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An Approach to Select the Best User Reviews on the Web

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ABSTRACT

The indexed Web increases every day, making the development of automatic methods for knowledge extraction more relevant. The area of Sentiment Analysis or Opinion Mining aims to extract opinions from the user-generated content and to define the semantic orientation of each individual opinion. This work proposes an approach to estimate the degree of importance of comments generated by web users by using a Fuzzy system. The system has three inputs: author reputation, number of tuples $\langle feature, quality\ word \rangle$*, and percentage of correctly spelled words and one output: importance degree of the comment. The importance degree was used to select the best comments in a Corpus. The paper also describes two experiments: the first was used to fit the system and was conducted with 350 reviews about smartphones (168 positives and 182 negatives). It achieved 63.17% in f-measure in the top 50 positive reviews, and 43.75% in f-measure in top 50 negative reviews. The second was used to compare the results of a sentiment orientation method before and after the selection of the best comments. It was conducted with 1620 reviews also about smartphones (982 positives and 594 negatives) and our approach improved the results of sentiment orientation method up to approximately 10% in f-measure in positive reviews and 7% in f-measure in negative reviews.*

KEYWORDS: Opinion Mining. Sentiment Analysis. Fuzzy Logic. Knowledge Extraction.

1 INTRODUCTION

It is a common practice that people search for opinions and references of users when there is an interest in purchasing a product or service. Many of companies that manufacture products or provide services are also interested in customers' opinions or feedback to guide marketing actions and decision-making process. Over 40% of people in the modern world depend on opinions and reviews over the web to buy products and request services [1, 2].

According to Liu [3], this interest has always existed, however, with the web's emergence, the way of sending opinions and making information available changed dramatically. With the web popularization, people and companies have been given new channels to deliver and collect opinions. On-line sales companies offer areas to store and view the comments of the customers. More recently, social networking sites emerged and increased the supply of available places to store the user-generated content about products and services.

The challenge of the researchers is to extract important information from unstructured data (Big Data). Due the large amount of data, the manual analysis process becomes a hard task. Therefore, there is a need to develop automatic methods to deal with this data.

The evolution of the works on extraction and analysis of opinions raised the area of Sentiment Analysis also called Opinion Mining [3]. Currently, this area gains strength both in the academic and industry of communication and marketing.

Sentiment analysis is defined as any study involving opinions, sentiments, evaluations, attitudes, affections, views, emotions and subjectivity expressed on a textual descriptions and can be structured, in a general way, in three stages [2, 4]:

- To identify the opinions expressed on certain characteristic or product in a set of comments;
- To define the semantic orientation or polarity of opinions. For example, if it is positive, negative or neutral;
- To present the results in summary form.

Although there are several researches in the first two steps, is still necessary to have several advances in this field in order to improve existing results, because still remain some limitations, such as Named-Entity Recognition (NER), Anaphora resolution (AR), negative polarity and ambiguity resolution [3]. The main aim of this work is to present an approach to estimate the degree of importance of comments about products generated by web users. The degree of importance of the comments allows to define which are the most relevant to the final evaluation of the product. The assumption is that before running the stages of sentiment analysis, you can select the best comments, and so, reduce the overall error of the existing methods. Our approach is multidisciplinary and uses some techniques of Natural Language Processing (NLP), Sentiment Analysis and Fuzzy Systems.

The experiments showed that the results are improved when comparing the metrics of set of best reviews with the entire set of comments. The proposed approach also allowed to improve the results of the negative reviews. And all these improvements were carried out on a set approximately 90% smaller than the original, allowing, furthermore, that people can manually examine this set of best reviews.

The rest of this paper is organized as follows: Section 2 discusses related works on opinion extraction, identifying the semantic orientation of words, and use of fuzzy sets in opinion mining system. In Section 3 we describe the fundamental aspects of Fuzzy Inference Systems. Next, in Section 4, we present an approach to estimate the degree of importance of comments about products generated by web users. The experiments and results are described in Section 5. Finally, in Section 6, we present the conclusions and future works.

