Proc. of Int. Conf. on Advances in Computer Science and Application 2012

Fuzzy Semantic Classifier to Determine the Strength Levels of Customer Product Reviews

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***Abstract*— Opinion Mining (OM) is one of the new paradigms of information retrieval and computational linguistic. Previous studies focused on the automatic identification of opinion i.e. classifying reviews into positive, negative and neutral only. However, for some applications like flame detection or information analysis, recognizing opinion only might not be sufficient. Thus, identifying strength of opinion is considered as one of the propounded problems from the early days. In this paper we proposed a Fuzzy Semantic Classifier (FSC) to classify customer product reviews at granularity levels such as very strong, strong, moderate, weak and very weak positive and negative class. We used fuzzy logic because it introduces the notion of linguistic variable to overcome the uncertainly of natural language. FSC has been tested on eight benchmark datasets and, the results showed that FSC gave various strength levels of classification in customer product reviews which leads to multi understandability of customer opinions.**

***Index Terms*— Semantic classification, fuzzy logic, opinion mining, customer product reviews**

I. Introduction

Opinion Mining (OM) is one of the challenging and novel issues which have taken a lot of efforts by researcher to solve it now. There are various tasks in OM. Classification of customer reviews into the positive, negative and neutral classes (also known as semantic orientation) is one of these tasks, that helps product manufacturers or businesses to easily identify semantic orientation of their products services.

On the other hand, as a result of the growth of the web, people are able to express their views and opinions. In addition, the number of product reviews has grown rapidly which makes it hard for manufacturers to manage customer opinions of their product. Therefore, automated opinion discovery is needed.

Previous researchers tried to solve the problem above using sentiment analysis or opinion mining [10, 6, 12, 1, and 7].

One of the existing methods for finding positive and negative orientation of customer reviews was called: holistic lexicon-based approach to opinion mining [3]. This approach utilizes semantic orientation of customer reviews based on each product features. The holistic lexicon-based approach uses some linguistic rules to classify customer reviews semantically. Although this approach was efficient and gives reasonable results, it did not consider the strength levels of customer opinion. Moreover, classification of customer reviews into the positive, negative and neutral classes (semantic classification) helps manufacturers to understand reviews easily; however it does not help manufacturers to understand the priority of reviews in each class.

The rest of this paper is as follows: section II investigates related work; section III defines the proposed Fuzzy Semantic Classifier (FSC); section IV shows the result and experiment and last section is the conclusion.

II. Related Work

A. Opinion Mining

Before the web, when people wanted to buy products, they asked opinions from their friends or family. Now with web, people are able to buy and sell products easily online. Therefore, the number of product reviews has grown rapidly. The sheer volume of reviews makes it hard for manufacturers to deal with customer opinions of their products and services. Thus, automated opinion discovery is needed. Opinion Mining (OM), also known as sentiment analysis, grows from this need. OM is a challenging area of Natural Language Processing (NLP) or Text Mining (TM).

----Based on the literature in [2], opinion mining is divided into sentiment classification and feature based opinion mining. Sentiment classification or semantic orientation is a method for automatic classification of customer product reviews into three classes: positive, negative and neutral, thus helping manager to classify them [7,5,15,16].Two subtopic of sentiment classification exist, which are named: document level and sentence level classification[11,12,4,14, 17,13,8,16].

The proposed classifier (FSC) is different from the document level approach, as we are interested in opinions expressed on each product feature rather than the whole review. Also, it is different from sentence-level approach as we consider finding opinions on each feature. A review sentence can contain multiple features and orientations of opinion expressed on the features can also be different. Therefore, we classify reviews based on each product feature.

In 2008, [3] proposed an approach called *holistic lexicon-based approach to opinion mining*. Although this method was simple and efficient, it did not consider the strength levels of opinion: whether it is strongly positive or weakly positive. In this thesis, we try to overcome this problem by applying fuzzy logic.

DOI: 02.CSA.2012.01.11

B. Fuzzy Logic in Opinion Mining

In 1965, Professor Lotfi Zadeh, the Iranian-American lecturer at the University of California Berkley published a paper which called it "fuzzy sets". For the first time in his paper the word "fuzzy" to mean "vague" is used. The aim of fuzzy logic (FL) is to improve the relationships between humans and computers.

Identifying the relationships between all parts of sentences might need specific knowledge; however relationships between individual nouns, adjectives and adverbs are mostly independent of context [9]. Due to the vagueness of natural languages, the relationships between words rarely defined in a clear fashion, and it does not be easily shown with statistical tools. Therefore, researcher has attended to fuzzy logic.

