Sentiment classification of e-commerce product quality reviews by FL-SVM

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ABSTRACT

In order to enhance the accuracy of sentiment classification for e-commerce product quality reviews, this paper proposed the FL-SVM approaches which measure the emotional polarity of sentiment reviews by constructed fuzzy theory sentiment dictionary on the HowNet, the support vector machine (SVM) is adopted to analyze and classify the sentiment tendency of e-commerce product quality reviews. Comparing the NB, kNN and SVM algorithm, the experiments of different data sets illustrate that FL-SVM approaches can achieve better sentiment classification accuracy increased from 1 to 3%, which verifies the effectiveness and robustness of the FL-SVM approaches on e-commerce product quality reviews.

Key words: E-commerce product quality review, sentiment classifier, sentiment dictionary, fuzzy logic, support vector machine (SVM).

INTRODUCTION

With the rapid growth of e-commerce, online shopping has been accepted progressively by people, where e-commerce brings convenience experience and low price products to consumers. Due to the geographical limited characteristics leads information shortages of e-commerce product quality, and the inconsistency between description information and reality commodity, consumers have to see reviews about the product before making shopping decision. The rapid growth on the Web has led to enormous amount and variety of personal reviews, thus making it difficult for customers to recognize the valuable on-line product comment. Pavlou and Dimoka (2006) utilized content analysis to quantify over 10,000 publicly available feedback text comments of 420 sellers in eBay’s online auction marketplace, which can be differentiated among sellers and prevent a market of lemon sellers for online market places.

The sentiment analysis simply refers to the text content classification technique used to distinguish between the positive or negative attitudes and opinions of consumer from the related information that appears in different forms like BBS, blogs, Wiki or forum websites (Abbasi et al., 2008).

More importantly, the producers and sellers can obtain feedback about their goods and services from consumers in order to improve products and services. In this paper, sentiment analysis techniques were incorporated into the domain of mining reviews from commodity comments. Specifically, the approaches based on the fuzzy sentiment dictionary and the support vector machine algorithms for sentiment classification of the reviews on e-commerce product which provide more reliable online shopping auxiliary information from one customer to the other are proposed in this research.

LITERATURE REVIEW

The research work of sentiment classification method can be divided into two categories: One is the semantic analysis method based on sentiment dictionary, where the quality of sentiment dictionary is very important, while the other is the machine learning method with extraction of feature words being the key factor (Zhang and Ye, 2007).

Semantic analysis method

The semantic analysis method determines the text sentiment
tendency through the statistics and analysis of the positive or negative sentiment word in the text. The semantic analysis methods mainly include: the corpus words mining method and the dictionary expansion method, which sentiment tendency of English dictionary mainly based on WordNet and GI (General Inquirer) (Huang et al., 2011). Somprasertrt et al. (2006) reported on mining product feature and opinion in online customer reviews based on the consideration of syntactic information and semantic information. Kim and Hovy (2004) analyzed the emotional tendency of text based on the synonyms, antonyms and hierarchies of the WordNet dictionary (Pak and Paroubek, 2010).

Turney and Littman (2003) used the point wise mutual information (PMI) to extend the commendatory and derogatory emotional vocabulary in order to analyze the emotional tendency in the English text (Kim and Hovy, 2004). The acquisition of sentiment tendency in Chinese text depends mainly on HowNet. Zhu et al. (2006) used the semantic similarity and correlation of HowNet to calculate the similarity between the new word and the datum word in order to distinguish the sentiment tendency of the text (Turney and Littman, 2003). The disadvantage of these methods is that it is dependent on the existing seed sentiment words.

