TEXTUAL EMOTIONS RECOGNITION WITH AN INTELLIGENT SOFTWARE OF SENTIMENT ANALYSIS

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Abstract

People when they speak, interact and write convey emotions. The life is an emotion. Emotions play a key role in any kind of decision in affective, social or business area. The emotions are manifested in verbal, facial expressions but also in written texts. Nowadays, with the growth of internet and web 2.0, many humans interact, in textual manner, with other people and exchange ideas, opinions in the web channel or web communities. Emotions in text are very important if we consider that textual interface with the computer is one of the most used. Emotions are treated largely in affective computing that focuses on improving the interaction between user and computer. In this paper we present a software with an original algorithm that we have developed for textual emotion recognition. From affectivity of single words and sentences we can estimate and polarize, from emotional point of view, an assertion or opinion in positive or negative also with its intensity.

1. INTRODUCTION

Emotion technology [1] is an important component of artificial intelligence, especially for human-computer communication. For emotion recognition by an artificial intelligent system we must take into account different contexts. Many kinds of physiological characteristics are used to extract emotions, such as voice, facial expressions, hand gestures, body movements, heartbeat, blood pressure and textual information. The face and the verbal language can reflect the outside deepest emotions: a trembling voice, a tone altered, a sunny smile, the face corrugated.

This paper focuses on textual emortion recognition. Nowadays in the web there is a large amount of textual information. It is interesting to extract emotions for different goals like those of business.

For example, in luxury goods, the emotional aspects as brand, uniqueness and prestige for purchasing decisions, are more important than rational aspects such as technical, functional or price. In this case customer is happy to buy a product even with high prices.

Emotional Marketing aims to stimulate emotions in customer for tying him to brand and so increase the sell of product/service.

Nowadays itsn't the product to be sold, since for each category there is a wide choice, but the focus is the relationship that the consumer establishes with the brand and with the emotions which the product communicates.

In our department we have developed an original algorithm for textual emotion recognition.

This paper is organized as follows: in the next section is shown the literature review while in the third section we give a description of different type of emotions. In the fourth section our research method to extract emotions from textual sources is discussed. The fifth and sixth sections are useful to show results and analyse them. Finally some conclusions are drawn.

2. LITERATURE

An emotion is a mental and physiological state associated with a wide variety of feelings, thoughts, and internal (physical) or external (social) behaviors.

Love, hate, courage, fear, joy, sadness, pleasure and disgust can all be described in both psychological and physiological terms. An emotion is a psychological arousal with cognitive aspects that depends on the specific context. According to some researcher, the emotions are cognitive processes. Emotion is a process in which the perception of a certain set of stimuli, follows cognitive assessment which enables people to label and identify a particular emotional state. At this point there will be an emotional physiological, behavioral and expressive response. For example, the primordial fear, that alert us as soon when we hear a sudden noise, allows to react to dangerous situations and provides instantly resources to face them as escape or close the door. The emotional stimuli may be an event, a scene, a face, a poster, an advertising campaign. These events, as a first reaction, put on alert the organism with somatic changes as heart rate, increase of sweat, acceleration of respiratory rhythm, rise of muscle tensions.

Emotions give an immediate response that often don't use cognitive processes and conscious elaboration and sometimes they have an effect on cognitive aspects as concentration ability, confusion, loss, alert and so on. This is what is asserted in evaluation theory, in which cognitive appraisal is the true cause of emotions [2].

Two factors that emerge permanently are those related to signals of pleasure and pain and characterizing respectively the positive and negative emotions. It’s clear that these two parameters alone are not sufficient to characterize the different emotions.

Many authors debate on primary and secondary emotions, other on pure and mixed emotions, leaving the implication that emotions can somehow be composed or added.

From the variations, shades, nuances of primary emotions it is possible arise others complex emotions. The basic emotions can be detected from the study of emotional expressions (facial or textual) and from their invariance respect to different individuals and different cultures.

Various lists, proposed in many studies, include the following primary emotions: fear, joy, sadness, anger, disgust, surprise.

The systems based on the analysis of physiological response as blood pressure, heart rate, respiration change present an initial phase where the signals are collected in configurations to be correlated with different emotional states and a subsequently recognition basing on the measure of indicators.

One of the interesting early work on the emotions was that one of Ortony [3]. From this work, through componential analysis, other authors constructed an exhaustive taxonomy on affective lexicon.

