The role of WordNet similarity in the affective analysis pipeline

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Abstract. Sentiment Analysis (SA) is a useful and important discipline in Computer Science, as it allows having a knowledge base about the opinions of people regarding a topic. This knowledge is used to improve decision-making processes. One approach to achieve this is based on the use of lexical knowledge structures. In particular, our aim is to enrich an affective lexicon by the analysis of the similarity relationship between words. The hypothesis of this work states that the similarities of the words belonging to an affective category, with respect to any other word, behave in a homogeneous way within each affective category. The experimental results show that words of a same affective category have a homogeneous similarity with an antonym, and that the similarities of these words with any of their antonyms have a low variability. The novelty of this paper is that it builds the bases of a mechanism that allows to incorporate the intensity in an affective lexicon automatically.

Index terms— Natural language processing, Computational linguistics, Affective computing, Sentiment analysis, Knowledge representation.

1 Introduction

Nowadays, Sentiment Analysis is a useful and important discipline in Computer Science which allows obtaining potentially valuable knowledge about user's perceptions, expectations and attitudes in order to improve the decision-making process regarding products and marketing strategies, among other uses. The SA has not only been applied in business but also in very different areas such as recommender systems [31][13], electoral analysis [20] management of virtual museums [3], multilingual processing [2] [28] among others.

In general terms, there are two approaches to perform this type of analysis [32]. The first one uses a corpus of tagged texts that allows the construction of a classifier trained to execute this task. This approach uses supervised learning techniques that come from machine learning and statistics [22]. The second approach uses lexical resources, such as dictionaries or lexicons. In SA a lexicon is defined as a previously tagged set of words [34], i.e., every word is tagged according to its orientation [6].

There are two main lines of work: The identification of both positive and negative opinions, emotions and evaluations, using computing tools to polarize the content [34].

The estimation of the affective aspect of a text [12] calls Affective Analysis (AA). In AA, a lexicon contains a set of words classified according to the emotions they represent [10] [30]. The emotion expressed in a sentence or text is obtained considering the emotion of the words contained in the text [8]. The sentiment analysis is simpler than the affective analysis. Polarity is classified into two categories, positive or negative, and emotion can do so in many depending on the model of emotions used. In addition, a text can express more than one emotion and even two different texts can express the same emotion but with different intensities.

In AA based on lexicon approach the results depend on the quality and completeness of the lexicon used in the process. The affective lexicons include the words grouped by affective category. This fact only allows a words-bag analysis since the words of each affective category do not contain affective intensity information expressed in a word. Therefore, is not possible determining affective profiling of a document. This work is the first step to find them by using the WordNet similarity metrics of words contained in affective categories.

In sentiment analysis, there are works having improved the quality of affective lexicons by adding information such as valence, arousal and dominance [4, 26, 33]. In case of affective analysis based on lexicon, studies are mainly aimed at increasing the number of words of an affective lexicon[24]. The objective of this paper is to enrich a lexicon of affects by the analysis of the similarity relationship between words. The hypothesis of this work states that the similarities of the words belonging to an affective category, with respect to any other word, behave in a homogeneous way within each affective category. We found evidences that similarities of the words belonging to an affective category, with respect to any other word, behave in a homogeneous way within each affective class. This finding will allow us to determine intensities for the emotions of an affective category and to improve automatic enrichment process of affective lexicons.

The rest of the article is structured as follows: Chapter 2 presents a background and a brief state of the art about the use of lexicons in affective analysis and similarity measures between two words. Chapter 3 presents the hypothesis and experiments performed to prove it. Chapter 4 presents the results and discusses the word's similarity behavior of the lexicon's affective classes. Finally, conclusions and future work lines are presented in Chapter 5.

