A new linguistic approach to assess the opinion of users in social network environments

Luigi Lancieri and Eric Leprêtre

Abstract This article describes an automated technique that allows to differentiate texts expressing a positive or a negative opinion. The basic principle is based on the observation that positive texts are statistically shorter than negative ones. From this observation of the psycholinguistic human behavior, we derive a heuristic that is employed to generate connoted lexicons with a low level of prior knowledge. The lexicon is then used to compute the level of opinion of an unknown text. Our primary motivation is to reduce the need of the human implication (domain and language) in the generation of the lexicon in order to have a process with the highest possible autonomy. The resulting adaptability would represent an advantage with free or approximate expression commonly found in social networks environment.

1 Introduction

In the last decade there has been an increasing effort in the linguistic and data-mining community to address the question of the computation of the opinion from a textual content. Opinion mining is often viewed as a sub-field of sentiment analysis that, as the discourse analysis or the linguistic psychology, seek to evaluate affective state through the analyze of natural language. Nevertheless, many researchers define sentiment, loosely, as a negative or a positive opinion [20, 22]. This relatively new field is promising from a scientific point of view because of its large possible applications. The challenges are linked to the huge quantity of data available. Thus,

Luigi Lancieri
Université de Lille1, Laboratoire d'Informatique Fondamentale de Lille, France e-mail: luigi.lancieri@univ-lille1.fr

Eric Leprêtre
Université de Lille1, Laboratoire d'Informatique Fondamentale de Lille, France e-mail: eric.lepretre@univ-lille1.fr

applications such as business intelligence, trend forecasting or recommendation systems would take benefits from opinion mining.

The basic principle generally starts with the necessity to use or to generate a lexicon that makes a link between words and their opinion value. Then, this lexicon will be used to rate a text by combining the opinion value of each of its words. Unfortunately, the generation of this lexicon is not obvious because of the complexity of the language rules or of the diversity of the modes of expression. Indeed, the language is alive, evolves and is subject to all kinds of exceptions or common mistakes. It is not rare to find sentences with mixed opinions, with several sources (e.g. quotation of other persons) or several targets of the opinion (e.g comparison of products or features). The literature is full of examples of expressions where the same word can be interpreted differently depending on its use in the sentence. All theses cases introduce biases in the opinion interpretation and reduce the performance of a computational evaluation. Denecke shows, for example, that Senti-WordNet (lexicon with opinion labels, see below) has difficulties to evaluate news articles that are generally wrote in central style. In such a case, the accuracy of the classification stood to 40 % [9]. The task is even more difficult in social networks environments that are heterogeneous and noisy by nature. The freedom of expression that tends to lead to abbreviations or malformed sentences does not fit to standard lexicons. It is important to point out that not only the generation of the lexicon is tough from a linguistic point of view but also, a lexicon is highly context dependent. In other words, each context in a specific language needs a dedicated effort to solve these unobvious problems. In the same way, existing lexicons cannot be easily transposed in other languages or other contexts.

In consequence, facilitate the production of the lexicon seems to be a major research issue. Apart the manually generated lexicons, there are several, more or less, automated solutions. Often using machine learning techniques, researchers attempt to make easy the lexicon generation and try to offer a better adaptivity to these multiple variations. But, how far can we go into this simplification?

It is difficult to have a clear answer to this question but the state of the art shows that there is a huge potential of progress. Indeed there are very few works focusing on the adaptable generation of the lexicon. In contrast, obtaining a better performance in the polarity computation has been extensively discussed and seems to have a limited margin of progress. Indeed, we can notice that in the 29 studies from 1997 to 2009, reported by Mejova, 19 reveal more than 80 % of accuracy and 6 of them more than 90 % [22].

In this paper, we present our contribution that takes profit of the natural asymmetry of the expression of opinions. In short, this psycholinguistic feature of the human behavior makes that negative narrations are longer than positive ones. This is observable in situations of ”free expression” such as when users give, on-line, their feeling on their buy or on the merchants quality. Probably because there is less to say when all is going well than when it is going bad, negative posts are statistically longer than positive ones. We find that, with enough of such independent narrations, the length of the text can be used to automatically differentiate positive from negative vocabulary and generate a list of words with polarity tags. Such lexi-

cons can then be used to evaluate the opinion of an unknown text. Since the need of prior knowledge is limited, the human involvement in the generation process is very low and do not need to be technically or linguistically specialized. This allows to create a lexicon as frequently as needed, for a specific domain or language. In order to validate our theory, we collected consumers textual feedbacks and their associated (stars) ratings. First, we generate the lexicon with a first subset of the users' comments. The ratings are not used in the lexicon generation phase. Then, we compute the opinions values of the second subset and we compare the result with the users' ratings.

