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Using Fuzzy Sentiment Computing and Inference Method to Study Consumer Online Reviews

Narisa Zhao

Yuan Li

Jianjun Wang

USING FUZZY SENTIMENT COMPUTING AND INFERENCE METHOD TO STUDY CONSUMER ONLINE REVIEWS

Narisa Zhao, Yuan Li, Jianjun Wang
School of Management, Dalian University of Technology, Dalian, China
Email: nmgnrs@dlut.edu.cn

Abstract

As a new type of word-of-mouth information, online consumer reviews possess critical information regarding consumer's concerns and their experience with the product or service. Such information is considered essential to firms' business intelligence which can be utilized for the purpose of production recommendation, personalization, and better customer understanding. This paper considers the problem of online reviews sentiment mining based on the theory of consumer psychology and behavior. Given the fuzzy attribute nature of the online reviews, we have established fuzzy group bases of consumer psychology. Four fuzzy bases, including features, sense, mood and evaluation, are established. The consumer attitude elements are reflected by natural language reviews. A fuzzy sentiment computing algorithm of online reviews for consumer sentiment is developed, and a fuzzy rule base is also presented based on consumer decision-making process. Finally it shows by means of an experiment that the proposed approach is very well suited as an analysis tool for the online reviews sentiment mining problem.

Keywords: Online reviews, fuzzy group bases, fuzzy sentiment computing, fuzzy inference

1. Introduction

Following the development of network technology, especially for the Web 2.0, the Internet is permeating almost every aspect of life [1]. One recent phenomenon is the popularity of online community. The attraction of the online community is mainly due to a new form of word-of-mouth (WOM) communication, comprising vast amounts of consumer information on opinions, attitudes, feelings, emotions and recommendations on products/services from experienced consumers [2]. Researchers often refer to this online review as electronic word-of-mouth (eWOM) [3-4]. Users tend to trust peer reviews more than advertising and other content created by marketing departments and advertising agencies [5], so people often make the buy/not buy decision on the basis of online reviews. Now the online reviews are regarded as the best to represent the interests of the potential consumers and reduce the inherent risks and anxiety in purchasing new products [6-7].

As the most convenient and abundant resources, the online reviews has become the important sources of experience information [8]. This sentimental information has a bright prospect in many fields, such as reputation analysis, public voice monitoring, opinion mining, product reviews, and personalized recommendation and so on [4, 9-10].

There some academic literatures appear to study the online reviews. Turney and Littman [11] introduced a method for inferring the semantic orientation of a word from its statistical association with a set of positive and negative paradigm words: pointwise mutual information (PMI) and latent semantic analysis (LSA). Some opinion mining prototyping systems such as Pulse [12], Opinion Observer [13], and WebFountain [14] etc. have also been developed. Xu, Lin and Zhao [15] brought forward a text orientation identification mechanism based on semantic understanding, and introduced their experience in building a sentiment corpus. Zhan, Loh and Liu proposed an automatic summarization approach based on the analysis of online reviews' internal topic structure to assemble consumer concerns, their approach can discover and extract salient topics from a set of online reviews and further ranks these topics [16]. In Ye, Zhang and Law's research [17], sentiment classification techniques were incorporated into the domain of mining reviews from travel blogs. They compared three supervised machine learning algorithms of Naïve Bayes, SVM and the character based N-gram model for sentiment classification of the reviews on travel blogs for seven popular travel destinations in the US and Europe. Pang and Lee [18] took use of the minimum graph approach to identify the subjective fragment of the document. Prabowo and Thelwall [19] presented a combined approach of sentiment analysis based on the rule-based classification method and supervised learning. Missen and Boughanem [20] proposed an opinion detection method using WordNet's semantic similarity relations. Li and Wu [21] took use of the text mining and sentiment analysis for online forums hotspot detection and forecast

Although the current text-based sentiment computing has made great progress, there is also much urgent improvement needed for the growing subjective information, particularly on the consumer sentiment analysis of online reviews which we are concerned with. The earlier sentiment computing did not focus much on the fuzzy attributes of natural language and also the consumer fuzzy sentiment and psychology. Most of the application systems or research methods adopted the classical mathematical methods to give sentimental words commendatory and derogatory derivation value. Andreevskaia and Bergler[22], based on the concept that the sentiment orientation of a word is fuzzy, presented a method for extracting sentiment-bearing adjectives from WordNet using the Sentiment Tag Extraction Program (STEP). But it is only about the semantic tagging of phrases and texts. There is a dearth of literature that addresses the fuzzy behavior inference or decision making process from the consumer's perspectives while some only on the enterprise strategy decision-making [23].

In this paper, the research purpose are sentiment identification and behavioral inference of consumer online reviews based on the fuzzy sentiment group bases guided by cognitive linguistics and consumer psychology. We conduct the discussion from three levels, vocabulary level, review statement level and inference level.

The remaining of this paper is organized as follows: in Section 2, based on the fuzzy theory, sentimental semantic fuzzification of online reviews is given. This followed in Section 3 with the establishment of fuzzy group bases of consumer psychology. In section 4, a fuzzy sentiment computing algorithm of online reviews is developed, and in section 5, the inference rule base is presented according to the consumer decision-making process. Section 6 provides an experiment to illustrate the effectiveness of the presented algorithm. Conclusions and future researches are given in Section 7.