2 Background and Related works

In lexicons commonly used in AA, consider different classifications of basic emotions, assuming that all other emotions would depend on these subsets. For

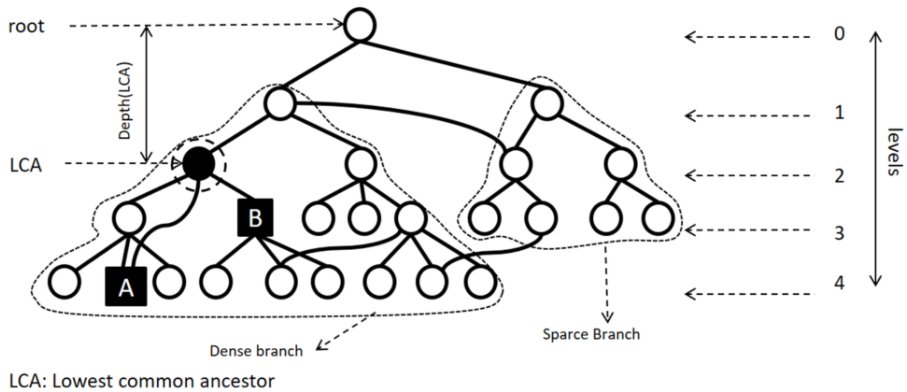

Fig. 1. Depth of the lowest common predecessor.

example, Ekman [9] proposes 6 categories: anger, disgust, fear, joy, sadness and surprise. A study conducted by [30] propose an affective lexicon called WordNet-Affect. This lexicon was built based on the WordNet knowledge base, through the selection and tagging of affective concepts. This initial base was extended using sentences and patterns extracted from Open Mind Commonsense [29]. WordNet-Affect classifies words into the 6 categories of Ekman. Each word in the lexicon contains lexical and affective information, for example, the role of the word in speech (POS, part-of-speech), classification according to emotion theory or representation, among others. Another affective lexicon is the one created by [19] that considers 8 affective categories: anger, anticipation, disgust, fear, joy, sadness, surprise and trust. This lexicon is generated from a list of affective words extracted from the Thesaurus WordNet-Affect and the most frequent words in Google n-gram corpus [5].

In case of affective analysis based on lexicon, studies are mainly aimed at increasing the number of words of an affective lexicon [24] which present an approach for the Japanese language where a similarity metric was used to expand a small group of emotionally-charged words (containing 503 nouns) into an emotions dictionary (containing 15612 verbs). Other studies have improved the lexical resources, for example, through the integration [7] or the creation of lexicons for specific domains [15] [23].

One aspect to consider is that a lexicon can be used in different domains. This may imply that one word may represent different affects in different domains [16]. On the other hand, in order to incorporate the concept of semantic similarity among words in AA, it is necessary to analyze both, the metrics based on the structure and the metrics based on the Information Content (IC).

The semantics' similarity measures based on structure add variables such as lowest common ancestor (LCA) or least common subsumer (LCS), local specificity of the subtree that contains the concepts, the distance between concepts

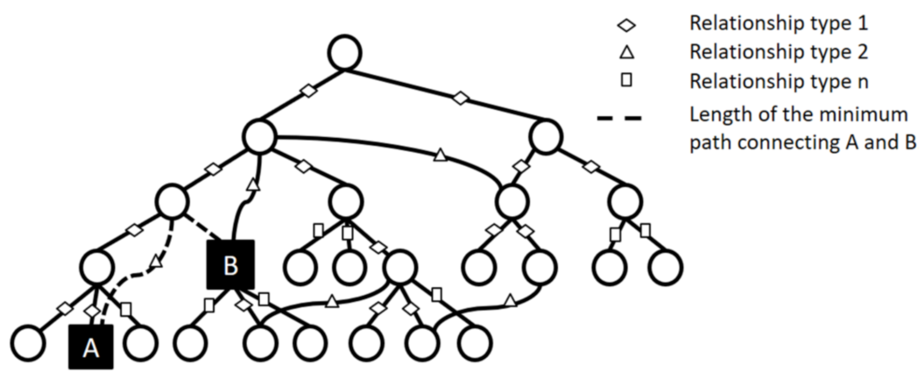

Fig. 2. Local density of the subtree, distance between concepts and types of relationships involved between two concepts.

and the types of relationships involved between them (see Figure1 and Figure 2). For example, the Path measure proposed by Rada et al.[25] is based on the shortest path that connects the senses in the "is-a" relationship of WordNet (Equation 1). The measure proposed by Wu and Palmer [35] is calculated based on the depth of the LCA and the number of links between concepts and predecessor (Equation 2). The measure proposed by Al-Mubaid and Nguyen[1] is calculated based on the depth of each of the concepts, the LCA depth and the shortest distance between concepts. Another proposal from the same authors [21] also includes local specificity. Finally, in [18] the shortest route between concepts, LCA depth and empiric information are considered.