The rest of this paper is organized in 5 other sections where we first develop a state of the art on opinion-mining. In the section three, we develop the basis of our main hypothesis regarding the relation between the opinion polarity and the length of the expression. Then we present our proposal and the associated results and finally we discuss its perspectives and limitations.

2 State of the art on opinion-mining

Opinion mining techniques can be roughly segmented in two categories as they are bottom-up or top-down. Even if a lexicon is always needed, the way to create it can widely differ. The first category needs the most prior knowledge and starts from existing lexicons often manually adapted to include sentiment knowledge tags. The second approach uses a series of textual documents that have been globally annotated. An example is a 5 lines long text of a customer comment provided with a 4 stars rating. These couples of comments / ratings are used to infer the polarity of words and to generate a reference lexicon containing words and their polarity. These two opposed approaches have also been combined.

2.1 Lexicons generation

In this study, we define a lexicon as a list of words with one or several language attributes. This can include a basic list of words with polarity tags or a more complex dictionary with grammatical and sentiment class attributes. The polarity or the affect annotations can be added in several manners but in all cases it needs prior knowledges.

Most of the time, sentiment based lexicons have been manually constructed by extending general purpose lexicons associating words with affects categories and degree of relatedness with these categories [26, 8]. The probably well-known example is the public domain Princeton WordNet lexicon [21] that has lead to several other versions. The original WordNet is now available in around 80 languages but it is rather static and difficultly open to new languages, to emerging words or to multiple domains. As examples of sensitive lexicons extended from WordNet, we

can mention WordNet-Affect that contains labels linking words with several affective categories [25] or Senti-WordNet that adds polarity and subjectivity labels [13]. WordNet has also been used to automatically generate basic lists of positive and negative terms [16, 15]. Let us also mention, among other examples, the Harvard General Inquirer lexicon from both the "Harvard" and "Lasswell" general-purpose dictionaries [24].

The Scientific communities also provide manually annotated databases [1] that can be used as language resources or for studies validation. Other initiatives as MIT media Lab Open Mind Common Sense focus on the build of a large knowledge from the contributions of thousands of people across the Web. Basic facts including emotional ones are provided by users (e.g The sun is very hot). Such sentences are analyzed in order to extract concepts, ontologies or basic positive-negative lists of words (see also Cyc.com), [19, 27]. In other cases, resources manually rated such as movies, products or merchant rating available on customer opinion web sites are also often used (CNET, Ebay, TripAdvisor, IMDB). The idea is here to use a machine learning algorithm in order to extract a link between words and the rated comment and predict the opinion of an unrated text [7, 14].

2.2 Identifying the polarity of words

The automation of the lexicon generation involves the use of heuristics that, in short, provide to the algorithm a part of the human expertise. Thus, the identification of the polarity of words can be done using more or less complex methods. In bag-of-words, terms are considered as independent parts of the speech. Elementary grammatical features of words that are known to have polarity values (adjectives, adverb, negation, intensifier, diminisher) are used to separate them. Adjectives or adverbs are then organized in binary classes or associated to a position in a continuum between the two extreme polarities [23]. But, adjectives are not always the best opinion descriptors. For example, in the sentence There was a lot of noise in this hotel, all the negative weight resides in the noun noise. If we replace it by the noun facilities, the sentence become positive. This shows that, beyond adjectives or adverbs, the polarity depends on a larger range of terms individually or in association. Unfortunately, bags of words neglect the position of words in the sentence and only take into account their presence or their frequency. Alternatively, as suggested by common sense and experiments, the n-gram technique that uses the parts-of-speech patterns has a better efficiency. A basic example is the following where a negation (no, not) involves a very different polarity depending on its position in the sentence (this book was not good - no wonder, every one love this book). The co-occurrence of words is also a key criterion. In short, it is assumed that words that have the same polarity are often found together or more or less close in a sentence. This relationship between words can be computed following different techniques as LSA

[1] TREC (Text Retrieval Conference), NTCIR (NII Text Collection for IR), CLEF (Cross Language Evaluation Forum)

(Latent Semantic Analysis), PMI (Pointwise Mutual information), Chi-Squared test of independence [7].

