Sentiment Analysis of News Comments Based on Improved Intuitionistic Fuzzy Reasoning

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Abstract. With the development of the Internet, public opinion monitoring emphasizes the need to obtain a more accurate mood prediction model, so as to grasp the public opinion tendency and thinking process more accurately. In addition, the need to process real-world datasets of sentiment analysis without using sampling techniques can introduce noise into the data being used. In this paper, we propose an extraction method based on compact interval valued intuitionistic fuzzy rules for the classification of news comment pages based on IVFS, for modeling and predicting real-world Sentiment Analysis applications. The web pages are partitioned based on DOM tree, and the emotional tendency of news comments is classified by the improved intuitionistic fuzzy reasoning algorithm. Finally, this method is used to extract news comment web pages. To test the quality of our recommendations, we will present an experimental study that includes a dataset of 9 news pages with comments. We will demonstrate that this method is superior to the original C4.5 decision tree, Type 1 and Region 1, which are preprocessed.5. Decision tree. Type 1 corresponds to the interval value fuzzy and approximates the original fuzzy classifier. Our approach avoids a lot of unnecessary trouble and provides interpretable models that allow for more accurate results.

Keywords: News commentary, Intuitionistic fuzzy reasoning, Intuitionistic fuzzy set, Affective polarity analysis.

1. Introduction
With the help of web crawler technology, we can quickly access a large amount of public web data from the Internet, analyze and mine these data, and extract valuable information from them to help and guide us in business decision making, public opinion analysis, social investigation, policy making, etc. However, most of the web data is presented in the form of semi-structured data, and the information we need is often drowned in the large number of ads, icons, links and other "noisy" elements on the page. How to effectively extract the required information from web pages has been one of the key concerns of the Internet data processing industry. The content of a web page is basically contained in the text, especially news pages. It is a basic idea to eliminate the content outside the body of the web page to reduce the difficulty of analysis. At the same time, the quality of content extraction directly affects the quality of the analysis work that follows.
This paper is organized as follows: Section 2 provides some needed background information and related work. Section 3 presents the intuitive fuzzy inference sentiment analysis algorithm IVFS. Section 4 presents the experimental framework, and section 5 presents the conclusion.

2. Related Work
Sentiment analysis of texts can help people to better understand the opinion orientation and values of current events and to process texts in a more detailed way [1]. Currently, the research areas of text sentiment analysis cover a wide range of fields such as opinion monitoring, automatic summarization, speech recognition, information extraction, and decision making. The research is also getting hotter and hotter, and text sentiment analysis is the future focus of natural language processing research direction. Sentiment analysis tasks according to the base unit group and synthetic part tasks; according to the application area can be divided into sentiment analysis based on commodity evaluation and sentiment analysis based on topical opinionality; according to the type of tasks it studies can be divided into opinion classification, opinion retrieval and tendency extraction and other subtasks [2].

Sentiment analysis, as an important part of data mining research at a deeper level, has also been the subject of much research by many scholars [3]. Sentiment analysis, also known as sentiment classification, focuses on making deeper category judgments on text by mining the text for information such as positions and opinions expressed based on words and sentences. Sentiment analysis predictions based on machine learning [4] and a part of the research room classifies sentiment of texts by the cumulative degree of sentiment of the text [5], and this type of research has shown that in some cases the classification results can be effectively improved by quantitative description of the ambiguity of the feature terms.

2.1. Research status of web page extraction
Most of the current research on the extraction of comment-based web pages can be divided into two categories, including tag-based web page extraction, data mining-based web page extraction.

Tag-based [6] web extraction is a specific method of extraction using the structural characteristics and specifications of HTML documents themselves [13], which can be subdivided into tag window-based extraction algorithms, tag density-based extraction algorithms and DOM tree-based extraction algorithms [8]. The main idea of tag window-based extraction algorithm is to use various combinations of tags and the correspondence between the content of tags to extract the page content.