According to Ortony, stimuli that cause emotional processes are of three basic types: events, agents and objects corresponding to three classes of emotions: satisfied/ unsatisfied (reactions to events), approve/disapprove(reaction to agents), appreciate/unappreciate (reaction to objects).

According to Osgood [4] an emotion consists of a set of stages: stimulus (neural and chemical changes), appraisal and action readiness.

Continuing the studies of Charles Darwin, the canadian psychologist Paul Ekman [5] has confirmed that an important feature of basic emotions is that they are universally expressed, by everybody in any place, time and culture, through similar methods.

Some facial expressions and the corresponding emotions are not culturally specific but universal and they have a biological origin.

Ekman, analyzed how facial expressions respond to each emotion involving the same type of facial muscles and regardless of latitude, culture and ethnicity. This study was supported by experiments conducted with individuals of Papua New Guinea that still live in a primitive way.

Damasio [6] affirms that the decisions are choices mainly emotionals. To support this assertion, Damasio shows the cases of some patients who, with neurological damage in certain brain areas, are completely unable to make a decision, despite being perfectly able to make a correct evaluation of all factors involved.

Daniel Goleman [7] is one of the major experts in the world of emotional intelligence. Goleman, in his experiments, noted the success of people without a great cognitive intelligence of logical-mathematical type but with a strong emotional sensitivity.

3. EMOTIONS

Human emotions are deeply joined with the cognition. Emotions are important in social behavior and to stimulate cognitive processes for strategies making. Emotions represent another form of language universally spoken and understood. Identification and classification of emotions has been a research area since Charles Darwin's age. In this section we consider facial, vocal and textual emotional expressions.

3.1 Facial expressions

Facial expression recognition [8] [9], coupled with human psychology and neuroscience, is an area which can bridge psychology and computations. Expressions of a human face can be captured through facial features.

There are two types of facial expression features, transient (wrinkles and bulges) and intransient (mouth, eyes and eyebrows).

The feature points of a face, for recognizing facial expression, are located at eyebrows, eyelids, cheeks, lips, chin and forehead.

The first and the most important step in feature detection is to track the position of the eyes. Thereafter, the symmetry property of the face with respect to eyes is used for tracking the rest of the features like eyebrows, lips, chin, cheeks and forehead.

The systems for treatment of facial expressions [10] are based on computational images. The model can contain information on the geometry of the face and facial muscles or on movements of various portions of the face during a change of expression. In some sophisticated models, the patterns of expression are obtained combining together significant portions of the face such as mouth, eyes or eyebrows.

3.2 Vocal expressions

In the case of voice analysis, the parameters considered are typically volume, speed, regularity of speech. The vocal expression is also strongly influenced from the mood of the speaker, context and culture. For example, an hold orator, engaged in a major speech, hardly shows any tension level. He takes the same behaviour in any context.

3.3 Textual emotions

The core of our project is to recognize the emotion sensing from textual information. This field or research is known as emotion recognition or emotion computing. Human-machine interface technology has been investigated for several decades. Recent research has placed more emphasis on the recognition of non verbal information. Textual information can be collected from many sources, such as books, newspapers, web pages, e-mail messages, etc. Nowadays Internet is the most popular communication medium also rich in emotion. With the help of natural language processing techniques, emotions can be extracted from textual input by analyzing punctuation, emotional keywords, syntactic structure and semantic information. We believe that text is a particularly important modality for emotion sensing because the most important of user interfaces today are textually based. With textual emotions recognition [11] the text-based user interfaces become socially intelligent. In addition, improve textual sensing can reinforce the accuracy of sensing in other modalities like speech or facial expressions. For textual emotional recognition it's better to focus on concepts, rather than words, so that words are related to emotional states through a structure of conceptual representation. In this way we shift from ontological semantics to conceptual semantics.

In the natural language, there are many words of a language that contain, in their semantic representation, information about an emotional state. If we split the phrase in part of speech (names, verbs, adjectives,..), we can consider different emotional terms: names (fear, awe, gratitude, disorientation), verbs (admire, hate, get angry, rejoice), adjectives (angry, furious, sad, happy), adverbs (sadly, joyfull), interjections (ooh, perbacco).

In textual case it is necessary to extract affective terms, relative to emotions or context, from statements in natural language. This operation requires the availability of a pre-existing structure where collocate affective words. With the lexical approach it’s possible to infer the properties of emotions from the analysis of linguistic labels.