2. Fuzzification of Online Reviews

It is an important topic to measure or quantify the word meaning in complex system or decision-making process for a long time. In the traditional research of word meaning quantification, for example, Mosier's one-dimensional fixed-point or Osgood's multi-dimensional characterization [24], they all considered that meaning is accurate. For example, an orientation scale [-4, 4] is defined, then the word 'beautiful' can be assigned +2, 'old' can be assigned -1. The sentimental semantic quantification research also used this pattern mostly.

However, language is vague. Based on Zadeh's fuzzy theory, the meaning of a word corresponds to a fuzzy set instead of binary logic which cannot appropriately describe the fuzzy process of thinking. Natural language consists of basic words (atomic terms) and their composition (composite terms), which are defined as the elements and sets in the domain of natural language. Domain X is defined as an interpretation of the understanding or an expression of a word meaning. Suppose a special atomic term α in the domain of natural language, and a fuzzy set $\underset{\sim}{A}$ corresponding to its specific meaning in the interpretation domain X. The fuzzy set $\underset{\sim}{A}$ represents the mapping ambiguity between the atomic term α and its 'interpretation'. $\underset{\sim}{A}$ is characterized by a membership function $\mu_{\underset{\sim}{A}}(x)$ in interval [0, 1] which indicates the membership degree of the interpretation x of α in $\underset{\sim}{A}$. We call this "the natural language variable's 'value' can be defined by fuzzy sets $\mu_{\underset{\sim}{A}}(x)$".

Sentiment is a very broad concept, and has fuzzy attributes in nature. In the research of sentimental analysis of review text, it is necessary to make fuzzy processing to the sentimental words. The measurement of the meaning of sentimental words can be divided into five ranking separately on positive and negative category continuum, micro (*A*), small (*B*), neutral (*C*), large (*D*) and extreme (*E*). Each rank corresponds to a fuzzy membership function, namely,-*E*,-*D*,-*C*,-*B*,-*A*, +*A*, +*B*, +*C*, +*D*, +*E*. According to the subjective experience, that in a series of intensity, the possible psychological reaction distribution to a weak stimulate on the category continuum (weak-strong) is top-down, generally monotone decreasing, the peak of its curve is left-biased (weak side). To stimulus of moderate intensity, it seems like the normal distribution curve. For greater intensity, the peak is right-biased. To the strongest stimulus, the curve shows monotonically increasing, contrary with the weakest stimuli.

According to the principles of establishing membership functions, that should be convex fuzzy sets, symmetric, balanceable, and should conform to people's language sequence, avoid improper overlap, etc., the Gaussian function is chosen as a template to define fuzzy membership functions for 10 sentimental ranks in domain [-4, 4]:

$$\mu_{\underset{\sim}{w}}(x) = gaussmf_{\underset{\sim}{w}}(x, \sigma_{\underset{\sim}{w}}, a_{\underset{\sim}{w}}) = \exp\left[\frac{-(x-a_{\underset{\sim}{w}})^2}{2\sigma_{\underset{\sim}{w}}^2}\right] \quad (1)$$

Here, $\underset{\sim}{w} \in \{-E,-D,-C,-B,-A,+A,+B,+C,+D,+E\}$, $\sigma_{\underset{\sim}{w}}, a_{\underset{\sim}{w}}$ are expectation and standard deviation of Gaussian membership function respectively corresponding to the sentimental rank $\underset{\sim}{w}$. For the intersection of the membership function is neither for very low values nor for very high values, choose $\sigma_{\underset{\sim}{w}} = 0.4$. For negative pole, $x \in [-4, 0]$, $a_{-E} = -4$, $a_{-D} = -3$, $a_{-C} = -2$,

$a_{-B} = -1$, $a_{-A} = 0$. For positive pole, $x \in [0, 4]$, $a_{+A} = 0$, $a_{+B} = 1$, $a_{+C} = 2$, $a_{+D} = 3$, $a_{+E} = 4$. For example, the membership functions of the variable 'evaluation' are shown in Figure 1.

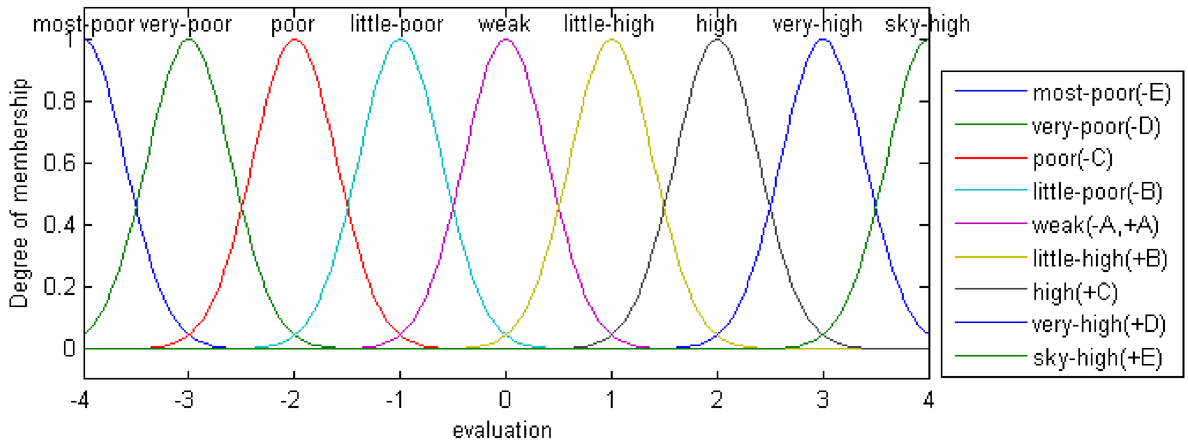


FIGURE 1. Membership function

3. Fuzzy Group Bases for Consumer Psychology

At the early 20th century, the British psychologist William McDougall has studied the relationship between people's feelings and behavior. In his view, all the people's purposive behavior is affected by the complicated sentiment, consumer behavior is no exception. Consumer's positive sentiment has a significant positive effect on their re-purchase intentions and word of mouth recommendation intentions. Allen et al. [25] found that people's behavior intention is predictable by sentiment, and corporate managers can determine the consumer's re-purchase and word-of-mouth publicity intention on the basis of consumer sentiment.

