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A Swift Classification of Attitude for Natural English Text Corpus

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Abstract

Attitudes have been widely studied in psychology and behavior sciences, as they are an important element of human nature. They have also attracted the attention of researchers in computer science, especially in the field of human computer interaction, where studies have been carried out on facial expressions or on the recognition of attitudes through a variety of sensors. In computational linguistics, all words can potentially convey affective meaning. Every word, even those apparently neutral, can evoke pleasant or painful experiences due to their semantic relation with concepts or categories. In this paper, we address the task of the classification of attitude in Text documents. In order to achieve truly natural classification of attitude in text documents, we set focus in our research to Sentiment Classification from text.

1. Introduction

Some words have meaning with respect to an individual story, while for many others the affective power is part of the collective imagination (e.g. words such as .mum., .ghost., .war.). The automatic detection of attitude in texts is becoming increasingly important from an applicative point of view. Consider for example the tasks of opinion mining and market analysis, affective computing, or natural language interfaces such as e-learning environments or educational/edutainment games. Possible beneficial effects of attitudes on memory and attention of the users, and in general on fostering their creativity are also well-known in psychology field[2].

For instance, the following represent examples of applicative scenarios in which affective analysis would give valuable and interesting contributions:

1.1 Sentiment Analysis. Text categorization according to affective relevance, opinion exploration for market analysis, etc. are just some examples of application of these techniques. While positive/ negative valence checking is an active field of sentiment analysis, we believe that a fine-grained attitude checking would increase the effectiveness of the field.

1.2 Computer Assisted Creativity. The automated generation of evaluative expressions with a bias on some polarity orientation are a key component for automatic personalized advertisement and persuasive communication.

1.3 Verbal Expressivity in Human Computer Interaction. Future human-computer interaction, according to a widespread view, will emphasize naturalness and effectiveness and hence the incorporation of models of possibly many human cognitive capabilities, including affective analysis and generation. For example, attitudes expression by synthetic characters (e.g. embodied conversational agents) is considered now a key element for their believability. Affective words selection and understanding is crucial for realizing appropriate and expressive conversations. The .Affective Text. task is intended as an exploration of the connection between lexical semantics and attitudes, and an evaluation of various automatic approaches to attitude recognition. The task is not easy. Indeed, as (Ortony et al., 1987) indicates, besides words directly referring to attitude states (e.g. .fear., .cheerful.) and for which an appropriate lexicon would help, there are words that act only as an indirect reference to attitudes depending on the context (e.g. .monster., .ghost.). We can call the former *direct affective words* and the latter *indirect affective words* (Strapparava et al., 2006)[1,2].

2. Need

Recognition and analysis of human attitudes have attracted a lot of interest in the past two decades and have been researched extensively in neuroscience, psychology, cognitive sciences, and computer sciences. Attitudes have been widely studied in psychology and behavior sciences, as they are an important element of human nature. They have also attracted the attention of researchers in computer science, especially in the field of human computer interaction. Most of the past research in machine analysis of human attitude has focused on recognition of prototypic expressions of six basic attitudes based on data that has been posed on demand and acquired in laboratory settings. In computational linguistics, the automatic detection of attitudes in texts is becoming increasingly important from an applicative point of view [2].

With the development of Internet, the information which appears by text form are more and more frequent. It becomes us one kind of the most easily to gain and the richest interactive resources. Presently, however, the text attitude analysis aspect's research is little. Nowadays, with the un-causing development of natural language technology, people could extract attitude information from text through analyzing grammar structure, Semantic information and attitude glossary methods etc. From the massive texts withdraws the attitude information which is contained in them has the broad application prospect in many aspects. For example, automated analysis the received mail attitude information, and give relevant attitude computing result before user reads. Through attitude analysis to the information in homepage, it may examine the homepage which contain violent attitude, realize homepage filtration and ensure the net's information security. Along with natural language processing technology unceasing development, the text attitude computation has a richer method and reliable theory basis. At present, the text attitude computation has the widespread application prospect in many domains. For example, speech synthesis, information security, intelligent robot, pattern recognition, personalized text, and analysis article attitude structure aspects and so on [4].