Recent works exploit the research and the analysis of seeds words in an unknown text. Seeds [27] have an evident polarity (well, good, bad, .) and are used to collect other connoted words. The criterion used to extend these lists can be the level of proximity with the seeds.[12]. A statistic analysis of the collected words helps to refine the lists. This technique needs less expert implication but it requires a good knowledge of the target language and domain. Not only the seeds have to be chosen carefully but in case of domain oriented vocabulary some words may be connoted differently (cold is negative for the evaluation of a restaurant but can be positive in other domains as for describing the quality of a fridge). Actually, the influence of the domain is known as a key issue not only for the opinion mining but also for the knowledge management in general. Consequently, several researches have tackled the sensitivity to the domains or in other words to see how to use a lexicon from one topic to another [4, 12].

3 Opinion and length of expression

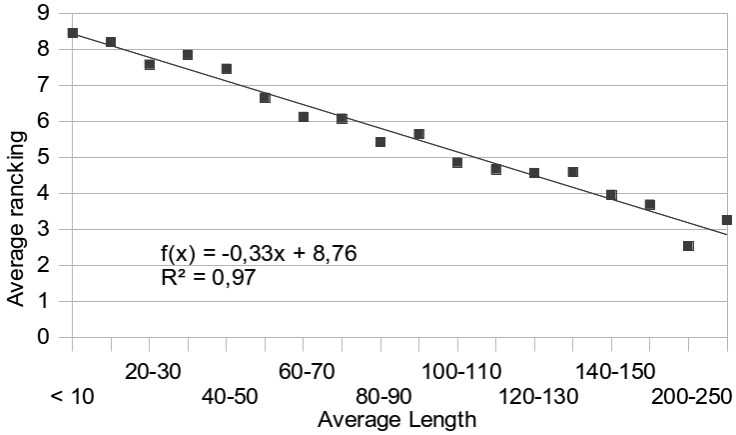
Even if it is clear that taking into account associations of words (n-gram, seeds, ..) provides better performances than a simple bag-of-words method, it is still a question to identify the optimal length of this association [26, 1, 23]. This issue has raised the attention of the community with the spread of micro-blogging platforms, as Twitter, where the size of the message is strongly limited [3, 11, 5].

Nevertheless, from our knowledge, the literature does not provide example of study that takes into account the difference of the expression length in order to statistically separate positive from negative vocabulary and generate lexicons. Though, this psycholinguistic feature of the human expression has already been observed by researchers.

Anderson, for example, has stated that unsatisfied customers engage themselves in greater word-of-mouth than satisfied ones [2]. In the same domain, another study based on reviews of customers shows that positive opinions contain 4 times less words in average than negative ones [17]. In another context, observing the expression of emotions in computer mediated communication as e-mails, Derks sees that in case of negative situations as conflicts, Emoticons are not enough. This leads to more communication between individuals to solve the problem, whereas in positive situations, a simple smiley can be sufficient [10]. It is also surprising to observe that the performance of automated sentiment miners tends to be better within positive texts than within negative ones. This confirms the observation of Gindl [14] and leads to the assumption that positive words are more used in negative opinions that negative words in positive opinions. This would imply that positive opinions are less ambiguous probably due to its conciseness.

In order to confirm the strong link between the polarity of an opinion and the length of its expression, we present a first statistical view involving three different

Fig. 1 Relation between text length and ranking of appreciation



languages. The figure 1, corresponds to a data set that contains 5014 users' opinions in French collected on the mareduc.com website. This website is convenient because the rating is given on a wide range (from 0 to 10), which gives a better precision. This is pretty rare because, comparatively, most of the ranks range from 1 to 5. Each point in this plot represents the average rating for a class of opinions corresponding to a range of length. For example, the first dot means that the opinions having less than 10 words have an average rank of 8,5 (ie. very good). The second dot involve that all opinions between 10 and 20 words have an average rank of 8,1, etc.

