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Opinion Extraction and Classification of Real Time E-commerce Websites Reviews

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***Abstract*— with the recent explosive growth of e-commerce, and online communication, a new kind of text, opinion text become available in many application areas, such as Instant Messages, online Chat and review websites.**
However, Opinion mining is developed simultaneously therewith then used for product feedback analysis, and for decision making to users and companies. According to these big needs we realized a tool for the benefit of the Opinion Mining and Sentiments Analysis. This tool is based on the combination of both SVM machine learning algorithm and approaches in terms of extraction opinion text features. Our tool collects data in real time from (Amazon, Cnet and TrustedReviews) websites according to user request product. After it filters reviews from the other content then extracting opinions (subjective sentences) and classifies them. Moreover, to improve the performance of our system we proposed some algorithms that constructed on sentiment bag, based on emoticons and injections.

***Keywords*—Opinion Mining, support vector machine, product reviews, opinion extraction, Ecommerce, emoticons, injection, subjectivity.**

I. Introduction

"What do the others think?" has always been an important piece of information for most people in the decision-making process [5]. Sentiment Analysis is the study that analyzes people's opinion and sentiment towards entities such as products, services in the text [1]. Many interactive sites have emerged with the birth of Web 2.0. They offer to user to give his opinion on a several kind of products (books, movies, mobiles, laptops) through discussion groups, blogs, forums and other sites specializing in critical products (such as Amazon). As a result the number of reviews that a product receives grows rapidly. Therefore, a necessity of analyzing and understanding these online generated data has arisen.

The massive interest in opinion mining is directly linked to a strong social demand, namely the rapid expansion of online business. How to access private judgments about a particular product to better anticipate needs and better evaluate the impact of marketing to a particular consumer segment? Whatever the quality of the product or service, since the emergence of online commerce (e-commerce), large and small, that have opinion mining and sentiment analysis as part of their mission due to the fact that the industrial landscape tends to change quite rapidly, so that lists of companies risk falling out of date rather quickly.[5] So know and understand the customer's needs are central to any successful business. The user also can know the merits and demerits of the product from the experiences shared by people on the web, which can be useful for them in decision-making.

In this paper, we propose a tool that extract automatically and in real time opinions, approach based on important features of subjectivity and opinion in the text. Then classify the extracted opinion with the help of constructed injections and emoticons dictionary.

II. Related work

A. *Opinion mining*

In [20] and [18], the term "sentiment" used in reference to the automatic analysis of evaluative text and tracking of the predictive judgments. Some research focus on Subjectivity detection which can be defined as a process of selecting opinion containing sentences [21]. The purpose of subjectivity and objectivity classification in opinion mining research is to distinguish between factual and subjective (expressing an opinion or emotion) remarks present in customer reviews [6] and [26]. The authors in [2] aims to propose methods for identifying subjective sentences from customer reviews for mining product features and user opinions.Others research are interested by sentiment analysis which is a process of finding users opinion about particular topic [28]. It performed on different domain data such as Movie [29], Restaurants [12], Books and Products [8] [11], etc.Most of the researches about products reviews were focused on automatically Classification of the products into 'recommended" or ''not recommended" [5][7][24]. but maybe people are interested by a specific product as in ([23], [9],[22]). The authors [6] [16][27] proposed a novel framework for analysing and comparing consumer opinions of competing products.

B. *Emoticons and injections*

There are various affect types; in specific here the concentration is on the six "universal" emotions as in [17]: anger, disgust, fear, happiness, sadness and surprise. These emotions could be easily associated with an interesting application of a human-computer interaction, where when a system identifies that the user is upset or annoyed, the system could change the user interface to a different mode of interaction as in [15]. [19] Used a lexicon of the most used emoticons and injections.

In our case we cover all that to obtain a complete system and useful to make decision process for consumers and complains.

III. Proposed System Architecture

Our system works as follow:

A. Step1:send the reqest

The entire document should be in Times New Roman or our system users enter the product name in the field and select the desired websites.

B. Step2: corpus collection

Using the search engine "google", our system will retrieve automatically the URLs of Web pages of sites selected containing opinions on the product entered in the field in question. Then from these URLs, it sets the contents of Web pages in text files (.txt).