3. Attitude Categories

In human-human communication, we can observe a lot of attitude states including "happy," "sad," "surprise," "fear," and so on. These categories of attitude help the conversational agent like the chatbot or intelligent robot to give more human-like responses based the attitude state of the user. However, in task-oriented application like spoken dialog systems, it need the notion of application dependent attitudes, and thus focuses on a simplified set of attitudes such as negative, neutral and positive. For example, the detection of negative attitudes can be used as a strategy to improve the quality of the service in call center application. Thus, the attitude categories are dependent on the corpus and application domain. In my work, we define the attitude set which is categorized in Table 1.1. This is similar to the set used by Feeler [19]. In particular, neutral is used in the place that there is no attitude present in the utterance or that there is no attitude discernable.

Table 1.1 : Attitude Categories in the data

Primary attitude	**Secondary attitude**	**Tertiary attitudes**
Love	Affection	Adoration, affection, love, fondness, liking, attraction, caring, tenderness, compassion, sentimentality
	Lust	Arousal, desire, lust, passion, infatuation
	Longing	Longing
Joy	Cheerfulness	Amusement, bliss, cheerfulness, gaiety, glee, jolliness, joviality, joy, delight, enjoyment, gladness, happiness, jubilation, elation, satisfaction, ecstasy, euphoria
	Pride	Pride, triumph
Surprise	Surprise	Amazement, surprise, astonishment
Anger	Irritation	Aggravation, irritation, agitation, annoyance, grouchiness, grumpiness
	Disgust	Disgust, revulsion,

		contempt
Sadness	Suffering	Agony, suffering, hurt, anguish
	Disappointment	Dismay, disappointment, displeasure
Fear	Horror	Alarm, shock, fear, fright, horror, terror, panic, hysteria, mortification
	Nervousness	Anxiety, nervousness, tenseness, uneasiness, apprehension, worry, distress, dread

4. Methods to Recognize Attitude From Text

4.1 Basis for Affective Text Classification. As the purpose of affect recognition in a remote communication system is to relate text to avatar attitude expressions, affect categories should be confined to those that can be visually expressed and easily understood by users. We analyzed attitude categorizations proposed by theorists, and as the result of our investigation, for affective text classification, we decided to use the subset of attitude states as follows [16]: "anger", "disgust", "fear", "guilt", "interest", "joy", "sadness", "shame", and "surprise". Izard's [16] theory postulates the existence of discrete fundamental attitudes with their motivational, phenomenological properties, and personal meanings. Besides specific or qualitatively distinct affective states, we defined five communicative functions that are frequently observed in online conversations ("greeting", "thanks", "posing a question", "congratulation", and "farewell"). In order to support the handling of abbreviated language and the interpretation of affective features of lexical items, the Affect database was created. The Affect database includes the following tables: Emoticons, Abbreviations, Adjectives, Adverbs, Nouns, Verbs, Interjections, and Modifiers. The affective lexicon was mainly taken from WordNet-Affect [17]. Attitude categories with intensities were manually assigned to the attitude-related entries of the database by three independent annotators. Attitude intensity values range from 0.0 to 1.0. Emoticons and abbreviations were transcribed and related to named affective states (with intensity), whereby each entry was assigned to only one category (e.g., emoticon ":-S" [worry] was related to "fear" with intensity 0.4). Considering the fact that some affective words may express more than one attitude state, annotators could relate words to more than one category (e.g., the final annotation for noun "*enthusiasm*" is "interest:08, joy:0.5"). Two annotators gave coefficients for intensity degree strengthening or weakening (from 0.0 to 2.0) to the adverbs of degree, and the result was averaged (e.g., coeff("*significantly*") = 2.0).

4.2 Affect Analysis Model. While constructing our lexical rule-based approach to affect recognition from text, we took into account linguistic features of text written in a free informal style [18]. Our Affect Analysis Model was designed based on the compositionality principle, according to which we determine the attitude meaning of a sentence by composing the pieces that correspond to lexical units or other linguistic constituent types governed by the rules of aggregation, propagation, domination, neutralization, and intensification, at various grammatical levels. By analyzing each sentence in sequential stages (symbolic cue processing, detection and transformation of abbreviations, sentence parsing, and word/phrase/sentence-level analyses), our method is capable of processing sentences of different complexities, including simple, compound, complex (with complement and relative clauses), and complex-compound sentences.

