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Statistical Approach for Sentiment Analysis of Product Reviews

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Abstract – Analyzing Internet statistics, the most popular online activities are communication via e-mail and searching for information on goods and services. For getting the idea about buying items customer reads reviews and feedback for evaluation of a product. Sentiment analysis is a Natural Language Processing (NLP) and Computational Linguistics (CL) processing technique that defines extract, identifies, analyzes and characterizes the sentiments or opinions in the form of textual information. Most of the existing work done in this domain is by using machine learning. Statistical approach has been proposed for extraction of features, their intensity and polarity.

Keywords – *Sentiment Features, Sentiment Score, Aspects, LSA.*

1. Introduction

Between the initiation of internet and the dawn of 2003, social media sites like Facebook, Linkedln, MySpace were carrying a few dozen exabytes of information on the web whereas same amount is generated weekly [1]. Also, the most prevalent form of communication on the web exists in the form of text which offers a rich platform for expressing emotions. In the absence of face-to-face contact to detect facial expressions and intonations in voice, the alternative option is to decipher sentiments from text in online forums.

Sentiment analysis from text documents is popular domain for the research in Natural Language Processing (NLP) and text mining. The basic task towards this direction is sentiment analysis and emotion recognition. Emotion extraction focuses on extracting a set of emotion labels and Sentiment Analysis is usually a binary classification task with outputs such as “positive” versus “negative,” “thumbs up” versus “thumbs down,” or “like” versus “dislike” [2].

Individuals/institutions/Companies are paying increasing attention to sentiment analysis. Companies are interested in what customers are saying about their products. Politicians are interested in knowing how their image is building through news media. Sentiment analysis focuses on assigning a polarity or a strength to subjective expressions (words and phrases that express opinions, emotions, sentiments, and so on) in order to decide the objectivity, subjectivity orientation of a document or the positive/negative/neutral polarity of an opinion sentence in a document. Even as a part of business intelligence and decision support system, sentiment analysis is carried out on the enormous volume of text data acquired from various sources. Many systems exist today for accomplishing the task of sentiment analysis.

Many researchers have become interested in sentiment analysis, as more people learn of the scientific challenges posed, and the scope of new applications enabled, by the processing of subjective language. Major deficiency of the previous work is that it only focuses on detecting the overall sentiment of a document, without performing an in-depth analysis to discover the latent topics and the associated topic sentiment. The contribution of this paper is to introduce statistical approach of categorizing product features, sentiment features and stop words.

2. Literature Survey

As researchers find many applications in Sentiment Analysis and as there are many research issues to deal with, researchers are getting attracted towards this topic Many papers that have been studied in [3] illustrate this fact.

Bruno Ohana et al. evaluated the use of the SentiWordNet opinion lexicon in the task of sentiment classification of film reviews. Results are obtained by simple word counting [4]. In this work, positive and negative scores of words were collected from SentiWordNet according to its part-of-speech tag then applied. A Term Counting method is used to classify review as positive or negative. In this method the lexicon was applied by counting positive and negative words found in a review and determining sentiment polarity based on which class received the highest score. These techniques do not consider the positivity, negativity, and objectivity magnitude for each word. For example, both 'good' and 'OK' terms are counted as positive words regardless of their positive magnitude.

Clues for subjectivity have been exploited from information extraction techniques. [5] have bootstrapped from a lexicon of subjectivity clues, they developed a subjective-objective sentence classifier which work without annotated data. This classifier is useful to improve information extraction performance on data which have not been annotated for subjectivity and also helps in improving precision.

[6] calculated valence and arousal on a real valued scale for non-review social media. They have predicted emotional responses of online communication. They have developed new dataset for this purpose. They have provided complete methodology for this task. They have also evaluated correlations between different affective dimensions and inter-coder agreement.

Random Forest-based classifiers have been exploited in [7].They have predicted the impact of reviews on sales and their perceived usefulness accurately. This is the pioneering work which integrates econometric, text mining, and predictive modeling techniques toward a more complete analysis of the information captured by user-generated online reviews in order to estimate their helpfulness and economic impact.

In general, automatic sentiment classification can focus on words, sentences, or documents. There are two approaches of sentiment classification methods for documents: lexicon-based and corpus-based.