2 Related Works

2.1 *Opinion Extraction*

The approaches based on rules of data mining are widely preferred by researchers.

Liu et al. [5] proposes a methodology to research opinions in comments involving multiple products. The authors identify all the phrases related to the domain, and then, they classify them in two groups: characteristics and products. The Pointwise Mutual Information (PMI) technique is used to calculate the score of each candidate phrase according to the difference in occurrence between domain-specific and general corpus. The authors also present an algorithm to predict dependence between characteristics and products. All opinions are indexed as triple $\langle product, feature, quality\ word\rangle$, and next they are used to retrieve opinions that "match" with the interests of users.

Another approach to extract features was proposed by Aciar et al. [6] and uses an ontology. Although this method works well semantically, the drawback is maintaining the ontology to solve the problem of continuous data expansion in comments. In this approach the ontology was build manually, and updates should be performed when new features are added.

Jeong et al. [7] proposes the extraction of features based on nominal phrases. However, they select only the features which have opinion words. Beside this, they propose a stage to merge the features, for example, the words *photo*, *picture* and *image* are considered homogeneous (i.e. they represent the same feature).

In our approach, the extraction step is similar to the proposal by Jeong et al. [7], however, we additionally use the phrasal structure of the sentence to identify the features and its respective quality words. Thus, from a textual review, all tuples $\langle feature; quality\ word\rangle$ are identified.

2.2 *Semantic Orientation*

In scientific literature, there are also various approaches to identify the semantic orientation of opinions (quality words), which can be based in lexicons, statistical techniques and machine learning techniques. The first ones are more common, but are dependent on the quality of sentiment lexicon.

The *WordNet* [8] is the largest and well-known lexicon. Some methods have used it as a base to create more specific lexicons [9–11]. An extended version of this lexicon, the *SentiWordNet*[1], was built to support applications of opinion mining and sentiment classification. It is important to mention that the *WordNet* is available for the English language, but there is a version for Brazilian Portuguese language called *WordNet.BR*[2]. There is also a sentiment lexicon for Portuguese from Portugal that is called *SentiLex-PT* [12], made up of 7,014 lemmas, and 82,347 inflected forms.

With respect to statistical techniques, Turney and Littman [13] used Pointwise Mutual Information (PMI) and Latent Semantic Analysis (LSA) to infer the semantic orientation of words. Their approach is based on the supposition of a word semantic orientation tends to correspond to the semantic orientation of its neighbors.

Another way to determine the semantic orientation of opinions is to use machine-learning techniques. These techniques use training corpus (labeled documents) as a source of knowledge to find out the polarity of words. A manually labeled data set is available through TREC, CLEF and NTCIR projects [14], however, they are destined to European languages (English, French, German, Italian and Spanish).

Normally, in opinion mining, if a sentence has many positive (or negative) opinions, the sentence opinion is considered positive (or negative). If number of positive opinions is equal to the negative opinions, then it is considered neutral polarity. In this case, two

[1] available on *http://sentiwordnet.isti.cnr.it/*.
[2] available from *http://www.nilc.icmc.usp.br/wordnetbr/ (base verb only)*

actions can be taken: assigning to the average orientation of the comment or the previous sentence orientation [15].

In our approach, the polarization step uses the sentiment lexicon *SentiLex-PT* [12] to identify semantic orientation of comments.

2.3 *Fuzzy-Based Aspects in Opinion Mining*

In scientific literature, there are few works trying to use fuzzy aspects in systems of opinion mining. Guohong & Wang [16] presented a fuzzy set theory based on framework for Chinese language sentence-level sentiment classification. They calculate the sentiment intensities for morphemes, words and phrases by using Chi-square techniques. After determining the sentence sentiment intensity, a membership function is used to identify to which set a sentence belongs and then decide its polarity under the principle of maximum membership. The obtained results are considered only on average, and the authors did not show how to address any problems like negations, vague or ambiguous words, and so on.