$$SimPath(c_1, c_2) = -\log(pathLen(c_1, c_2)) \tag{1}$$

$$SimWu(c_1, c_2) = \frac{2 * DepthLCA}{Depth_1 + Depth_2} \tag{2}$$

$$SimLCh(c_1, c_2) = -\log(\frac{Len(LCA)}{2 * maxDepth(LCA.pos)}) \tag{3}$$

where
$Depth_1$= min(depth(tree in T1|tree contains LCA))
$Depth_2$= min(depth(tree in T2|tree contains LCA))

In addition to the previous ones, the Leacock Chodorow metric (Equation 3) was used in this work, since it determines how similar two senses are, based on the shortest path that connects the senses (as above) and the maximum depth of them.

Semantics' similarity measures based on information content consider the IC of the nodes derived from the model and statistical corpus, for example, through measures such as term frequency and inverse document frequency (tf-idf). The more information (IC) they share; the more similar concepts are. Some measures in this category are the ones proposed by some authors [27, 17, 18]. In Resnik's metric, the IC of the LCA is considered, and Jiang & Conrath and Lin's proposals include improvements to Resnik's measure as shows Equation 4, where the IC of each of the concepts is added. Lin's measure (Equation 5) is based on Jiang & Conrath's proposal (Equation 6):

$$SimRes(c_1, c_2) = -\log P(LCA(c_1, c_2)) \tag{4}$$

$$SimLin(c_1, c_2) = \frac{2 * IC(LCA(c_1, c_2))}{IC(c_1) + IC(c_2)} \tag{5}$$

$$SimJC(c_1, c_2) = \frac{1}{IC(c_1) + IC(c_2) - 2 * IC(LCA(c_1, c_2))} \tag{6}$$

where c_1 and c_1 are concepts compared, information content of c1 and c2, IC (LCA): Information content of the LCA, IC(c): Information content of c1 and c2.

Recent works incorporate a metric [11] that uses IC and the amount of nodes to try to simplify and improve the calculation of similarity between pairs of words contained in graphs. In sentiment analysis based on lexical approach, there are works having improved the quality of affective lexicons by adding new information such as valence, arousal and dominance [4, 26, 33]. The above, basing on pointwise mutual information (PMI), latent semantic analysis (LSA) and the semantic proximity determine by a co-occurrence between the words and the benchmarks to obtain an index of proximity. To prove our hypothesis an experiment was designed using the affective lexicon in English proposed by Strapparava and Valitutti [30], due to its availability and reputation in affective computing area. Such a lexicon has 1080 words (w_1, $w_2 \ldots w_{1080}$), grouped into 6 affective categories (including repetitions). Anger class has 242 words, disgust has 50, fear has 143, joy has 387, sadness has 195 and surprise has 63 words. From each of the categories the words selected were those with an affective connotation, some 371 in total (34.35%).

3 Method

The concept of affective connotation is used to refer to words that have at least a synset in WordNet, whose hypernyms coincides with at least one of the following concepts: emotion, affect, emotionality, feeling and moods, which hereinafter will be called affective ancestor. From the words selected, it was detected that four belong to more than one affective class; these are horror fear, disgust, dismay fear, sadness, suspense joy, fear and admiration joy, surprise. Out of the 371 words selected, 100 belong to the anger category, 6 to disgust, 46 belong to fear, 145 to joy, 66 to sadness and 8 to surprise. Considering that similarity

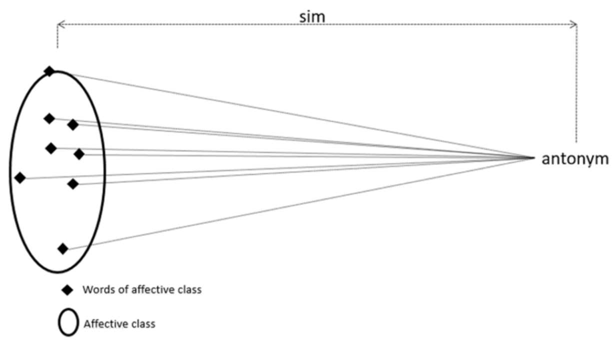

Fig. 3. Research hypothesis and experiments (1/2).

