Three-Way Framework Using Fuzzy Concepts and Semantic Rules in Opinion Classification

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Abstract. Binary classification is a critical process for opinion mining, which classifies opinions or user reviews into positive or negative classes. So far many popular binary classifiers have been used in opinion mining. The problematic issue is that there is a significant uncertain boundary between positive and negative classes as user reviews (or opinions) include many uncertainties. Many researchers have developed models to solve this uncertainty problem. However, the problem of broad uncertain boundaries still remains with these models. This paper proposes a three-way decision framework using semantic rules and fuzzy concepts together to solve the problem of uncertainty in opinion mining. This framework uses semantic rules in fuzzy concepts to enhance the existing three-way decision framework proposed by authors. The experimental results show that the proposed three-way framework effectively deals with uncertainties in opinions using relevant semantic rules.

Keywords: Opinion mining · Fuzzy logic · Semantic rules · Three-way decision

1 Introduction

Online reviews are one of the vital opinion sources on the Web. These reviews are analysed using machine learning algorithms. This has become a challenging issue with the uncertainity of reviews. Today, people write a large number of opinions and make them available via the Internet [1]. Most review collections are very long, and the reviews range widely between positive and negative views. Therefore, online customers find it challenging to make decisions based on such reviews. The growth of online customers has led to a reliance on reading previous customer opinions before new customers decide. A three-way framework has been proposed for opinion mining using fuzzy concept [5]. However, with the semantic

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structure of the text data, these models can create unexpected results in some cases. In opinion classification models, the mechanism for managing uncertainties is a challenging task [10] as much user generated opinions contain uncertainties.

The critical challenge is to automatically deal with opinion uncertainties to enhance the performance of machine learning algorithms. Also, uncertainties are a problematic issue in opinion mining since many frequently used words may be non-relevant to a class. Therefore, a three-way decision framework is proposed using fuzzy concepts and deep learning [5]. The authors argue that using patterns or concepts to link several features to make the meaning clear is a possible solution for dealing with uncertainties in opinions. They put uncertain reviews into an uncertain boundary provisionally, and then design a more specific method to make the right decision [5].

The semantics of opinion is linguistic and philosophical meaning of opinions. It considers the relationship between words, phrases, signs, and symbols [19]. Most of the models ignore the semantics of opinion data, which is an important feature in opinion classification. People write text data in reviews and may use different semantic structures. In opinion mining models, it is a challenging task to consider the semantic rules within text data [16]. Some are developed considering the semantic aspects of opinions [15–17]. These models are less accurate than fuzzy models [5,7,17]. In binary opinion classification, it is hard to understand the difference between positive and negative categories. We used semantic rules in feature selection, which may result in a significant improvement in opinion classification using the three-way framework proposed by Subhashini et al. [5]. We propose to extend the three-way decision framework to select relevant reviews according to semantic rules [17], then identify the uncertain boundary and use a deep learning. The proposed three-way decision framework provides an elegant way to integrate fuzzy logic and semantic rules in a single umbrella to enhance the binary opinion classification.

We have conducted many experiments on two well-known datasets, the movie review and ebook review datasets. The proposed model achieved impressive performance in terms of F-measure. The significance tests show that the proposed framework is better than the baseline models. This paper is organized as follows: Sect. 2 presents the related work, Sect. 3 describes the proposed framework, and Sect. 4 gives evaluation results. Finally, conclusions are presented in Sect. 5.

2 Related Work

2.1 Opinion Mining

Liu [11] defined the opinion mining task that consists of a target of the opinion (entity), attributes of the target at which opinion mining is directed, and the sentiment (polarity), which are labeled as the positive, negative or neutral. The opinion mining includes feature selection, knowledge discovery and classification.

2.2 Feature Selection

Statistical feature selection methods are used to extract term-based features from a collection of reviews [5,7]. Term based features are TF-IDF, BM25, Uniformity (Uni), and Inverted Conformity Frequency (ICF). The BM25 is a ranking function used to rank matching documents according to their relevance to a given query. When the Uni value is larger, it means that the term is more distinctive in a specific category. Li and Tsai [7] used Uni > 0.2 as a threshold value for feature selection. The ICF indicates term should frequently appear in a specific category. The smaller ICF value indicates, the term frequently appears in specific category. Li and Tsai [7] used $ICF < log(2)$ as a threshold value for feature selection.