Sentiment Lexicon carries scores for the words. Lexicon-based methods compute a sentiment score for texts by referring these sentiment lexicons. The sentiment orientation of customer reviews using the semantic orientation scores of the constituent adjectives was estimated. They have measured orientation of the adjectives with their co-occurrence frequency on the Web with several positive or negative seed adjectives [8].

A deep syntactic-semantic approach is presented in [9]. They used lexicon model for subjectivity description of Dutch verbs which provides a framework for the development of sentiment analysis and opinion mining applications..The model attempted to describe the detailed subjectivity relations that exist between the participants of the verbs, expressing multiple attitudes for each verb sense.

Improvement in Chinese sentiment analysis [10] has been attempted and developed both Chinese and English lexicons. They used it for Classification performance with latent affective embedding. Latent affective embedding found to be slightly better than latent affective folding, presumably as former's ability to more richly describe the affective space. Both techniques used standard LSA-based approaches. They have also use weighted word accumulation.

To sufficiently capture information from various aspects, [11] proposed an aspect-based segmentation algorithm. Algorithms segregate a user review into multiple single-aspect textual parts. They exploited aspect-augmentation based approach to generate aspect-specific feature vector of each aspect for aspect-based rating inference.

Supervised machine learning approaches are typically used for extraction of sentiments from product reviews Drawbacks of these approaches need labeled training data. Development of sufficient labeled data is very exhaustive and time consuming. It is desirable to develop a learning algorithm that does not require large amounts of labeled training data [12].

Because of these drawbacks, statistical approach has been proposed which is domain independent and need not to have any trained data.