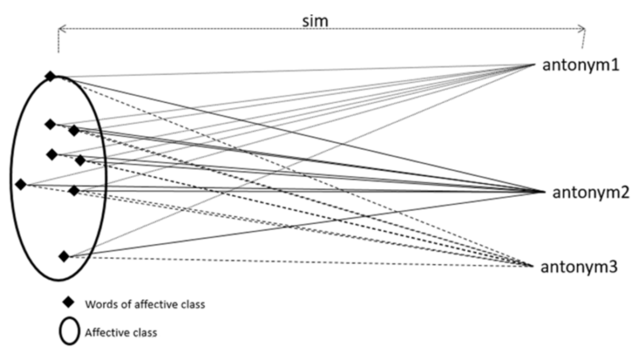

Fig. 4. Research hypothesis and experiments (2/2).

between two words indicates the closeness between them, this work calculated the similarity between words of an affective class and an antonym. The experiment is divided into two parts: The first analyzes the behavior of words of an affective class based on the similarity of these words with an antonym (see Figure 3). Regarding this, it is expected that, within each affective class, the variability of the similarity of words with their antonym is homogeneous.

The second part (see Figure 4) analyzes the similarity of words with 3 antonyms of the affective class. For this case, it is expected that the variability of the similarity of words, with each of their antonyms, is homogeneous and low.

The opinion of an expert was used to identify antonyms, who selected the three best antonyms for each affective class. It is worth mentioning that, although WordNet does not provide an antonym for each affective class, the ones

Table 1. List of antonyms for affective categories.

CLASS	RANKING	ANTONYM
Anger	1	happiness#n#1
	2	calmness#n#3
	3	peace#n#3
Disgust	1	fondness#n#1
	2	admiration#n#1
	3	love#n#1
Fear	1	fearlessness#n#1
	2	bravery#n#2
	3	confidence#n#2
Joy	1	sorrow#n#1
	2	sadness#n#1
	3	melancholy
Sadness	1	happiness#n#1
	2	joy#n#1
	3	gladness#n#1
Surprise	1	expectation#n#3
	2	calmness#n#3
	3	coolness#n#2

proposed by experts are available in WordNet. Table 1 shows the three antonyms arranged according to the importance determined by the expert. It was verified that each antonym also had an affective connotation, in the table the antonym is indicated with the sense that gives it the affective connotation, in the form word#pos#sensenumber.

To obtain similarities between the words of each affective class and each antonym, a Java application that uses WS4J[4] (WordNet Similarity for Java) was developed, where the following measures of semantic similarity are implemented Wu & Palmer, Jiang & Conrath, Leacock & Chodorow, Lin, Resnik, Path, Lesk and Hirst & St-Onge [14]. The last two measures were not used in this analysis since their implementation reported errors when calculating using these metrics.

4 Results and Discussion

The behavior analysis of the similarity between words, and their three antonyms using the six metrics allows observing a homogeneous behavior in each class, this is, the ranges of values in which the similarities move are small. As an example, Figure 5 and Figure 6 show the results of the six-metrics obtained for the words of the anger class considering their three antonyms (calmness#n#, happiness#n#1, peace#n#3).