C. Step3: pre-processing dataset and feature selection

- Algorithm1 then Algorithm2,
- Pre-processing1,
- Using TF-IDF Feature Selection.

D. Step4: subjectivity detection

In this step the system extract automatically opinions “reviews” from the generated text files in the previous step, eliminating texts that bear no opinion.

E. Step5: pre-processing dataset and feature selection

- Algorithm3 then Algorithm4;
- Pre-processing2;
- Using TF-IDF Feature Selection.

F. Step6: sentiment classification

Classify those collected reviews into pre-chosen classes as positive, and negative through the classifier model build.

G. Step7: getting the results

The system count and view the number of positive comments, and negative. It then displays the percentage and comments for each selected site, and then it displays the overall percentage, and a graphical representation in the form of a sector. And also our system users can see all the comments classified according to their polarity.

All those steps are showed in fig.1:

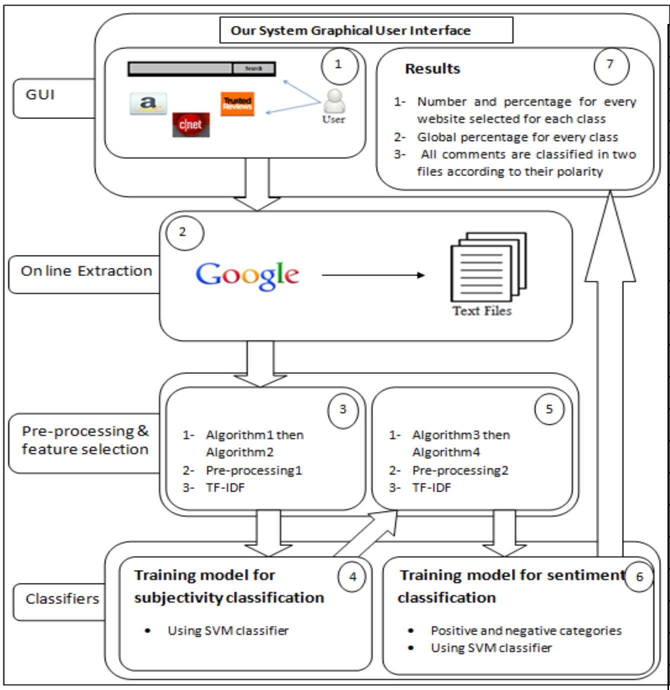

Fig. 1 Proposed system Architecture

IV. Methodology

All our proposed analysis for the both of classifications is showed in this section.

1. Bags development

This step focuses on the informal language of online websites specialized on critical products. In this work, we have two types of bags were created: bag for emoticons and bag for interjections.

A. *Emoticons’ bag.*

We create a bag of the used emoticons on those websites, whether they express a positive or a negative sentiment. After a deep analysis, we concluded the results in the Table 1.

TABLE I
EMOTICONS’ BAG WITH ASSOCIATED SENTIMENT

Positive emoticons	Negative emotions
O :-)	X-(
~ :0	:-#
*< :o)	</3
B-)	O.o
\ :D/	:_(
_	:’(
:*), :*	:-(, :(
:p, =p	:/
8-)	
:->, :>	
:), =), :-)	
<3	
XP, X-p	
XD, :D, =D, :-D	

B. *Injections’ bag.*

We create a bag of the injections used on those websites, (Table 2).

TABLE II
INJECTIONS’ BAG WITH ASSOCIATED SENTIMENT

Positive injections	Negative injections
Wow, waw	Oh dear
Aha	No way
Haha, hehe, hihi	Argh
Thank you	Boo, booh
Oy	Brr, brrr
Ahh, ahhh	D’oh, doh
Gah	Duh
Gee	Eep
Hmm, hm, hmmm	Eww, ewww
Hah, heh	Nah, nuh-uh, nuhuh
Hurrah	Oomph, umph
Mhm	Oops
Mm, mmm, mmh	Ow, oww, ouch, yeow
Oh-lala, ooh-la-la	Pff, pffh, pssh, pfft
Ooh, oooh	Uh-oh, oh-oh, oh no
Wee, whee, weee	Yuck, ich, blech, bleh
Yahoo, yippie	
Yay, yeah	
Yee-haw, yeehaw	
Yoo-hoo, yoohoo	
Zing	

2. Classification using Support Vector Machine algorithm

In the both classifications we used Support Vector Machine [25] classifier.