For classifying documents using fuzzy logic [20] proposed a new method which has been verified for the case of location of submitted abstract into low, medium, high and very high categories. Although their got reasonable results, they just focus work on document levels classification not as a sentence level classification.

[21] described a fuzzy set theory based framework for Chinese sentence level sentiment classification. Their method can identify increase and decreased opinion by considering three types of sentiment units, namely sentiment morphemes, sentiment words and sentiments phrases. Although their method provides a straight forward way to model the vagueness in conceptual division of sentiment polarity, it can just classify sentence into the positive, negative and neutral only.

For classifying customer product reviews' opinion [22] proposed a supervised approach named Fuzzy Opinion Miner (FOM). FOM consists four parts namely Documenting Preprocessing, Feature Decider, Opinion Word/Phrases Extractor and Intensity Finder. Document preprocessing and feature decider were used to preprocess the review and collect the product features. Adjective /Adverb Intensity Map are the ontology if the lost of weighted opinion words. Intensity Finder is to Measure the weight of the opinion phrases using fuzzy approximation and rank products accordingly. Although experimental results indicate that the FOM technique was effective in decision making about product choice, it could not determine which features customers strongly like or dislike.

Regarding to solve above problem, we propose a fuzzy semantic classifier (FSC) which is able to determine the strength levels of customer product reviews based on each product reviews. Next section we describe FSC classifier.

III. Fuzzy Semantic Classifier (FSC)

The classification process starts with identification of opinion words and phrases from customer reviews. Opinion words and phrases are words and phrases that express positive and negative orientation. These words usually are adverb, adjective, verb and noun. For example, "extremely" as adverb, "great" as adjective, "enjoy" and "like" as verb and "weakness" as a noun. In order to utilize opinion words we perform part of speech tagging (POS). In this study we use NLP processor 2000[11]. After extraction opinion words, we need to recognize semantic orientation of each opinion words which will be used to predict the orientation of each reviews. Words which have a desire state like "good" and "excellent" belongs to positive orientation, while words that signify undesirable states have a negative orientation such as "awful". In this paper, we apply the strategy that was done by [3].

In order to speed up the classification task, stop-words removing and stemming are used to prepare reviews for Fuzzy Semantic Classifier (FSC). After cleaning customer reviews and fined the orientation of the opinion words the classifier is applied. The proposed classifier (FSC) classifies opinion expressed on each product review semantically into the ten granularity levels. For example, consider these sentences:

1. *We **extremely enjoy** this camera.*
2. *We **like** this camera.*
3. *The picture quality is **good**.*

By human interpretation it is obvious that the intensity of these sentences is different due to the difference of intensity for such opinion words as "extremely", "enjoy", "like" and "good". For example sentence number one has the highest intensity due to the intensity of "extremely" is high.

In order to classify those sentences, at first we identify opinion words in each of the sentence, then for each of the features in a sentence the strength of opinion is discovered. We apply some linguistic rules which are defined by [3]. In order to identify the strength levels of review we apply fuzzy set method. This method has four steps: fuzzification, membership function designing, fuzzy rules designing and defuzzification.

In our proposed classifier we have four inputs: adverbs, adjectives, verbs and nouns in which noun as opinion words. In order to do fuzzification, we prepare a list of positive and negative adverbs, adjectives, verbs and nouns. And, we use 10 human experts in the linguistic field to associate the appropriate degree (1-10), for each of these words based on the strength of their meaning. After that we use averages for interpreting the results. For example, the fuzzy value for "enjoy" is 4.7.

In the second step we design membership function. In the proposed classifier (FSC) three membership functions which are called low, moderate and high are used. There are some types of membership functions such as triangular, trapezoidal, Gaussian and so on. Triangular membership function is the most popular membership function [19]. Therefore in this research triangular membership functions are applied for all of the positive and negative opinion words. Rank of membership function depended on the specified rank by human experts for each of opinion words (i.e. adverbs, adjectives, verbs and nouns).sample of membership function is illustrated in Fig. 1.