Semantic features are used to extract the structure of the opinions [17,18]. People write different semantic structures in their opinions. According to Samha et al. [17], there are frequent tags relevant for opinion mining. First, they did Part-of-Speech (POS) tagging for all the review collections. After that, they have identified frequent tags that appear first as aspect or opinion.

2.3 Knowledge Discovery

Fuzzy logic and pattern mining are the latest successful knowledge discovery methods in the area of opinion mining. Fuzzy Formal Concept Analysis (FFCA) [7] is a theory that combines fuzzy logic and Formal Concept Analysis (FCA) to represent the uncertainty of data. With the enhancement of fuzzy logic, researchers attempt to evaluate the fuzzy logic classifiers in opinion mining research [7,12]. A fuzzy composition is a new approach to procuring classification. Pattern-based methods are also used as a higher-level method of discovering knowledge from text data [8,9]. Pattern mining can discover sequencing terms that frequently co-occur in a customer review, and such set of terms can represent the knowledge of reviews effectively. Frequent patterns and closed patterns are frequently employed to represent knowledge and trends in a dataset [8]. These trends can be used to make decisions in business as well as for customers.

It is vital to select a reliable pattern, which enhances the efficiency of generating frequent itemsets without losing any item. The closed pattern [13] was proposed for handling a large number of frequent patterns.

2.4 Classification

In the classification process, the reviews can be classified into the relevant category. There are supervised, unsupervised and semi-supervised algorithms available for the classification process. Recently, deep learning is employed for the classification using a set of hidden layers. Convolutional Neural Networks (CNNs) is the most popular neural network model used in recent years for opinion mining with a significant performance [3,4]. The advantage is that parameter sharing saves memory when compared to traditional models. The fuzzy composition is a recently used method for classification [7].

3 Proposed Model

In our model, we first select the reviews according to frequent tags defined in Samha et al. [17]. We select the reviews based on the defined frequent tags. As there are many uncertainties in user reviews, there is an uncertain boundary, a margin that includes both positive and negative samples, between positive and negative reviews [10]. A three-way based classification framework was used to address the problem of uncertain boundary for binary classification [5]. It includes two transformations: 'two-way to three-way' (obtaining three regions: the positive region, negative region and uncertain boundary), and then 'three-way to two-way' (classifying the uncertain boundary into positive and negative regions) [10]. It also used a vector space model to find the uncertain boundary and then classify the uncertain boundary. The problem with using this existing framework for opinion mining is that the uncertain boundary is huge since people are writing different format of semantic structures when they expressed their opinions. Unexpected results could occur due to different semantic structure used in opinions. In this paper, we extend the three-way decision framework for opinion mining using semantic rules [5].

3.1 Select Relevant Reviews and Features for Generating Formal Concepts

In our model, we first select the reviews according to Samha et al. [17] defined frequent tags as in Algorithm 1. According to the algorithm, a collection of reviews are POS tags using Stanford POS tagger. Our post tags algorithms are implemented using Samha et al. [17] frequent tags as follows.

- [NN] [VBZ] [RB][JJ] e.g. "software is absolutely terrible"
- [NNS][VBP] [JJ] e.g. "pictures are razor-sharp"
- [NN][VBZ][RB][JJ] e.g. "earpiece is very comfortable"
- [NN] [VBZ] [JJ] e.g. "sound is wonderful"
- [NNS] [VBP] [RB] e.g. "transfers are fast"
- [VBZ][JJ] e.g. "looks nice"
- [JJ][NN] [IN] [NN] e.g. "superior piece of equipment"
- [JJ] [NN] [CC] [NN] e.g. "decent size and weight"
- [RB][JJ][TO][VB] [DT] [NN] e.g. "very confusing to start the program"
- [VBD] [NN] e.g. "improved interface"
- [JJ] [VBG] e.g. "great looking"

Relevant reviews are selected 93.7% and 95.6% from movie and ebook review datasets respectively. After that, features are selected using three feature selection indexes [5].

We found that term-based feature selection approaches suffered from polysemy and synonymy [9] when using them for dealing with uncertainties within user reviews. Currently, a popular way of solving this problem in text mining is to extend low-level term spaces to higher-level patterns or concepts [5,8].