Kar and Mandal [17] proposed a system of opinion mining called Fuzzy Opinion Miner (FOM) which uses fuzzy weights that are assigned to the opinion words (adjectives and adverbs). For example, *“good” = 0.6*; *“very good” = 0.7746*; *“non proper” = 0.4*; and so on. However, they do not group the features according to the strength of the opinions that have been expressed on them. Certainly, this would help to show which features customers like or dislike. The system was not compared to others to show its performance and advantages.

Samaneh et al. [18] proposed a *fuzzy logic system* that performs sentiment classification of customers’ reviews. The reviews are classified in various categories (e.g., strongly positive or negative, moderately positive or negative, weakly positive or negative, and very weakly positive or negative). They used adjectives, adverbs, verbs and nouns as opinion words. For example, *‘excellent’ = 6*; *‘good’ = 3*; *‘like’ = 4*; *‘very’ = 5*; among others. The values were defined by human experts. The authors used three triangular membership functions which are low, moderate and high. The boundaries for these sets were also defined by human experts. Based on these fuzzy sets, some fuzzy rules were designed to address each case and, consequently, find the orientation when a condition is met. The authors did not also report any results.

In Jusoh and Alfawareh [19], the authors proposed the use of fuzzy sets and a fuzzy lexicon to define the degree of polarity (positive or negative) of reviews. They considered only adjectives and adverbs as opinion words and conducted a small experiment with reviews about hotels. However, they did not calculate the precision, recall and f-measure results.

Our approach is different from all above related works in the sense that it proposes the use of fuzzy sets to estimate the importance of comments and not only the strength of opinion word. Thus, the great advantage of our approach is to model a fuzzy system to infer the importance of comment and set the *TOP(N)* most significant reviews. It is important to highlight that our approach reduce the task of analyzing the uncountable user reviews of product or service.

3 Fuzzy Inference Systems

The concept of Fuzzy Sets has been used in the area of Sentiment Analysis to infer the degree of positivity or negativity of an opinion. These concepts were introduced by Zadeh [20] and refer to classes of objects that do not have a strictly defined border, but instead all objects have a degree of relevance in each class. The fuzzy sets are characterized by allowing the change of membership degree of an object from one class to another, smoothly. This concept allowed to create the Fuzzy Logic [21, 22].

A fuzzy inference system is a computational model that uses the Fuzzy Set Theory and Fuzzy Logic in order to deal with highly complex processes, associated with inaccuracies, uncertainty and qualitative information [23].

The most used fuzzy inference models are: Mandani Model [24] and Takagi-Sugeno-Kang (TSK) [25, 26] model. The Mamdani model was one of the first control systems to be developed based on the fuzzy set theory and fuzzy logic. The TSK model is very similar to Mamdani model in many aspects. The main difference between models is on the consequent of the fuzzy rules. In Mandani model, linguistic variables are used ate the consequent, in TSK model, polynomial functions are used at the consequent.

In summary, the development process of fuzzy inference system usually consists the following steps [27]:

- Specify the problem, and define linguistic variables;
- Determine fuzzy sets, namely the membership functions for each variable;
- Build the rules of fuzzy inference system that shall be included in the rule base, which will be used to execute the required inferences;
- Evaluate and adjust the system.

Thus, when values are applied to input variables, they will be submitted to the fuzzification process that determines the membership degree of these values in each fuzzy set of variable. After the fuzzification process, all active linguistic instances of the input variables of system will be submitted to an inference process that will determine the general fuzzy output solution for each fuzzy rule. With the result of all inferred rules, the system will perform a composition of the results. Lastly, the defuzzification process is performed, producing a crisp numerical value as output of the system.

In this work, we used the Mamdani model because it allows using linguistic variables as input and output of the system. Therefore, the modeling process becomes more simple and with better interaction of the specialist who sets the operation rules.