[4] http://ws4jdemo.appspot.com

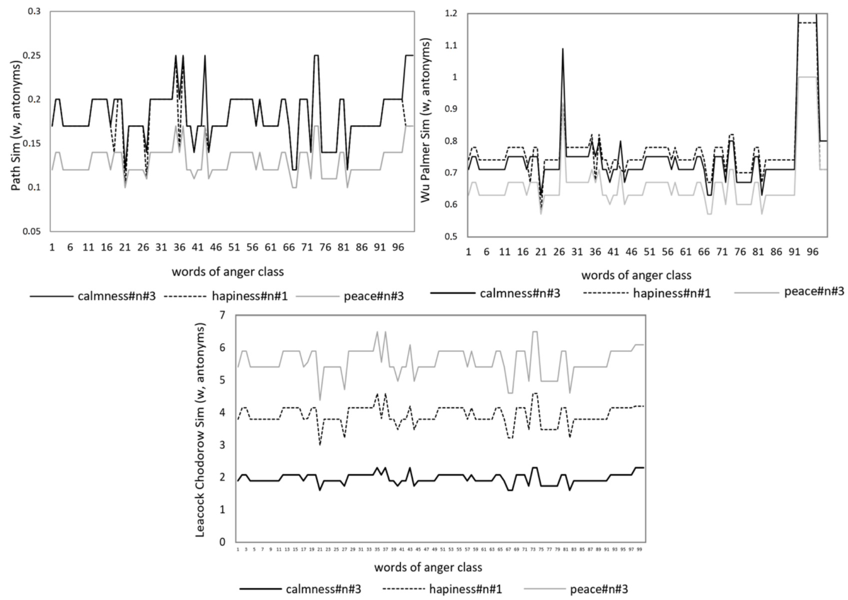

Fig. 5. Behavior of the six metrics based on structure applied to words of the anger affective class, with their 3 antonyms.

In Resnik's case, the similarity provides modest results for all words. This can be explained by the fact that his calculation is based exclusively in IC of the LCA (Equation 4) , where the closest common ancestor is determined, which for many words of the class and their antonyms, is the same, and coincides with the words used to differentiate the affective character of a word (see Figure 7). For example, considering the antonym gladness#n#1 of the sadness class and one of the words of this category w_1=dispiritedness#n#1, the result of Resnik's metric is (antonym, w_2) = 4.627, a value that repeats for 100% of the sadness class and 98% of all the words of the other affective categories, since most words share the common ancestor feeling#n#1. The IC calculation proposed in Resnik (Equation 4) is based on the frequency of the corpusẃords, for this predecessorś example feeling#n#1= 4.627. In general terms, for the metrics based on the IC, a low similarity or a similarity equal to zero could be due to the low frequency of some of the concepts in the vocabulary, even when both concepts are semantically related. This could explain many of the values equal to zero obtained with the Jiang & Conrath and Lin metrics. In most cases, these values repeat for the same words regarding their three antonyms. In addition to this, when Lin's metric is undetermined in Equation 5 the implementation of the API WS4J results in a zero value. The same API yields a zero value when the IC of any of the two words is zero. The variabilities between the similarities of the words of each class with their antonyms, this is Sim($antonym_1$, w_1), Sim($antonym_1$, w_2),. . . , Sim($antonym_1$, w_n) are summarized in Table 2. The minimum standard

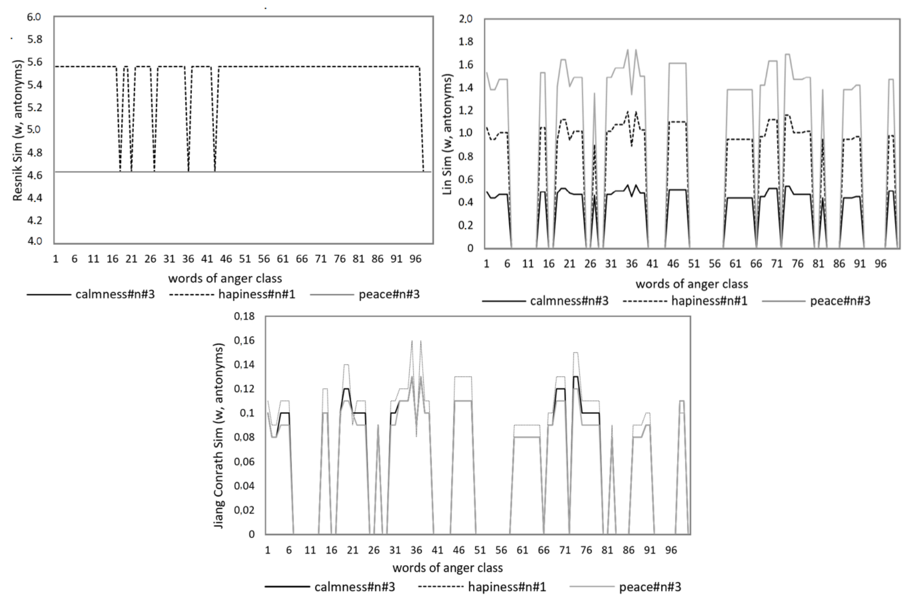

Fig. 6. Behavior of the following three metrics based on IC applied to words of the anger affective class, with their 3 antonyms.