**Machine learning method**

Support vector machine (SVM) is described as the seeking optimal margin classifier based on the Vapnik Chervonenkis dimension of statistical learning theory and the structural risk minimization theory, which was first proposed by Cortes and Vapnik in 1995. Compared with other algorithms, it has better advantages in the small sample, non-linear and high dimensional pattern recognition problem. As the supervised learning classification method, Support vector machine is widely used in Word Sense Disambiguation (WSD), text automatic classification and information filtering in the field of Natural Language Processing (NLP). Pang et al. (2002) first applied the machine learning method of N-Gram into the emotional analysis field, while the experiment showed that the N-Gram reached highest classification accuracy of 81.9% (Zhu et al., 2006).

Go et al. (2009) proposed the supervised learning method to classify the positive or negative emotional information in Twitter by the naive Bayes, maximum entropy and SVM classification algorithms based on the training set of extracted messages with emoticons in Twitter, where the experiment show 80% classification accuracy (Pang et al., 2002). The literature (Go et al., 2009; Tang et al., 2007; Guerini et al., 2013) applied the sentiment classification methods such as Naive Bayesian (NB), K-Nearest Neighbor (kNN), Maximum Entropy (ME) and Support Vector Machine (SVM) to analyze the text emotional tendency, which the experiments show that the support vector machine (SVM) is obviously superior to other classification methods in large training sets and reach the highest classification accuracy of 83%.

**The combined classify methods**

The subjective factors in the classification process lead the semantic method to obtain the inaccuracy result. The quality of feature selection will directly affect the effect of the machine learning classifier. At present, the typical research method of text emotion analysis is to extract the text features with emotion dictionary, and to classify the text emotional tendency with machine learning method. Guerini et al. (2013) used the sentiment dictionary combined machine learning method to research the polarity problem of feature words (Go et al., 2009). Due to hardness of the sentiment analysis in solving the contextual un-correlation problem, Tripathy et al. (2016) analyzed online comment reviews by the N-gram model combined machine learning methods and the experiments showed that the SVM combined unigram, bigram and trigram features achieved the best classification results (Tang et al., 2007).

According to the sentiment dictionary which have e-commerce reviews domain limitations, this paper analyzes the characteristics of sentiment words based on the fuzzy theory and text sentiment analysis method. The classification method was adopted to judge the sentiment tendency of sentence by the word feature, the POS feature and the semantic feature. Finally, the support vector machine (SVM) is used with the emotional feature vectors to distinguish the emotional polarity of the on-line reviews, which automatically recognizes the sentiment words and sentiment sentences in the training corpus. Figure 1 shows
the flow chart of subjective tendency analysis for e-commerce product quality review.

THE SENTIMENT DICTIONARY FOR THE E-COMMERCE PRODUCT QUALITY REVIEW BASED ON FUZZY THEORY

The review of e-commerce product quality often includes "bao bei heng bang!", "wu liu heng kuai!", "wai guan heng mei!" and "mei xiang xiang de hao!" etc. These words and sentences can generally reflect the emotional descriptive structure of sentences used in this field. If these fixed words or phrases can be analyzed, then the sentiment polarity of comment will be determined. This paper proposes the fuzzy theory to identify the emotion words of e-commerce product quality, which improve the HowNet dictionary to make it applicable to the sentiment analysis on e-commerce product reviews.

Fuzzy theory

This section may be divided by sub-headings. It should provide a concise and precise description of the experimental results and their interpretation as well as the experimental conclusions that can be drawn. Zadeh (1965) first proposed Fuzzy Theory (Guerini et al., 2013), where the fuzzy information can be depicted by membership degree. Membership function converted the object of the given fuzzy subset into the interval [0, 1]. The fuzzy set is the quantitative description of fuzzy concepts, which can be expressed as:

\[ \bar{L} = \frac{\rho_T(u_1)}{U_1} + \frac{\rho_T(u_2)}{U_2} + \ldots + \frac{\rho_T(u_n)}{U_n} \]  

(1)

The parameter \( \rho_T(u_i) \) represents the membership degree of ui that is the ith element in the domain U, while the range of membership degree is: \( 0 \leq \rho_T(u_i) \leq 1 \). According to the inherent semantic fuzziness feature in natural language, this paper proposes the membership function of emotional intensity evaluation based on Fuzzy theory and fuzzy operation under this research background.