Satisfaction is only a cognitive concept. From the mid 80's of the 20th century, many scholars have pointed out that the post-purchase responses of customers include not only perceptual evaluation of products and service quality, but also a variety of emotional responses [26].

In the traditional consumer decision-making process [26], the consumers first perceive the internal and external characteristics of goods, resulting in the emotional feelings to meet the need, leading to consumption desires and demands. When the demands reach certain intensity, it will activate the purchase motivation pointing to specific targets. Driven by the motivation, they will search for information related to goods; then based on individual preferences, make analysis and comparison of the quality, price, and brand and so on to make a final purchase decision, and then take actions to buy. After purchase, consumers will make evaluation according to their own feelings to form purchase experience and then trigger the next purchase. With the arrival of Web2.0 era, consumer behavior is also changing. Through online reviews, consumers can search more information from other consumers on various features about products, even mood, to strengthen or weaken the consumption desire in order to support or block decision-making process [5].

In order to mine the business knowledge in the network community, based on the consumer psychology and behavior theory, we established fuzzy group bases including features, sense, mood and evaluation. The Infrastructure shows in Figure 2. Based on the fuzzy group bases, it can aid decision making and guide consumer behavior. According to the consumer attitude elements reflected in online reviews and the establishing methods of the membership function introduced above, the reviewers' intention can be inferred.

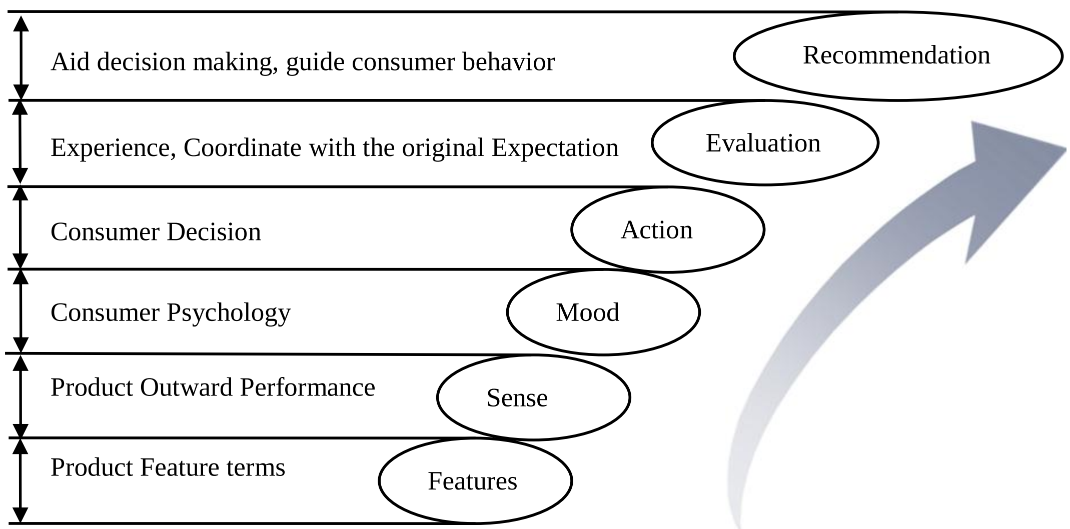


FIGURE 2. Infrastructure of fuzzy group bases

TABLE 1. Fuzzy group bases example of a certain brand of notebook computer

Features	Sense		Mood		Evaluation	
	Words	Degree	Words	Degree	Words	Degree
Monitor, chassis, cable, touch screen, processor, appearance, price, performance, memory, hard disk, display card, sound box, mainboard, keyboard, fan, heat dissipation, weight, after sale, repair rate	forward	+*D*	overjoyed	+*E*	right	+*B*
	traditional	-*A*	confused	-*B*	common	+*A*
	cumbersome	-*C*	lingering fear	-*D*	grating	-*C*
	fashion	+*C*	furious	-*C*	splendid	+*E*
	mediocre	-*D*	hesitate	-*A*	jumbled	-*D*
	magnificent	+*E*	excited	+*C*	comfortable	+*C*
	exquisite	+*B*	gloomy	-*C*	defective	-*C*
	old-fashioned	-*C*	perplexed	+*A*	unique	+*E*
	graceful	+*D*	collapse	-*E*	poor	-*C*

We take a certain brand of notebook computer as an example in Table 1(part). At present the sense base and the evaluation base are combined as evaluation terms.

4. Sentence Fuzzy Sentiment Computing

To achieve the fuzzy computing of mood and evaluation degree at the sentence level, firstly we need to determine the language operators and characterize the semantic transfer caused by qualifiers.

4.1 Fuzzy Operator of Qualifiers

Language operator indicates a class of prefix in language system, usually added in front of a phrase or word to adjust the meaning of it, such as the emphasized prefix or negative prefix. And this will infer to the sentiment transfer problem caused by Modified-Orientation. In order to resolve these two problems, we have defined two dictionaries: the Intensifier Dictionary and Privative Dictionary.