deviation value is zero and the maximum value is 0.614. Regarding minimum values, these were obtained in the following cases: for the 3 antonyms of the surprise class, for the 3 antonyms of the fear class, for 2 antonyms of disgust, for 2 antonyms of anger and for 1 antonym of sadness. These variability values were mainly obtained in Resnick's metric. However, minimum variability was also obtained with Jiang & Conrath and Lin's metric for the antonym gladness#n#1 of the sadness class. On the other hand, the maximum variability value was obtained for the antonym happiness#n#1 of the sadness class with Resnick's metric. In general terms, as is presented in Table 2, the deviations obtained were low.

It is worth mentioning that a certain degree of variability in the results is reasonable since in a same class there are words with different affective intensity. For example, when calculating the similarities of the words grief#n#1 and sorrow#n#1, both belonging to the sadness class, with their antonym joy#n#1, SimLin (joy#n#1, grief#n#1) = 0.50 and SimLin (joy#n#1, sorrow#n#1) = 0.52 and the SimWu (joy#n#1, grief#n#1) = 0.70 and SimWu (joy#n#1, sorrow#n#1) = 0.75 were obtained. This would show there are variations of similarity between words of a same class, indicating differences in the affective intensity of words. On the other hand, the standard deviation analysis of the similarity of each word, with their 3 antonyms, was performed, this is [Sim($antonym_1$, w), Sim($antonym_2$, w), Sim($antonym_3$, w)] (see Table 3), and since the antonyms were selected by the expert as "the best antonyms", it is logical to expect a

Table 2. Variabilities of the similarity of words with their antonyms per class.

CLASS	ANTONYM	WU	JCN	LCH	LIN	RES	PATH
Anger	calmness#n#3	0.123	0.051	0.159	0.237	0.000	0.029
	happiness#n#1	0.108	0.057	0.159	0.271	0.252	0.028
	peace#n#3	0.093	0.049	0.117	0.234	0.000	0.017
Disgust	admiration#n#1	0.015	0.037	0.067	0.180	0.000	0.011
	fondness#n#1	0.015	0.034	0.067	0.169	0.000	0.011
	love#n#1	0.041	0.050	0.151	0.210	0.347	0.030
Fear	bravery#n#2	0.037	0.039	0.160	0.185	0.000	0.031
	confidence#n#2	0.032	0.038	0.117	0.184	0.000	0.018
	fearlessness#n#1	0.037	0.039	0.160	0.185	0.000	0.031
Joy	melancholy#n#1	0.086	0.044	0.190	0.218	0.576	0.031
	sadness#n#1	0.096	0.053	0.225	0.238	0.576	0.044
	sorrow#n#1	0.086	0.045	0.190	0.220	0.576	0.031
Sadness	gladness#n#1	0.081	0.000	0.145	0.000	0.000	0.026
	joy#n#1	0.080	0.054	0.139	0.244	0.159	0.025
	happiness#n#1	0.074	0.052	0.139	0.231	0.614	0.025
Surprise	calmness#n#3	0.034	0.013	0.158	0.024	0.000	0.042
	coolness#n#2	0.018	0.004	0.058	0.005	0.000	0.006
	expectation#n#3	0.034	0.013	0.158	0.027	0.000	0.042

similar behavior of the words of a same class, regarding similarity, regardless of the antonym chosen. In general terms, it is expected that the similarity calculation of a same word with the 3 antonyms yields a low variability. This is ratified in all affective categories; there were even cases with zero deviation. As shown in Table 3, the similarities calculated between the words of the class and their antonyms, with most metrics, have a low variability, which leads us to the verification of the hypothesis. These results indicate that the antonym's selection performed by the experts was accurate since antonyms are similar to each other, see Table 4. As shown in Table 3, for each metric there were small differences between minimums and maximums, especially low in the fear class for each of the metrics.

