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# Product Fuzzy Recommendation of Online Reviews Based on Consumer Psychological Motives

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# PRODUCT FUZZY RECOMMENDATION OF ONLINE REVIEWS BASED ON CONSUMER PSYCHOLOGICAL MOTIVES

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## Abstract

Sentiment analysis of online comments and their application has become a hot topic. Meanwhile the evaluation and emotion method has challenged researchers and practitioners. This paper proposes a fuzzy modeling for the evaluation and emotion of online review texts by means of the theory of consumption motivation type and establishes corresponding fuzzy corpus. A calculation method of comprehensive evaluation and emotion with respect to the consumer's preference for product attributes provide reasoning antecedents. Establishment of fuzzy inference rules give results of recommendation to consumers of four different motivations. Experimental results prove the validity of the proposed method.

**Keywords:** behavior research, consumption motivation type, attitude mining, fuzzy semantic, fuzzy inference

## I. Introduction

With the rapid development of Web 2.0 and e-commerce technologies many consumers prefer to use free form of text to express their opinions ,attitude and emotion in review forums, discussion groups and virtual community logs in the work of [1, 2]. There is growing evidence that such forums could influence consumers' purchase decisions according to [3, 4]. 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 understand the users' consuming habits and public opinions which play an important role in decision-making for the enterprises and the government. Semantic polarity analysis and opinion mining is the process of analysis the sentences and texts with sentiment orientation (positive, negative and neutral) and the intensity.

For English texts, the work of [5] provided standard classification of corpus such as Reuters and statistical evaluation method .The corpus on the syntax specification such as news reports [6, 7] and forum with fixed format or clear categories are given in [8]. The work of [9] illustrated a sentiment analysis approach to extract sentiments associated with polarities of positive or negative for specific subjects from a document. One method combining HowNet knowledge base with a semantic similarity of characteristic words and phrases by using HowNet was given in [10]. And they adopt the positive and negative terms as features of sentiment classifier. However the present researches mainly adopt statistical methods and rarely identify the positive or negative polarity without further subdivision respectively or simply assign real number for the rank of intensity, whereas the affect domain is ambiguous and imprecise. First, because this is the nature of human emotion, and second, because it is characteristic of words in meaning of natural languages are actually ambiguous. Although fuzzy Semantic Typing method improved the statistical approaches through the qualitative representation of free text ideally, a representation which accommodates ambiguity and imprecision the lexicon entries are assigned with numerical intensities which represent the strength of the affect level described by that word.

It is based on the normative hypothesis that people are rational agents. Behavior scholars of [11] realized the description or prediction of people's behavior totally depending on the standardization of models and theories will lead to systematic errors in [12].The actual behavior of people follows Simon's "Bounded Rationality" theory referring to [13, 14] and there in [15] explained a person's capacity of study, thought and action is limited whereas mental and emotion play a significant role in purchase intention and behavior. Meanwhile online there is no uniform measurement of the perceived risks and benefits. Therefore it's more important of mental and emotion than the consumer's ability and experience for consumer behavior prediction. This paper focuses on the subsection of polarity intensity with fuzzy method. Instead of numerical intensities we use continuous function to represent the strength of the affect level. We proposes a fuzzy modeling for online review texts .We have built fuzzy corpus of consumer evaluation and emotion and a calculation method of them is given combined with the consumer's preference for product attributes. Furthermore, using the theory of consumption motivation type this paper presents fuzzy inference rules with comprehensive evaluation and emotion as antecedents. Consequently it accomplishes reasoning recommendation to consumers with four different motivations. Through the calculation and analysis of practical problems, it verifies the validity of the proposed methods.

## II. Semantic Fuzzification of Online Reviews

The application of Fuzzy Mathematics is able not only to solve the problem of language uncertainty but also to improve the quantification method 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.

### A. 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 instance ,Mosier's (1941) one-dimensional fixed-point and Osgood's (1952) multi-dimensional characterization.