Sentiment classification of text is very important in applications like attitude text-to-speech (TTS) synthesis, human computer interaction, etc. Past studies on attitude classification focus on the writer's attitude state conveyed through the text. This research addresses the reader's attitudes provoked by the text. The classification of documents into reader attitude categories has novel applications. One of them is to integrate reader attitude classification into a web search engine to allow users to retrieve documents that contain relevant contents and at the same time produce proper attitudes. Another is for websites to organize contents according to reader attitude categories and provide users a convenient browse.[19]

5. Attitude Classification

Attitude classification in texts is to classify texts into certain attitude categories, like the six basic attitudes, namely, Anger, Disgust, Fear, Happiness, Sadness and Surprise. It can be viewed from two perspectives, the writer's perspective and the reader's perspective. The writer conveys certain attitudes through a piece of text. The writer or agents present in the text may be experiencing the attitudes. By detecting the feelings the writer of the text was expressing, we can quickly learn how people feel about a particular event or item. Past studies concentrated on this perspective. The reader's perspective tries to find out what attitudes the text provokes in their readers. Distinctions exist between reader and writer attitudes, because they do not always agree. For example, a politician's blog entry describing a miserable day may not cause its readers to feel the same way. Such research has novel applications. One of the applications is to integrate reader attitude classification into a web search engine, and thereby enabling users to retrieve documents that contain relevant contents and produce desired attitudes as well. Nowadays, more and more news websites provide attitude voting systems for users to choose their attitudes after reading a news article, and then group news articles into attitude categories for users to browse. Such websites provide a large-scale data source for reader attitude classification research. On the other hand, automatic attitude classification will relieve the websites' drawback of requiring efforts on the part of readers for attitude categorization. We explore sentence level reader attitude classification and take news headlines as the target data. Headlines typically consist of a few words and are often written by creative people with the intention to provoke attitudes, and consequently to attract the readers' attention.

6. Proposed Work

We are focusing on the attitude classification of text document. The text documents typically consist of a few words and are often written by creative people with the intention to provoke attitudes, and consequently to attract the readers' attention i.e. news or news headlines, reviews of movie or product or any type of services etc. These type of data may be collected from web or it may be written by any customers or writer. These characteristics make these text document particularly suitable for use in an automatic attitude recognition setting, as the affective/attitude features (if present) are guaranteed to appear in these short sentences. The structure of the task was as follows:

6.1 Corpus: News titles, Product reviews, Movie Reviews, extracted from news web sites (such as Google news, CNN) and/or newspapers/ or any company web site or any movie web sites or any search engine. In the case of web sites, we can easily collect a few thousand titles in a short amount of time.

6.2 Objective: Provided a set of predefined six attitude labels (i.e. Anger, Disgust, Fear, Joy, Sadness, Surprise), classify the titles with the appropriate attitude label and/or with a valence indication (i.e. positive/negative) (positive/negative).The attitude labeling and valence classification were seen as independent tasks, and thus a team was able to participate in one or both tasks. The task was carried out in an unsupervised setting, and consequently no training was provided. The reason behind this decision is that we want to emphasize the study of attitude lexical semantics, and avoid biasing the participants toward simple texts categorization. approaches. Nonetheless supervised systems were not precluded and in this case participating teams were allowed to create their own supervised training sets. Participants were free to use any resources they wished. We have provided a set words extracted from WordNet Affect, relevant to the six attitudes of interest. However that the use of this list of words was entirely optional.

6.3 Data Set: We have mainly used sentences from ISEAR [52] dataset, attitude words from Wordnet-Affect. The data set may consists of news headlines drawn from major newspapers such as New York Times, CNN, and BBC News, as well as from the Google News search engine. We tried to focus our attention on headlines for two main reasons. First, news have typically a high load of attitude content, as they describe major national or worldwide events, and are written in a style meant to attract the attention of the readers. Second, the structure of headlines was appropriate for our goal of conducting sentence-level annotations of attitudes.

6.4 WordNet: WordNet is a large lexical database of English, with words grouped into synonym sets called *synsets*. A problem we encountered with this resource is that often times the only candidate in the synset is the target word itself. Thus, to enlarge the set of candidates, we use both the synonyms and the hypernyms of the target word. We also remove the target word from the synset, to ensure that only viable candidates are considered.