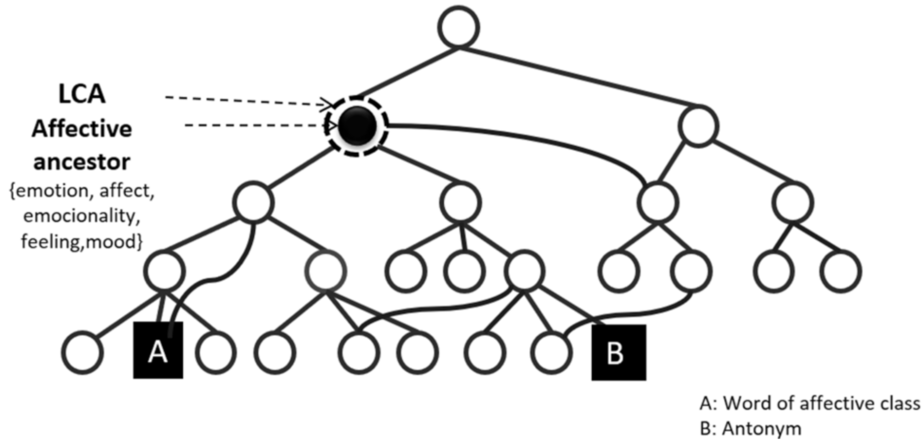

Fig. 7. Low similarity case in Resnik.

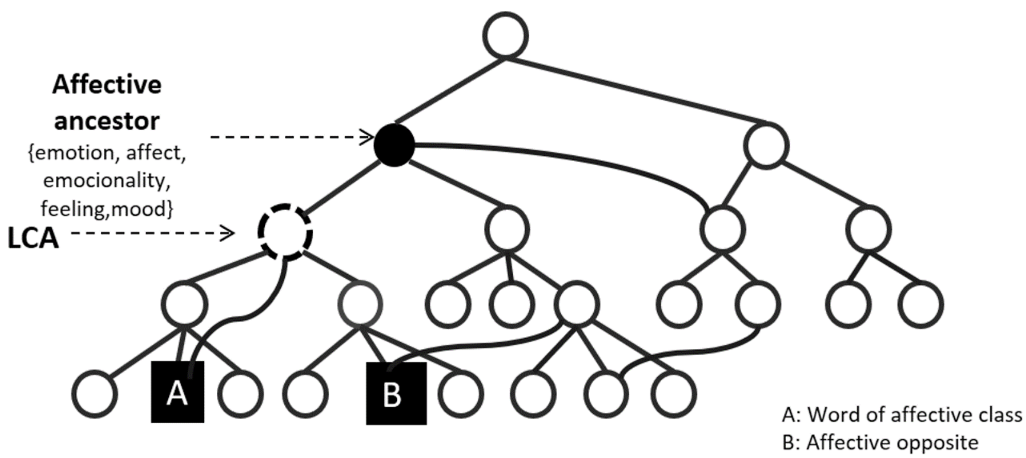

Fig. 8. Use of opposite concept to improve problem of common affective ancestor.

Table 3. Variabilities of similarities between antonyms.

CLASS		WU	JCN	LCH	LIN	RES	PATH
Anger	max	0.088065632	0.014142136	0.188561808	0.044969125	0.4384062	0.0377124
	min	0.028284271	0	0.103708995	0	0	0.0094281
	max-min	0.059781361	0.014142136	0.084852814	0.044969125	0.4384062	0.0282843
Disgust	max	0.051854497	0.030912062	0.188561808	0.078740079	0.4384062	0.0377124
	min	0	0	0	0	0	0
	max-min	0.051854497	0.030912062	0.188561808	0.078740079	0.4384062	0.0377124
Fear	max	0.042426407	0.004714045	0.188561808	0.004714045	0	0.0377124
	min	0.032998316	0	0.11785113	0	0	0.0141421
	max-min	0.00942809	0.004714045	0.070710678	0.004714045	0	0.0235702
Joy	max	0.051854497	0.014142136	0.136707311	0.026246693	1.11E-16	0.0377124
	min	0.004714045	0	0.032998316	0	0	0
	max-min	0.047140452	0.014142136	0.103708995	0.026246693	1.11E-16	0.0377124
Sadness	max	0.070395707	0.098432154	0.230362034	0.34127213	1.5167143	0.0449691
	min	0.018856181	0	0.061282588	0	0	0.0094281
	max-min	0.051539526	0.098432154	0.169079446	0.34127213	1.5167143	0.035541
Surprise	max	0.188561808	0.035590261	0.565685425	0.224251843	1.8149074	0.108423
	min	0.164991582	0.023570226	0.414835978	0.193448242	1.8149074	0.0565685
	max-min	0.023570226	0.012020035	0.150849447	0.030803601	0	0.0518545

Table 4. Similarity between antonyms for each affective class and each metric.

