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Product Approximate Reasoning of Online Reviews Applying to Consumer Affective and Psychological Motives Research

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Consumer psychology and sentiment analysis become more and more flourishing. This paper presents fuzzy inference rules with comprehensive evaluation and emotion as antecedents and accomplishes reasoning recommendation to consumers with four different motivations. A fuzzy model for the evaluation and emotion of online review texts is proposed using the theory of consumption motivation type. It has an inbuilt fuzzy corpus of consumer evaluation and emotion and has given a calculational method of comprehensive evaluation and emotion combined with the consumer's preference for product attributes.

Keywords: Consumer behavior, Consumption motivation, Attitude mining, Approximate reasoning.

1 Introduction

Many consumers prefer to use free form of text to express their opinions, attitudes and emotions in review forums, discussion groups and virtual community logs in the work of [1]. There is growing evidence that such forums could influence consumers' purchase decisions according to [2]. Effectively collecting and analyzing this information can be valuable to e-business managers and analysts. Mining and analyzing these online reviews, especially their sentiment, can greatly help better to understand the users' consuming habits and public opinions which play an important role in decision-making for enterprises and the government.

For English texts the work of [3] provided standard classification of corpus such as Reuters and statistical evaluation methods. The work of [4] illustrated a sentiment analysis approach to extract sentiments associated with polarities of positive or negative for specific subjects from a document.

This paper focuses on the subsection of polarity intensity with fuzzy method. Instead of numerical intensities we use a continuous function to represent the strength of the level of the effect. We propose a fuzzy model for online review texts. Furthermore, using the theory of consumption motivation, this paper presents approximate reasoning rules with

comprehensive evaluation and emotion as antecedents. Consequently it accomplishes reasoning recommendation to consumers with four different motivations.

2 Problem Statement and Preliminaries

Most existing systems of recommending use collaborative filtering methods, content-based methods or hybrid filtering methods that combine both techniques. However, the widely used free forms of texts which are especially online reviews of products are great resources of consumer opinion and sentiment. More detail can be seen in [5-6].

The application of Fuzzy Mathematics is able not only to solve the problem of language uncertainty but also to improve the method of quantification by using a continuous function to represent the meaning and emotion intensity of words. It is imperative to define the variables, fuzzy membership function and fuzzy sets.

2.1. Semantic Fuzzification Methodology

Traditionally, regarding to the quantification of word meaning, it comes to the common point that all researches consider the word meaning as accurate (Ma Mou-chao, 1994). For using a fuzzy method to process evaluation and emotion, the measurement of polarity words can be divided into four ranks separately on positive and negative category: small (*S*), middle (*M*), large (*L*) and very large (*VL*). Each rank corresponds to a fuzzy membership function, namely *-VL,-L,-M,-S, Z, +S, +M, +L, +VL* which we together call "basic evaluation fuzzy set". Evaluation of appraise is denoted as *G* (Good), *B* (Bad) and the degree of emotion is represented as *H* (High), *L* (Low).

For the sake of simplicity these basic evaluation fuzzy sets may generally be regarded as convex fuzzy sets. We choose the Gaussian function as a template to define fuzzy membership functions for 9 semantic ranks in domain [-4, 4]. Eq.1 is the template of the Fuzzy Membership Function.

$$y = gaussmf_k(x, \sigma_k, c_k) = \exp\left(\frac{-(x-c_k)^2}{2\sigma_k^2}\right) \tag{1}$$

where $k \in \{-VL, -L, -M, -S, Z, +S, +M, +L, +VL\}$, σ_k, c_k are parameters of the Gaussian membership function corresponding to the sentimental rank*k*. When $x=c_k$, $y=1$, namely, the value of membership function is 1 at the function center point, then $\sigma_k = 0.4$. From $-V$ to Z, $x \in [-4, 0]$, C_{-VL}=-4, C_{-L}=-3, C_{-M}=-2, C_{-S}=-1, C_Z=0. Conversely a negative sign is difference.

2.2. Establishment of Consumer Psychological Fuzzy Corpus Bases.

Table 1. Evaluation and Emotion Fuzzy Corpus of Online Reviews

Ontology	Evaluation		Emotion	
Monitor, chassis, cable, touch screen, processor, appearance, hard disk, price, weight, after sale, fan, repair rate	words	degree	words	degree
	unique	VLG	happy	LH
	ideal	LG	enjoyable	MH
	comfortable	MG	fortunately	SH
	good	SG	hesitate	Z
	ordinary	Z	faint	SL
	expensive	SB	gloomy	ML

On the above basis a semantic fuzzy corpus is established. Products and their attributes are objective ontology upon which consumers comment. We take a notebook computer as an example to give the base of ontology. We build a fuzzy corpus of evaluation and emotion according to the established methods of the membership function introduced in Section 1. The fuzzy corpus is then stored by a two-dimensional table, for the case of fuzzy evaluation, the words are in the first column and the basis evaluation fuzzy set are stored in the second ones, as shown in Table 1.