The words with emotional tendency which reflect evaluation and emotion are referred as Polarity Word. In the current research on semantic analysis and opinion mining of online reviews, most of all provide accurate mathematical methods by describing the meanings of word with real number. For example "fine" with assignment "+2", "rough" with assignment "-1" and so on. However, the meaning itself is ambiguous due to the linguistic nature. From the perspective of fuzzy theory, a word meaning corresponds to a fuzzy set rather than a simple binary logic answer of 'yes' or 'no'. For using 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. In order to comply with linguistic sequence laws and avoid inappropriate overlap we choose the Gaussian function as a template to define fuzzy membership functions for 9 semantic ranks in domain [-4, 4]. Formula (1) is template of Fuzzy Membership Function.

$$y = gaussmfk(x, \sigma_k, c_k) = e^{\frac{-(x-c_k)^2}{2\sigma_k^2}} \qquad (1)$$

Where $k \in \{-VL, -L, -M, -S, Z, +S, +M, +L, +VL\}$,$\sigma_k$, $c_k$ are parameters of 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 $Z$ , $x \in [-4,0]$ , $c_{-VL} = -4$ , $c_{-L} = -3$, $c_{-M} = -2$, $c_{-S} = -1$ , $c_Z = 0$;

From $Z$ to $VL$, $x \in [0,4]$ , $c_Z = 0$ , $c_S = 1$ , $c_M = 2$ , $c_L = 3$ , $c_{VL} = 4$

Let us consider the following example of Fuzzy Set.

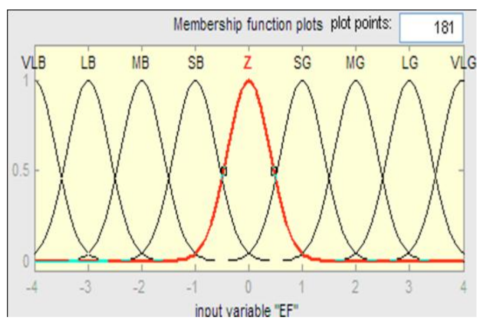


Fig.1 Basic Evaluation Fuzzy Set

Table 1. Evaluation and Emotion Fuzzy Corpus of Online Reviews

| Ontology | Evaluation | | Emotion | |
|---|---|---|---|---|
| | 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 | unique | VLG | happy | LH |
| | ideal | LG | enjoyable | MH |
| | comfortable | MG | fortunately | SH |
| | good | SG | hesitate | Z |
| | ordinary | Z | faint | SL |
| | expensive | SB | gloomy | ML |

### B. Establishment of Consumer Psychological Fuzzy Corpus Bases

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

### C. Fuzzy Operator of Modifiers.

In this section, we present how to deal with the language operator and characterize the semantic transfer caused by modifiers. For adverb or negative prefix modifiers may change the semantic polarity and degree of the basic evaluation fuzzy set .So to achieve the fuzzy calculation of evaluation and evaluation degree at the sentence level, it is indispensible to determine.

#### (a)Intensifier Operators

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 Modified-Polarity will lead to the sentiment transfer problem. Subsequently we define the processing methods of these language operators and two dictionaries: the Privative Dictionary and Intensifier Dictionary so as to achieve the width change of its membership function and the corresponding shift of the center.

In this paper, we use the word Set in 'HowNet' which is created by [16]. After being screened and refreshed, they are divided into five ranks, namely, extreme, very, more, little and insufficient. The following table lists some of the typical intensifier words:

The categories of 'extremely', 'very' and 'more' with the effect of strengthen the tone are called 'Strengthen Operator', also known as 'Centralized Operator'. While the rest which is used to weaken the tone are regarded as 'Freshening Operator', also known as 'Loose Operator', as indicated in the ranks of 'little' and 'insufficiently'.