Intensifier operators. In our research, we use the word set in 'HowNet' which is created by Professor Dong, et al. [27]. After screening and refreshing, finally divide it into five ranks, namely, extreme/most, very, more, little and insufficiently. The following table lists some of the typical intensifier words (Table 2).

TABLE 2. Examples of some representative intensifier word ranks

Ranks	Extreme/Most	absolutely, amazingly, extremely, completely, exceedingly, beyond comparison, bitterly
	Very	considerably, especially, much, quite, particularly, too far, a lot, too much
	More	by far, comparatively, even more, further, furthermore, increasingly, relatively
	Little	a bit, a little, a little bit, fairly, more or less, passably, slightly, somewhat, some
	Insufficiently	a little less, just, less, merely, ultra, undue, unduly, surplus, to a fault

In the intensifier words, the ones which are used to strengthen the tone are called 'Strengthen Operators', also known as 'Centralized Operators', such as the ranks indicated in 'extreme/most', 'very' and 'more' in Table 2. The ones which are used to weaken the tone are called 'Freshening Operators', also known as 'Loose Operators', as indicated in the ranks of 'little' and 'insufficiently'.

Take evaluation word M as an example, the general form of the intensifier operators is:

$$H_\lambda \mu_{\underset{\sim}{w}}(M) = [\mu(x, a_{\underset{\sim}{w}} \pm \lambda')]^\lambda$$
$$= [gaussmf_{\underset{\sim}{w}}(x, \sigma_{\underset{\sim}{w}}, a_{\underset{\sim}{w}} \pm \lambda')]^\lambda$$
$$= \exp\left(\frac{-[x-(a_{\underset{\sim}{w}} \pm \lambda')]^2}{2\sigma_{\underset{\sim}{w}}{}^2} \cdot \lambda \right) \quad (2)$$

Here, $\sigma_{\underset{\sim}{w}} = 0.4$, $\underset{\sim}{w}$ is the evaluation rank of the target word, H_λ is the Intensifier Operator, λ is a positive real number, when $\lambda > 1$, H_λ is a Centralized Operator, when $\lambda < 1$, H_λ is a Loose Operator. $a_{\underset{\sim}{w}}$ is the desired value of the Gaussian function for evaluation rank $\underset{\sim}{w}$, for negative pole, it will shift $-\lambda'$ units, for positive pole, it will shift $+\lambda'$ units.

The five intensifier ranks should be determined by the specific situations. We select the value of λ and λ' after experiment in the actual calculation as in Table 3.

TABLE 3. The value of variables λ and λ'

Intensifier Rank	Extreme/Most	Very	More	Little	Insufficiently
λ	4	2	1.5	0.5	0.25
λ'	+2	+1.5	+0.5	-1	-1.5

For each sentimental word with intensifier operator prefix, after transferring and width change of its membership function by means of formula (2), we can achieve the corresponding change of sentiment degree.

Privative operators. For the sentimental words with negative prefix, it is obviously unreasonable to simply reverse their orientation. For example, 'not satisfied', 'not very satisfied', 'very dissatisfied', etc., although they all have a negative prefix, but the strength of the negative tone is different.

Yao and Lou [28] dealt with the Modified-Orientation (*MO*) due to privative prefix as follows:

$$MO(word) = -MO(word)/2$$

Here the classical (accurate) mathematical sentiment assignment method was employed, but their approach, also to fuzzy sentiment membership function, will induce contradiction in some special situations. For example, an evaluation word 'satisfied' whose sentimental rank is *+B*. For 'not very satisfied', firstly change the membership function according to the intensifier operator "very" (from formula (2), narrow and shift to right), then take half after reverse by this approach. Apparently, the desired value is lower than that of 'not satisfied' (directly take half after reverse). However, according to our subjective judgment, the fact is the degree of 'not very satisfied' should be much higher than that of 'not satisfied'. So the Privative Operators should be further discussed.

We divided the negative prefix into three cases, such as *PM*, *PIM* and *IPM*, in which '*P*' represents Privative prefix, '*I* 'represents Intensifier prefix, and '*M*' is the sentimental target word, $\underset{\sim}{w}$ is the sentimental rank, $\underset{\sim}{w} \in \{-E,-D,-C,-B,-A,+A,+B,+C,+D,+E\}$. The corresponding membership function is

$$\begin{aligned}\mu_{\underset{\sim}{w}}(M) &= gaussmf_{\underset{\sim}{w}}(x,\sigma_{\underset{\sim}{w}},a_{\underset{\sim}{w}}) \\ &= \exp\left(\frac{-(x-a_{\underset{\sim}{w}})^2}{2\sigma_{\underset{\sim}{w}}^{\ 2}}\right)\end{aligned} \tag{3}$$

The three cases are described respectively as follows:

For case *PM*, order $a_{\underset{\sim}{w}} = -a_{\underset{\sim}{w}}/2$, then

$$\begin{aligned}\mu_{\underset{\sim}{w}}(M) &= gaussmf_{\underset{\sim}{w}}(x,\sigma_{\underset{\sim}{w}},-a_{\underset{\sim}{w}}/2]) \\ &= \exp\left(\frac{-(x+a_{\underset{\sim}{w}}/2)^2}{2\sigma_{\underset{\sim}{w}}^{\ 2}}\right)\end{aligned} \tag{4}$$