3 Fuzzy Calculation of Product Evaluation and Emotion

The emotion value is obtained through the comprehensive calculation of massively emotional words. Also we take customer preferences of certain features into account to calculate evaluation of products with multi-attributes. Thus the fuzzy calculation steps of evaluation and emotion go as follows:

Step 1. Firstly conduct part-of-speech tagging and syntactic analysis and then get *n* evaluation words, $EF_i(i=1,...,n)$, *m* emotional words, $EM_i(i=1,...,m)$, and their corresponding intensive or negative modifiers.

Step 2. Regarding evaluation and emotion words, $EF_i(i=1,...,n)$, $EM_i(i=1,...,m)$, query the corresponding basic evaluation fuzzy set $\mu(EF_i)(i=1,...,n)$ and $\mu(EM_i)(i=1,...,m)$ from the evaluation and emotion fuzzy corpus.

Step 3. According to the intensive and negative processing approach accomplish shift the width and center of its membership function, and get modified evaluation fuzzy set, $\mu'(EF_i)(i=1,...,n)$, and modified emotion fuzzy set, $\mu'(EM_i)(i=1,...,m)$.

Step 4. Execute the "and" operation to $\mu'(EF_i)(i=1,...,n)$ and $\mu'(EM_i)(i=1,...,m)$, respectively, and then get the evaluation of the certain attribute and the total emotion fuzzy set *EF*, *EM*.

Step 5. Defuzzify *EF*, *EM* separately by means of "centroid", afterwards obtain the attribute evaluation value and the overall emotion value of the product.

Step 6. A final score of the product based on the valuation of each feature is Overall Assessment that is calculated as the weighted sum of several attributes.

$$OA = \sum EF \cdot ImportanceIndex \quad (2)$$

We compiled a program in Matlab in accordance with the rules above, whereby we can calculate the evaluation and emotion degree of a product.

4 Recommendation Methodology

In order to achieve the product recommendation, based on the theory of consumption motivation, we calculate and reason by way of product evaluation and emotion values and then we generate the extent of recommendation effect of product reviews-recommendation degrees. That requires setting up reasoning rule bases representing knowledge.

4.1. Fuzzy reasoning rule bases

In various methods of Knowledge Representation the commonest way is the form of natural language rules: IF premise (antecedent), THEN conclusion (consequent).

We own evaluation (*EF*) and emotion (*EM*) as antecedent and recommendation (*R*) as consequent to establish fuzzy reasoning system (*FIS*). The form is as follows: IF antecedent 1 (Customer Type) and antecedent (*EF*) and antecedent 3(*EM*), THEN consequent (*R*)(5).

There are several ways to classify users such as lifestyle theory, demographic filtering, shopping motive and so on. Nevertheless the lifestyle theory is difficult to explain that the values influence on a user's purchase behavior in [7]. Demographic filtering does not provide any individual adaptation particularly as the user's interests tend to change over time referring to [8] and reference in [9] provided that the shopping motive can be defined as the driver of behavior that brings consumers to the marketplace to satisfy their internal needs. In the work of [7] the shopping motive was classified into four shopping types as shown in Fig 4.1.

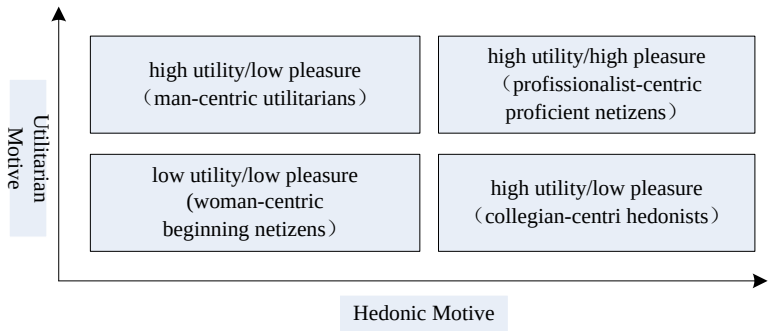

Fig 4.1: User Classification by Shopping Motive

The low-utility/low-pleasure type includes woman-centric beginning netizens for whom the utility is quantized by the emotion value and the degree of pleasure need is characterized as emotion value. The basic principle of constructing the inference rules: the consequent increases as the antecedent strengthens; When antecedent 2(*EF*) and antecedent 3(*EM*) are both large negative values, the recommendation degree is intense opposition (*VLO*); On the premise of the theory of Bounded Rationality, although one of the antecedents is a negative value, the other is very high and this antecedent is demanded by the consumer, then the purchase intention is the consumer and then the purchase intention is strong. Therefore the extent of recommendation degree should advance along with the growth of the high antecedent. Four types of rules of the consumer's analysis go as follows:

Regarding the type of high utility/high pleasure consumers, the higher the utility of the product as well as the better the emotion satisfies the consumer the more willing to buy. Namely the recommendation intensity should be bigger.