3. Proposed System

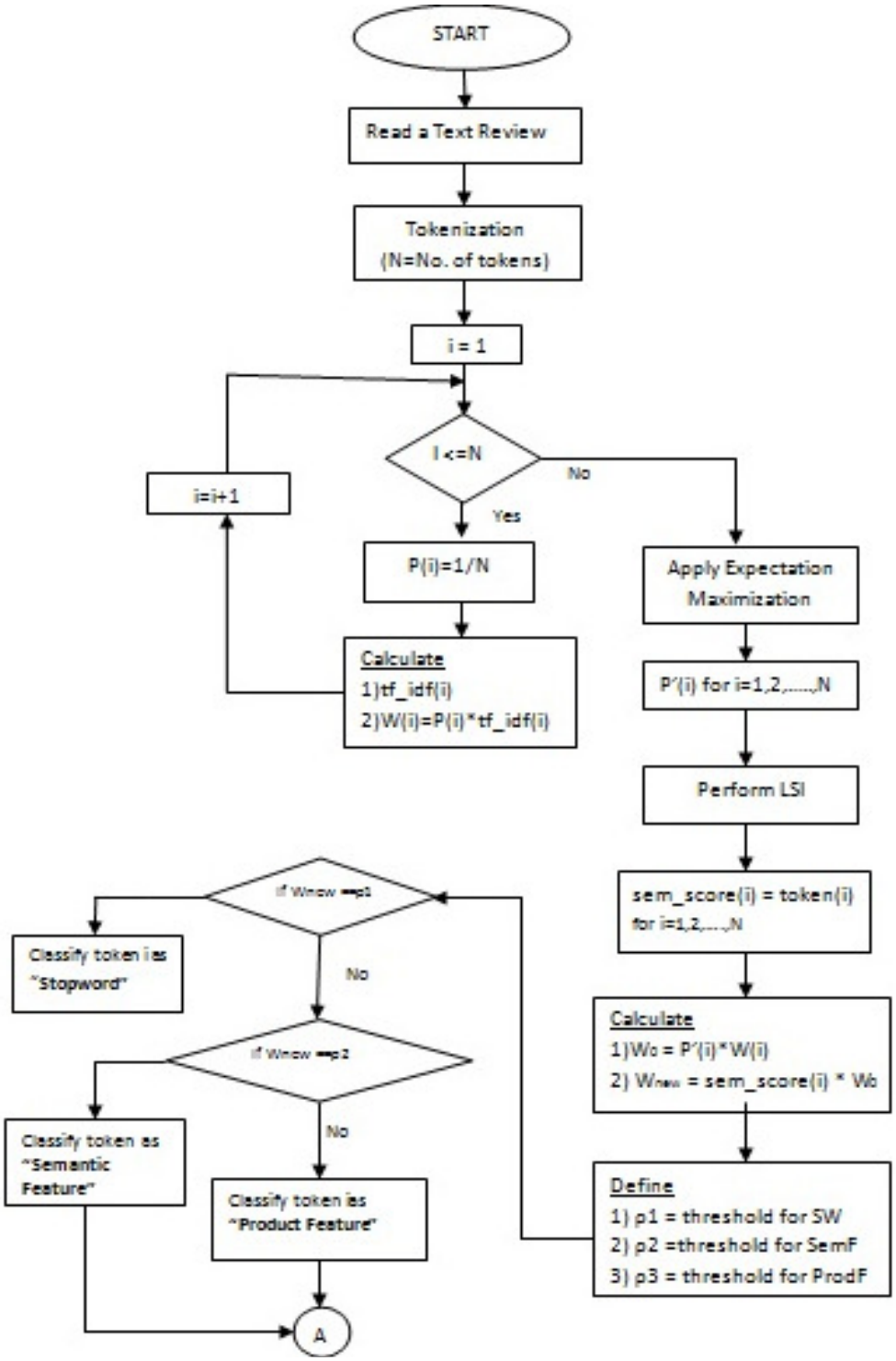

Fig. 1 Flowchart of the proposed system part A

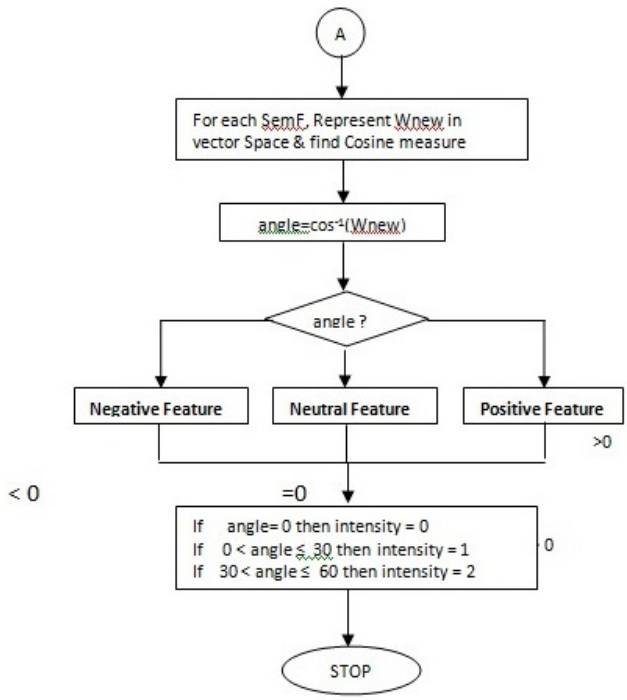

Fig. 2 Flowchart of the Proposed System Part B

Proposed system has been evaluated by doing experiments on customer reviews of various domains like digital cameras, vehicles, restaurant etc. Reviews have been collected from Amazon.com. Products in these sites have a large number of reviews. Proposed system is self explanatory from flowchart Fig. 1 and Fig. 2. This is purely a statistical approach in which no dictionary/repository is used. Initially given review is tokenized and review is given weight =1. Then that weight is divided equally amongst individual tokens of the review. For example if the review contains 5 words then individual tokens weight will be 0.2. Then term frequency of every individual has been calculated. Now total weight is the product of weight of individual token and its term frequency. Expectation Maximization Algorithm has been exploited in which Gaussian probability distribution is used to increase the variance and standard deviation amongst the tokens. Latent Semantic Indexing Algorithm have been used for calculating unit overlapping of the individual tokens. By deep analysis weight thresholds are decided. With the help of these thresholds, tokens can be divided into stop words, product features and semantic features. Intensity of the individual tokens have been calculated by taking the $\cos^{-1}$ of the individual token as depicted in Fig.2.

4. Experimental Setup and Results

MatLab tool has been used for coding. Proposed research work is domain independent. For illustration purposes results of restaurants reviews are shown here. 800 restaurants reviews were available for experimentation. Following evaluation parameters have been evaluated.

