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AGILE ENTERPRISE THAT SENSE THE MARKET WITH OPINION MINING ALGORITHM

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Abstract

Nowadays, enterprise is open and flexible in the use of technological tools to "sense" customers and market. Acquiring information in real-time allows the company to be agile and to develop "Sense and Response" capabilities. An agile enterprise respond immediately to any internal or external event as customer demand or customer opinions. Knowing what the customer thinks of a given product/service helps top management to introduce improvements in processes and products. Customer opinions are very important for enterprise and represent a potential of knowledge so high that it can be considered a true strategic asset for the acquisition of competitive advantages. In our paper we present an original opinion mining algorithm to polarize customer opinions.This algorithm that we have developed focuses on emotions expressed in opinion text.

1 Introduction

Nowadays, in the global market, an enterprise, for the acquisition of competitive advantages, needs of an agile structure to adapt continually to market changes. Agility [1] means rapid response, high flexibility, thin structure, high speed transmission of information. The company must know how to react quickly to situations that are not repetitive. The agile enterprise transmits useful information to decision and business makers so they can quickly identify and resolve problems.

Agile enterprise hears customers to understand the level of satisfaction and behaves accordingly. The dysfunctions about product/service can be sent to competent offices for the necessary improvements [2]. Nowadays, the enterprise can collects and analyses customer opinions by web 2.0 tools and instruments of social networks (forum, chat, blog, wiki). There are various web sites that collect and make free available customer reviews [3]: epinions.com, cnet.com, complaints. com, planetfeedback.com, ecomplaints.com, ciao.it, dooyoo.it . The coming of web 2.0 promoted the birth of a sharing business philosophy and stimulated conversations and exchange among people [4]. The enterprises often encourage exchange of opinions, by making available virtual communities, e.g. Italian Nikon's Camera forum, where people review Nikon products (http://www.nital.it/forum/), the blog on Benetton products (http://benettontalk.com), and so on.

For obtaining an enterprise add value it is important to process and polarize automatically the opinion as positive, negative or neutral. The original algorithm and software that we have developed to polarize customer opinions mainly focuses on six Ekman emotional indexes [5]. We use these indexes because, according to us, each textual opinion expresses sentiments and emotions.

In both processes, consumption and purchase, the satisfaction of emotional needs is searched. The consumer shift its purchase behavior from needs to emotions/experiences. Many times the emotional/symbolic traits are highly representative of the specific identity and brand. 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.

Another factor that influence purchasing customer is, for example, the disgust that plays a key role in the inverse relationship between attitude and intention to purchase. Customer don't buy products disgusting. The disgust is a repugnance toward any object, action or person. The disgusting is an index of variation of the intention to purchase.

In our algorithm we measure words and statements affectivity and polarity. The polarity(p) depends from affectivity (a) of words: $p = f(a)$. For the polarity we take in consideration the sign and the amplitude. With sign we observe if the customer is satisfied (+) or unsatisfied (-). If the customer is very dissatisfied (amplitude) the enterprise must intervene with urgency and priority. It is interesting for enterprise to know also the statement affectivity for following strategic moves: *Fear*(special promotional campaigns for closing the customer), *Anger*(reassure and accompany customer in post-sale paths), *Sadness*(gladden customer with unique gadgets), *Disgust*(improve immediately the product design).

This paper is organized as follows: in the next section we present related works for opinion mining. The sections, from third to seventh, are devoted to present our methodology and approach to customers opinions polarization. In the eighth section we give a description of results in case study. Finally some conclusions are drawn.

2 Related works

In the literature, for polarizing opinions, various methods of opinion mining and sentiment analysis [6] have been proposed.

In the Keyword Spotting [7] approach, text is classified into affective categories based on the presence of fairly unambiguous affective words like distressed, happiness and anger. All terms that describe emotional states represent the most direct way to communicate emotion by text. The simplest and most used analysis is based on the search for keywords (like happy, sad, angry, etc). This is at the basis of the Elliot's Affective Reasoner [8] that watches for almost 200 affect keywords and intensity modifiers (e.g. extremely, somewhat, mildly).

The Lexical Affinity [9] method assigns to words a probabilistic affinity (trained from linguistica corpora) for a particular emotion. For example, "accident" might be assigned a 80% probability of being indicating a negative affect, as in "car accident", "hurt by accident". In this case there are two types of problems. First, lexical affinity, operating solely on the word-level, can easily be tricked by negative sentences like "He avoided an accident" and others word senses like "She met her boyfriend by accident". Second, lexical affinity probabilities are often biased toward a text of a particular genre, derived by the specific source of the linguistic corpora.