In order to have an alternative view of the polarity-length relation, we made another measure with 2 other languages having a different graphic representation form (English and Chinese). This measure is not completely comparable with the previous one in French, for several reasons. First, the ranking system is not the same, from 1 to 5 (stars) instead of 0 to 10. Secondly the context is different (hotel instead of High Tech). This is important to consider since it seems reasonable to think that some contexts induce more verbalization than others. We do not test this hypothesis here, we only focus on the polarity-length relation. The set in English is the same as that used for the main experiment (see detailed statistics in the methodology section), the Chinese set is composed of 808 opinions. We find the following repartition synthetised with the 2 main polarities (Positive stand for rank 4 and 5, Negative for rank 1 and 2)

Table 1 Average number of words (or ideograms) per opinion

Languages	Positive polarity	Negative polarity
English (words)	98	169
Chinese (ideograms)	177	200

Even if the difference between the average length may differ from one language (or one context) to another, we see that the polarity-length relation is consistent. Messages with a positive opinion tend to be shorter than the negative ones. Of course, a larger statistical experiment is needed with more languages, more contexts and a more significant number of opinions. Nevertheless, we have reasonable clues showing that this relation is true whatever the language and whatever the context. This is a psycholinguistic invariant of the human behavior.

4 Methodology

The core of our proposal consists in to take advantage of this natural relation in order to build a contextualized lexicon that will be used to compute the opinion of an unknown text. In order to validate our approach, we propose two experiments allowing to compare two methods of lexicons generation. The first one uses the polarity-length relation. The second uses the seeds method. Both experiments use the same set of data.

We collected 20400 users' reviews in English that include comments (68 words average length) and the rating (0 to 5 stars) from the well known epinion.com web site. This dataset was divided in two parts. The validation set (V) was randomly composed of 1381 texts (96488 words) from the initial set. The rest of the initial set was used to compose several learning sets (L) in order to evaluate the influence of the size of the learning set. The L subset contains only the comments (i.e. without rating) and is used for the generation of the lexicon. Then we use this lexicon to compute the opinion value of the comments of the V subset (each text independently) and we compare the results with the users rating. In order to estimate the quality of the lexicon generation process we use the recall, precision, and f-index ratios for the positive (Rp,Pp,Fp) and the negative class of opinions (Rn,Pn,Fn).

$$R = \frac{RI \cap Rt}{RI} \qquad P = \frac{RI \cap Rt}{Rt} \qquad F = 2.\frac{P.R}{P+R} \tag{1}$$

In these formula, a relevant document (Rl) is an opinion text that corresponds correctly to its rating (positive or negative class). A retrieved document (Rt) is a text that has been affected by the process to a specific rating class. Thus, the recall is the percentage of all relevant items identified by the process or in other word, the average probability of complete identification. Symmetrically, the precision is the number of correctly affected items divided by the number of all affected items or in other words, the average probability of relevant affectations. The F-measure as an harmonic mean, balances the precision and recall into an unique indicator. More details and useful links can be found on wikipedia if an introduction is needed on these indicators.

4.1 Polarity-length Method

At the beginning, the comments of the L set were randomly dispatched into two subsets P0 and N0 that can be viewed as two kinds of bag-of-words with a loss of organization between words. These two sets will be progressively refined through several iterations where new sets (P1, N1 to Pn,Nn) will be generated from the previous ones. At each iteration i, Pi and Ni will be used to generate 2 steps lexicons Lpi, Lni. Let us remark that whereas Pi,Ni aggregate the same number of comments and thus can contain several times the same words, the union of Lpi and Lni sets contains only one occurrence of a word. At the last iteration Lpn and Lnn are expected to contain words with respectively a positive and a negative polarity.

At the second step, the frequency of P0 and N0 words are computed in order to generate the Lp0 and Ln0 lexicons. Thus, a specific word will be stored in Lp0, in Ln0 or discarded depending on the difference of frequency it has on the two subsets P0, N0. This operation applied at each iteration allows to eliminate articles or others neutral words that have a similar frequency in all kind of texts. Since connoted words are less frequents, they will be kept in the Lp0, Ln0 lexicons with a higher probability than neutral words (even with a random classification).