Construct the e-commerce sentiment dictionary based on Fuzzy theory

Definition 1: Sentiment class- The sentiment class set consisted of positive, negative and neutral words. The text sentiment analysis contains a total of three emotional categories: positive class (P), negative class (N) and neutral class (M).

Definition 2: Label consistency- The same word is affective tagged with different people or tools (including at least two different annotators, also known as cross-taggers). If the results of each tagging are the same, the word is labeled to the same emotional class. Then, the annotation process across the annotator is consistency.

Definition 3: The core and edge of sentiment class- If the word has strong emotional tendency, then it belongs to the core of sentiment class. If the word has fuzzy sentiment tendency and non-tagging consistency, then it belongs to the edge of sentiment class.

Definition 4: The centrality and intensity- The centrality indicates the degree of words belonging to a certain sentiment class. The intensity indicates the intensity of sentiment tendencies of words in the class.

Some Chinese words have explicit sentiment attribute, but others have difficulty in labeling the sentiment class. In order to solve this problem, the sentiment tagging process of word is treated as the continuous rather than discontinuous process. The sentiment class can be defined as the fuzzy class in this paper. Some words belonging to the core of the sentiment class have explicit emotional tendency, such as "good" or "bad". However, some words may be interpreted by different people with different meanings. Therefore, these words at the edge of the sentiment class have fuzzy emotional tendency, which does not belong to the core of the sentiment class in the tagging process. Some words tagged inconsistencies are more likely to belong to the edge of sentiment class.

There is the partial overlap in the list of tagged words. Those words marked the same as emotion have greater centrality of corresponding categories in several experiments. The tagged number of words by fuzzy logic theory can be measured by the overlapping tagged index in the experiments. The net overlap scores (NOS) of words can solve the emotional inconsistency of the tagged word. The \( P_i \) is defined as the marked times of \( w_i \) as positive word. The \( N_i \) is defined as the marked times of \( w_i \) as negative word in the experiment. The formulation of NOS, is as follows:

\[ NOS_i = P_i - N_i \]  

(2)

The NOS is equal to the total marked number of positive word excluding the total marked number of negative word. Therefore, the marked times of word in several experiments is more and the consistency of tagged emotional word is higher, which indicate that the NOS of word \( w_i \) is higher.

In order to make the NOS applicable to tag the sentence and text emotional tendency, the absolute value of NOS should be standardized and mapped to the interval [0, 1]. The value of NOS varies with the number of experiments;
the standardization and mapping method can minimize the impact of the NOS, from the number of experiments. After standardization, the score of NOS be set as an argument into the fuzzy membership function $S$, which can map the absolute value of NOS into the [0, 1] interval, where 0 means that members do not appear in the corresponding emotional class (that is, neutral words), and 1 means the highest possibility of members appear in the class. The function is given as:

$$S(\mu, \alpha, \beta, \gamma) = \begin{cases} 0 & \mu \leq \alpha, \\ 2\left(\frac{\mu - \alpha}{\gamma - \alpha}\right)^2 & \alpha \leq \mu \leq \beta, \\ 1 - 2\left(\frac{\gamma - \mu}{\gamma - \alpha}\right)^2 & \beta \leq \mu \leq \gamma, \\ 1 & \mu \geq \gamma \end{cases}$$

(3)

The $\mu$ is the score of NOS, for the word, and $\alpha$, $\beta$, and $\gamma$ are the control parameters: $\alpha$ set as 1, $\gamma$ set as 15, and $\beta$ represent the cross point, that is, $\beta = \alpha + \gamma/2 = 8$. When $\mu \geq 15$, the membership function $S$ of the corresponding word can define the maximum membership degree (that is, 1). The accuracy rate of the fuzzy theory is 100% on this subset. The accuracy rate decreases with the degree of membership and when it reaches 59%, the membership degree becomes the lowest.