	SIMILARITY	WUP	JCN	LCH	LIN	RES	PATH
Anger							
	calmness-happiness	0.75	0.90	2.07	0.474	4.62	0.20
	happiness-peace	0.66	0.09	1.74	0.4664	4.62	0.14
	peace-calmness	0.87	3.14	2.59	0.9833	9.36	0.33
	σ	0.02	4.98	0.36	0.1755	14.98	0.02
Disgust	admiration-fondness	0.87	0.25	2.59	0.806	8.15	0.33
	fondness-love	0.75	0.10	2.07	0.4981	4.62	0.20
	admiration-love	0.75	0.12	2.07	0.5294	4.62	0.20
	σ	0.01	0.012	0.17	0.0574	8.29	0.01
Fear							
	fearlessness-bravery	1.00	1.3E+07	3.68	1.00	9.81	1.00
	confidence-fearlessness	0.87	6.48	2.59	0.9922	9.82	0.33
	bravery-confidence	0.87	6.48	2.59	0.9922	9.82	0.33
	σ	0.01	1.1E+14	0.80	0.00004	0.00004	0.30
Joy							
	melancholy-sadness	0.93	0.56	2.99	0.903	8.21	0.50
	sadness-sorrow	0.93	0.67	2.99	0.9175	8.21	0.50
	melancholy-sorrow	0.87	0.30	2.59	0.8352	8.21	0.33
	σ	0.002	0.071	0.10	0.0039	0.00	0.02
Sadness	gladness-joy	0.75	0	2.07	0	4.62	0.20
	happiness-joy	0.82	0.14	2.30	0.613	5.55	0.25
	gladness-happiness	0.70	0	1.89	0	4.62	0.17
	σ	0.007	0.013	0.08	0.2505	0.57	0.00
Surprise							
	calmness-coolness	0.50	0.06	1.49	0.227	2.39	0.11
	coolness-expectation	0.5	0.06	1.49	0.237	2.39	0.11
	calmness-expectation	0.85	0.11	2.59	0.5189	4.62	0.33
	σ	0.08	0.001	0.80	0.0549	3.31	0.03

During this work, the use of antonyms to analyze the behavior of the words of each affective category was very useful, since it allowed validating that similarity has a homogeneous behavior and a low variability. It is important to highlight that in order to analyze the similarity values and their relationship with the affective intensity or the diffuse belonging of a word to more than one affective category, it is necessary to use another word as a pivot, not an antonym, just an opposite word. This way, the problem mentioned in Figure 7 would be eliminated, and more significant values of similarity would be obtained for future analysis as visualized in Figure 8.

5 Conclusions and future work

This article evidences that words of a same affective class have a homogeneous similarity, as stated in the hypothesis. This statement is supported by the results, which show a low standard deviation of the similarity of words that make up an affective class.

The results obtained so far show the usefulness of similarity to enrich a lexicon, for example, when identifying words regarding their diffuse classification or when determining the intensity of words that belong to a same affective class. Regarding this, it is possible to add words that do not have affective ancestors to a lexicon tagged with intensities using synonymy relationships. For this, it is important to identify the words that will be used as pivots. Although an antonym was used in this work, we believe that an intensity analysis requires a pivot that provides more meaningful information and that reduces the problem of metric's calculation based on IC, explained in the previous section. A priori, we believe it would be possible to obtain better results if a word with an opposite affective sense is used. For example, using Plutchik's taxonomy (8 emotions), this would require the re-classification of the lexicon based on Ekman's taxonomy (6 emotions). The existence of mechanisms that improve the treatment of antonym relationships in WordNet, as well as the implementation of other similarity semantic metrics, would allow, with less effort, to improve affective knowledge bases, such as lexicons or dictionaries, considering, for example, the use of relationships of transitivity and of the semantic type for the analysis of knowledge structures.

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