Differential frequency algorithm

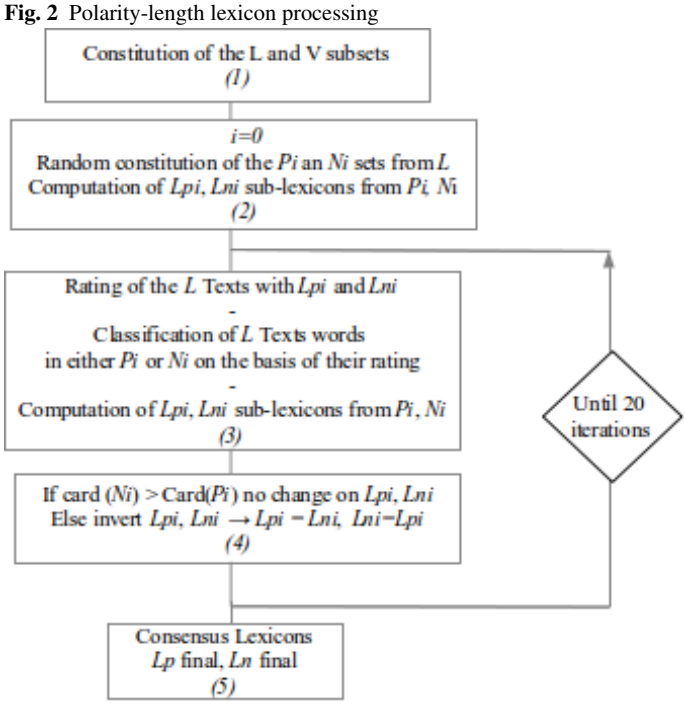
```
For each unique word :Wi C (Pi U Ni)

if (Freq(Wi) in Pi) > (2*freq(Wi) in Ni)
    then Wi is stored as unique in Lpi
        else if (Freq(Wi) in Ni) > (2*freq(Wi) in Pi)
            then Wi is stored as unique in Lni
            else Wi is discarded
End for
```

In the third step, the goal is to start the agglomeration of words having the same polarity in the same sets (Lpi or Lni). We take again the L subset and, for each comment, we compute its level of polarity (Pij) with the following formula. For example, if a comment is composed of 13 words where 10 appear in Lp0 and 3 in Ln0. The polarity of this comment would be equal to 0.53 (i.e 10-3/10+3).

$$Pij = \frac{Card(T\,jWords \in Lpi) - Card(T\,jWords \in Lni)}{Card(T\,jWords \in Lpi) + Card(T\,jWords \in Lni)} \tag{2}$$

If Pij is ranging between +1 and K (see below), it is assumed to be of positive polarity. Negative, if it is between -K and -1 and neutral if its between -K and K. Then, if Pij is positive, all words of the text Tj, recognized either in Lp0 or Ln0, are stored in P1. If Pij is negative, the text words recognized are stored in N1. Then the frequency algorithm is processed again but now on P1 and N1 in order to generate Lp1 and Ln1. Statistically speaking, each set (Lp1, ln1) should be a bit more consistent in term of polarity than Lp0 and Ln0, even if this polarity (positive or negative) is not yet known.

Fig. 2 Polarity-length lexicon processing

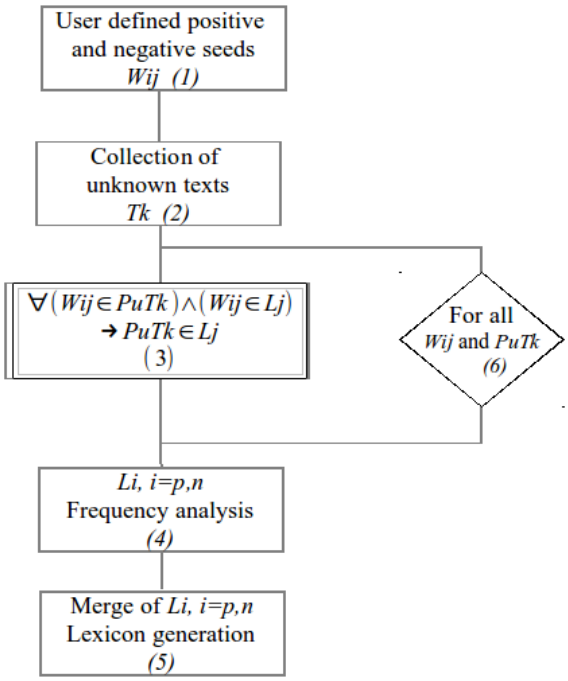


In the fourth step, the number of words in P1 and N1 will decide of this polarity. If N1 has more words than P1 then Ln1 is considered as the negative step sub-lexicon and Lp1 the positive one, else Lp1 become the negative one (and is renamed Ln1) and Ln1 the positive one.