Algorithm 1. Select relevant semantic tags

Require: collection of reviews R and Frequent tag list F_t
Ensure: $R_{POS} \in F_t$

```
for each r do
    POS tagging = R_ipos
end for
for R_ipos ∈ R_POS do
    if (R_ipos ∈ F_t ) then
        L_i = R_ipos
        L_i append L_ipos
    end if
end for
```

Formal concepts [14] have elegant properties; however, closed patterns only discuss terms' binary appearances and long-closed patterns have very low frequency [21]. To solve these issues, fuzzy concepts were proposed by researchers [5]. They select some relevant term features firstly to reduce the time complexity for finding concepts; then using fuzzy composition to find the associations between concepts and categories.

In this research, selected frequent tags [17] are pre-processed and applied BM25, Uni and ICF (three feature selection techniques) to find the relevant terms [5]. The output will be a set of terms as shown in Table 1. In the table r1,r2,r3,...r7 are refers to reviews.

Table 1. Reviews after feature selection

Review	Funny	Good	Pretty	Great	Comedy	Awful
r1	x		x			
r2	x	x		x		
r3	x		x			
r4		x		x		x
r5	x		x		x	
r6	x	x		x		
r7	x	x				x

In this model multiple indexes of $BM25 > 30$, Uni > 0.2 and $ICF < \log(2)$ are used [5]. The three conditions were checked simultaneously and if one condition did not satisfy, the term is eliminated. Table 1 shows an example of feature selection, where we assume that term set $T = \{funny, good, ..., comedy, awful\}$ and review set $R = \{r_1, r_2, ..., r_7\}$.

The frequency of terms might vary according to user reviews' size. The normalization values of BM25 weights are calculated [5]. A threshold is used to reduce the number of noisy terms. Table 2 shows a simple example of the normalized BM25 weights, where the threshold is 0.5 and we simply assume that all selected terms' normalized weights $nBM25 > 0.5$.

Table 2. Reviews after normalization

Review	Funny	Good	Pretty	Great	Comedy	Awful
r1	0.82		0.70			
r2	0.82	0.69		0.61		
r3	0.82		0.70			
r4		0.69		0.61		0.63
r5	0.82		0.70		0.68	
r6	0.82	0.69		0.61		
r7	0.82	0.69				0.63

All closed patterns and their cover sets which are generated from Table 2 is shown in Table 3. We found that identified patterns are larger than the terms. The minimum support is used to control the size of discovered patterns. The discovered closed patterns are further processed to determine the formal concepts using a suitable minimum support as the threshold [5]. Table 4 shows the selected formal concepts from closed patterns $CP = \{p_1, p_2, p_3, p_4, p_5\}$.

Table 3. Closed patterns

Patterns	Terms	Coverset
p1	Funny, Pretty	r1, r3, r5
p2	Funny, Good, Great	r2, r6
p3	Good, Great, Awful	r4
p4	Funny, Pretty, Comedy	r5
p5	Funny, Good	r2, r6, r7

Table 4. Selected formal concepts

Concept	Intent	Extent	Original pattern
c1	Funny, Pretty	r1, r3, r5	p1
c2	Funny, Good	r2, r6, r7	p5

3.2 Fuzzy-Based Three-Way Decisions

According to the three-way decision framework proposed by Subhashini et al. [5] the relationship between concept and category is generated using fuzzy composition. Algorithm 2 illustrates the idea for classifying user reviews into three regions: the positive region (POS), negative region (NEG), and the uncertain boundary (BND). It firstly describes the training process (the first for loop) to calculate the relation I_{C-Catg} (a concept-category matrix) by using the fuzzy composition. It then calculates a fuzzy value for each new review r to a category j (see the second for-loop). At last, it determines the three regions (POS, NEG, and BND) based on these fuzzy values for a given unlabeled review set U.