3. Algorithms development

In this section we show all algorithms developed and used to improving our classifications. Which emoticon or injection is used by the consumers is not really important. The important is the sentiment reflected by them. The classifier takes etch emoticon or injection as a different word. But if we replace all (positive emoticon by PosEMO, positive injection by PosINJ, negative emoticon by NegEMO and negative injection by NegINJ) in sentiment classification, and all (emoticons by EMO and injections by INJ) in subjectivity classification. The classifier takes them like the same word.

TABLE III
ALGORITHMS

Algorithm1. replace all injection with the same string "INJ"	**Algorithm2**. replace all emoticon with the same string "EMO"
W• Corpus I• set of Injections Foreach w ∈ W Foreach i ∈ I If w = i w • "INJ" EndIf EndForeach EndForeach	W• Corpus E← set of Emoticons Foreach w ∈ W Foreach e ∈ E If w = e w • "EMO" EndIf EndForeach EndForeach
Algorithm3. Replace all positive injection with "PosINJ" and negative injection with "NegINJ".	**Algorithm4.** Replace all positive emoticon with "PosEMO" and negative emoticon with "NegEMO
W• Corpus PI• set of positive Injections NI← set of negative Injections Foreach w ∈ W Foreach pi ∈ PI If w = pi w • "PosINJ" EndIf EndForeach Foreach ni ∈ NI If w = ni w • "NegINJ" EndIf EndForeach EndForeach	W• Corpus PE• set of Positive Emoticons NE• set of Negative Emoticons Foreach w ∈ W Foreach pe ∈ PE If w = pe w • "PosEMO" EndIf EndForeach Foreach ne ∈ NE If w = ne w • "NegEMO" EndIf EndForeach EndForeach

4. Creating a training model for the text subjectivity

This step consists of extracting 10000 comments (5000 subjective and 5000 objective) from websites specialized on products critics (Amazone, Cent and TrustedReviews).

A. *Approach proposed*

Our approach is as follow

- V1: the original dataset Pre-Processed + TF-IDF feature selected.
- V2: the original dataset pass firstly on Algorithm1 then Algorithm2, the result is Pre-Processed + TF-IDF feature selected.

B. *Data pre-processing1*

- Keeping stopwords;
- Removing numbers and punctuations;
- Removing all word appears less than 5 times;
- Stemming: removing prefix and suffix finding the stem or the root of the word. The lovinsStemmer [13] is a well-known like stemming algorithm.

C. *Feature Selection*

- Using Term frequency inverse document frequency TF-IDF [4]
- Part of Speech (POS) tagging: consists of tagging a word in a text to a particular part of speech based on its context and its definition. In English, it has 9 parts of speech: noun, verb, article, adjective, preposition, pronoun, adverb, conjunction and interjection [19]. We use POS as features just for show which parts appear in which category more than the other.

5. Creating a training model for the text polarity

This step consists of extracting 2000 comments (1000 positive and 1000 negative) from websites specialized on products critics (Amazone, Cent and TrustReviews).

A. *Approach proposed.*

Our approach is as follow

- F1: the original dataset Pre-Processed + TF-IDF feature selected.
- F2: the original dataset pass firstly on Algorithm3 then Algorithm4, the result is Pre-Processed + TF-IDF feature selected.

B. *Data pre-processing2*

The aim of this step is to clean the dataset by:

- Removing stopwords like 'of',' and', 'my' that don't have an influence on sentiment classification.
- Removing numbers and punctuations.
- Removing all word appears less than 3 times.
- Stemming: removing prefix and suffix finding the stem or the root of the word. The lovinsStemmer [13] is a well-known like stemming algorithm.

C. *Feature selection.*

Term frequency inverse document frequency TF-IDF [4] is used.