All the process from the third stage is iterated until Lpn, Lnn is considered as stable. (experimentally, N=20 iterations was found as enough, see figure 1). Then we built the final consensus lexicons on the basis of the words present in the Z=N/2 (i.e. 10) last step learning lexicons of the same polarity (lp11, lp12,..,lp20 $\rightarrow$ final Lp; Ln11, Ln12,..,Ln20 $\rightarrow$ final Ln). Words are kept in the final consensus lexicons if they appear in more than C=Z/2 (i.e. 5) of the Z lexicons. The organogram of the figure 2 synthesizes the whole processing operations.

The value of the K, Z and C parameters is important. The distance [-k, +k] correspond to the neutral polarity proportion. In order to simplify, we considered that each category (positive, negative and neutral) are proportionally equivalent (ie K=0,3). That means that the probability that a text fall in one of these categories is estimated as identical (33 %). Actually, this depends on the context and it even seems that, most of the time, negative messages are over represented [17]. K should, also, be different from zero in order to avoid oscillations in the learning process. The N parameter, linked to the need of having a complete learning process, results mainly from the experimental observation. As that can be seen in the figure 4, the iterated

Fig. 3 Seeds method lexicon processing



process stabilizes itself pretty rapidly. Furthermore, it is important to have in mind that since we choose to limit prior knowledge, we have no means, except the use of a heuristic to know when the learning process would be at its optimum. The Z and C parameters as in a vote process define the level of consensus to build the final lexicon.

4.2 Seeds method

As explained in the state of the art, the seeds method starts from few key words which polarity is known. These words will be used to look for similarities into unknown texts in order to collect new words which polarity will be induced from the nearness with seeds words. All these words (including seeds) will compose the generated lexicon.

In the organogram of the figure 3, Wij represents the seeds with i[1,n] the index number and j[p,n] the polarity negative or positive. Lj represents the positive or negative sub lexicon with j[p,n]. Tk represents the unknown texts with k[1,m] the index number among texts. Pu with u[1,q] is the phrase that is associated to a text. For example, P4T2 would represents the fourth phrase of the second text.

In the first step (1), the user defines several initial seeds words. Then (2), we collect the texts needed for this learning step. In the iteration loop (3)(6), for all phrases Pu of the texts Tk, if a seed word (of p or n set) appears in the phrase PuTk, then all the words of the phrase are stored in the appropriate sub-lexicon (p or n). The frequency of occurrence of each of these words is also stored in the p or n sub-lexicon. A this stages, the Lp and Ln sub-lexicons may have several words in common such as articles or neutral words that can be encountered as well in phrases of positive or negative connotation. The frequency analysis step (4) consists in comparing the frequency of a word appearing in both Lp and Ln in order to decide if it will be discarded or kept in one of the sub-lexicons. This algorithm is the same as that used in the previous section (see differential frequency algorithm). Finally(5), the two sub-lexicons will be merged and ready to use for the opinions computation.

5 Results

In this section, we compare the results of the polarity-length method with those of the seeds approach.

5.1 Experimental validation of the polarity-length method

In order to have a synthesis of the performances, we define 3 classes of opinions with their rating (negative: 1 to 2 stars, neutral: 3, positive: 4 to 5 stars). The estimated opinion was computed from the textual comment in order to fit the same scale (ie adapted from the Pij formula). In the ideal situation the user stars rating should correspond to the computed one. The sensitivity of the L size on the performances was evaluated with 8 tested sizes (from 364 to 7053 kBytes). The performances are reported in the two following tables. The table 2 presents the ratios with the final consensus lexicons. These results of the full automated process can be compared with that of the table 3 with the best values during the 20 steps. This comparaison shows that most of the time the consensus lexicons give the best results.