6.5 Data Annotation: To perform the annotations, we developed a Web based annotation interface that displayed one headline at a time, together with six slide bars for attitudes and one slide bar for valence. The interval for the attitude annotations was set to [0; 100], where 0 means the attitude is missing from the given documents, and 100 represents maximum attitude load.

The interval for the valence annotations was set to [-100; 100], where 0 represents a neutral text document, -100 represents a highly negative headline, and 100 corresponds to a highly positive headline. Unlike previous annotations of sentiment or subjectivity, which typically relied on binary 0-1 annotations, we decided to use a finer-grained scale, hence allowing the annotators to select different degrees of attitude load.

The test data set was independently labeled by six annotators. The annotators were instructed to select the appropriate attitudes for each text based on the presence of words or phrases with attitude content, as well as the overall feeling invoked by the headline. Annotation examples were also provided, including examples of headlines bearing two or more attitudes to illustrate the case where several attitudes were jointly applicable. Finally, the annotators were encouraged to follow their .first intuition, and to use the full-range of the annotation scale bars.

6.7 Inter-Annotator Agreement: We conducted inter-tagger agreement studies for each of the six attitudes and for the valence annotations. The agreement evaluations were carried out using the Pearson correlation measure, and are shown in Table 1.2. To measure the agreement among the six annotators, we first measured the agreement between each annotator and the average of the remaining five annotators, followed by an average over the six resulting agreement figures.

Table 1.2: Inter-annotator agreement

ATTITUDES
Anger 49.55
Disgust 44.51
Fear 63.81
Joy 59.91
Sadness 68.19
Surprise 36.07
VALENCE
Valence 78.01

7. Methodology

Converting a piece of text into a feature vector or other representation that makes its most salient and important features available is an important part of data-driven approaches to text processing. There is an extensive body of work that addresses feature selection for machine learning approaches in general, as well as for learning approaches tailored to the specific problems of classic text categorization and information extraction. A comprehensive discussion of such work is beyond the scope of this survey. In this section, we focus on findings in feature engineering that are specific to sentiment analysis.

7.1 Term Presence vs. Frequency: It is traditional in information retrieval to represent a piece of text as a feature vector wherein the entries correspond to individual terms. Term frequencies have traditionally been important in standard IR, as the popularity of tf-idf weighting shows; but in contrast, Pang et al. obtained better performance using *presence* rather than frequency. That is, binary-valued feature vectors in which the entries merely indicate whether a term occurs (value 1) or not (value 0) formed a more effective basis for review polarity classification than did real-valued feature vectors in which entry values increase with the occurrence frequency of the corresponding term.

7.2 Term-based Features Beyond Term Unigrams: Position information finds its way into features from time to time. The position of a token within a textual unit (e.g., in the middle vs. near the end of a document) can potentially have important effects on how much that token affects the overall sentiment or subjectivity status of the enclosing textual unit. Thus, position information is sometimes encoded into the feature vectors that are employed. Whether higher-order *n*-grams are useful features appears to be a matter of some debate. For example, Pang et al. report that unigrams outperform bigrams when classifying movie reviews by sentiment polarity, but Dave et al. find that in some settings, bigrams and trigrams yield better product-review polarity classification. Also some techniques explore the use of a sub sumption hierarchy to formally define different types of lexical features and the relationships between them in order to identify useful complex features for opinion analysis. Some system apply a Markov Blanket Classifier to this problem together with a meta-heuristic search strategy called Tabu search to arrive at a dependency structure encoding a parsimonious vocabulary for the positive and negative polarity classes.

7.3 Parts of Speech: Part-of-speech (POS) information is commonly exploited in sentiment analysis and opinion mining. One simple reason holds for general textual analysis, not just opinion mining: part-of-speech tagging can be considered to be a crude form of word sense disambiguation. Adjectives have been employed as features by a number of researchers. One of the earliest proposals for the data-driven prediction of the semantic orientation of words was developed for adjectives. Subsequent work on subjectivity detection revealed a high correlation between the presence of adjectives and sentence subjectivity. This finding has often been taken as evidence that (certain) adjectives are good indicators of sentiment, and sometimes has been used to guide feature selection for sentiment classification, in that a number of approaches focus on the presence or polarity of adjectives when trying to decide the subjectivity or polarity status of textual units, especially in the unsupervised setting. Rather than focusing on isolated adjectives, Turney proposed to detect document sentiment based on selected phrases, where the phrases are chosen via a number of pre-specified part-of-speech patterns, most including an adjective or an adverb.