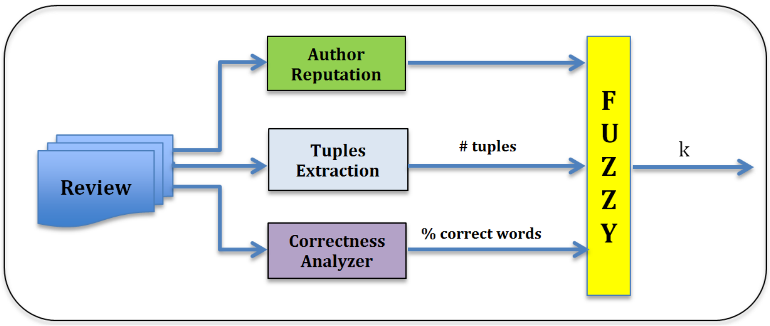

Fig. 1. General Structure of Proposed Approach

4 Proposed Approach

To estimate the degree of importance of comments generated by web users about products and services, we propose a fuzzy inference system that has three input variables: author reputation, number of tuples $\langle feature, quality\ word\rangle$ and percentage of correctly spelled words and one output variable: importance degree of the comment. The general structure of our approach can be shown in Figure 1. In figure, the output k represents the degree of importance of the comment.

Empirically, we believe that these variables are the most important to specify the importance degree of reviews of products and services on the web. These variables are described in the following text.

4.1 *Author Reputation*

There are many researches in literature that try to solve the problem of the large amount of spam-messages on the network. Normally, these spams are generated by professional spammers or by companies interested in increasing their sales and credibility. For example, the works [28] and [29] are aimed to detect spam in comments about products on the web. Among techniques more used to detect spams, are the written text analysis and the analysis of the author profile. Therefore, the author reputation has great relevance to estimate both validity and importance of web comments. Besides this, we believe that opinions of specialists on issues within their areas of expertise have a greater weight than opinions of persons that do not have the same experience level.

However, to estimate the author reputation is not a trivial task and in this work, the value of reputation was setted to 1, which means that all authors are considered important. It is important to highlight that in our research group there is a work-in-progress to infer the author's reputation. Our hypothesis is that whom often write messages has better reputation than occasional authors. Another ongoing research work we are trying to measure author reputations in social media through their relationships.

4.2 *Number of Tuples*

It is common in opinionated texts about products and services finding feature that is cited by authors near to its respective qualities. About these features and qualities many researches have been developed, such as [30, 5, 31, 6]. The identification these tuples $\langle feature, quality\ word \rangle$ becomes relevant to the final result of the sentiment analysis process. Therefore, how much more features are cited and qualified by customers, more this comment becomes important. The tuples extraction stage follows three steps, as shown in Figure 2.

In the first step, the comments are analyzed according to phrase structure of sentences. In sentences with "subject + primary verb + predicate of subject", the subject (core) defines the feature and the predicate (core) indicates the quality word. For example, in the sentence *"the screen is very good"*, the extracted tuple is $\langle screen, very\ good \rangle$. In this step, no preprocessing of the text should be performed. In the second step, the comments are analyzed again, according to linguistic patterns, specified from Turney's patterns [32] and some extensions of Kar and Mandal [17]. Figure 3 shows the seven patterns used in our approach. In this step, one preprocessing routine becomes necessary to remove words of unwanted word-classes (e.g., article, pronoun, numeral and conjunction), since these classes do