We can see that the size of the learning set is not a clear criterion to have good performances (see in table 2, F-index for 5014 kB, 6124 kB and 7053 kB). It is important to remind that each L set was composed randomly from the original set. This involves that words are not always the same and can cause different lexicons even if the process was run several times with the same set size. This is the main reason that causes important changes in performances even in the final lexicons. This means that the aggregation process that generate these lexicons does not completely catch the optimum performances but succeed to avoid the lower ones. Nevertheless, as shows the figure 4 (with 3 examples of L size), the learning process converge pretty rapidly with stable results in the last steps. Also, we see that a size of learn-

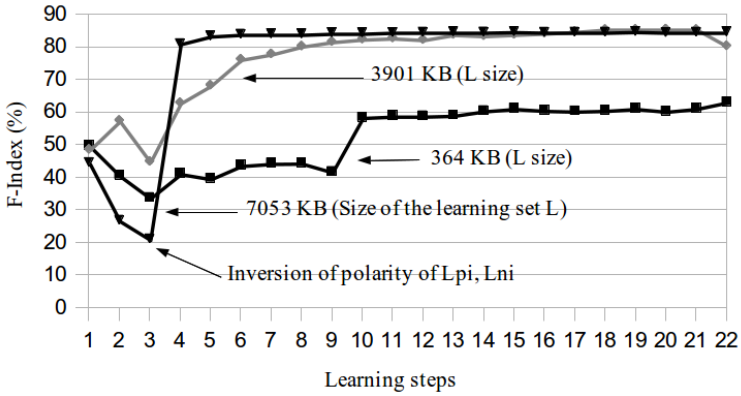
Table 2 Results with the consensus lexicon

Size (kB)	Pp	Pn	P	Rp	Rn	R	Fp	Fn	F
364	65,1	65,2	65,1	62,3	60,7	61,5	63,7	62,9	63,3
1111	70,3	68,9	69,6	65,9	68,7	67,3	68,0	68,8	68,4
2045	64,6	72,2	67,5	76,2	51,4	63,8	69,9	60,0	65,6
2971	67,8	66,6	67,2	63,5	66,8	65,2	65,6	66,7	66,2
3901	93,2	74,9	81,4	64,3	94,8	79,5	76,1	83,7	80,4
5014	86,8	80,7	83,4	74,9	86,7	80,8	80,4	83,6	82,1
6124	74,7	74,8	74,8	73,5	72,3	72,9	74,1	73,5	73,8
7053	85,8	86,0	85,9	84,8	82,3	83,6	85,3	84,1	84,7

Table 3 The best F-index results

Size (kB)	Pp	Pn	P	Rp	Rn	R	Fp	Fn	F
364	65,1	65,2	65,1	62,3	60,7	61,5	63,7	62,9	63,3
1111	77,6	86,4	81,4	83,9	68,7	76,3	80,7	76,5	78,7
2045	64,6	72,2	67,5	76,2	51,4	63,8	69,9	60,0	65,6
2971	65,9	73,3	68,9	75,8	57,1	66,5	70,5	64,2	67,7
3901	89,1	85,4	87,2	81,4	86,6	84,0	85,1	86,0	85,6
5014	85,7	82,6	84,1	79,2	85,0	82,1	82,4	83,8	83,1
6124	74,3	78,6	76,3	77,1	69,1	73,1	75,6	73,6	74,7
7053	84,9	86,7	85,8	85,0	82,5	83,8	84,9	84,6	84,8

Fig. 4 Convergence of the Learning process



ing set L from 4 to 7 MB provides reasonable results. In this figure, we can also observe the oscillations of the F-index near the inversion of the lexicons polarity (fourth learning step, see figure 2) generally observed at the third iteration. At this point, the lexicons start to become consistent from the polarity point of view. Before this point of equilibrium, the content of the lexicons are still too random to allow to identify the appropriate polarity.

It is also interesting to analyze the influence of the learning set (L) size on the features of the final lexicon. The table 4 provides this information for the 8 possible sizes of L. We can observe that the number of words in the final lexicon is not proportional to that of L. The ratio of the number of words of L over that of the final lexicon vary from 0,24 % to 1.25 % depending on the size of the learning set.