To organize the natural language relating to emotions, the first step is to gather statements and terms from the vocabularies [12] or corpus of statements extracted from emotional literary or journalistic texts.

Inside affective terms it is possible extract emotional terms. For example, the adjective abandoned isn't an emotional term, but has a sentimental meaning in sentences as "Mary feels abandoned". In this case the term abandoned refers to an emotional state which is not expressed explicitly.

The emotional terms set is splitted in groups of synonyms labeled by the term most representative. These terms are marked with properties (attributes or parameters). These parameters derive from lists containing up to 200 affective adjectives; with statistical techniques it is possible reduces the number of latent factors.

4. OUR METHODOLOGY OF RESEARCH

In our department we have developed an original algorithm of sentiment analysis to extract emotions from textual customer opinion expressed in virtual communities that use web 2.0 tools (blog, chat, forum, ...). There are various web sites that collect and make free available customer reviews[13]: epinions.com, cnet.com, complaints.com, ecomplaints.com, ciao.it, dooyoo.it, planetfeedback.com.

Our algorithm [14] mainly focuses on six Ekman emotional indexes :

happiness, surprise, fear, sadness, anger, disgust.

Ekman, use these indexes for the study of facial expressions subsequently a certain emotional state. He noticed that all human beings respond with the same facial movements to the same emotional states that derive, from the main six emotions.

In our opinion, these indexes, allows to better capture the emotional state of customers about purchase.

Our case study is a turistic resort of Sharm-El-Sheik and therefore customer opinions are relative to kicthen, restaurant and general services (room, administration,...).

When a customer goes to restaurant he/she may be:

- *happy* to have eaten well or have received good service.
- *surprised* in a positive (wonder) or negative (disappointment) way.
- *angry, sad* for the food and the service
- *fearful* to spend much or eat bad
- *disgusted* from food/service received

Customer don't eat products disgusting. The disgust is a repugnance toward any object, action or person.

The proposed methodology includes the following steps:

- Preprocessing
- Emotional annotations
- Word affectivity computing

4.1 Pre-processing

Since opinions are written in Natural Language, to process them, we need specific pre-processing techniques. The goal of this phase is to obtain for each opinion significant words. The preprocessing consists of the following steps: elimination of stop words, sentence extraction, tokenization, stemming, lemmatization, part of speech.

From every web post, eliminating all interrogative clauses, we extract minimum sentence. After we divide the sentences in single tokens or words. With stemming and lemmatization we derive the root of words, removing affixes and endings. In the Part of Speech phase, every word of a statement is labeled by a tag with the correct part of speech: noun, verb, adjective, adverb, etc…

After pre-processing phase we obtain a statements-words matrix W (n x m) :

$$\begin{vmatrix} w_{11} & w_{12} & - & w_{1m} \\ w_{21} & w_{22} & - & w_{2m} \\ - & - & - & - \\ w_{n1} & w_{n2} & - & w_{nm} \end{vmatrix}$$

where the element wij represents the frequency or number of occurrence of a word j in a statement i, with i = 1 ... n and j = 1..... m.

When we apply the pre-processing phase to our case study, the software saved into database 1303 sentences and 2300 words.

4.2 Emotional annotations

In our algorithm we classify words [15] in:

- Direct Affective Word (DAW)
- Indirect Affective Word (IAW)

The DAW group is formed by words expressing a direct emotional state in the specific domain. Other words belong to IAW group.

For example, the word happiness and cheerful carry a positive emotional state; the word ice by itself doesn't convey any emotional state.

If we insert in the phrase “I like ice” the word acquires a positive emotional state clearly different from “I hate the ice”.

In order to test the validity of our methodology we have gathered 800 posts from web forums on customer opinions about a resort in Sharm el-Sheikh and in particular we selected opinions about services: Kitchen, Restaurant, Room Service, and Administration.

We labeled manually 374 DAW. The value of affective index (happy, surprise, fear, sad, angry, disgust) for each DAW varies between 0 and 10 (values controlled by the software). Zero means no affectivity while the value 10 express an highest amplitude of affectivity. For example, if we associate to the word ”stench” the affective vector (0, 0, 0, 2, 2, 6), it means that in the definition of the affective meaning of the word stench, the elements sad and angry contribute with a small value, the element disgust with a high value and other elements don’t produce any contribution.