V. RESULT AND DISCUSSION

We have to experiment the two training models, using 10-fold cross-validation [14] with WEKA [10] where SVM classifier is already implemented.

A. *Experiment of the subjectivity training model*

We started our experiment with showing which parts of speech is the most appeared in etch class subjective and objective. The result is showing in Fig.2

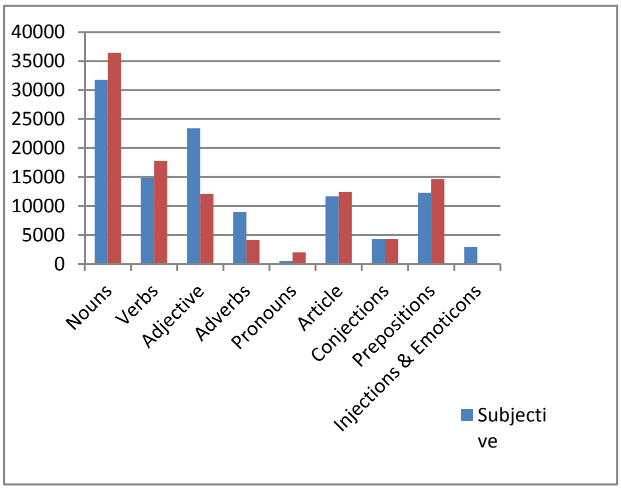

Fig. 2 Number of words in etch part of speech in etch class.

According to Fig.2, we note that injections and emoticons appear only in subjective text, which it also contains more adjectives and adverbs, this due to its nature which refers to how someone's judgment is influenced by personal opinion and feeling, Contrasted with objective text which is related more to nouns, pronouns, verbs and preposition to express existence and facts.

Using this characteristics of the subjectivity in the text (the appearance of injections and emoticons) in the subjectivity classification as the following table shows the obtaining results with applying V1 data version then V2 (using algorithm1 then algorithm2) data version.

TABLE IV
SUBJECTIVITY CLASSIFICATION RESULTS

Version of data	SVM			
	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
V1	89.87 %	90.05	89.9	89.85
V2	93.07 %	93.3	93.05	93.05

Comparing SVM results, it was clear better results were produced after applying the V2. The improvement between accuracy results applying V1 and V2 is almost 3.2%. The same goes with the precision, recall and the F-measure. Table 4 shows the results of each class using V2

TABLE V
RESULTS BASED ON V2 DATA VERSION USING ALGORITHM3 AND ALGORITHM4

Class	SVM			
	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
Subjective	89.4	96.5	89.4	92.8
Objective	96.7	90.1	96.7	93.3

Table 4 calculates the performance results for the classification of the binary classifiers at the stage of using V2.

B. *Experiment of the sentiment training model*

The following table shows the obtaining results with applying F1 data version then F2 (using algorithm3 and algorithm4) data version.

TABLE VI
SENTIMENT CLASSIFICATION RESULTS

Version of data	SVM			
	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
F1	83.7 %	83.65	83.7	83.7
F2	88.4%	88.4	88.4	88.4

Regarding the effect of using algorithm3 then algorithm4 on the sentiment classification performance, we can note that there was an improvement of 4.7% in the accuracy, the recall and the F-measure while there was an improvement of 4.75 % in precision. (Table5).

TABLE VII
RESULTS BASED ON F2 DATA VERSION USING ALGORITHM3 AND ALGORITHM4

Class	SVM			
	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
Positive	87.7	88.9	87.7	88.3
Negative	89.1	87.9	89.1	88.5

Table 6 shows the performance results for the classification of the binary classifiers at the stage of using F2.

VI. CONCLUSION

This paper proposes a system for opinion extraction and classification automatically on real time from a several websites specialized on critical products. Firstly our system collects contents about a product in user request. Next step is to filter undesired texts (objective texts) using SVM classifier which have 93.07% of accuracy. Then to classify this subjective texts (the reviews) into positive or negative class using the model built by SVM classifier which have 88.4% of accuracy. Our system can classify the products into 'recommended" or ''not recommended" and also compare between products.

In future work we will improve our system considering other opinion text features, and the specific characteristics of products

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