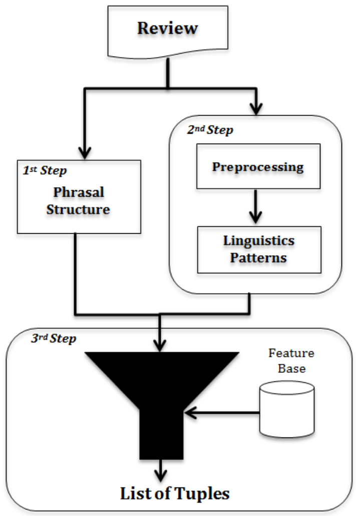

Fig. 2. Tuples Extraction Process Flow

not present semantic content. In addition, all punctuation marks and digits were also excluded.

```
pattern1: ADJ NOUN (PREP? NOUN)*;

pattern2: ADV ADV? ADJ (NOUN (PREP? NOUN)*)?;

pattern3: NOUN (PREP? NOUN)* (ADJ) ADV ADV?;

pattern4: NOUN (PREP? NOUN)* (ADV)? ADJ+ ;

pattern5: ADV VERB;

pattern6: VERB ADV;
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Fig. 3. Linguistic Patterns

The third step consists on filtering the desired features to prevent unwanted tuples from being analyzed. This step depends on database with features, which must be defined by the user. So, this database becomes our approach dependent on application domain.

4.3 *Vocabulary Richness*

Several authors indicate that words written incorrectly become a problem when web reviews are analyzing in sentiment analysis area. For example, Tumitan and Becker [33], recognize that these words can disturb the results and spell checking becomes necessary. Paltoglou and Giachanou [34], state that a significant part of textual descriptions in social media contains non-standard language, including misspelled words and others problems such as abbreviations, phonetic substitutions and emoticons. These problems cause errors in the process of tokenization, POS tagged, named entity recognition, affecting negatively the results of the analysis.

In our approach, the hypothesis that defines the use of variable "vocabulary richness" (or correctness) is: how much better a review has been written, more useful is user opinion. Thus, an opinion emitted with noisy form has many misspelled words, and therefore will be considered less important.

At first, we used only the percentage of words correctly written in reviews. However, it is possible to use other metrics to evaluate the vocabulary richness, for example, vocabulary size, number of "hapax legomena" (word occurring only once in a given corpus).

Finally, to calculate the percentage of correct words of comments we use the Wiktionary[3] for Portuguese language.

4.4 *Fuzzy System Configuration*

In our approach, for each input variable are associated three linguistic values: low, medium and high. The pertinence functions associated to linguistic value of each system variable can be observed in Figure 4.

For output variable (importance degree), we use four linguistic values: excellent, good, sufficient and insufficient. These values were set in a universe of discourse U[0,10]. The inference method used to obtain the output of the rules was the MAX-MIN and the

[3] available from *http://pt.wiktionary.org*.

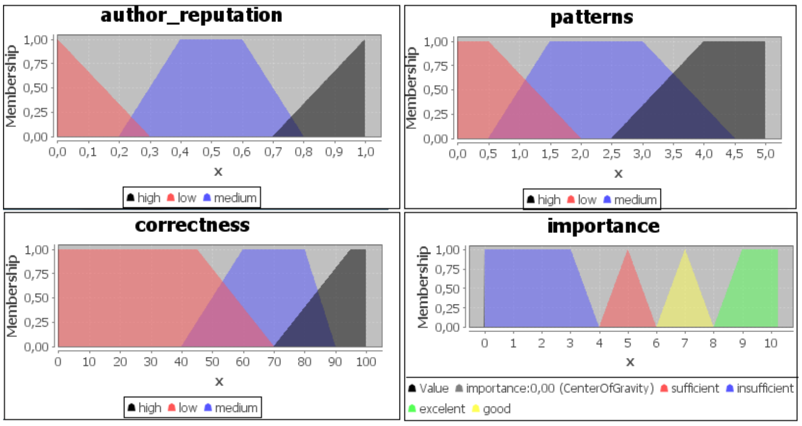

Fig. 4. Final Fuzzy Pertinences Values

defuzzification method to get the numeric value associated to induced importance degree was the Center of Gravity [35].

Table 1. Rule Base

	Patterns/Correctness								
Author	L/L	L/M	L/H	M/L	M/M	M/H	H/L	H/M	H/H
L	ISF	ISF	SF	SF	SF	SF	SF	GD	EXC
M	ISF	ISF	SF	SF	SF	GD	GD	EXC	EXC
H	ISF	SF	SF	SF	GD	GD	GD	EXC	EXC

The fuzzy rule base is a set of production fuzzy rules, which determine the decision-making strategy to application. The typical structure of a fuzzy rule is: **IF** $(x = a)$ **AND** $(y = b)$ **AND** $(z = c)$ **THEN** $(k = d)$, where x, y and z are the input variables and k is the output variable. Thus, for example, x, y, z and k being, respectively, *author reputation*, *number of tuples*, *correctness* and *importance degree*. Then, for input values *low*, *low* and *low*, the output k is *insufficient*. The fuzzy rule base was defined empirically by the experts. The rules are summarized in Table 1.

5 Experiments and Results