We assign manually values to DAW set using an interface of software that we have developed (Figure 1).

4.3 Word affectivity computing

The value of new affective vectors of IAW depends on the affective vector of the most similar DAW in the statements-words space. The idea is that similar words transport also similar affective state. For computing we take in consideration the coefficient of similarity k that measure the euclidean distance [15] between the words.

$$\mathrm{A}w_p = \mathrm{A}w_q \quad k > s \quad \mathrm{w_p} \in \mathrm{IAW} \quad \mathrm{e}\ w_q \in \mathrm{DAW} \qquad \text{(WA1)}$$

$$\mathrm{A}w_p = \mathrm{kA}w_q \quad k > s \quad \mathrm{w_p} \in \mathrm{IAW} \quad \mathrm{e}\ w_q \in \mathrm{DAW} \qquad \text{(WA2)}$$

where w_p, w_q are affective vectors of words and s represents a threshold that plays an important role on the error control. For low threshold values also affective vectors of non-similar words are calculated. Increasing this threshold value, affective vectors are calculated for similar DAW. In this case the estimated error decreases. This threshold s avoids to calculate the affectivity of words of the training set too dissimilar. Words, with their affective vectors, whose k is below a threshold s don't are considered.

In the first method WA1 we consider that the affective vector of IAW is egual to similar vector of DAW. In the method WA2 we consider also the coefficient of similarity k.

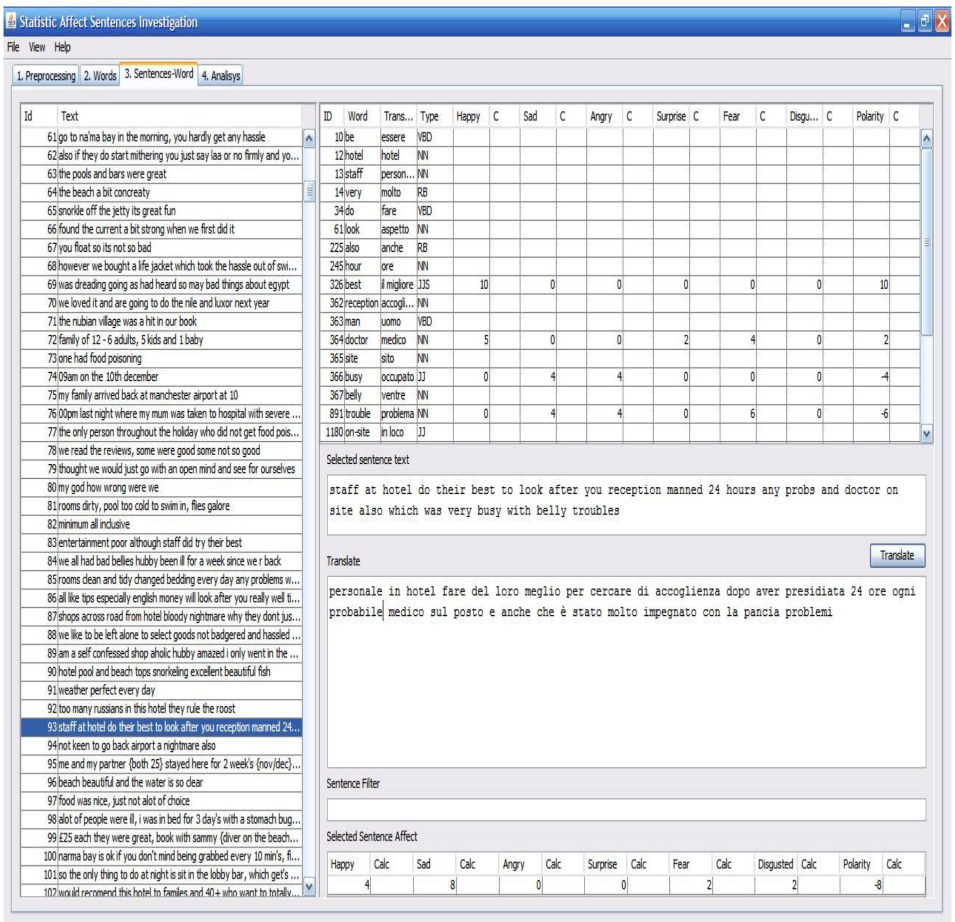

Figure 1. Software interface for manually assignment.