In the Statistical Method [10] by feeding a machine learning algorithm with a large affective training corpus, it is possible for the system to learn the affective valence of keywords (like keyword spotting) and take into account the valence of other arbitrary keywords (like lexical affinity) and co-occurrence frequency of words. We can do an analysis on lists containing so many emotional adjectives and after, with appropriate statistical techniques, reduce these lists on a shortlist of latent variables or factors. Statistical methods such as latent semantic analysis (LSA) have been more used for affective text classification. This method has an acceptable accuracy with a sufficiently large text in input.

Esuli and Sebastiani [11] have created SentiWordNet, a lexical resource for opinion mining, where they assign to each synset (set of synonyms) of WordNet a sentiment scores: positivity, negativity and objectivity (i.e. neutral). The opinion is positive if the positivity of its terms is higher than negative and objective scores.

WordNet Affect [12] is a linguistic resource for a lexical representation of affective knowledge. In WordNet Affect each synset of WordNet is labeled by one or more affective-labels, representing the affective meaning of the synset. Examples of affective-labels are emotion, mood, trait, cognitive state, physical state, etc...

Paul Ekman [5], in the study of facial expressions and emotions, proposed six universal emotions: happiness, disgust, sadness, anger, surprise, fear. All human beings respond with the same facial movements to the same emotional states. We perceive and interpret certain facial movements as expressing distinct emotions.

In the same way, in our algorithm, we thing that there is a connection with sentiments, emotions, affectivity present in the text (words and sentences) and a polarity of customer opinion.

3 The methodology to polarize customer opinions

The goal of our approach is to polarize customer opinions about a topic, that is a characteristic of a (part of) product/service.

The proposed methodology is formed by the following steps:

- Preprocessing
- affective annotations
- Affective vectors computing
- Polarization estimation

4 Preprocessing

Since opinions are written in Natural Language, to process them, we need specific pre-processing techniques and in particular to this end we have used the General Architecture for Text Engineering (GATE) library. The goal of this phase is to obtain statements and significant words for each opinion. The preprocessing consists of the following steps:

4.0.1 Sentence extraction.

From every post we extract minimum sentences. In this step we eliminate all interrogative clauses. These clauses don't carry affective information.

4.0.2 Statement extraction.

The goal of this case is to divide the sentence in statements. A statement is an elementary sub-sentence that expresses a single positive, neutral or negative polarity. A single sentence can express more than one opinion. For example the sentence "The restaurant is beautiful but the waiters are ungracious" may be splits into 2 statements with different polarity: "The restaurant is beautiful" (positive polarity), "but the waiters are ungracious "(negative polarity). To divide sentences in statements it is necessary to separate the words in the proximity of those conjunctions that link two propositions with opposite polarity; for example "but" (coordinative conjunction) or "although, even, thus, whereas, while" (subordinate conjunctions).

4.0.3 Tokenization.

In this stage various statements are divided into units called tokens where each token is a word or a number, a punctuation mark, a date, etc... The token boundary is represented by a whitespace (space, tab or beginning of line).

4.0.4 Stemming.

This stage extracts the root of a word removing affixes and endings. For example *inhibits*, *inhibition*, *inhibited* have as common root *inhibit*. Stemming operate on single words.

4.0.5 Elimination of stopwords.

In this phase the software identifies and removes the words with low discriminating capacity, such as articles, prepositions and conjunctions. These words are too common to be useful for our analysis and they don't add any affective information.

4.0.6 Selection of index terms.

In our case the index terms are all those words that could carry, either alone or in group, affective content.

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

$$\mathbf{W} = \begin{pmatrix} w_{11} & w_{12} & \dots & w_{1m} \\ w_{21} & w_{22} & \dots & w_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nm} \end{pmatrix}$$

where the element w_{ij} represents the frequency or number of occurrence of a word j in a statement i, with $i = 1, \dots, n$ and $j = 1, \dots, m$.