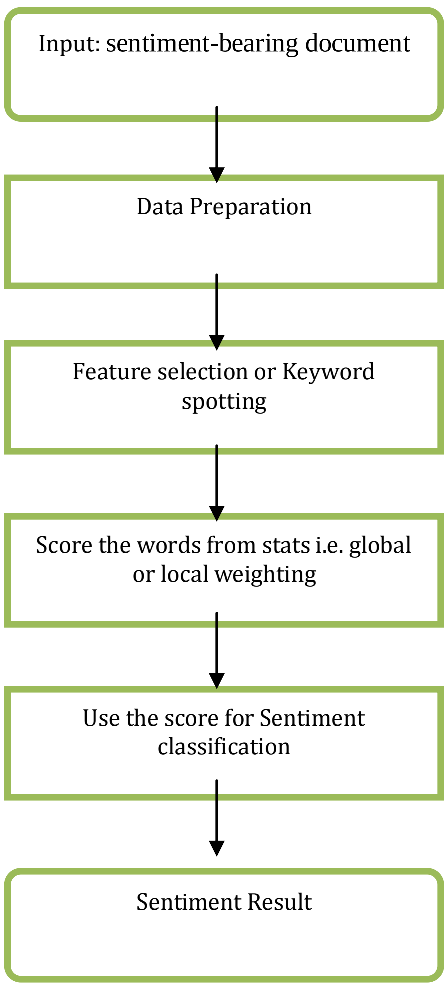

Fig 1.1: General framework of Sentiment classification from text

The fact that adjectives are good predictors of a sentence being subjective does not, however, imply that other parts of speech do not contribute to expressions of opinion or sentiment. In fact, in a study by Pang et al. on movie-review polarity classification, using only adjectives as features was found to perform much worse than using the same number of most frequent unigrams. The researchers point out that nouns (e.g., “gem”) and verbs (e.g., “love”) can be strong indicators for sentiment. There have been several targeted comparisons of the effectiveness of adjectives, verbs, and adverbs, where further sub categorization often plays a role.

Following Figure shows a framework of sentiment classification. It is logically derived from critical analysis of existing research in automated sentiment classification from text. As shown in the figure there are mainly one methods of sentiment classification.

8. Proposed Algorithm

This system deals with predicting the sense of given text document. For example, if user has written a product review then sentiment analyzer tries to predict whether user is criticizing the customer product or he is praising the consumers product. In this implementation, a seed list of six primary attitude is used. The list is prepared manually with the help of WordNet. At sentence level, if more attitude words of certain polarity are used then sentence have that polarity. If there is negation words i.e. not, don’t, never etc. left to an attitude word then current polarity is negated and give attitude with antonym/opposite attitude. In this system, we have used Vector Space Model for sentiment classification. Sentiment output with negative valence represent negative polarity and output with positive valence represent positive polarity. For polarity we score 1-100 to representing the overall sentiment can be expressed about the topic or intersection of topic. This score is based on the posterior estimate of the ratio of frequency of positive to negative comment. This classifier is used to determine attitude i.e. sentiment with its polarity.

We conduct a set of experiments to examine whether automatically trained models can be used to recognize the attitude of unseen subjects. Our approach can be summarized in following steps:

1. Collect individual corpora;
2. Extract relevant features from the texts;
4. Build *tf-idf* score based on the features;
5. Test the learned models on the sentiment outputs of unseen individuals.

The following sections describe each of these steps in more detail.

8.1 Steps involved in Attitude classification:

8.1.1 Removal of numbers and punctuation marks from the documents
8.1.2 Conversion of all alphabets into lower case characters (to avoid the distinctions between capitalized and lower case word)
8.1.3 Removal of the stop words (words like a, the, and…)
8.1.4 Stemming – conversion of words to root form (so as to avoid differentiation between different forms of the same word)
8.1.5 Negation – conversion of attitude those words came after negation words For example :- 'not good' in this word 'not' is negation word and good word represent the attitude 'joy' but it came after the negation word so it get reverse so this word represent the attitude 'sad'
8.1.6 Feature extraction using the lists generated from the WordNet Database
8.1.7 Computation of TF-IDF score of the features do obtained
8.1.8 Creation of the term – document matrix
8.1.9 Training and Testing with the specified classifier using cross validation technique

8.2 Features of Implemented System:

8.2.1 Use of sentences from ISEAR dataset, attitude words from Wordnet-Affect and polarity of words from WPARD datasets.
8.2.2 Use of Vector Space Model for classification of text in attitudes.
8.2.3 Measurement of the attitude intensity i.e. attitude polarity/valence on attitude classification in text .
8.2.4 High dimensional input space- when learning text classifiers, one has to deal with very many features. Since VSMs use over fitting protection, which does not necessarily depend on the number of features, they have the potential to handle these large feature spaces.