4.4 Experimental planning

In our experimental planning, we consider as training set the 50% of DAW manually assigned. Remaining 50% represents the test set. In this way we can compare manual assigned values with values calculated by software.

Other parameter that we take in considerazion is the threshold *s*.

We vary the TrainW (train set of words) from 20% to 100% and the threshold s from 0,1 to 0,5. In the words affectivity estimation we consider both methods WA1 and WA2.

As error in the affectivity estimation we take in consideration the Mean Squared Error (MSE):

$$e = MSE(x) = E(x-x_s)^2$$

where x is the estimator and x_s the estimated value.

5. RESULTS

In this section we show the results of our algorithm in term of estimation error for word affectivity. Table 1 shows the results of experiments. The values enclosed in round brackets represent standard deviation error. Applying WA1, increasing the training set size and decreasing the threshold s, the error decreases. This is mainly due to the fact that decreasing s there are many words for comparisons. In the method WA2 increasing the training set the error increases, because there is the negative influence of the similarity coefficient k with an intrinsic error. The estimation error becomes larger when increasing the size of TrainW. With a reduced TrainW the error is acceptable.

s	Training Set									
	20%		40%		60%		80%		100%	
	WA1	WA2	WA1	WA2	WA1	WA2	WA1	WA2	WA1	WA2
0,1	8,96 (1,98)	6,16 (2,22)	6,57 (4,41)	5,94 (2,70)	5,84 (3,74)	6,43 (2,67)	6,70 (4,73)	5,81 (3,32)	5,85 (3,31)	6,44 (2,83)
0,2	8,76 (2,48)	6,20 (2,30)	6,41 (4,29)	5,50 (3,06)	5,73 (3,76)	6,24 (2,79)	6,33 (4,70)	5,73 (3,34)	6,00 (3,79)	6,26 (2,85)
0,3	8,33 (2,73)	6,17 (2,69)	6,15 (4,20)	5,46 (3,41)	5,85 (4,04)	6,25 (3,28)	6,29 (4,58)	5,78 (3,52)	6,40 (4,01)	6,05 (3,14)
0,4	6,76 (3,56)	5,09 (3,15)	6,33 (3,81)	5,52 (3,67)	6,23 (3,82)	6,02 (3,42)	6,55 (4,40)	5,85 (3,62)	7,03 (3,97)	6,19 (3,27)
0,5	6,39 (3,51)	5,31 (3,53)	6,39 (3,51)	5,31 (3,53)	6,53 (3,88)	5,76 (3,71)	6,38 (4,25)	5,89 (3,83)	6,58 (4,14)	6,08 (3,59)

Table 1. Word affectivity error and (standard deviation) – methods WA1 and WA2

Analysing with major detail the results of word affectivity in methods WA1 and WA2 (Figure 3 and Figure 4), for low values of training set in the method WA1 we have more errors than the method WA2. With low value of s, in the computing, we must consider many words and since we have a low training set, these words can be dissimilar and therefore the error increases. With the coefficient of similarity k (method WA2) that takes in account the distance, this error is lower. It is important to see that with high values of training set, the graphic of method WA1 oscillates when varying the threshold s. This oscillation don't appear in method WA2.

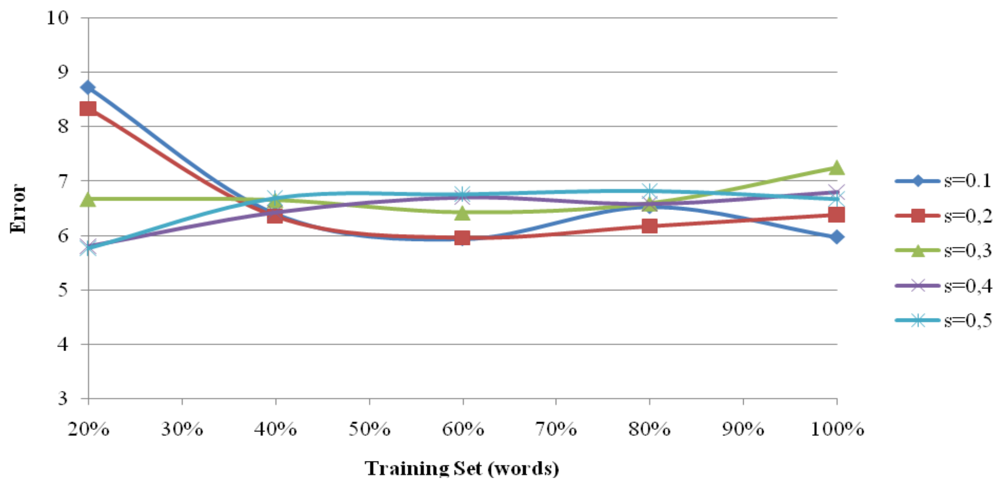

Figure 3. Word affectivity error – Method WA1.