DOI: 02.CSA.2012.01.11

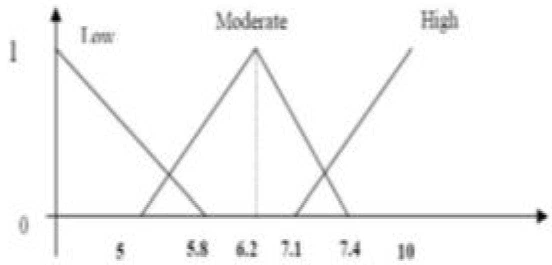

Figure 1. Sample of Membership Function

After defining MF, we design IF-THEN rules which support the entire possibility of the combination of the opinion words. The general form of fuzzy rule can be expressed as:

if *x_1 is A and x_2 is B* ***THEN*** *the strength is C*

Fuzzy rule designing in current research is divided into two discrete parts: general rules designing and rules reduction. General rules are created based on the permutation in fuzzy set. Rules reduction is done to eliminate some non logical rules for some combination which has never happened. For instance, adverb is never modifying nouns, so the combination of adverb and noun is never happened. The experts in this step help to find the non logical rules. Sample of rules is shown below:

If ***Adverb*** *is* ***Low*** *and* ***Adjective*** *is* ***low positive*** *then the strength is* ***very weak positive****.*

Later than defining the rules, we should identify degree of membership for the consequent fuzzy number. In this study, we use AND operator, so to find the consequent fuzzy number we should select the minimum degree of membership function of the two antecedent variables. Subsequent to compute the final output, defuzzification function should be used to convert rules into the crisp value. We use Mamdani's defuzzifier, as the best known defuzzification [18]:

$$Y^* = \frac{\sum_{i=1}^{n} \mu(i) y(i)}{\sum_{i=1}^{n} \mu(i)} \quad (1)$$

In Equation (1) µ(i) indicates membership values and y is a finite set of possible normalized output values of a Mamdani-type {y1…yi…yn} where 0d”µ(i)d”1 represent the discrete set of corresponding membership values. In this study we define: {0: neutral, 0.2: very weak, 0.4: weak, 0.6: moderate, 0.8: strong and 1: very strong} as an output values. Based on these values and Y (fuzzy output) the strength levels of reviews will be determined. For example, if Y=0.3 then the strength levels of the review is very weak positive. Otherwise if Y= -0.3 then the strength levels of the review is very weak negative.

IV. Emprical Evaluation

The data instances applied in experiments in this approach are eight product reviews presented [3]. It includes two digital cameras, one DVD player, one MP3 player, two cellular phones, one router and anti-virus software. All the reviews are drawn from the official website of amazon.com.

A performance metric which is used in this study is percentage similarity. Percentage Similarity is used to evaluate the proposed classifier (FSC) against human classification. In this study, percentage similarity is defined:

$$\text{Percentage of similarity} = \frac{\text{number of true answer}}{\text{total number of sentence}} \quad (2)$$

Where

The number of true answer refers to number of true answers in each category; i.e. very strong, strong, moderate, weak and very weak for each positive and negative class. And, total number of sentence is referring to the total number of reviews in each category. In this study for each category we chose ten reviews from the dataset randomly. In this research from 445reviews; we select 100 reviews randomly (for each of the 10 classes).

In order to evaluate the FSC, we recruited 10 master students to classify the reviews into the very strong, strong, moderate, weak and very weak positive and negative. The results and analysis all of the answers provided by the students are taken into the Table I.

As can be clearly seen, positive and negative customer product reviews are divided into five categories; very strong, strong, moderate, weak and very weak. Considering the table we can say that the moderate category, with 90% similarity, has the highest similarity among the categories. This is because identifying modest strength is easy for humans. Strong and weak categories have the same similarity, about 80%, because for human determining strong and weak is easier than determining very strong and very weak. Finally, the last category, very weak, has the least similarity among the categories since humans agreed that most of the weak reviews belong to the weak rather than the very weak. In general we can say that the similarity ratio in the proposed classifier (FSC) is 74%.

Table I. Results of Positive and Negative Customer Reviews

Subclasses of Positive and Negative	Percentage Similarity
Very Strong	70%
Strong	80%
Moderate	90%
Weak	80%
Very Weak	50%
Average	74%

Conclusions

In this paper we proposed a Fuzzy Semantic Classifier (FSC) to identify the strength levels of customer reviews in smaller categories. The FSC was tested on eight product reviews from benchmark datasets introduced by [3]. Based

DOI: 02.CSA.2012.01.11

on the FSC all of the positive and negative reviews were classified into very strong, strong, moderate, weak and very weak by the combinations of four parts of speech; adverb, adjective, verb and noun. Although the proposed classifier is able to classify reviews into the ten smaller groups, rather than just two positive and negative classes, it is not able to classify reviews which contain more than two combinations. For example when we have the combinations of two adverbs and adjective “extremely very good”, the FSC cannot classify it. In future we are going to build a comprehensive classifier that is able to classify customer reviews which have more than two combinations. Moreover, the propose classifier (FSC) classify customer product reviews to the marketing. In future we are going to work on drug reviews forums in medical science area.

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DOI: 02.CSA.2012.01.11