Data mining [7] based web extraction, also known as machine learning based web extraction, requires training a large number of web pages to obtain the features of the content of the web pages and then determine whether these features match the content of the web pages. The accuracy and generality of these methods can be greatly limited by the different forms of web pages.

2.2. Research Status of Sentiment Analysis
On the other hand, there are two main types of sentiment polarity analysis for text: sentiment lexicon based methods and machine learning based methods. The lexicon-based [11] approach mainly specifies a series of sentiment dictionaries [12] and rules to split sentences, analyze and match the dictionaries, calculate sentiment values, and then use the magnitude of sentiment values as the basis for judging sentiment tendency. However, the lexicon-based method has high accuracy but low recall, and the difficulty and construction cost of building sentiment lexicon is high.

Machine learning [9] based sentiment analysis method is to use sentiment analysis as a supervised classification problem. jie Zhou et al. use the characteristics of news commentary to summarize, select feature words of different dimensions [10], the calculation of weights and various lexicons for training, and use various matching effects of sentiment words and arguments to perform on sentiment analysis.

These features of intuitionistic fuzzy sets and the ability to specify and extend the relevant theorems based on previous research results, so that new theorems and their derivatives can be constructed and proved accordingly. Second, both classical and fuzzy sets that are part of theoretical studies have corresponding algorithms, and intuitionistic fuzzy numbers are no exception. Many prior works
validated illustrate the relationship between these existing basic algorithms and present some basic computational formulas and special derivation procedures for intuitionistic fuzzy sets. Finally, the use of metrics such as distance and correlation has a tremendous role in practical problems such as data mining, economic development, and pattern recognition, which have been studied in more depth by many scholars at home and abroad.

By preprocessing the comment text extracted from the visual information extraction based web comment method utilized above, the sentiment feature words needed for classification and the degree words and transitions etc. that modify the sentiment feature words are obtained, and then the pure interval intuitionistic fuzzy numbers of sentiment feature words are derived according to the method of intuitionistic fuzzy theory, and then the pure interval intuitionistic fuzzy numbers of degree words, transitions etc. are derived. Finally, the sentiment tendency synthesis is then performed for the phrase part, sentence part and text part, and finally the sentiment classification of the review text is derived.

3. Improved Intuitionistic Fuzzy Inference Based Classification Method

There are some fuzzy phenomena in the objective world. For example, "tall" and "short" are all fuzzy words, which have no clear measurement boundaries. However, there are few misunderstandings and ambiguities when using these words. It can be said that value logic is only a model of the ideal world, rather than the real world. In Cantor's set theory, the intermediate transition of difference is not recognized, that is, for a certain set, the logical relations of elements only belong to and do not belong to two cases. From the perspective of set mapping, the range of eigenfunction of set is {0,1}, not [0,1]. Therefore, Cantor's set theory has some limitations, which can not adequately describe the inexact and incomplete fuzzy information.

Fuzzy set theory is the most basic characteristics of admit that excessive relationship exists between difference, that is to say, subordinate relations has the characteristics of the gradient, that is, a fuzzy set F is conform to one (or several) of the nature of object relations, each object is not the same on the membership degree of fuzzy set, membership function \( u(x) (x \in E) \) for each object is assigned a numerical value for the membership degree between 0 and 1.

3.1. Description of classification methods

Intuitionistic fuzzy proposes and expands on the basic theory of fuzzy sets to include the three aspects of affiliation, non-affiliation and hesitation, and Atanassov and Gargov derive the values of affiliation and non-affiliation from the numbers in the interval [0,1] to an interval [0,1] on this basis, so that the intuitionistic fuzzy inference method has better results in dealing with uncertainty problems.