### Construct the dictionary of sentiment tendencies for the quality of e-commerce products

In this paper, Segmentation Dictionary simply means adopting word segmentation system ICTCLAS of CAS. This paper adopts the ICTCLAS segmentation system of CAS (Chinese Academy of Sciences) and construct the sentiment dictionary for the e-commerce products quality based on the HowNet lexical semantic similarity calculation method and Fuzzy theory (Tripathy et al., 2016) (Table 1). When constructing the domain sentiment dictionary, the dimension of domain emotion dictionary is divided into two dimensions: emotion classification and emotion intensity. Sentiment polarity is divided into positive, neutral and negative. The range of sentiment dictionary weight is [-9, 9], while 0 represents the neutral emotional intensity, +“ represent positive emotional intensity and -“ the negative emotional intensity. The positive emotional intensity is divided into 1, 3, 5, 7, 9, where 9 means the maximum of positive sentiment intensity. The negative emotional intensity is divided into -1, -3, -5, -7, -9, where -9 means the maximum of negative sentiment intensity.

This paper constructs the sentiment dictionary and marks the emotional intensity for each word of the dictionary based on the NOS method and fuzzy theory. This dictionary can match the emotion of words in the sentence and get the emotional polarity and intensity of sentences. Through the extraction of emotional information from the sentence, the negative word and the degree adverb can be matched.

According to the respective scoring principle, the emotional polarity and intensity is obtained and modified by sentiment dictionary, which make more accurate sentiment polarity and intensity of word to be matched. This paper constructs the sentiment tendency dictionary for the e-commerce product quality based on Fuzzy theory, improve the weakness of indistinguishable intensity between the sentiment words in traditional sentiment dictionary, adopts the emotional polarity of positive, neutral and negative, which consider the influence on sentiment value calculation from network language, net emotions, modal particles, degree adverb and negative word.

### THE SENTIMENT TENDENCY ANALYSIS OF E-COMMERCE PRODUCT QUALITY BASED ON SVM

#### Support Vector Machine (SVM)

The theory of SVM is to obtain the hyperplane that make the point near this hyperplane the furthest between the two classes. The main idea of SVM can be summarized as two points: 1) For the case of linear inseparability, the nonlinear mapping algorithm transforms the linear inseparability sample of low dimensional input space into the high-dimensional feature space, and make it linear...
separable. It is possible to use linear algorithm to analyze the sample in high dimensional feature space for the non-linear features; 2) Based on the mini-structure risk theory, construct the optimal separating hyperplane in the feature space, which makes the learner get global optimization, and the expected risk of the whole sample space satisfies certain upper bound with certain probability. The specific process is shown as:

Suppose we have a set of training samples \( D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n) \} \), the dimension of each sample is \( d \) and \( y \) is the category label, then the problem of solving the optimal hyper plane can be transformed into an optimization problem under inequality constraints and can be solved by Lagrange multipliers:

1. Introduce a Lagrangian coefficient for each sample:
   \[ \alpha_i \geq 0, i = 1, 2, \ldots, N \]. Through the solution of the dual problem, the decision function can be obtained as:

\[
L(w, b, \alpha) = \frac{1}{2} \|w\|^2 + \sum \alpha_i (1 - y_i (w^T x_i + b)) \tag{4}
\]

2. The advantage of SVM is to deal with non-linear problems. By introducing the feature transformation, the non-linear problem in the original space is transformed into a linear problem in the new space. The inner product of two samples in the original feature space \( \langle x_i \cdot x_j \rangle \) becomes the inner product in the new space \( \langle \phi(x_i) \cdot \phi(x_j) \rangle \) called kernel function. The formula is given as:

\[
K(x, x') = \langle \phi(x) \cdot \phi(x') \rangle \tag{5}
\]

Hence, the ultimate decision function is:

\[
\min_{w, b} \frac{1}{2} \|w\|^2 \\
\text{s.t. } y_i (w^T x_i + b) - 1 \geq 0, i = 1, 2, \ldots, N
\] \tag{6}