System (2).is the general form of the intensifier operators Take evaluation word M as an example:

$$\begin{aligned} H_\lambda \mu_k(M) &= [\mu(x, c_k + \lambda')]^\lambda \\ &= gaussmf_k(x, \sigma_k, c_k + \lambda')^k \\ &= e^{\left(\frac{-[x-(c_k+\lambda')]^2}{2\sigma_k^2}\right)\cdot\lambda} \end{aligned} \quad (2)$$

Here, $\sigma_k = 0.4$; $x \in [-4,4]$; $k$ is the evaluation rank of the target word; $H_\lambda$ is the Intensifier Operator; $\lambda$ is a positive real number; when $\lambda > 1$, $H_\lambda$ is a Centralized Operator; when $\lambda < 1$, $H_\lambda$ is a Loose Operator. $c_k$ is the original value of the Gaussian function for evaluation rank $k$, with the addition of the intensifier word, whose value will shift $\lambda'$ units to the left or right side. The corresponding value of $\lambda$ and $\lambda'$ also see table:

Table 2. Examples of Some representative Intensifier Word Ranks

| Rank | Intense | Examples | $\lambda$ | $\lambda'$ |
|---|---|---|---|---|
| 1 | insufficiently | a little less, just, less, merely, not really | 4 | +2 |
| 2 | little | a bit, a little, a little bit, more or less, slightly, somewhat, some | 2 | +1.5 |
| 3 | more | by far, comparatively, even more, further, fairly relatively, at least, | 1.5 | +0.5 |
| 4 | very | considerably, especially, much, quite, , too far, a lot, particularly, | 0.5 | -1 |
| 5 | extremely | absolutely, amazingly, completely, ultra exceedingly, beyond comparison, | 0.25 | -1.5 |

Consequently, by means of the above operations which transfer the width change or shift the center of its membership function we can achieve the corresponding change of evaluation degree

#### (b)Privative Operator

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

Through taking half of the sentimental polarity after reverse weaken the negative tone in[19]. But this approach will induce contradiction in some special situations. For example, the evaluation word 'satisfied', whose sentimental rank is +B, for 'not very satisfied', if in accordance with this algorithm, first change the membership function according to the intensifier operator (narrow, shift to right) to raise the evaluation degree, and then take half after reverse. It is clear that the desired value of the membership function at this time is lower than that of 'not satisfied' (directly take half after reverse), that is, low evaluation degree. However, the fact is, the degree of 'not very satisfied' should be much higher than that of 'not satisfied', so the algorithm about the Privative Operator should be further to discuss.

For this reason, 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, $\omega$ is the sentimental rank this word belongs to, $k \in \{-VL, -L, -M, -S, Z, +S, +M, +L, +VL\}$, the corresponding membership function is

$$\mu_k(M) = gaussmf_k(x, \sigma_k, c_k) = e^{\frac{-[x-c_k]^2}{2\sigma_k^2}} \qquad (3)$$

The three cases are described respectively as follows.

For case *PM*, order $c_\omega = -c_\omega/2$, then

$$\mu_k(M) = gaussmf_k\left(x, \sigma_k, -\frac{c_k}{2}\right) e^{\frac{-\left[x+\frac{c_k}{2}\right]^2}{2\sigma_k^2}} \qquad (4)$$

For case *PIM*, given the variables corresponding to the intensifier operator $\lambda$ and $\lambda'$, then

$$\mu_k(M) = \left[gaussmf_k\left(x, \sigma_k, -\frac{c_k+\lambda'}{4}\right)\right]^\lambda = e^{\left\{\frac{-[x+(c_k+\lambda')/4]^2}{2\sigma_k^2}\right\}\cdot\lambda} \qquad (5)$$

For case *IPM*, the same,

$$\mu_k(M) = \left[gaussmf_k\left(x, \sigma_k, -\frac{c_k}{2}+\lambda'\right)\right]^\lambda = e^{\left\{\frac{-\left[x-(-\frac{c_k}{2}+\lambda')\right]^2}{2\sigma_k^2}\right\}\cdot\lambda} \qquad (6)$$

In this paper, the Privative Dictionary is established through 'HowNet'. By the selection of the original privative words in the 'HowNet', and then extracting the words having the original negative meaning definition, we got 18 privative after filtering such as 'not', 'no', 'never', 'hardly' and so on.