5 Affective Annotations

We classify words of statements in: Direct Affective Word(DAW) and Indirect Affective Word(IAW).
The DAW group is formed by words expressing an emotional state in the specific domain. For example, the word *happiness* and *delight* carry a positive emotional state. For our goal DAW are the more important words. These words, contain minor errors, are independent from the context and convey always the same emotional state.
Words that directly don't express any emotional state belong to IAW group. For example, the word *ice-cream* by itself doesn't convey any emotional state. If we insert in the statement *I like ice-cream* the word acquires a positive emotional state clearly different from *I hate ice-cream.* Therefore, this group includes words whose affectivity depends on the context in which they are included.
Respect to statements we can make the same distinction: Direct Affective Statement (DAS) and Indirect Affective Statement (IAS).
For every directly affective word and statement we associate a vector of six Ekman emotional indexes: Happy, Surprise, Fear, Sad, Angry, Disgust.

6 Affective vectors computing

The goal of this phase is to calculate affectivity of IAW and IAS from the manual assignment of DAW and DAS. Then from the affective vectors of IAS the polarity of statements can be estimated.

6.1 Word affectivity

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.

Therefore the computation bases on similarity concept evaluated by the normalized scalar product k

$$k = \frac{w_p . w_q}{\|w_p\| . \|w_q\|}$$

where w_p, w_q are affective vector of word p and q, $w_p \in IAW$ and $w_q \in DAW$ and $w_p \cdot w_q$ is the scalar product of two vectors.

The similarity measures the degree of correlation between words.

For calculating new affective vector of IAW [13] we use two methods:

$$w_{ap} = k \cdot w_{aq} \quad k > s \quad \forall w_p \in IAW \; \exists \, w_q \in DAW \qquad (WA1)$$

$$w_{ap} = w_{aq} \quad k > s \quad \forall w_p \in IAW \; \exists \, w_q \in DAW \qquad (WA2)$$

In the last case we consider that affective vectors of IAW are egual to similar vectors of DAW.

In both cases s represents the 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. An high error in word affectivity influences the statement affectivity estimation. Words, with their affective vectors, whose k is below a threshold s don't are considered.

6.2 Statement affectivity

For the calculation of statement affectivity of IAS we consider DAW and IAW. In the IAW, the context plays a key role. Obviously, to make IAW more reliable, we consider an average value between different emotional contexts in which they are inserted. If the word is used for 90% in affective positive statements (high value of happy) and the remaining 10% in negative statement (high values of disgust, angry, sad, fear) statistically it will have a positive weight in the calculation of affective vector and polarity. If that word is used for 50% of statements with positive emotions and the remaining 50% with negative emotions, it should have minimal affect in the affectivity and polarity.

The estimated error in the calculation may be reduced if we consider a corpus large and statistically independent with various examples of the contexts. The method that we use to calculate the affective vector for statement i (s_{ai}) is the following:

$$s_{ai} = \frac{\sum DAW}{n_{DAW}} \cdot \alpha + \frac{\sum IAW}{n_{IAW}} \cdot (1-\alpha) \qquad \forall s_i \in IAS \quad \alpha \in [0,1] \qquad (SA)$$

The $\sum$ is the sum of possible DAW e IAW that are present on the statement. The parameter α indicate the weight of DAW on estimation of statement affectivity. In this estimation (1- α) is the weight of IAW.

n_{DAW}, n_{IAW} are respectively number of words directly and indirectly affective.

7 Polarity estimation

We propose three methods to estimate the polarity p of a statement.

In the first method the polarity is given as the weighted difference between positive and negative affective indexes. Since the "surprise" sometimes may assume negative meaning, in the second method we assign the value positive or negative depending on predominant sentiment in the statement (difference between "happy" and negative indexes). The third method uses a linear regression for polarity estimation.

7.0.1 Method SP1.

Surprise index is considered a positive element.

$$p = \frac{1}{2}\sum_{i=1}^{2} e_i \cdot \alpha_p - \frac{1}{4}\sum_{i=3}^{6} e_i \cdot (1-\alpha_p) \quad \alpha_p \in [0,1]$$

where $(e_1, e_2, ...e_6)$ are indexes of affective vector ("happy", "surprise", "fear", ..."disgust"), α_p is the weight assigned to positive indexes, $(1-\alpha_p)$ correspond to α_n (weight assigned to negative indexes).