The following sections will explain the two realized experiments. The first experiment was helpful to fit the system that would select the best comments. The second was performed to test the whole approach. The respective results are shown in each section.

5.1 *Experiment One - Fitting the Fuzzy System*

We performed a preliminary evaluation of proposed approach with a sample of 350 reviews of products (specifically smartphones). The reviews were collected from site Buscape[4] in October 2013. The original Corpus has 2000 reviews, being 1000 positive and 1000 negative reviews. Next, an expert in linguistic issues evaluated manually 350 reviews to create a gold standard subcorpus, setting one of importance levels: insufficient (ISF), sufficient (SF), good (GD) or excellent (EXC). The result of this evaluation produced the distribution shown in Table 2.

Table 2. The Distribution of Feedback for Levels of Importance

Importance Degree	Positive	Negative
Excelent	8	7
Good	46	49
Sufficient	80	81
Insuffficient	34	45

As we can be seen in Table 2, 15 comments were defined as excellent (8 positive and 7 negative); 95 were defined as good (46 positive and 49 negative) and so on. This subcorpus will be called *control sample* in rest of this paper.

For each one of reviews the three input variables were calculated and the value of the output variable was observed. Then the $TOP(x)$ most important reviews of the sample were selected.

[4] available from *http://www.buscape.com.br*

Next, we compare the $TOP(x)$ indicated reviews using our approach with $TOP(x)$ reviews of *control sample* (selected manually). The results are shown in Table 3. The precision (P) was defined as the ratio between the amount of reviews indicated ($TOP(x)$ more important) that belong to $TOP(x)$ of *control sample* and the value of x.

Table 3. Results of Experimentation

Positive				**Negative**			
	P (%)	**R (%)**	**F (%)**		**P (%)**	**R (%)**	**F (%)**
TOP(8)	19.23	62.5	29.41	**TOP(7)**	0	0	0
TOP(54)	60	66.7	63.17	**TOP(56)**	52.5	37.5	43.75

Table 3 shows the results of four experiments that were executed on the *control sample*: $TOP(8)$ and $TOP(54)$ positives and $TOP(7)$ and $TOP(56)$ negatives. These definitions refer to the number of positive reviews excellent and excellent+good, and negative reviews excellent and excellent+good (see Table 2). Notice also in Table 3 that the best results occurred on positive reviews. In relation to the amount of reviews extracted, considering excellent + good $TOP(54)$ e $TOP(56)$ presented a f-measure of 63.17% for positive and 43.75% for negative, respectively.

It is important to mention any problems that caused errors in our experiment:

1. Incorrect tags can be generated by POS Tagger, and it can become difficult to detect several linguistic patterns, besides to detect others patterns that should not be extracted;
2. In spite of using adapted patterns, some tuples were not extracted correctly because they do not have explicit features or qualify words;
3. The fixed value defined to input variable "author reputation" can influence on the result directly, and many reviews can have not been adequately evaluated.

Therefore, more experiments need to be done to resolve the problems highlighted.

5.2 *Experiment Two - Improving the Results*

This experiment aims to conduct a comparison between the results of a semantic orientation method on a full corpus and a set of best reviews, selected by our approach. Specific cuts were made in order to choose the better subset of the selected texts by approach.

The corpus used in this experiment was composed by 1620 reviews, with 982 positive, 594 negative and 44 neutral. In this evaluation we will only use the positive and negative reviews. This corpus was generated from 2000 comments mentioned in the previous subsection. These 2000 comments were manually reviewed by three linguistics experts and this new set is composed of the reviews where there was agreement from all reviewers. We will call this set of *Revised Corpus*.