Algorithm 2. Three-way Classification

Require: C, I_{C-T}, I_{T-Catg}, U, two categories: $j = 1$ and $j = 0$ and an experimental coefficient δ
Ensure: I_{C-Catg} and three regions: POS, NEG, BND

for each j **do**
  for $c_i \in C$ **do**
    $I_{C-Catg}(i, j) =$
    $max_{k \in T} min[I_{C-T}(i, k), I_{T-Catg}(k, j)]$
  end for
end for
for $r \in U$ **do**
  $C_r = \{c \in C | intent(c) \subseteq r\}$
  for j **do**
    $f_j(r) = max_{c_i \in C_r}[I_{C-Catg}(i, j)]$
  end for
end for
for $r \in U$ **do**
  $POS = \{r \in R, f_{j=1}(r) - f_{j=0}(r) > \delta\}$
  $NEG = \{r \in R, f_{j=0}(r) - f_{j=1}(r) > \delta\}$
  $BND = \{r \in R, |f_{j=0}(r) - f_{j=1}(r)| \leq \delta\}$
end for

3.3 Boundary Classification

Algorithm 3. Deciding parameter δ

Require: R, I_{C-T} two categories: $j = 1$ and $j = 0$
Ensure: δ

for $r \in R$ **do**
  for each j **do**
    $f_j(r) = \sum_{t_k \in r, intent(c_i) \subseteq r} I_{C-T}(i, k)$
  end for
  $f(r) = \frac{f_0(r) + f_1(r)}{2}$
end for
for $r \in R$ **do**
  let $\mu = \frac{1}{|R|} \sum_{r \in R} f(r)$
end for
let $\delta = \sqrt{\frac{\sum_{r \in R}(f(r) - \mu)^2}{|R| - 1}}$

Algorithm 3 [5] uses a parameter δ (a very small value) to classify reviews into three regions. It is tough to decide the class of a review when its fuzzy values to the two classes are very close.

Error rates of the three regions when we use fuzzy values to determine the positive and negative regions for two datasets, where we let $\delta =$ very small value.

It is evident that the uncertain boundary (BND) includes a lot of uncertain reviews. Table 5 and Table 6 show the size and the percentage of the uncertain boundary in both movie review and ebook review datasets, respectively [5].

Table 5. Boundary reviews-movie review dataset

Category	Boundary reviews	Percentage
Positive	115	11.5%
Negative	102	10.2%
Total	217	21.7%

Table 6. Boundary reviews-ebook review dataset

Category	Boundary reviews	Percentage
Positive	104	10.4%
Negative	101	10.1%
Total	205	20.5%

In this sub-section, we also develop a method to further classify the uncertain boundary (BND) as the data in BND are not linearly separable. In this paper we use word embedding to do the mapping [5]. It can find a higher dimensional space easily. Word embedding models map each word from the vocabulary to a vector of real numbers. We use word2vec model [2] in our experiments and each word was encoded by an 8-dimension vector, that is,

$$\overrightarrow{w} = (x_1, x_2, ..., x_8)$$

for all words $w \in \Omega$, where x_i are real numbers. Algorithm 4 describes the new idea for integrating word embedding vectors and the terms (with assigned fuzzy values) in the formal concepts. The first for loop firstly get the related concepts of each word $w \in \Omega$ for the positive class j. It then uses the average fuzzy value to update the word vector, where $\overrightarrow{e_i}$ are unit vectors. In the second for loop it uses Z-core normalization to normalize the word vectors by using the average vector (μ) and the standard deviation s. The time complexity is $O(|\Omega| * |C|)$ that is decided by the first for loop.

CNN classifier for the uncertain boundary, which consists of an input layer, two convolution layers, two max-pooling layers, and a fully connected layer with softmax as the activation function. The outputs of algorithm 4 are fed to the CNN for the input layer [5].

For using deep learning, people usually transfer textual features into numerical vectors (e.g., using word2vec [2], a word embedding technique to generate a vector for each word). This process requires a huge collection of documents that are related to the given topic; however, normally, the extensive collection is not designed specially for this opinion classification task. Therefore, the input vectors to a deep leaning algorithm describe more general knowledge for the opinion classification. Also, deep learning does not have the capacity for dealing with uncertainties in features; therefore, it is tough to produce satisfactory results for using deep learning directly.

Algorithm 4. New Word Embedding Vector

Require: Ω is a set of words, each word $w \in \Omega$ is a word2vector $\overrightarrow{w}$; and C is the concept set

Ensure: new word vectors $\hat{\overrightarrow{w}}$ for all words $w \in \Omega$.