For the type of low utility/low pleasure the product utility and the emotion satisfaction have little impact on purchase intention. If it can meet the consumer's basic need, namely evaluation and emotion is nonnegative, the consumers are willing to buy. So when antecedents 2(EF) and antecedents 3(EM) rise to zero, consequent (R) jumps rapidly to an intense degree of recommendation.

High utility/low pleasure consumers tend to buy high-utility product the online reviews of which are good, but they are less influenced by the emotion of the comments, namely, the purchase intention rises with the utility evaluation rather than the pleasure. The low utility/high pleasure is on the contrary. Mamdani reasoning method is adopted and the Centroid method is employed for defuzzification.

4.2. Experiment design and analysis

From the related posts of Baidu Post Bar (http://tieba.baidu.com/) using the page collection tool, 'bget_share', downloaded more than 1200 reviews of which there are 437 sentences commented on X brand of notebook computer and 328 on Y. After being screened 160 reviews are identified as the final corpus respectively.

For each one of these 160 reviews the comprehensive evaluation and the emotion degree were calculated. By the above inference method the recommendation degree is obtained for four types of consumers. The abscissa in the graph represents the number of the comments. In order to facilitate the observation of recommendation laws we sort the evaluation value of X from low to high while the emotion value of Y is sorted the same way. The effects of the two experiments are shown in Figg 4.2-4.3:

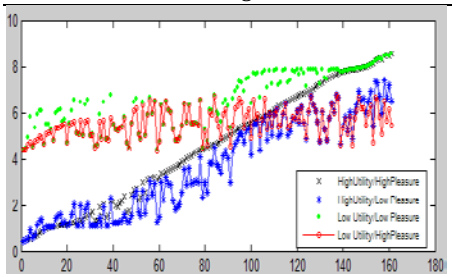

Fig 4.2: Recommendation effect of product X to four consumer types

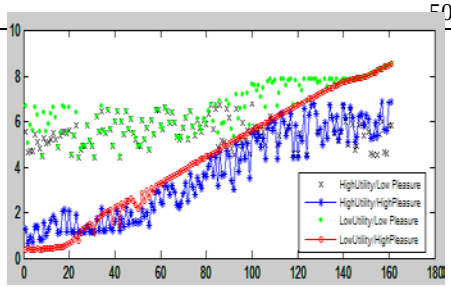

Fig 4.3: Recommendation effect of product Y to four consumer types

From Fig 4.2 the recommendation degree of the consumers with strong need of product utility (black and blue) is enhanced with the increasing of evaluation value. From 120 comments the recommendation degree of high utility/high pleasure (blue) consumers slows gradually. Given that both are at the same emotional level and the low pleasure (black) types do not ask so much pleasure, the recommendation degree is not limited by the antecedents.

The evaluation value has minimal impact on the recommendation degree of the consumers without strong utility demanding (red and green). Thus their values remain at a high level. As can be seen in the comments between the 80 and 100, when the evaluation value accelerate to a certain extent, the recommendation degree of low utility/low pleasure (green) consumers shoots up and remains at a high level.

From Fig 4.3 high utility/high pleasure and low utility/low pleasure consumers adopt the same recommendation law as the analysis of Fig 4.2. However, the recommendation degree of low utility/high-pleasure is gradually enhanced with the growth of emotion value and the one of high utility/low-pleasure tends to be horizontal. The experiments verify the validity of reasoning rules.

5 Conclusion

This paper considers consumers' psychological factors and the inherent fuzzy properties of the natural language. Based on the fuzzy model for the evaluation and emotion of online review texts, fuzzy corpus are established using evaluation and emotion words. Combined with consumer preferences of product attributes, the comprehensive evaluation and emotional value is calculated. Regarding them as inference antecedents towards different consumer types with bounded rationality we achieve the recommendation degree. Experiments of a large number of comments on *X* and *Y* notebook products are given as well as a detailed analysis of recommended levels and trends. The validity of the method is proved. In the future it is necessary to enrich and verify the corpus. Meanwhile experiments on different product types and improvement of inference rules are to be continued.

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