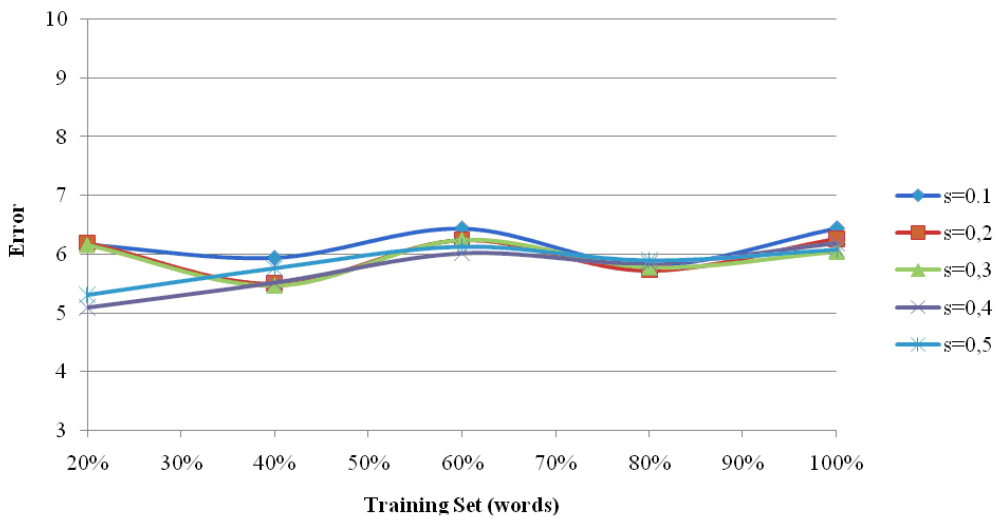

Figure 4. Word affectivity error – Method WA2.

6. RESULTS ANALYSIS

Regarding the estimation of words affectivity we must consider a small difference between method WA1 and WA2.

Method WA1. With small training set if the value of the threshold *s* decreases, in the estimation there are many words, but having a small training, words can be distant between themselves and then the error increases. Therefore with small training set it's better to have an higher values of s. In this manner we don't risk to take in consideration many dissimilar words.

With an high training set if the threshold s decreases, the number of words to compare increase and having an high training set there is a probability to have more similar words and therefore the error decreases. In this case the system has more words DAW and we can estimate better IAW.

It is important a tradeoff between training set and threshold parameter s. In the WA1 method error increases when increasing the training set ; above a certain value of TrainW the threshold s plays an important role. Error decreases for lower values of s.

Method WA2. In this case we consider the coefficient of similarity k. The error increases when increasing the dimension of training set and when the treshold s decreases, for the intrinsic approximation introduced by the parameter k.

The parameter k estimates the distance between DAW and IAW. In the estimation of word affectivity, for low values of training set, the method WA2 has better performances. In fact, with a low training set and with words, that may be distant from themselves, k measuring the distance improves the estimation and then the error decreases.

Comparing the two methods WA1 and WA2 we can say that the method WA2 it's the better. Therefore in emotion recognition it is important to consider a coefficient of similarity.

For best configuration of our system, with this method, we can reach a word affectivity error of 21%. To improve the results, in future works, we want realize the following steps :

- Take in consideration a major number of textual opinions to increase the dimension of training set.
- Improve manual labeling for training set with stricter rules. We must involve a greater number of people for DAW labeling and consider also only the predominant effect of negative indexes (fear, angry, sad, disgust) with no intermediate value.
- A better choice of weights in the features of pre-processing matrix.

7. CONCLUSIONS

In this paper we examined a methodology to extract emotions from textual information and in particular from customer opinions collected from different virtual communities.

In the article, we have described an algorithm of sentiment analysis that we have developed in our department for textual emotion recognition. A specific software that implements this algorithm can discover the emotions hidden in textual information. We are improving the automatical system with a better choise of parameters and in particular optimizing the weights of features of pre-processing matrix.

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