For case *PIM*, given the variables corresponding to the intensifier operator λ and λ', then

$$\begin{aligned}\mu_{\underset{\sim}{w}}(M) &= [gaussmf_{\underset{\sim}{w}}(x,\sigma_{\underset{\sim}{w}},\text{-}(\mathrm{a}_{\underset{\sim}{w}} \pm \lambda')/4)]^{\lambda} \\ &= \exp\left(\frac{-(x+(a_{\underset{\sim}{w}} \pm \lambda')/4)^2}{2\sigma_{\underset{\sim}{w}}^{\ 2}} \cdot \lambda\right)\end{aligned} \tag{5}$$

For case *IPM*, the same,

$$\begin{aligned}\mu_{\underset{\sim}{w}}(M) &= \left[gaussmf_{\underset{\sim}{w}}\left(x,\sigma_{\underset{\sim}{w}},\left(-a_{\underset{\sim}{w}}/2\right) \pm \lambda'\right)\right]^{\lambda} \\ &= \exp\left(\frac{-[x-(-a_{\underset{\sim}{w}}/2 \pm \lambda')]^2}{2\sigma_{\underset{\sim}{w}}^{\ 2}} \cdot \lambda\right)\end{aligned} \tag{6}$$

In formula (5) and (6), $+\lambda'$ is chosen when $\underset{\sim}{w}$ in positive pole, $-\lambda'$ is chosen when $\underset{\sim}{w}$ in negative pole.

The Privative Dictionary is established through 'HowNet'. By selecting the original privative qualifiers and extracting the words that have the original negative meaning definition in HowNet, we got the Privative Dictionary such as 'not', 'no', 'never', 'hardly' etc. ultimately after filtering.

4.2 Fuzzy Sentiment Computing Algorithm of Online Reviews

After the formulation of the modified rules, we can conduct fuzzy computing at the sentence-level.

Taking evaluation as an example, the Fuzzy Sentiment Computing Algorithm of Online Reviews (FSCA-OR) go as follows:

Step 1. First, conduct part-of-speech tagging and syntactic analysis (take use of the Language Technology Platform (LTP) for online presentation developed by Harbin Institute of Technology Laboratory of the language information retrieval [29], then select all the evaluation words M_i (i=1, 2, ⋯ n) of the target sentence and the corresponding Intensifier and Privative qualifiers, and then determine the sequence relationship between its qualifiers.

Step 2. From the established fuzzy group bases of consumer psychology, determine the fuzzy function $\mu_{\underset{\sim}{w}}(M_i)$ of each word, $\underset{\sim}{w} \in \{-E,-D,-C,-B,-A,+A,+B,+C,+D,+E\}$, as well as its corresponding Intensifier ranks 'I' (0-none, 1-insufficiently, 2-little, 3-more, 4-very, 5-most). The Privatives 'P' are denoted by N (Negative) and 0(none) respectively. If 'P' and 'I' do not appear together, then record 'I' first, 'P' second. As, 'not well' can be analyzed as '0N+B';

Step 3. For the analysis results of all the evaluation words M_i (i =1, 2, ⋯ n),

i. If 'I==0, P!=0', only Privative qualifier, $\mu_{\underset{\sim}{w}}(M_i) = Formula\ (4)$.

ii. If 'P ==0, I! =0', only Intensifier qualifier (the corresponding parameters are λ and λ', see 4.1, $\mu_{\underset{\sim}{w}}(M_i) = Formula\ (2)$.

iii. When the form is 'IPM_i', $\mu_{\underset{\sim}{w}}(M_i) = Formula\ (6)$.

iv. When the form is 'PIM_i', $\mu_{\underset{\sim}{w}}(M_i) = Formula\ (5)$.

Step 4. The Sentence Fuzzy membership function is

$$Sentence\text{-}Function = \bigcup_{1}^{n} \mu_{\underset{\sim}{w}}(M_i),$$

$$(i=1, 2, \cdots n)$$

Step 5. Defuzzification = Centroid (Sentence-Function), get the evaluation degree of the sentence employing Centroid method to defuzzy.

The fuzzy computing algorithm of *mood* is similar. Thereby the evaluation and mood degree of a sentence can be calculated by the compiled program in Matlab 7.0. An Example is given as follows.

Example 4.2.1. *Some consumer wrote her/his feelings and evaluations about a certain brand of laptop on a forum as follows:*

'The design of this series is defective, its heat dissipation is not well, battery is too short-lived, not so desirable, and main board easily to burn, I bitterly regret it, depressing …'

The evaluation and mood terms and their QULIs are analyzed in Table 4.

TABLE 4. The results of the analysis

1	none (0)	none (0)	defective (-*C*)
2	none (0)	not (N)	well (+*B*)
3	too (4)	none (0)	short-lived (-*D*)
4	not (N)	so(3)	desirable (+*C*)
5	bitterly(5)	none(0)	regret(-*D*)
6	none(0)	none(0)	depressing(-*C*)

This review contains 4 evaluation words and 2 mood words. According to FSCA-OR, after computing, the overall degree (*evaluation*) = -3.5210, degree (*mood*) = -2.5614, which shows that this reviewer had higher dissatisfaction about this brand of laptop and had bad post-purchase sentiment.

5. Construction of the Inference Rule Base

In the various methods that express knowledge, the most common way is to express it as the rules of natural language form:

IF premise (antecedent), THEN conclusion (consequent)

This knowledge expression, as it expresses the human experience and heuristic knowledge with their own language, has a superficial knowledge characteristic which is particularly suited to express the relationship between contexts. Usually these restrictions are established by the fuzzy sets and fuzzy relations.