7.0.2 Method SP2.

Surprise index follows prevalent sentiment of statement.

$$p = \frac{1}{2}\sum_{i=1}^{2} e_i \cdot \alpha_p - \frac{1}{4}\sum_{i=3}^{6} e_i \cdot (1-\alpha_p)$$

if happy $\geq$ (sad+angry+fear+disgust), otherwise

$$p = e_1 \cdot \alpha_p - \frac{1}{5}\sum_{i=2}^{6} e_i \cdot (1 - \alpha_p)$$

7.0.3 Method SP3.

We estimate statement polarity by linear regression.

$$p = a + \sum_{j=1}^{6} a_j \cdot s_{aj} + e$$

where a is intercept of straight line, a_j are regression coefficients of six affective indexes, s_{aj} the six elements of statement affective vector and e the statistical error.

There is a linear relationship between the values of statement affective vectors and its polarity. Regression allows us to calculate the coefficients a_j.

The parameter vectors based on the training set (DAS) are estimated. Using the criterion of optimality of least squares, the parameters a_j can be obtained by minimizing the square of euclidean distance. For estimating regression coefficients and error, this method needs of a labeled training set of statements.

8 Case study

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. Opinions were collected from various Internet sites, like alpharooms.com and realholidayreports.com.

8.1 Preprocessing.

After gathering web posts and running the pre-processing phase of our software we obtain the statements-words matrix W. In the assignment of weights to various elements $w_{i,j}$ of this matrix, we considered $w_{ij} = freq_{ij}$. We considered also the case of a double weight to DAW but the result were worse and therefore we have discarded it. After the pre-processing phase, the software saved into database 1303 statements and 2300 words.

8.2 Affective annotations.

In this phase we manually label and categorize directly affective words and statements . We labeled manually 900 DAS and 374 DAW. The remaining words are IAW and the remaining statements are IAS.

For DAS we manually assign also a polarity value. We varied polarity p between -10 and +10. The amplitude is useful for agile enterprise to process high negative opinions with a certain priority.

For each DAW and DAS we assign six dimensional affective vectors with the support of the interface of software that we have developed (Fig. 1).

The value of these index can vary between 0 and 10 (values controlled by the software). Zero means no affectivity while the value 10 expresses an highest amplitude of affectivity. For example, we can associate to the word "stench" the affective vector (0, 0, 0, 2, 2, 6). It means that in 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. Statements with high values of contrasting affective indexes are ambiguos. For example: Happy = Disgusted = 10 and Sad = Angry = Surprise = Fear = 0.

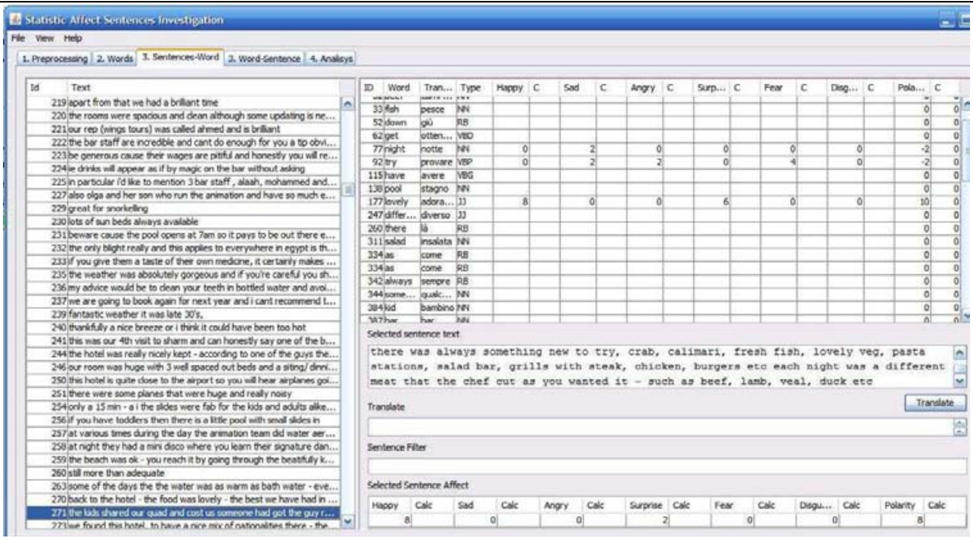


Figure 1: Software interface for manually assignment.

8.3 Experimental planning.

In our experiments we consider a training set and a test set for words (TrainW and TestW) and for statements (TrainS and TestS). In both case we consider as training set the 50% of DAW and DAS manually assigned. Remaining 50% is used as test set. In this way we can compare values manual assigned with values calculated by software.

As error in the affectivity estimation we consider the mean squared error (MSE) or Euclidean distance and the standard deviation (σ) of it.

$$e = MSE(\widehat{\theta}) = E((\widehat{\theta} - \theta)^2)$$

where $\widehat{\theta}$ is the *estimator* and θ the estimated value.