9. Training & Results Analysis

For training, we have used combination of ISEAR, Wordnet-Affect and WPARD datasets. Testing is performed on ISEAR data set. Our main training dataset, ISEAR, is further expanded by adding attitude words from Wordnet-Affect and WPARD (Wisconsin Perceptual Attribute Rating Database) to improve the attitude classification of sentences. Each word in Wordnet-Affect and WPARD is replicated up to average number of terms per document which is in our experiment to make ISEAR like sentences. In this case, the sentences are constructed using the same words.

We have analyzed the Experimental Results for Sentiment Classification from Text using F1- Measure.

Table1.3:Result Analysis for Sentiment classification from text using F1-measure

Traing Set	Test Set	
	ISEAR Dataset	
	Attitude Name	**F1-Measure**
ISEAR Dataset + WordNet-Affect+WPARD	Anger	0.9175
	Disgust	0.9239
	Fear	0.8950
	Joy	0.9814
	Sad	0.8512

We have used the F1-Measure method for performance measurement of attitude classification from text system. In this experiment, we have used the ISEAR, WPARD, Wordnet- Affect as our training set and for testing we have used the ISEAR dataset. To F1-measure method, we have calculate the precision and recall for each attitude separately.

In this experiment, we have considered the effect of adding attitude words from WPARD and WordNet-Affect and ISEAR into our training set. Result shows that classification performance increased for SVM and VSM respectively. VSM gives drastic and improved difference compared to other classifiers.

Table 1.4 : Comparative result analysis for different classifiers

	Test Set	
	ISEAR Dataset	
Training Set	**Classifiers**	**Mean F1-Measure**
ISEAR+WPARD+ WordNet- Affect	Naïve Bayes Classifier 5 Class Attitudeal Classication	61.20
	Support Vector Machine 5 Class Attitudeal Classification	68.30
	Vector Space Model For 5 Class Attitudeal Classification	**91.38**

10. Conclusions & Future Works

Human attitude can be expressed through many kinds of medium such as speech, image, audio, facial expression and so forth. This work totally focuses on textual data of them. Text does not only communicate informative contents, but also attitudinal information, including attitude states. Narrative text is often especially prone to having attitude contents. In the literary genre of fairy tales, attitudes such as HAPPINESS and ANGER and related cognitive states, e.g. LOVE or HATE, become integral parts of the story plot, and thus are of particular importance. Moreover, the story teller reading the story interprets attitudes in order to orally convey the story in a fashion which makes the story come alive and catches the listeners' attention. In speech, speakers effectively express attitudes by modifying prosody, including pitch, intensity, and durational cues in the speech signal. Thus, in order to make text-to-speech synthesis sound as natural and engaging as possible, it is important to convey the attitude stance in the text. However, this implies first having identified the appropriate attitude meaning of the corresponding text passage. Thus, an application for attitude text-to-speech synthesis has to solve two basic problems. First, what attitude or attitudes most appropriately describe a certain text passage, and second, given a text passage and a specified attitude mark-up, how to render the prosodic contour in order to convey the attitude content.

Through comparative evaluations of several knowledge-based and corpus-based methods carried out on a large data set of 1,000 deadlines, we have tried to identify the methods that work best for the annotation of attitudes. Recognition methods based on the cognition introduced the cognition linguistics and the psychology knowledge into the attitude recognition, attempts to solve the existing problem from a new angle.

In our future study we will investigate those issues and explore the possibilities to overcome the current limitations of the system. As our system is completely lexical and the language of online conversations is "evolving", we are planning to realize a procedure for the automatic updating of the Affect database. With respect to the rules for composition of attitude vectors of terms comprising phrases or clauses, we believe that the approach aiming at learning rules from corpora would be useful.

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