To realize the consumer recommendation to a degree, based on online reviews, according to consumer decision making process, we take fuzzy variables '*evaluation*' and '*mood*' as inference antecedent, '*recommendation*' as inference consequent, to establish Fuzzy Inference System (FIS).

The input variable '*evaluation*' consults to section 2. For the input variable '*mood'*, we put it into ten ranks too, respectively, super-bad: -*E*, very-bad: -*D*, bad: -*C*, little-bad: -*B*, so-so: -*A*, +*A*, little-good: +*B*, good: +*C*, very-good: +*D*, super-good: +*E*. The inference consequent '*recommendation'* is divided into seven levels in domain [-1, 1] with $\sigma_w = 0.1$ taking Gaussian function as membership function style， respectively strongly-resist, resist, negative, neutral, positive, recommend, strongly-recommend. The principle to set a rule is '*evaluation'* occupy a leading position, '*mood'* subordinate.

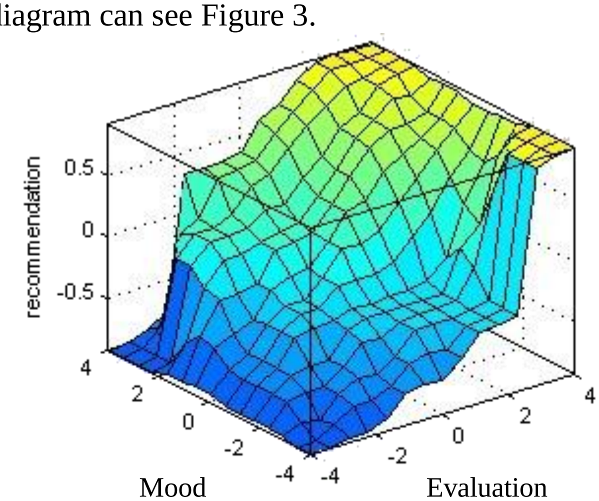
Some of the inference rules established are listed as below:

Rule 1. If (evaluation is very-poor) and (emotion is super-bad) then (recommendation is strongly-resist).

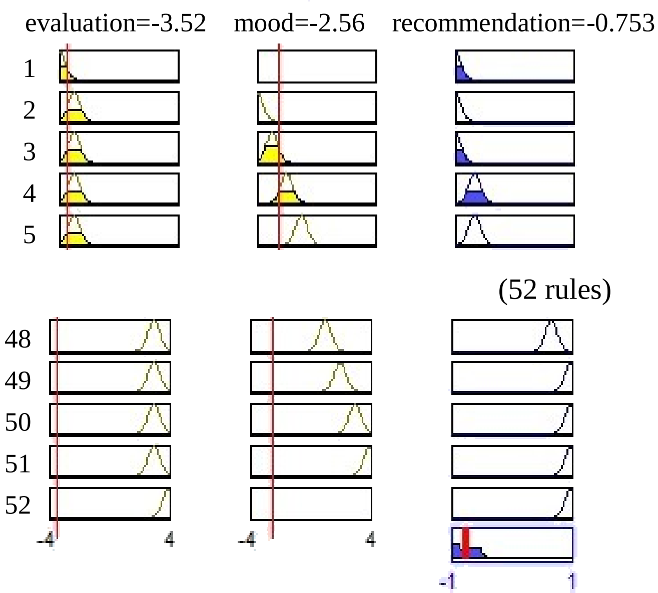
Rule 2. If (evaluation is little-poor) and (emotion is very-bad) then (recommendation is resist).

Rule 3. If (evaluation is so-so) and (emotion is bad) then (recommendation is negative).

A total of 52 rules are established here, and different rules give different weights. Mamdani-based inference method is used. Defuzzification employs Centroid method. From the example 4.2.1, degree (*evaluation*) = -3.5210, degree (*mood*) = -2.5614, we can get degree (*recommendation*) = -0.7526 ($x \in [-1,1]$), which shows that the recommendation degree of this reviewer is very low, and he/she is strongly resist to purchase. The specific reasoning process diagram can see Figure 3.



(a) Surface of the Rules



(b) Mamdani-based Inference
FIGURE 3. Inference demo

6. Experiment

Using page collection tools ‘bget_share’, this experiment downloaded more than 1200 online reviews of a certain brand of notebook computer from the related posts of Baidu Post Bar (http://tieba.baidu.com/). On the corpus style, we chose relatively standardized, rigorous reviews as much as possible. Generally, the choice of reviews emphasized on the ones which have rich sentimental expression. 549 sentences with views are selected after screening. The so-called sentence with views refers to the sentence contains at least one orientation word. Once more, after the second screening based on typicality, ultimately 100 representative reviews were identified as the final corpus.

For each one of these 100 reviews, the *mood* and *evaluation* degree are calculated through the algorithm FSCA-OR, and then according to the inference rule base, we can obtain the *recommendation* degree of each review ultimately. Figure 4 shows the *recommendation* degree sorting from low to high. In order to be unified into a table, the degree was normalized to range in [-1, 1], that is,

$$\text{degree} = \text{degree}\ (\textit{evaluation}\ \text{or}\ \textit{mood})\ /\ 4 \tag{7}$$

We followed the evaluation index of the text topic classification, namely, precise (P), recall (R) and F values. Set a_1 as the number of correct texts judged as positive emotion (evaluation, mood >= 0), a_2 as the number of correct texts judged as negative emotion, b_1 as the number of texts judged as positive emotion, b_2 as the number of texts judged as negative emotion, c_1 as the actual number of texts of positive emotion, c_2 as the actual number of texts of negative emotion. Obviously $c_1 + c_2 = b_1 + b_2$. Formulas of evaluation index show in Table 5.