By preprocessing the comment text extracted from the visual information extraction based web comment method utilized above, the sentiment feature words required for classification and the degree words and transitive words, etc. that modify the sentiment feature words are obtained, and then the pure interval intuitionistic fuzzy numbers of the sentiment feature words are derived according to the method of intuitionistic fuzzy theory, and then the pure interval intuitionistic fuzzy numbers of the degree words and transitive words, etc. are derived. Finally, the sentiment tendency synthesis is synthesized for the phrase part, sentence part and text part, and finally the sentiment classification of the review text is derived. Let the classifier contain Z features, denoted as \( t_{r_z}, z = 1, 2, \ldots, Z \). The feature \( t_{r_z} \) supports the probability that the comment text belongs to pos, neg class, and the probability that it belongs to positive or negative class can be represented by a fuzzy set: \( [t_{r_z}, u_z, v_z] \), where \( u_z \) and \( v_z \) denote the minimum probability that the text belongs to pos, neg class when the feature \( t_{r_z} \) appears, respectively. The minimum probability that the text belongs to pos, neg class, where \( 0 \leq u_z \leq 1, \ 0 \leq v_z \leq 1 \) and \( 0 \leq u_z + v_z \leq 1 \). For the text x to be classified, after the word division and lexical annotation, the feature words are searched in it. In order to facilitate the calculation and synthesis of weights in the following, the text x is first divided into N sentences using punctuation, and let the nth (n = 1, 2, ..., N) sentences have a total of \( M_n \) feature words, denoted as \( x_{ni} \) (i = 1, 2, ..., \( M_n \)), and there are \( L_{ni} \) modifiers (including only degree adverbs) of feature \( x_{ni} \). The task of the problem is to determine the class of sentiment tendencies of the text using the information of feature words as well as degree adverbs, transitions, negation words, etc.
3.2. Determination of fuzzy sets
For the feature \( t_r \in \{1, 2, \ldots, Z\} \), the affiliation degree of its corresponding intuitionistic fuzzy set is determined by equation (1), and the unaffiliated degree is determined by equation (2):

\[
u_z = P(pos|t_r) = \frac{P(pos|t_r)}{P(t_r)} \tag{1}
\]
\[
u_z = P(neg|t_r) = \frac{P(neg|t_r)}{P(t_r)} \tag{2}
\]

Obviously, \( P(pos, t_r) + P(neg, t_r) \leq 1 \), so \( 0 \leq u_z + v_z \leq 1\), \( <t_r, u_z, v_z> \) can constitute a fuzzy set. The fuzzy set \( <t_r, u_z, v_z> \) designed in this paper represents the degree that the feature \( t_r \) supports the text belongs to pos class and neg class, where \( u_z, v_z \) has and only one is equal to 0. Among them, the judgment of positive words and negative words is calculated by the method of lexical semantic tendency based on HowNet.

3.3. Handling of degree adverbs, transitive words and negation words
Adverbs of degree play an important role in expressing emotional tendencies, for example, "somewhat useful" and "quite useful" have a very different emotional color. In this paper, the degree adverb is used as one of the main factors in the weight of the feature word it modifies, and is expressed as a number between 1/9 and 9. If the weight of a degree adverb is less than 1, it has a mitigating effect on the emotionality of the feature, and on the contrary, if the weight of a degree adverb is greater than 1, it has an enhancing effect on the emotionality of the feature. According to the knowledge of cognitive psychology and linguistics, the degree adverbs and their weight coefficients used in this experiment are shown in Table 2.

| Adverbs of degree                        | Weight coefficient |
|-----------------------------------------|--------------------|
| Absolutely, altogether, completely, entirely, extremely | 8                  |
| Enormously, far, greatly, heartily, ghly | 7                  |
| Just, merely, mildly, moderately, only  | 5                  |
| Slightly, little, a bit                 | 2                  |
| Barely, hardly, scarcely               | 1/2                |