Different types of non-linear support vector machines can be obtained by using different kernel functions. There are three main types of kernel functions that are commonly used at present:

**Linear kernel function:**

\[
K(x, x') = (x \cdot x') \tag{7}
\]

**Polynomial kernel function:**

\[
K(x, x') = [(x \cdot x') + 1]^q \tag{8}
\]

**RBF kernel function:**

\[
K(x, x') = \exp \left(-\frac{\|x - x'\|^2}{\delta^2}\right) \tag{9}
\]

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**Sentiment classification recognition for quality review text of e-commerce based on SVM**

**Text pre-processing:** Use the Chinese word segmentation tool to deal with the reviews, delete the stop words and punctuation etc (Figure 2).

**The representation of text vector space model (TVSM):** The reviews can be expressed as the vector of high dimensional space with each review corresponding to the
The feature vector and each dimension of vector corresponding to the feature item of the review.

In this paper, the feature item is the word in the review, while the value of the feature item is the frequency of the word in the corresponding reviews. The two-dimensional matrix consists of the reviews and feature items in each category expressed as:

\[
D_i = \begin{bmatrix}
tf_{i11} & tf_{i12} & \cdots & tf_{i1n} \\
tf_{i21} & tf_{i22} & \cdots & tf_{i2n} \\
\vdots & \vdots & \ddots & \vdots \\
tf_{im1} & tf_{im2} & \cdots & tf_{imm}
\end{bmatrix}
\]

Where, \(tf_{ijk}\) represents the frequency and feature word, \(tf_k\) of category \(c_i\) in review \(j\). The row of matrix \(D_i\) represents the feature vector of reviews, while the column of matrix \(D_i\) represents the frequency of each feature word in the different reviews.

**Feature choice:** This paper adopts the CHI statistical method to select feature for all the reviews in the training set. The feature extraction module extracts the feature of reviews constructed by the sentiment dictionary including emoticons, sentiment words, network words, negative words and degree adverbs. According to the sequence, the algorithm extracts the value weight of sentiment word \(M\), network word \(W\), emoticons \(O\), negative word \(N\) and degree adverbs \(C\) in each sentence. In terms of the CHI statistics method, each feature word \(w\) belongs to the class \(c\) and the calculating method of \(X^2\) is as shown in Equation (10):

\[
X^2(w, c) = \frac{N(AD - CB)^2}{(A + C)(B + D)(A + B)(C + D)}
\]

(10)

The value of feature weight is the weight of feature word in the text, that is, the word vector, which is the important classification basis for the classifiers. This paper classified and compared sentiment tendency by the word frequency and Boolean value. In general, feature weights can be calculated after the participle processing and selected features put into the classifier.

**Normalized vector representation:** According to the selected features, calculate the average feature frequency \(ff_{ik}\) of the feature \(f_k\) for each category \(c_i\), which calculate the normalized vectors of each category \(ci\) and normalize the average feature frequency by normalization function.

**The normalization vector idea includes two aspects:** One is that the text of the training set is converted to the normalized feature vector, which is compresses the three-dimensional space into two dimensions. The other is that normalized function (NLF) transforms the weights of feature frequency (FF), in order to keep the classification ability of the high-frequency words, strengthen the classification ability of low-frequency words, narrow the gap of feature weight and accelerate the convergence of training network.

The normalized feature vector of category \(c_i\) is expressed as \(NLV_i = (w_{i1}, w_{i2}, \cdots, w_{in})\), while \(w_{ik}\) represents the normalized weight of feature \(f_k\). In order to represent all the comments of one class by one normalized vector, this paper adopts the average feature frequency to calculate the weight of feature. Feature frequency \(ff_{jk}\) is the times of feature \(f_k\) appeared in the review \(d_j\) divided by the sum of all features that appeared in the review \(d_j\):

\[
ff_{jk} = \frac{N_{jk}}{N_j}
\]

(11)