For polarity estimation we consider the amplitude and the sign. The amplitude error is given from the normalized difference between assigned and estimation polarity:

$$e = |p_a - p_e|$$

where p_a is the assigned polarity and p_e is the estimated polarity.

The percent sign error (misclassification) will be given by the sum of false positives and false negatives divided by the total statements of the test set.

In our case study we take in consideration the following experimental planning:

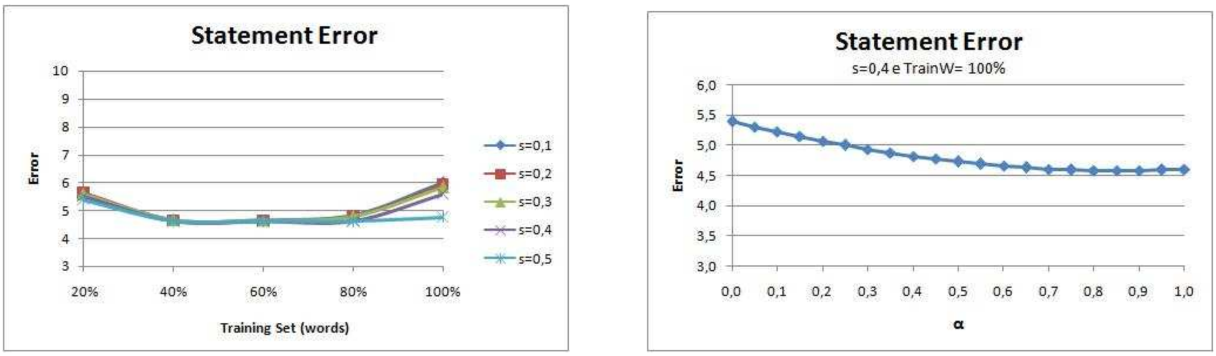
Word affectivity estimation. We vary the TestW from 20% to 100% and the threshold s from 0,1 to 0,5. We consider both methods WA1 and WA2 in the words affectivity estimation. Figure 2 shows the results of experiments. The values enclosed in round brackets represent σ error. Applying WA2, increasing the 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 WA1 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. In our case the better method is WA2.

Sentence affectivity estimation. We vary the TestW from 20% to 100%, the threshold s from 0,1 to 0,5 and α from 0 to 1. The parameter α represents the weight of DAW set in the statement affectivity (SA). Since SA depends on word affectivity, we considered also, in this case, both methods WA1 and WA2. Figure 3(a) refers to WA1. Initially as the training set (TrainW) increases the error decreases. For

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

Figure 2: Error (MSE $\pm$ (σ)) of word affectivity in methods WA1 and WA2 varying TrainW and s.

high values of TrainW, the error introduced by the coefficient k is high and therefore the statement error increases. To this point the threshold s is important. When the value of s is 0.5, the number of words contributing in the estimation decreases reducing MSE . Figure 3(b) refers to method WA2. A low value of α means a more influence of IAW and then the error is high. Increasing the value of α, the contribution of DAW is greater than IAW and error decreases. For α value near 1 the error may lightly increase in presence of ambiguity. For example "The spaghetti are a beautiful disgusting". In the statement there are only two direct affective contrasting words (beautiful and disgusting). In this case the meaning of statement depends of the context and then the error increases. The error increasing is more evident in the method WA1.



(a) (b)

Figure 3: Error of statement affectivity varying TrainW, s and α_p.

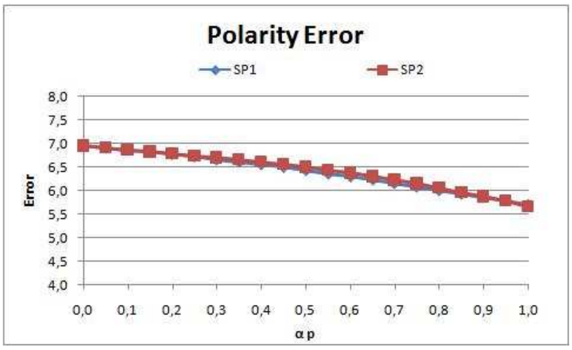
Polarity estimation. For polarity estimation (Fig. 4) we consider three methods SP1, SP2, SP3. The polarity error for methods SP1 and SP2 is shown in Fig.4(a) and for method SP3 in Fig.4(c). Fig. 4(b) represents the misclassification error for the first two method while Fig.4 (d) refers to last method SP3.