Some conjunctions, especially transitions, often indicate where the central idea of the text lies. These words are rare and can be sorted out directly in advance. Similarly, the number between 1/9 and 9 is used to indicate their role. For the sake of experimental simplicity, the role of conjunctions that indicate parallel or progressive relationships is ignored for the time being, since such relationships are already reflected in the step of synthesizing the emotional tendencies of the text. The transitions used in the experiment and their weighting coefficients are shown in Table 3.

| Adversative                        | Weight coefficient |
|------------------------------------|--------------------|
| Unexpectedly                       | 8                  |
| Always, still                      | 7                  |
| But                                | 6                  |
| However, even though               | 3                  |
| Only, only                         | 1/4                |
| Besides, not to mention            | 1/5                |
| In addition, however               | 1/7                |

In the classification of affective tendency, negation cannot be ignored as a deactivator. If a feature corresponds to the intuitionistic fuzzy set \(<t_r, u_z, v_z>\), then the intuitionistic fuzzy set corresponding to
the phrase "negation" should not be the remaining set \(<t_r, u, v>_x\) directly, which is set to \(<t_r, u, v>_x\) in this paper.

How-Net aroused great enthusiasm among domestic NLP academics around 2000, and its important applications in similarity calculation of semantic meaning, text classification and sentiment classification were studied, reflecting the international exploration of WordNet at that time. Combined with the needs of this experiment and the current situation of the world's new crown epidemic, the intuitive fuzzy numbers of some of these feature words are extracted as shown in Table 3 below.

Table 3. The intuitionistic fuzzy number of affective characteristic words (partial)

| Key words   | Intuitionistic fuzzy number | Key words   | Intuitionistic fuzzy number |
|-------------|----------------------------|-------------|----------------------------|
| Health      | (0.842, 0.149)             | Serious     | (0.025, 0.965)             |
| Stability   | (0.816, 0.176)             | Urgent      | (0.112, 0.879)             |
| Peaceful    | (0.863, 0.128)             | Significant | (0.088, 0.902)             |
| Efficient   | (0.896, 0.095)             | Severe      | (0.129, 0.862)             |
| Solid       | (0.871, 0.119)             | Difficult   | (0.079, 0.913)             |

Meanwhile, the following provisions are made in this experiment: the scope of the degree adverb is the first feature word after it in the sentence; the scope of the transitive word is from the position of the transitive word to the next transitive word or the end of the text.

3.4. Synthesis of affective tendency

Previous sentiment classification algorithms for sentence and paragraph sentiment synthesis only use simple computational methods such as summation of weights, which are obviously very flawed and ineffective. This method combines a set of arithmetic summation operators with intuitionistic fuzzy information for phrase-level, sentence-level and paragraph-level sentiment synthesis based on the definition of intuitionistic fuzzy theory.

Step 1: After text pre-processing, negative words are processed as described in Section 3.3.

Step 2: Phrase-level sentiment tendency synthesis. The sentences are divided into sets of phrases by feature word \(x_{ni}\), the \(n\) sentence contains a total of \(M_n\) phrases, where \(i=1, 2, ..., M_n; n=1, 2, ..., N\). Let the fuzzy set corresponding to feature \(x_{ni}\) be \(<t_r, u, v>_x\>, and the words modifying the feature contraction correspond to \(K_{ni}\) weight coefficient is \(w_j\), where \(j = 1, 2, ..., K_{ni}\). The emotional tendency of the \(i\)th word group can be expressed by the fuzzy number \((u_{ni}, v_{ni})\), which is calculated as shown in equation (3).

\[
(u_{ni}, v_{ni}) = \sum_{j=1}^{K_{ni}} w_j (u_x, v_x)
\]  

Step 3: Sentence-level sentiment tendency synthesis. The sentiment tendencies of \(M_n\) phrases of the \(n\)th (\(n=1, 2, ..., N\)) sentence are represented by \((u_n, v_n)\) and synthesized using the arithmetic mean set operator, as shown in equation (4).

\[
(u_n, v_n) = \frac{1}{M_n} \sum_{j=1}^{K_{ni}} (u_{ni}, v_{ni})
\]  