Table 4 Relations between the learning set and the final lexicons features

Size L (kB)	Nb Texts in L	Nb words in L	Nb words in Lpn+Lnn
364	980	66654	773
1111	2980	202981	1214
2045	5480	373352	1624
2971	7980	541472	2067
3901	10480	710905	1767
5014	13480	913963	2908
6124	16480	1116462	3079
7053	18980	1286107	3224

Finally, in order to have a general view of the performances, we computed the average result with 4 learning sets (average of 7172 reviews) an 4 validation sets (average 716 reviews). We applied the main algorithm (figure 2) to each learning set and we measured the results on each validation set. The statistical data corresponding to these 16 tests are reported in the table 5.

Table 5 Average results

	F index for 16 tests
Average	81,6
STD	3,8
Max	86,9
Min	73,4

5.2 Seeds based method

The use of seeds seems to be the most powerful actual method but the choice of the initial key words (the seeds) may have a strong influence on the final results. In this part of the experiment, we take again the learning set that provide the better results (7053 KB) and the validation set and we build the final lexicon on the basis of the seeds method. In order to show the sensitivity to the initial seeds, we use four examples of 6 seeds (3 positives and 3 negatives) and we compute the precision, recall and F ratio. The first set provides equivalent performance compared with our

method. In the second and the third set we changed only one world respectively with negative (set 2) and positive polarity (set 3). In the last set, we change several words for each polarity.

- Seeds set 1: super, excellent, perfectly, bad, poor, expensive;
- Seeds set 2: super, excellent, perfectly, bad, noisy, expensive;
- Seeds set 3: super, excellent, recommend, bad, poor, expensive;
- Seeds set 4: good, excellent, friendly, poor, noise, bad;

Table 6 Recall, precision and F-index using the seeds method

Seed set	Pp	Pn	P	Rp	Rn	R	Fp	Fn	F
1	90	83	86	75	89	82	82	86	84
2	86	73	78	64	85	74	73	79	76
3	83	74	78	63	83	73	72	78	75
4	39	44	42	23	52	38	29	48	40

The results show clearly that the seeds method is very sensitive to the choice of the worlds even with a careful attention to the context (here, users' comments on hotels). The case of the last set is very interesting. We can observe that even with words that are evidently consistent in polarity and in context, the performances are very bad. The reason is probably due to the representativity level of the seeds words in the learning set. It is important to say that each of these words is present in the learning set but with a different frequency of occurrence.

5.3 Comparison between methods

As landmarks, let us remind (see introduction section) that most of the studies obtain more than 80 % of accuracy [22]. Moreover, we see that the seeds and polarity-length method have at best, similar performances but with less stable results for seeds method that in addition is more knowledge greedy. It needs more prior knowledge and the process has to be controlled precisely (lexicon generation). Indeed, the seeds method needs either a linguistic and a domain expertise in order to chose the most accurate seeds words or a good learning set in order to statistically compensate the lack of representativity of a specific seed. The lesser stability of this method could be explained by the difficulty to evaluate the added value of this expertise and the effort necessary to gather the proper learning context (seeds, learning set, ...)

6 Discussion

In this paper, we developed several hypothesis related to the psycholinguistic feature of the free individual human expression. First, we present the polarity-length relation that states that the length of the free expression is as long as the opinion polarity is negative. Second, that this feature is true whatever the language and whatever the topic domain of this expression. Finally, we show that this feature can be used, practically, to enhance an automated process designed to compute the opinion. Even if these hypothesis need more in-depth evidences, we provide steady clues presenting the polarity-length as an invariance of the human behavior. Not only our approach allows a better adaptivity to multiples languages and domains but also a better tolerance to errors, misspellings or approximate expressions (e.g linguistics shortcuts as in twitter).

Anyway, our methodology has some limitations. Even if we do not need to have a strong knowledge about the collected texts, we need to know that they contain opinions for a majority of them (customer or blog feedbacks,..). The other limit is that the inconsistency of the sources, in terms of domains, is difficult to be controlled if we want to completely avoid the human interventions. Thus, a complete blind approach could reduces the performances but this can be enough if the goal is a rough classification. Furthermore, as our first goal was to validate the interest of the polarity-length heuristic, we spent low efforts on the question of the syntactic analysis which could be improved. Indeed, our basic bag-of-words strategy can takes benefits from the lot of studies done on this field (n-gram).

In terms of perspectives, outside the improvements that we have just evoked, we wish to evaluate the potential of this approach in several practical applications where the opinion is a key added value.

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