Table 1: Evaluation Measures

Comments	TP	FP	TN	FN
10	4	1	5	0
20	5	5	9	1
30	8	8	11	3
40	15	8	12	5
50	22	11	11	6
60	30	8	15	7
70	40	7	14	7

$$\text{Precision} = tp / (tp + fp)$$

$$\text{Recall} = tp / (tp + fn)$$

$$\text{Accuracy} = (tp + tn) / (tp + fp + fn + tn)$$

$$F_{1=}\ 2^* (\text{precision}^*\text{recall})/(\text{precision}+\text{recall})$$

Table 2: Evaluation Parameter

Comments	Recall	Precision	FM	Accuracy
10C	1	0.8	0.88	0.9
20C	0.833	0.5	0.625	0.7
30C	0.72	0.5	0.59	0.63
40C	0.75	0.65	0.69	0.67
50C	0.78	0.66	0.72	0.66
60C	0.81	0.78	0.8	0.75
70C	0.85	0.81	0.85	0.79

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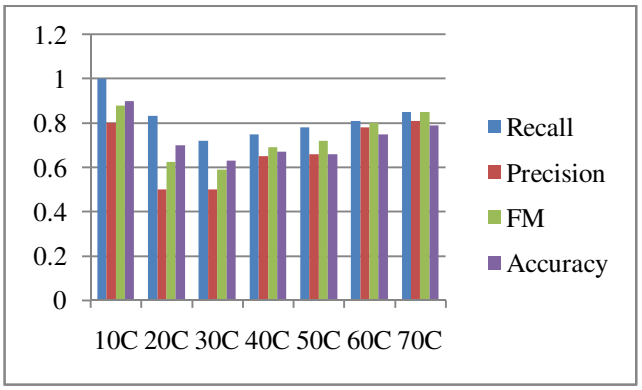

Fig. 3 Evaluation Parameters for Restaurant Reviews

5. Applications

5.1 Applications as a Sub-Component Technology

Detection of "flames" (overly-heated or antagonistic language) in email or other types of communication is

another possible use of subjectivity detection and classification.

Additionally, there are potentially relations to citation analysis, where, for example, one might wish to determine whether an author is citing a piece of work as supporting evidence or as research that he or she dismisses.

5.2 Applications in Business and Government Intelligence

The field of opinion mining and sentiment analysis is well-suited to various types of intelligence applications. These opinions greatly impact on customers to make their choices regarding online shopping, choosing events, products and entities. Indeed, business intelligence seems to be one of the main factors behind corporate interest in the field.

5.3 Applications across Different Domains

As is well known, opinions matter a great deal in politics, proposed work has high utility on understanding what voters are thinking, whereas other projects have as a long term goal the clarification of politicians' positions, such as what public figures support or oppose, to enhance the quality of information that voters have access to.

5.4 Applications to Mobile Phones

Today's mobile phones represent a rich and powerful computing platform, given their sensing, processing and communication capabilities. Application of the proposed work has high utility for developing an exceptionally suitable tool for conducting social and psychological experiments in an unobtrusive way on the mobile phones.

6. Future Scope

We have to solve the following issues in the future. Inclusion of context awareness in the algorithms is essential. We have not solved the issue of Anaphora Resolution - the problem of resolving what a pronoun, or a noun phrase refers to. "We watched the movie and went to dinner; it was awful." What does "It" refer to? Issue of implicit opinion is to be addressed. Implicit opinions like *"The battery lasted for 3 hours"*. Present sentiment analysis models will not be able to detect this implicit opinion as a negative opinion. Moreover, A comparative sentence expresses a relation based on similarities or differences of more than one object. Also the order of words in comparative sentences manifests differences in the determination of the opinion orientation. E.g. The sentence, ―*Car X is better than Car Y* communicates a completely opposite opinion from ―*Car Y is better than Car X*. Opinion summarization finds application when the number of online review of a product is large. This may make it hard for both the customer and the product manufactured. The consumer should be able how many consumers are satisfied with specific feature like resolution, batter or display of mobile.

7. Conclusion

Despite all the challenges and potential issues that threatens Sentiment analysis, one cannot ignore the value that it adds to the industry. Because Sentiment analysis bases its results on factors that are so inherently humane, it is bound to become one the major drivers of many business decisions in future. We have used Statistical approach for product feature sentiment analysis. User interface has developed using MatLab. The method used here is very simple and domain independent. In this paper we present our experiment with restaurant reviews. However it is working same for the other domains like camera, vehicles, books etc.

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