Where \(N_{jk}\) is the number feature \(f_k\) that appeared in the review \(d_j\), and \(N_j\) the total number of all features that appeared in the review \(d_j\). The average feature frequency, \(\bar{ff}_{ik}\) represents the number of feature \(f_k\) that appeared in class \(c_i\) divided by the number in all reviews of class \(c_i\) which describes the importance of the feature \(f_k\) and reduces the effect of the noise data on the classification results. The formula is given as:

\[
\bar{ff}_{ik} = \frac{1}{m} \sum_{j=1}^{m} ff_{jk} = \frac{1}{m} \sum_{j=1}^{m} \frac{N_{jk}}{N_j}
\]

(12)

Where \(m\) is the review number in class \(c_i\).

**Feature selection:** This established the feature vector of untagged comment and make feature selection for the sentiment tendencies of untagged comment. The formula of feature weight \(w_{ik}\) is given as:

\[
w_{ik} = \phi(\bar{ff}_{ik})
\]

(13)

\(\phi(x)\) is normalized function; this paper adopts the root type normalization function, that is:

\[
\phi(x) = \sqrt[\eta]{x}
\]

(14)

Where \(\eta\) is the root index, the average feature frequency is taken into Equation (14), the equation of final normalized vector feature weight is given as:

\[
\phi(\bar{ff}_{ik}) = (\bar{ff}_{ik})^\eta = \left(\frac{1}{m} \sum_{j=1}^{m} \frac{N_{jk}}{N_j}\right)^{-\eta}
\]

(15)
Table 2: Classification result confusion matrix.

<table>
<thead>
<tr>
<th>Real situation</th>
<th>Prediction results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>True positive (TP)</td>
</tr>
<tr>
<td>Negative</td>
<td>False negative (FN)</td>
</tr>
</tbody>
</table>

**Classification by classifier:** Here, the similarity degree between the feature vectors of unlabeled sentiment tendency and the normalized vectors of each class in training set which predict the category of the unlabeled reviews is calculated.

The emotional classification on review can be predicted by the normalization vector of each sentiment class obtained from the sentiment tendency of the labeled reviews in the training set. The similarity of the reviews can be predicted where the normalized vector of certain class is more and the probability belong to higher class. The judgment methods of text similarity vector include the inner product type and the cosine type function. In this paper, the inner product type method is adopted to calculate the similarity between the reviews and the normalized vector. If the inner product value of two vectors is more, then the similarity of two vectors becomes more.

The emotional classification on review can be predicted by the normalization vector of each sentiment class obtained from the sentiment tendency of the labeled reviews in the training set. The similarity of the reviews can be predicted where the normalized vector of certain class is more and the probability belong to higher class. The judgment methods of text similarity vector include the inner product type and the cosine type function. In this paper, the inner product type method is adopted to calculate the similarity between the reviews and the normalized vector. If the inner product value of two vectors is more, then the similarity of two vectors becomes more.

\[
S_{ip}(c_i, d_x) = NLV_i \cdot d_x
\]  

Take the vector expression of NLV_i and d_x into Equation (10), and obtain the formula given as:

\[
S_{ip}(C_i, d_x) = (W_{i1}, W_{i2}, \ldots, W_{in}) \cdot (W_{x1}, W_{x2}, \ldots, W_{xn})
\]

\[
= W_{i1} \times W_{x1} + W_{i2} \times W_{x2} + \cdots + W_{in} \times W_{xn}
\]

\[
= \sum_{k=1}^{n} (w_{ik} \times w_{ik})
\]  

**Performance evaluation:** This refers to output classification result and confusion matrix as shown in Table 2.

**EXPERIMENTAL DESIGN AND ANALYSIS**

**The collection and process of Chinese sentiment corpus**

This paper focuses on the typical product reviews of electronic product, clothes and electrical appliances from Jingdong, Taobao and other e-commerce websites. By considering the coverage and conciseness of corpus, the reviews of two types e-commerce products were selected: 3000 items of web review about the iPhone and brand mouse.