## III. Fuzzy Calculation of Product Comprehensive Evaluation and Emotion

The emotion value is obtained through comprehensive calculation of massive emotion 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:

**Step1.** Firstly, conduct part-of-speech tagging and syntactic analysis then get n evaluation words $EF_i(i = 1, \dots, n)$ and m emotion words $EM_i(i = 1, \dots, m)$ and corresponding intensive or negative modifiers.

**Step2.** Regarding evaluation and emotion words $EF_i(i = 1, \dots, n)$, $EM_i(i = 1, \dots, m)$, query the corresponding basic evaluation fuzzy set $\mu(EF_i)(i = 1, \dots, n)$ and $\mu(EM_i)(i = 1, \dots, m)$ from the evaluation and emotion fuzzy corpus.

**Step3.** According to the intensive and negative processing approach accomplish shift the width and center of its membership function, and get modified evaluation fuzzy set $\mu'(EF_i)(i = 1, \dots, n)$and modified emotion fuzzy set $\mu'(EM_i)(i = 1, \dots, m)$.

**Step4.** Execute "and" operation to $\mu'(EF_i)(i = 1, \dots, n)$ and $\mu'(EM_i)(i = 1, \dots, m)$ respectively, then get the evaluation of the certain attribute and the total emotion fuzzy set $EF$, $EM$.

**Step5.** Defuzzify $EF$, $EM$ separately by means of "centroid", afterwards obtain the attribute evaluation value and the overall emotion value of the product.

**Step6**. 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.

$$OA = \sum EF * ImportanceIndex \qquad (7)$$

We compiled program in Matlab in accordance with the rules of above, thereby can calculate the evaluation and emotion degree of a product. Example: "The design of this series is defective, its heat dissipation is comparatively poor, the battery is too short-lived, not so desirable, and the main board is easy-burned, regret having bought it, depressing …"

The evaluation and its modifiers are analyzed in table 3:

Negative word "poor" is used to appraise the attribute of "battery", membership function of this word in the basic evaluation fuzzy set is *LB*, and modified by the intensifier "too" whose rank is 4 expressing a strong emphasizing degree. Negative words are denoted by *N* (Negative) and 0(none).

In the 203 commentary sentences there are 35 evaluation words reviewed on "battery", the evaluation value is -2.6528; while 42 evaluation words on "heat dissipation", the evaluation value is -3.7922. Assume the important coefficient of these two attributes is 1, 0.5. Then

$$OA = \sum \frac{((-2.6528)*1+(-3.7922)*0.5)}{1.5} = -3.0326 \qquad (8)$$

Meanwhile, there are 71 emotion words; the comprehensive value is -1.8612. Massive commentaries hold high negative opinion on this notebook, thus the battery performance is ordinary and the one of the heat dissipation is bad. Hence the product is not welcome by the consumers.

## IV. Recommendation Methodology

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

### A. Fuzzy reasoning rule bases

In various Knowledge Representation methods, the most common 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*), whose 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 user's purchase behavior in [17]. Demographic filtering does not provide any individual adaptation, also when the user interests tend to change over time referring to [18] and reference in [19] provided that shopping motive can be defined as driver of behavior that brings consumers to the marketplace to satisfy their internal needs. In the work of [20] classified shopping motive into four shopping types showing in Figure 2.

Low-utility/low-pleasure type includes woman-centric beginning nedizens. Where the utility is quantized by the emotion value and the degree of pleasure need is characterized as emotion value.