In the first two methods we vary s from 0,1 to 0,5 and α_p from 0 to 1. The parameter α_p represents the incidence of words with positive affectivity in the statement polarity.

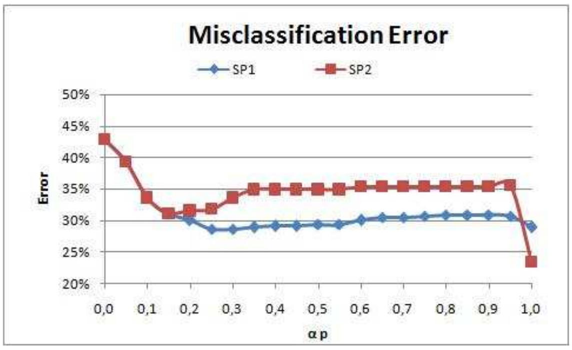
In the last method (SP3) we vary the TrainS from 20% to 100%.

In all three methods, in average, the polarity error decreases with the increasing of TrainS and parameter α_p.

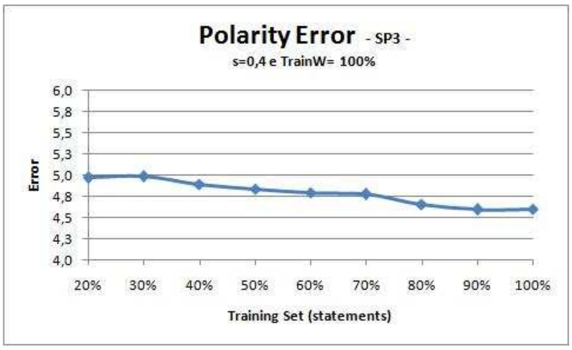
The accuracy of word affectivity improves with low values of threshold s but this worsens the statement affectivity because in the estimation many words are involved. Since the goal is to obtain a good estimate of affectivity and polarity, we must consider an intermediate threshold value. Analysing data output of our software we have observed that the better experimental method is the polarity estimation with linear regression (SP3). It is important to comment the Figure 4(b) and in particular the low value of error in correspondence of α_p equal to 1. This occurs because in this case we don't take into account negative indexes but only the positive one. Negative indexes (fear, anger, sadness,disgust) are more numerous than positive; with their lack, error decreases.



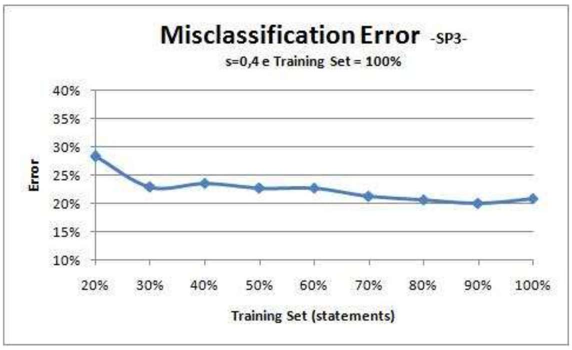
(a)



(b)



(c)



(d)

Figure 4: Polarity error (amplitude and sign) for three methods varying all parameters.

Concluding, with these experiments we can say that the better methods for word and sentence affectivity is WA2 method (word affectivity estimation without similarity coefficient k) and SP3 method (regression linear) for polarity estimation.
To improve the algorithm accuracy we must make manual labeling more rigid, with strict rules, and take in consideration only the affective index dominant without intermediate values. For example if, in a statement, both terms disgust and fear appear, we must consider only the dominant sentiment. It is important also consider a better weighting of parameters (α, s, k) for words and sentences affectivity. In the polarity estimation we can refine the linear regression with polynomial regression or neural networks.

9 Conclusions

Nowadays, for the enterprise, it is important gather a large amount of customer opinions on product/service. In this paper we illustrate an original approach to polarize opinions based on affective Ekman indexes. In our opinion, these indexes, allows to better capture the emotional state of customers about purchasing. The approach, based on the affective value of each single statement, produces good results on documents of medium-large dimensions. In this paper we have shown different schemes to calculate affectivity of single words or statements and mainly to calculate statement polarity. From single statement it is possible understand the positive or negative opinion with its amplitude and therefore if the customer is, more or less, satisfied. The polarity of opinion on (part of) product allows to agile enterprise to respond immediately to changes requests of the market.

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