In order to verify the validity of sentiment dictionary based on HowNet and the emotional classification method, this paper analyzes the sentiment tendency of e-commerce quality reviews by the proposed classification method and the emotional tendency calculation model according to the three indicators of precision and then recalls the F1 value.

The precision is the percentage that is text consistent with the results of artificial classification in the total number of all test sets. The formula is given as:

\[
\text{Precision} = \frac{TP}{TP + FP}
\]  

The recall is the percentage that correct predicted samples to all samples of the category in the test sets. The formula is given as:

\[
\text{Recall} = \frac{TP}{TP + FN}
\]  

The F1 value considers the balance between the recall and precision index. The formula is given as:

\[
F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100\%
\]  

The collection and process of Chinese sentiment corpus

In order to verify the validity of sentiment dictionary and the emotional classification method, the experiment environment used in this paper is window 10 and 64-bit operation system. The experiment tools are Jet Brains PyCharm 3.4.1, LIBSVM (Chang and Lin Chih-Jin, 2014), My SQL and Charles. The Charles focus on the historical sales information and customer reviews about product quality as
Table 3: Artificial polarity classification results of two e-commerce product quality comments.

<table>
<thead>
<tr>
<th>E-commerce products</th>
<th>Number of positive sentiment</th>
<th>Number of neutral sentiment</th>
<th>Number of negative sentiment</th>
<th>Total number</th>
</tr>
</thead>
<tbody>
<tr>
<td>A brand mouse</td>
<td>124</td>
<td>153</td>
<td>725</td>
<td>1002</td>
</tr>
<tr>
<td>iPhone</td>
<td>415</td>
<td>224</td>
<td>456</td>
<td>1115</td>
</tr>
<tr>
<td>Computer</td>
<td>137</td>
<td>185</td>
<td>712</td>
<td>1034</td>
</tr>
</tbody>
</table>

Table 4: Experimental 1 polar classification result.

<table>
<thead>
<tr>
<th>E-commerce products</th>
<th>Evaluation indicator</th>
<th>Positive sentiment</th>
<th>Neutral sentiment</th>
<th>Negative sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>A brand mouse</td>
<td>Precision</td>
<td>0.714</td>
<td>0.671</td>
<td>0.725</td>
</tr>
<tr>
<td></td>
<td>Recall</td>
<td>0.709</td>
<td>0.673</td>
<td>0.717</td>
</tr>
<tr>
<td></td>
<td>F1 value</td>
<td>0.711</td>
<td>0.682</td>
<td>0.721</td>
</tr>
<tr>
<td>iPhone</td>
<td>Precision</td>
<td>0.697</td>
<td>0.661</td>
<td>0.708</td>
</tr>
<tr>
<td></td>
<td>Recall</td>
<td>0.691</td>
<td>0.672</td>
<td>0.712</td>
</tr>
<tr>
<td></td>
<td>F1 value</td>
<td>0.694</td>
<td>0.666</td>
<td>0.710</td>
</tr>
<tr>
<td>Computer</td>
<td>Precision</td>
<td>0.718</td>
<td>0.686</td>
<td>0.728</td>
</tr>
<tr>
<td></td>
<td>Recall</td>
<td>0.715</td>
<td>0.678</td>
<td>0.736</td>
</tr>
<tr>
<td></td>
<td>F1 value</td>
<td>0.716</td>
<td>0.682</td>
<td>0.732</td>
</tr>
</tbody>
</table>

Table 5: Experimental 2 polar classification result.