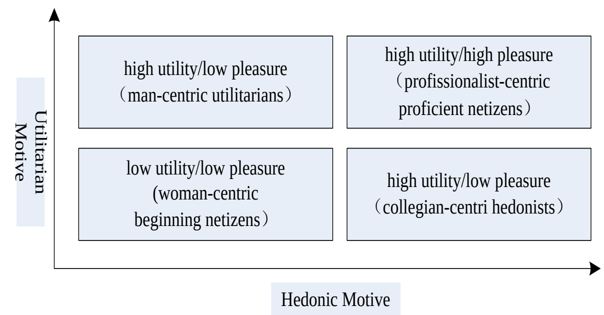


FIG.2 User Classification by Shopping Motive

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 great negative values the recommendation degree is intense opposition (*VLO*); On the premise of Bounded Rationality theory, 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 strong. Therefore, the extent of recommendation degree should advance along with the growth of the high antecedent. Four type 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. The specific inference rules are shown in table 4.

Table 3. Fuzzy inference rules for High Utility/Low Pleasure consumers

| EF / E / R | VLB | LB | MB | SB | Zero | SG | MG | LG | VLG |
|---|---|---|---|---|---|---|---|---|---|
| VLL | VLO | VLO | VLO | VLO | VLO | VLO | LO | MO | SO |
| LL | VLO | VLO | VLO | VLO | LO | LO | MO | SO | Z |
| ML | VLO | VLO | VLO | VLO | LO | LO | MO | SO | Z |
| SL | VLO | VLO | VLO | VLO | LO | MO | SO | Z | Z |
| Zero | VLO | LO | LO | LO | MO | SO | Z | Z | SA |
| SH | VLO | LO | LO | MO | SO | SA | SA | SA | MA |
| MH | LO | MO | MO | SO | Z | SA | MA | MA | LA |
| LH | MO | SO | SO | Z | Z | SA | MA | LA | VLA |
| VLH | SO | Z | Z | Z | SA | MA | LA | VLA | VLA |

Three-dimensional graphic of rules is shown in Figure 3-6. 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 non-negative, the consumers are willing to buy. So when antecedents 2(*EF*), antecedents 3(*EM*) rise to zero, consequent (*R*) jumps rapidly to intense degree of recommendation.

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

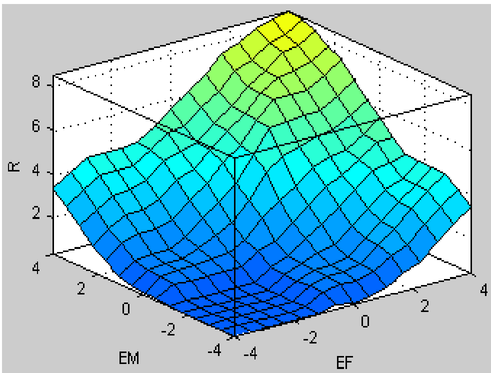


FIG.3 Fuzzy inference rules for High Utility/High Pleasure

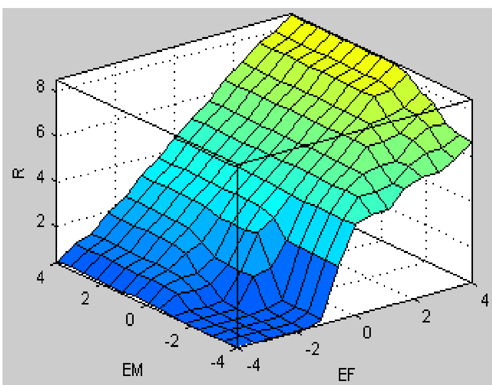


FIG. 4 Fuzzy inference rules for High Utility/Low Pleasure

## B. Experiment design and analysis

From the related posts of Baidu Post Bar (http://tieba.baidu.com/) using 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.

