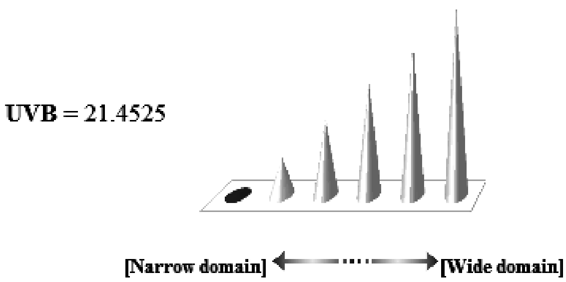

Fig. 2. *Unsupervised Vocabulary-Based* (*UVB*) result for our corpus.

On the other hand, VDR value indicates the average complexity of our corpus, considering that higher complexity implies a bigger vocabulary for each sentence (see Fig. 3.). Therefore, given a word w_i of an attitude categories a, the higher the VDR measure, higher is the probability that w_i occurred in $o \in O$ since we know that $w_{j \neq i} \in a$ occurred in o.

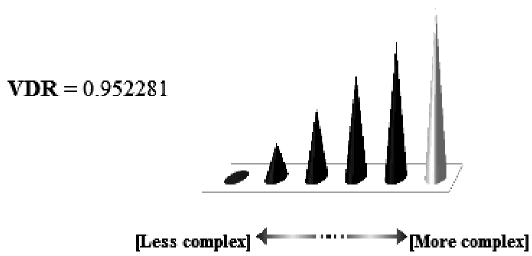

Fig. 3. *Vocabulary vs. Document cardinality Ratios* (*VDR*) result for our corpus.

As mentioned in Section 2, given word to classify, this is represented by a vector of the corpus vocabulary, where the i-entry of the associated vector is 1 if the word occurred with the i-th term of corpus in any sentence, and 0, otherwise. Previously, the sentences were pre-processed obtaining lemmas for each word. To accomplish it, we used the TreeTagger; a system for part-of-speech and extraction of lemmas of the words in a text, developed by Helmut Schmid at the University of Stuttgart[8] [22].

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8 http://www.ims.uni-stuttgart.de/projekte/corplex/TreeTagger/DecisionTreeTagger.html

4 EVALUATION

We have not found related works with which we can compare our results. Therefore, we use as reference of "*good-classification*", the five lists of words manually classified. Thus, the obtained results are compared against the human judgment. As it was explained in a previous section, we use as positive examples the words annotated in each class, and as negative examples the words in the opposite class, excluding the overlap with positive class. Since the number of examples could be minority in the negative set, we used an over-sampling method called Smote (Synthetic minority over-sampling technique), that increases the proportion of the instances in this set.

Regarding the classifiers, we used two of the suite of Data Mining algorithms that Weka system[9] provides; namely, Support Vector Machine (SVM), and Random Forest (RF). We maintained default parameter values for RF classifier, but for SVM, we opted for the probabilistic version of this algorithm, by setting as true the "buildLogisticModels" parameter, and we used a "PolyKernel" of degree 2. To measure the performance of classification, we divided each set in 50% to train and 50% to test, and computing Precision, Recall, and F-Measure (see Table 3).

The class *appreciation* is more clearly learned with RF than *affect* and *judgment*, in terms of F-measure, possibly because is less ambiguous. Also, RF showed an acceptable F-measure when classifying *positive*. We can note that SVM and FR algorithms show a good performance of attitude classification when we compared them with the human judgment. In all except one of the cases, the Recall is above 50%, with the a*ppreciation* class having lowest value. In terms of the values obtained for Precision, we observed that more than half are above 50% and up to 85%. These preliminary results are encouraging but still vague to make a concluding decision, and could happen because the terms selected to represent the words of attitude do not discriminate the classes appropriately. On the other hand, when we increased the previous words list and annotated them without consider their actual use in the corpus, we probably introduce some noise in the gold standard that we employed as classification references.

[9] http://www.cs.waikato.ac.nz/ml/weka/

Table 3. Precision, Recall, F-Measure of SVM, and RF classifiers for attitude.

Class	Precision	Recall	F-Measure		Precision	Recall	F-Measure
Positive							
SVM	0.64	0.53	0.58	**RF**	0.58	0.68	0.62
Negative							
SVM	0.49	0.77	0.60	**RF**	0.48	0.65	0.55
Affect							
SVM	0.60	0.51	0.52	**RF**	0.51	0.65	0.57
Judgment							
SVM	0.39	0.56	0.46	**RF**	0.42	0.65	0.51
Appreciation							
SVM	0.85	0.42	0.56	**RF**	0.81	0.61	0.70

Sentiment Classification is a difficult task that tries to discover the subjectivity in texts and it is further complicated when we works with noisy unstructured texts which prevail in the actual world. We expect that this performance could be improved if the sentences are reasonably well-separated in its different messages, and we do not consider all words in a sentence to be related with the word that we want to classify. We could only consider the words inside a window for representing the attitude, as well as we could use some part-of-speech tagging or shallow parsing tools to split the sentences.

5 CONCLUSIONS

In this paper, we showed classification of attitude words, which are words that convey the evaluation of sentiments or emotional states, about human behaviors, objects, processes, or people. Beside, these words can express affect, judgment, and appreciation; either positive or negative, according to the Appraisal Theory of language. Thus, we present an improved version of our experimental data collection.

The preliminary results show a good performance of the proposed classification strategy when is compared against human judgments. But, we noted that more than one item sometimes can be evaluated inside a single sentence. This is contrary to our assumptions (that in a single sentence, the evaluation of a single item prevails). Therefore, to reach a final conclusion in future work, we plan to use a window of certain number of words instead of whole sentences, to reduce the terms in the sentences used to represent the attitude words. In addition, we will work in classification of expressions (word sequences) rather than individual words.

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