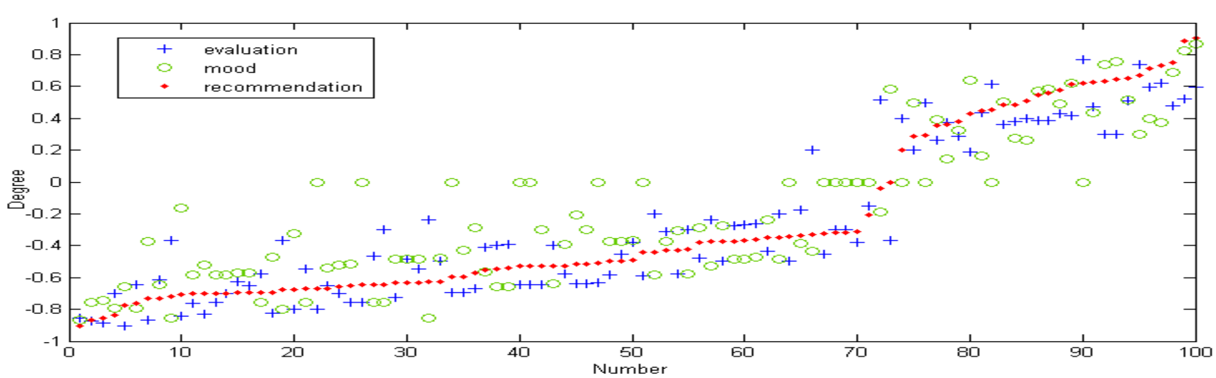


FIGURE 4. Diagrammatic presentation of the results of a certain brand of laptop

TABLE 5. Formulas of evaluation index

Index \ Category	Positive	Negative	Total
Precise	$PP = \frac{a_1}{b_1} \times 100\%$	$PN = \frac{a_2}{b_2} \times 100\%$	$F_1 = \frac{a_1 + a_2}{b_1 + b_2} \times 100\%$
Recall	$RP = \frac{a_1}{c_1} \times 100\%$	$RN = \frac{a_2}{c_2} \times 100\%$	$F_2 = \frac{a_1 + a_2}{c_1 + c_2} \times 100\%$
F-value	$FP = \frac{2 \times RP \times PP}{RP + PP}$	$FN = \frac{2 \times RN \times PN}{RN + PN}$	$F = \frac{2 \times F_1 \times F_2}{F_1 + F_2}$

TABLE 6. Index test results

	a_1 / a_2	b_1 / b_2	c_1 / c_2	PP(%) / PN(%)	RP(%) / RN(%)	FP(%) / FN(%)	F(%)
Evaluation	22	27	31	81.48	70.96	75.85	86.0
	64	73	69	87.67	93.78	90.62	
Mood	31	42	38	73.80	81.57	77.49	82.0
	51	58	62	80.95	82.26	81.60	

Because $c_1 + c_2 = b_1 + b_2$, obviously, F_1=F_2=F, we all recorded as F.

Table 6 is obtained by statistical method derived from real observations.

From Figure 4, we can see that, for this part of reviews, recommendation degree that less than zero occupies 72%, that greater than zero only 28%. This is because many online reviewers tend to express their sentiment of dissatisfaction. A small number of reviews both have higher value of sentiment and recommendation which are inconsistent with the majority, that because, here, we do not rule out the role of soft advertising reviews.

In addition, the emotional tendency of reviewers and the recommendation degree remain consistent basically, and the evaluation degree keeps consistent changes with mood. Their combination decides the degree of the recommendation. In Figure 4, 17% of the sentence does not contain the mood words, and the mood values distribution is relatively scattered, which largely because it has something to do with the situation at that time. We can see that this laptop brand reputation in the online reviews is poor, and more people do not recommend others to purchase. The experiment also shows the validity of the algorithm.

7. Conclusions and Future Researches

This paper studied consumer online reviews using fuzzy sentiment computing and inference method through three levels. In vocabulary level, fuzzy sentiment modeling for consumer online review texts is discussed based on fuzzy mathematics, and fuzzy group bases of consumer psychology is established. In review statement level, after sentiment membership functions' shift and transformation, a fuzzy sentiment computing algorithm of review sentences is proposed. Finally in inference level, a series of fuzzy inference rules are made for consumer recommendation through sentiment mining. Our experiment showed well performance in Precise and Recall. Our results yield interesting and important insights for both academic researchers and practitioners. It has an important scientific significance on some of the basic theory of text sentimental analysis and consumer aid-decision-making. In mining customer perspective and understanding the market response of the products, establishing interactive relations between producers and consumers, and in guiding consuming behavior, it also has application value.

It should be noted that free texts of reviews on internet are more arbitrary, and both wording and phrasing are not bound by syntax. So these subjective texts need to be further explored to analyze the language law from the view of linguistic. To take full advantage of features and sense base, it also needs to achieve product feature extraction and automatic association pairs (product feature and sentimental words) identification. All these will be discussed in our future researches.

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REFERENCES

[1] M. Y. Cheung, C. Luo, C. L. Sia, H. Chen, Credibility of Electronic Word-of-Mouth: Informational and Normative Determinants of On-line Consumer Recommendations, *International Journal of Electronic Commerce*, vol.13, no.4, 2009, pp.9-38.

[2] Y. Chen, J. Xie, Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix, *Management Science*, vol.54, no.3, 2008, pp.477-491.