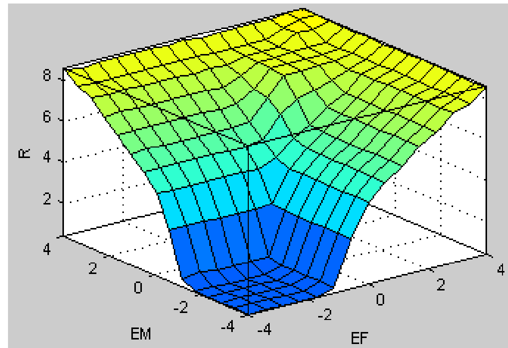


FIG. 5 Fuzzy inference rules for Low Utility/Low Pleasure

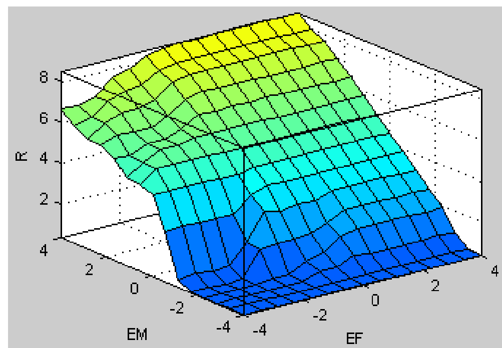


FIG. 6 Fuzzy inference rules for Low Utility/High Pleasure

For each one of these 160 reviews, the comprehensive evaluation and the emotion degree were calculated. By the above inference method recommendation degree is obtained for four types of consumers. The abscissa in the graphic 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 Figure 7, 8:

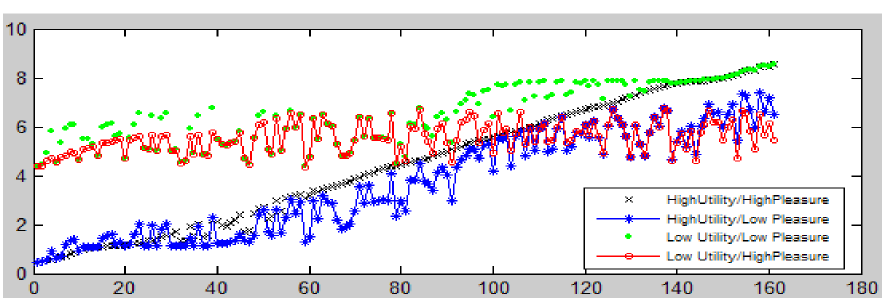


FIG.7 Recommendation effect of product X to four consumer types

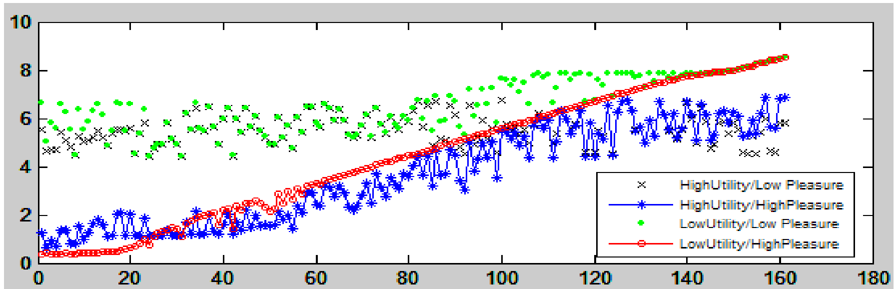


FIG.8 Recommendation effect of product Y to four consumer types

From Figure 7, 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 down gradually. Given that both are at the same emotional level and the low pleasure (black) types don't ask so much pleasure, the recommendation degree isn't 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 theirs maintain 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 shoot up and remain at a high level.

From Figure 8, high utility / high pleasure and low utility / low pleasure consumers take on the same recommendation law as the analysis of Figure 7. 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 tend to be horizontal. The experiments verify the validity of reasoning rules.