Step 4: Synthesis of positive affective tendencies at the textual level. The sentiment tendency of the sentence is represented by \((u, r)\), and the influence of the transitive is used as the weight of the sentence in the synthesis, which is synthesized using the weighted average set operator, as shown in equation (5).

\[
(u_{pos}, v_{pos}) = \frac{1}{Q_n} \sum_{j=1}^{K_{ni}} w_n (u_n, v_n)
\]  

Where \(w_n\) is the weight of the transitive word modifying the \(n\)th (\(n=1, 2, ..., N\)) sentence, and \(Q_n\) is the number of sentences in the whole text.

Step 5: Negative affective tendency synthesis of the text. In equation , the positions of \(u_2\) and \(v_2\) are exchanged to calculate the intuitive fuzzy number of negative sentiment, and then the sentence-level
sentiment synthesis formula of equation is continued, and then the weighted average set operator is applied to derive the negative tendency of the text, which is noted as \((u_{neg}, v_{neg})\).

Step 6: According to the final results obtained from the above steps, if \((u_{pos}, v_{pos}) > (u_{neg}, v_{neg})\), the comment is finally positive (pos); conversely if \((u_{pos}, v_{pos}) < (u_{neg}, v_{neg})\), the comment is finally negative (neg); if neither of the two cases mentioned above is met, the comment is finally neutral.

4. Experimental and comparative analysis

In this section, we present experiments and results to validate our proposed method. Section A introduces several better classification methods currently applied in sentiment polarity analysis, paving the way for subsequent sentiment analysis. In Section B we describe the sentiment analysis technology based on intuitionistic fuzzy reasoning and analyze the feasibility of this method. In both cases, we evaluated nine different Web data sets based on news reviews.

4.1. Experimental framework

We used 9 real datasets from different news pages. Each news page dataset was selected from 50 pages with a total of 8000 records. The description of each news dataset is as follows:

- Sina Weibo: it is the largest online social platform in China, with the largest number of participants, the widest range of services oriented to the most comprehensive, and the leader of new-style media, with an unusually large amount of platform data.
- Observer: It is a gathering place for young scholars, and the comments published are more in line with the current situation, with a very innovative web design and excellent data quality.
- NetEase Media: It is a professional commentary website under NetEase, with groups from various industries, which can improve the accuracy and quality of data collection on web pages.
- Phoenix Review: It is a platform organization for the general Chinese community around the world to publish current commentary on news, with a broader audience and more comprehensive data on its platform.
- Blog China: It is a blogging website established earlier in China, and is also the world's largest Chinese blogging community community and blogging Chinese station, with a larger Chinese commenting population.
- Douban Community: A commentary community platform mainly for youth groups for judging and commenting on news and current events, incorporating the mainstream thoughts of today's popular fashion groups.
- Tianya Community: A globally oriented online community with discourse power, a mainstream communication community and a large online commentary platform based on humanistic emotions.
- Xinhua Forum: A commentary-based website under the Chinese state news agency Xinhua, it is the platform with the largest audience and provides the most comprehensive and professional commentary data with great influence.
- China Review News: referred to as China Review Network, specializing in providing interaction for current news. It has a large number of netizen participants in various news commentaries and reliable data sources.

To conduct the experimental study, we segmented the data using a randomized hierarchical scheme, where 70% of the examples were used to train the system and the remaining 30% were used to test the generated model.

In this paper, we compare our proposed method, based on a combination of visual block extraction and intuitive fuzzy inference for sentiment analysis. And compare the experiments with other methods as follows.

IVFS: This is our proposed method for sentiment classification of extracted news comments in combination with visual block-based techniques.

FARC-HD [16] (FARCHD): It is the state-of-the-art type 1 fuzzy classifier.
C4.5 [17]: it is the classical C4.5 decision tree. It is included in the study because it is a widely used and interpretable method when dealing with classification problems.