[3] J. Lee, J. N. Lee, Understanding the product information inference process in electronic word-of-mouth: An objectivity–subjectivity dichotomy perspective, *Information & Management*, vol.46, no.5, 2009, pp.302-311.

[4] E. K. Clemons, G. Gao, L. M. Hitt, When Online Reviews Meet Hyperdifferentiation: A Study of the Craft Beer Industry, *Journal of Management Information Systems*, vol.23, no.2, 2006, pp.149-171.

[5] C. Park, T. M. Lee, Antecedents of Online Reviews' Usage and Purchase Influence: An Empirical Comparison of U.S. and Korean Consumers, *Journal of Interactive Marketing*, vol.23, no.4, 2009, pp.332-340.

[6] C. Dellarocas, X. Zhang, N. F. Awad, Exploring the value of online product reviews in forecasting sales: The case of motion pictures, *Journal of Interactive Marketing*, vol.21, no.4, 2007, pp.23-45.

[7] D. Godes and D. Mayzlin, Using online conversation to study word of mouth communication, *Marketing Science*, vol.23, no.4, 2004, pp.545-560.

[8] W. Duan, B. Gu, A. B. Whinston, Do online reviews matter? — An empirical investigation of panel data, *Decision Support Systems*, vol.45, no.4, 2008, pp.1007-1016.

[9] H. C. Yang and C. H. Lee, Semantic Matching and Annotation of Images by Self-organizing Maps, *International Journal of Innovative Computing, Information and Control*, vol.5, no.3, 2009, pp.677-688.

[10] J. Lee, D. H. Park and I. Han, The effect of negative online consumer reviews on product attitude: An information processing view,

Electronic Commerce Research and Applications, vol.7, no.3, 2008, pp341-352.

[11] P. D. Turney and M. L. Littman, Measuring praise and criticism: Inference of semantic orientation from association, *ACM Transactions on Information Systems*, vol.21, no.4, 2003, pp.315-346.

[12] M. Gamon, A. Aue, and O. Corston, et al, Pulse: mining customer opinions from free text, *Proc. of the 6th International Symposium on Intelligent Data Analysis, Lecture Notes in Computer Science*, Springer-Verlag, Madrid, 2005, pp.121-132.

[13] B. Liu, M. Hu, and J. Cheng, Opinion observer: analyzing and comparing opinions on the Web, *Proc. of the 14th international conference on World Wide Web*, Chiba, Japan, 2005, pp.342-351.

[14] J. Yi and W. Niblack, Sentiment mining in WebFountain, *Proc. of the 21st International Conference on Data Engineering, IEEE Computer Society*, Tokyo, Japan, 2005, pp.1073-1083.

[15] L. H. Xu, H. F. Lin, and J. Zhao, Construction and analysis of emotional corpus, *Journal of Chinese Information Processing*, vol.22, no.1, 2008, pp.116-122.

[16] J. Zhan, H. T. Loh and Y. Liu, Gather customer concerns from online product reviews – A text summarization approach, *Expert Systems with Applications*, vol.36, no.2, 2009, pp.2107-2115.

[17] Q. Ye, Z. Zhang and R. Law, Sentiment classification of online reviews to travel destinations by supervised machine learning approaches, *Expert Systems with Applications*, vol.36, no.3, 2009, pp.6527-6535.

[18] B. Pang and L. Lee, Opinion Mining and Sentiment Analysis, *Information Retrieval*, vol.2, no.1-2, 2008, pp.1-135.

[19] R. Prabowo and M. Thelwall, Sentiment analysis: A combined approach, *Journal of Informetrics*, vol.3, no.1, 2009, pp.143-157.

[20] M. M. S. Missen and M. Boughanem, Using WordNet's Semantic Relations for Opinion Detection in Blogs, *Advances in Information Retrieval*, vol.5478, 2009, pp.729-733.

[21] N. Li and D. D. Wu, Using text mining and sentiment analysis for online forums hotspot detection and forecast, *Decision Support Systems*, vol.48, no.2, 2010, pp.354-386.

[22] A. Andreevskaia and S. Bergler, Mining WordNet for Fuzzy Sentiment: Sentiment Tag Extraction from WordNet Glosses, *Proc. of the 11th Conference of the European Chapter of the Association for Computational Linguistics,* Trento, 2006, pp.209–216.

[23] Y. F. Chung, Y. L. Yu and T. C. Hsiao, A study on fuzzy decision and preferred enterprise strategy, *International Journal of Innovative Computing, Information and Control*, vol.5, no.11, 2009, pp.3809-3826.

[24] T Zétényi, *Fuzzy sets in psychology*, Elsevier Scientific Publishers, Amsterdam, 1988.

[25] C. T. Allen, K. A. Machleit and S. S. Kleine, A Comparison of Attitudes and Emotions as Predictors of Behavior at Diverse Levels of Behavioral Experience, *Journal of Consumer Research*, vol.18, no.4, 1992, pp.493-505.

[26] L. G. Schiffman, and L. L. Kanuk, *Consumer Behavior*, *8th Edition*, Prentice Hall, Upper Saddle River, 2003.

[27] Z. D. Dong and Q. Dong, HowNet, Computer language information center of CAS, http://www.keenage.com/html/e_index.html.

[28] D. C. Lou and T. F. Yao, Semantic polarity analysis and opinion mining on Chinese review sentences, *Computer Applications*, vol.26, no.11, 2006, pp.2622-2625.

[29] T. Liu, Language Technology Platform (LTP), Harbin Institute of Technology Information Retrieval Laboratory, http://ir.hit.edu.cn/demo/ltp/.