## V. Conclusion

This paper considers consumers' psychological factors and the inherent fuzzy properties of the natural language. Based on the fuzzy modeling 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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### References

[1] G. Eason, B. Noble, and I.N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions." Phil. Trans. Roy. Soc. London, vol. A247, pp.529-551, April 1955.

[2] C. Dellarocas, The digitization of Word-of-Mouth: Promise and challenges of online feed back mechanisms. Management Science, vol.49, no.10, pp.1407-1424, 2003.

[3] N.Curien, E. Fauchart, G. Laffond and F. Moreau, Online consumer communities: escaping the tragedy of the digital commons, Internet and Digital Economics, vol. 9, no.3, pp.407-424, 2005.

[4] J. Chevalier, and D. Mayzlin, The effect of word of mouth on sales: Online book reviews, Journal of marketing research, vol.43, no.3, pp.345-354, 2006.

[5] S.Senecal, and J. Nantel, The influence of online product recommendations on consumers' online choices, Journal of Relating, vol.80, no.2, pp.159-169, 2004.

[6] Y. M. Yang and X. Liu, A Re-examination of Text Categorization Methods, Proceedings of the 22nd Annual International ACM SIGIR Conf. on Research and Development in Information

Retrieval, Berkeley, California, pp.35-39, 1999.

[7] H. Yu, V. Hatzivassiloglou, Towards answering opinion questions: separating facts from op inions and identifying the polarity of opinion sentence, Proceedings of the 2003 Conf. on Empirical Methods in Natural Language Processing, Sapporo, Japan, pp.129-136, 2003.

[8] B. K. Y. Tsou, and YUEN R. W. M. Yuen, Polarity classification of celebrity coverage in the Chinese press, Proceeding of International Conference on Intelligence Analysis, Virginia, USA, pp.908-914, 2005.

[9] B. Liu, and M. Hu, Opinion observer: analyzing and comparing opinions on the web, Proceedings of the 14th International Conference on World Wide Web, Chiba, Japan, PP.342-351, 2005.

[10] T. Nasukawa, and J. Yi, Sentiment analysis capturing favorability using natural language processing, Proceedings of the 2nd international conf. on Knowledge capture, Sanibel Island, USA, pp.70-77, 2003.

[11] L. Yu, X. Y. Liu and F. J. Ren, Learning to classify semantic orientation on on-line document, International Journal of Innovative Computing, Information and Control, vol.5, No.12 (A), pp.4637-645, 2009.

[12] H. J. Weiss, and E. G. Mark, Production and Operations Management, Allyn and Bacon, 1989.

[13] R. H. Thaler, Towards a positive theory of consumer choice, Journal of Economic Behavior and Organization, vol.1, no.1, pp. 39-60, 1980.

[14] H. A. Simon, Rational choice and the structure of the environment, Psychological Review, vol.63, no.2, 129-138, 1956.

[15] H. A. Simon, Models of man, New York, NY, 1957.

[16] I. B. Choi, and S. H. Park, A contents recommendation scheme using user's affection and shopping motive, Proceedings of the 5th international conference on Pervasive services, Sorrento, Italy, pp.17-180, 2008.

[17] Z. D. Dong, How Net, http://www.keenage.com/html/e_index.html, 1998.

[18] P. Cheol, A comparison between Cyber Shoppers and Non-cyber Shoppers in Korea, Proceedings of the 5th international conference on Pervasive services, Sorrento, Italy, pp.177-180, 2008.

[19] M. Lenar, and J. Sobecki, Using Recommendation to Improve Negotiations in Agent-based Systems. Journal of Universal Computer Science. vol.13, no.2, pp.267-286, 2007.

[20] Y. C. Choe, D. R. H wang, M. Kim and J. Moon, Product Heterogeneity: Moderating Effect on Online Consumer Behavior, System Sciences 40th Annual Hawaii International Conference, Big Island, Hawaii, pp.153-162, 2007.