<table>
<thead>
<tr>
<th>E-commerce products</th>
<th>Evaluation indicator</th>
<th>Positive sentiment</th>
<th>Neutral sentiment</th>
<th>Negative sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>A brand mouse</td>
<td>Precision</td>
<td>0.750</td>
<td>0.702</td>
<td>0.792</td>
</tr>
<tr>
<td></td>
<td>Recall</td>
<td>0.762</td>
<td>0.713</td>
<td>0.811</td>
</tr>
<tr>
<td></td>
<td>F1 value</td>
<td>0.756</td>
<td>0.707</td>
<td>0.801</td>
</tr>
<tr>
<td>iPhone</td>
<td>Precision</td>
<td>0.773</td>
<td>0.701</td>
<td>0.751</td>
</tr>
<tr>
<td></td>
<td>Recall</td>
<td>0.762</td>
<td>0.724</td>
<td>0.758</td>
</tr>
<tr>
<td></td>
<td>F1 value</td>
<td>0.767</td>
<td>0.712</td>
<td>0.754</td>
</tr>
<tr>
<td>Computer</td>
<td>Precision</td>
<td>0.741</td>
<td>0.709</td>
<td>0.762</td>
</tr>
<tr>
<td></td>
<td>Recall</td>
<td>0.737</td>
<td>0.714</td>
<td>0.743</td>
</tr>
<tr>
<td></td>
<td>F1 value</td>
<td>0.739</td>
<td>0.711</td>
<td>0.752</td>
</tr>
</tbody>
</table>

experimental data forms the e-commerce website server, which are stored in My SQL. The Jet Brains PyCharm 3.4.1 implements the FL-SVM algorithm approaches. The experiment results of the artificial classification are as compared standard, which are shown in Table 3.

In experiment 1, the dictionary without the sentiment tendency analysis and the reviews emotional analysis method is the proposed formula in this paper. The results of experiment 1 are shown in Table 4.

In experiment 2, the dictionary with the sentiment tendency analysis included the degree adverb, the negative word, the emoticon, and the network language. The emotional classification method of the review text is the FL-SVM. The results of experiment 2 are shown in Table 5.

Comparing experiments 1 and 2, the sentiment tendency dictionary of more sentiment vocabulary can enhance the ability of the sentiment classification on the web reviews. The customers often express the negative emotions about product quality on the e-commerce site platform; hence, the text number of negative comments is relatively higher in
the constructed sentiment tendency dictionary. The FL-SVM algorithms proposed in this paper have better performance on the negative emotional reviews classification than the sentiment tendency dictionary. Therefore, the integrity and accuracy of sentiment tendency dictionary will affect the accuracy of emotion classification on the e-commerce product quality reviews.

In order to verify the performance of FL-SVM algorithm, this paper produces the experiments of different data sets using the NB, kNN, SVM and FL-SVM algorithms. Table 6 shows the classification results of NB, kNN, SVM and results of FL-SVM algorithm at 1500 dimension of experiment. The classification accuracy of NB is the experimental results at 800 feature dimension. The results show that kNN algorithm get higher classification accuracy when the value of k is 7 or 8. With the value of k increased the precision, recall and F1 value of kNN algorithm decrease slowly.

Table 6 shows that the average F1 value of FL-SVM algorithm is 87.5%, which is higher than the NB and kNN algorithms and is slightly lower than the SVM algorithm. Compared with kNN algorithm, the average F1 value of FL-SVM algorithm is obvious and 12.4% higher than that of kNN, while the average precision and recall increased by 7.7 and 11.4%, respectively. Table 6 also shows that the classification time of FL-SVM algorithm is less than the kNN and SVM due to the less complexity operations in algorithm. Through compared experiments, the sentiment tendency classification of FL-SVM algorithm has higher classification accuracy than the NB and kNN algorithm, which has higher convergence speed of classification than SVM.

### CONCLUSIONS

The e-commerce product quality reviews have great reference value for the public opinion monitoring on e-commerce product quality. In order to strengthen the calculating accuracy on the sentiment tendency of e-commerce product quality comment, this paper proposes the sentiment tendency classification model and approaches based on the Fuzzy Logic theory and Support vector machine. The experiments show that the FL-SVM classifier reached the accuracy at least 80%, which has high convergence speed and strong robustness on the sentiment classification of e-commerce product quality comment.}

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### REFERENCES


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