FURIA [18]: it is a state-of-the-art type-1 fuzzy approximative classifier.

Svm: It is one of the most robust and accurate methods among all well-known data mining algorithms, it is a binary classification algorithm and can support both linear and nonlinear classification.

Emotional dictionary (ED): Emotional dictionary introduced by Know.com, and polarity table for sentiment analysis. Among them, the Chinese Emotional Dictionary includes: evaluation, emotion, claim, degree (positive, negative) of emotion texts.

4.2. Web comment sentiment classification evaluation

The performance evaluation of the comment sentiment analysis algorithm based on intuitionistic fuzzy reasoning has the following two criteria. Since the affiliation degree, non-affiliation degree and hesitation degree can be well quantified by using the above method intuitionistic fuzzy reasoning, the results of analysis and classification are well obtained by reasonable fusion of uncertainty information.

(1) Whether all the emotional features of news reviews are classified.

(2) Whether the emotional polarity of news reviews is accurately classified.

The data used in this experiment are 8000 microblog comments extracted in the above experiment using the visual block-based method for comparison and demonstration, 5000 as training data and 3000 as experimental data. And four current algorithms with better sentiment analysis are used to compare with the algorithm IVFS algorithm in this paper. The accuracy, recall and F-value are used to compare the two algorithms.

| Classification method | Category | Accuracy | Recall rate | F1    |
|------------------------|----------|----------|-------------|-------|
| IVFS                   | Pos      | 0.926    | 0.903       | 0.914 |
|                        | Neg      | 0.894    | 0.914       | 0.903 |
| SVM                    | Pos      | 0.903    | 0.871       | 0.887 |
|                        | Neg      | 0.883    | 0.906       | 0.894 |
| FARC-HD                | Pos      | 0.795    | 0.886       | 0.841 |
|                        | Neg      | 0.71     | 0.89        | 0.8   |
| C4.5                   | Pos      | 0.76     | 0.883       | 0.822 |
|                        | Neg      | 0.631    | 0.848       | 0.741 |
| FURIA                  | Pos      | 0.832    | 0.866       | 0.849 |
|                        | Neg      | 0.786    | 0.86        | 0.823 |
| Emotional dictionary   | Pos      | 0.873    | 0.9         | 0.887 |
|                        | Neg      | 0.85     | 0.911       | 0.881 |

In Table 4, it is shown that the proposed algorithms IVFS, SVM and ED are the three methods with the best classification results. Among them, IVFS is better than SVM and ED methods. 92.6% and 89.4% of Pos and Neg accuracy are achieved by IVFS.

5. Conclusion

This paper improves the popular method of extracting public opinion comments and sentiment analysis based on visual block information, and carries out intuitive fuzzy reasoning sentiment analysis on the extracted public opinion comments on this basis. These features of intuitionistic fuzzy sets and the ability to specify and extend the relevant theorems based on previous research results, so that new theorems and their derivatives can be constructed and proved accordingly. Second, both classical and fuzzy sets that are part of theoretical studies have corresponding algorithms, and intuitionistic fuzzy numbers are no exception.

Many prior works validated illustrate the relationship between these existing basic algorithms and present some basic computational formulas and special derivation procedures for intuitionistic fuzzy
sets. Finally, the use of metrics such as distance and correlation has a huge role in practical problems such as data mining, economic development, and pattern recognition, which have been studied in more depth by many scholars at home and abroad.

Firstly, the visual display of the web page is preprocessed, and then the intuitionistic fuzzy reasoning is used to better represent the uncertain information by relational degree, unrelational degree and hesitance degree, and then the intuitionistic fuzzy theory is used to synthesize the features of the emotional tendency.

Through experiments, this method has achieved good results. However, how to better determine the extraction model and classification model to improve better accuracy, how to more accurately determine similar noise blocking and body extraction work, and how I can comment on the emotion analysis process in a deeper sense is the focus of future work.

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