To infer the semantic orientation of *Revised Corpus*, we use the sentiment lexicon SentiLex-PT [12] For each review in *Revised Corpus* the linguistic patterns explained in Section 4.2 was extracted, and each pattern has been polarized in accordance with SentiLex-PT. Additionally, the adverbs were manually weighted according to their possible modification rate. For example, in expression *bateria muito boa* (very good battery), according to SentiLex-PT, the word *Boa (Good)* has semantic orientation equals to 1 (positive). The word *muito (very)*, according to set of adverbs, has weight equals to 0.5, therefore, the semantic orientation of this expression becomes 1.5. The semantic orientation of one review is the sum of all values of patterns. The Table 4 the results of precision, recall and f-measure metrics, when we applied this method on all reviews of *Revised Corpus*. The precision obtained was 78.55% to positive reviews, and 82.97% to negative reviews. Considering to f-measure the values were 70.63% and 63.05%, respectively.

After calculating the semantic orientation, the importance degree was calculated for each comment. With the importance degree, the better comments can be selected according to specific cuts

Table 4. Result of the Method on the Entire Corpus

Positive			Negative		
P (%)	**R (%)**	**F (%)**	**P (%)**	**R (%)**	**F (%)**
78,55	64,15	70,63	82,97	50,84	63,05

$(TOP(x))$, varying in the range from 10 to 110. For each set of comments, Precision (P), Recall (R) and F-Measure (R) also was calculated. The Figure 5 and Figure 6 shows the variation of P, R and F for each cut-off point.

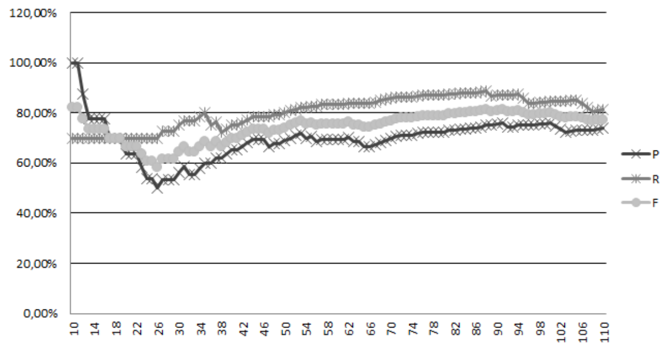

Fig. 5. Positive Reviews

We can seen in results shown in Figures 5 and 6, that the results of metrics was improved from approximately cut-off point on $TOP(50)$ in both positive and negative reviews. Notice that the results are enhancing until the set of $TOP(100)$ best comments, approximately.

The problems explained in the previous experiment continue to affect this experiment, therefore, the results can be improved.

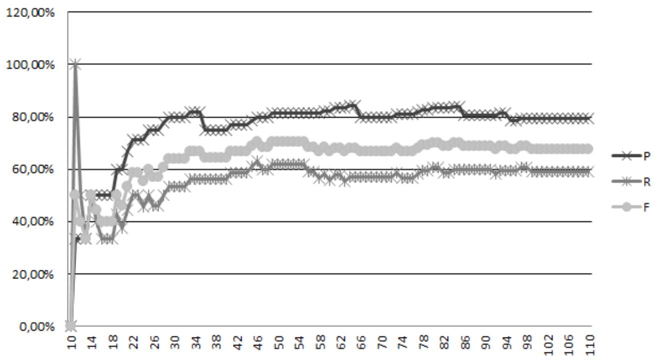

Fig. 6. Negative Reviews

6 Conclusions and Future Works

This paper presented an approach to estimate the degree of importance of comment on products generated by web users, in the field of sentiment analysis. The proposal approach use a fuzzy inference system composed of three input variables: author reputation, number of tuples, and percentage of correctly spelled words and one output variable: importance degree of the comment.

It is important highlight that the differential of our proposal is to apply a fuzzy sets to estimate the importance of comments and to define the $TOP(N)$ most important reviews. Our approach also permits to reduce the task of analyzing the uncountable user reviews of product or service.

We discussed two evaluations of approach, one with a *control sample* of comments (350 reviews) to adjust the system and another to test the whole approach. The performed experiments showed that our approach improved the results of semantic orientation method, with less than 10% of the texts of corpus. Some new experiments may be performed in order to ensure the good results.

The future works are:

- to define a metric to calculate the author reputation;

– use others semantic orientation methods, to investigate the approach behavior;
– apply the approach in others domains (books, movies, home appliances, and so on).

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