1: **for** $w \in \Omega$ **do**
2: let $C_w = \{c \in C | w \in \mathit{intent}(c)\}$ and $j = 1$
3: $\overrightarrow{w} = \overrightarrow{w} + \sum_{i=1}^{8}(\frac{\sum_{c_i \in C_w} I_{C-Catg}(i,j)}{|C_w|}\overrightarrow{e_i})$
4: **end for**
5: **for** $w \in \Omega$ **do**
6: let $\overrightarrow{\mu} = \frac{\sum_{w \in \Omega} \overrightarrow{w}}{|\Omega|}$
7: let $s = \sqrt{\frac{1}{|\Omega|}||\overrightarrow{w} - \overrightarrow{\mu}||}$
8: $\hat{\overrightarrow{w}} = \frac{1}{s}(\overrightarrow{w} - \overrightarrow{\mu})$
9: **end for**

4 Evaluation

To evaluate the performance of the proposed technique, we adopted three measurements namely, precision, recall, F-measure, and pair wise t-test. Then we compared these measures to the baseline models.

4.1 Dataset

The movie review and ebook review datasets [7] are used in this research. Both collections contain 2000 reviews, and 1000 reviews for each category. However, for evaluation, both positive and negative reviews in the testing sets are used.

4.2 Baseline Models

In this research, we provide a comprehensive evaluation of the proposed model, we have selected six baseline models.

- Three-way decision framework of Subhashini et al. [5].
- Li and Tsai's [7] fuzzy model.
- Support Vector Machine(SVM) which is outperformed model in opinion mining [7].
- CNN model of Kim [4] which is a deep learning model for opinion mining.
- Graph Convolutional Networks (GCN) [20] which is a recent model developed using GCN.
- Attention Network [6] used Multi-sentiment resource Enhanced Attention Network (MEAN) to alleviate the problem by integrating three kinds of sentiment linguistic knowledge.

4.3 Results

In order to evaluate the effectiveness of the proposed model, we compare the results with existing classification models as in Table 7 and Table 8. It is evident that the proposed model has the best performance in the two datasets comparing with baseline models. In Table 8 we have not included CNN [4], GCN [20] and Attention Network [6] because those models were not evaluated with the ebook review dataset.

We also conducted statistical significance testing (a two-tailed t-test). The results for the above models are shown in Table 9 and Table 10. It is obvious that all p-values <0.05 in the two tables, where 0.05 is a recommended threshold for the significance testing. The t-test results show that the proposed model is better than the five baseline models.

In our model we removed reviews which are not followed in Samha's [17] frequent tag list. Thereafter, feature selection is done based on three feature selection indexes. Experiment results are showed that selecting relevant reviews based on frequent tags can improve the F-measure of the model.

The main advantage of the proposed model is that it can ascertain uncertain reviews in the boundary, then conduct a deep learning algorithm. The model can identify the relevant semantic structures from a collection of reviews. Despite, there are different semantic structures that can be available for a extensive collection of reviews, therefore, important reviews may be omitted from the classification process of reviews. The main challenge is to identify all semantic structures from a collection of reviews.

Table 7. F-measure of state-of-the-art models: movie review

Model	Precision	Recall	F-measure
Proposed model	**0.9502**	**0.9512**	**0.9506**
Three-way decision framework	**0.9404**	**0.9509**	**0.9467**
FFCM	0.8870	0.8840	0.8800
CNN	Not available	Not available	0.8150
SVM	0.8770	0.8690	0.8730
GCN	Not available	Not available	0.7674
Attention	Not available	Not available	0.8450

Table 8. F-measure of state-of-the-art models: eBook review

Model	Precision	Recall	F-measure
Proposed model	**0.9811**	**0.9821**	**0.9815**
Three-way decision framework	**0.9710**	**0.9777**	**0.9744**
FFCM	0.9509	0.9508	0.9509
SVM	0.9382	0.9381	0.9382

Table 9. P-values-two tailed-movie review

Model	Precision	Recall	F-measure
Proposed model	**0.9811**	**0.9821**	**0.9815**
Three-way decision framework	**0.9710**	**0.9777**	**0.9744**
FFCM	0.9509	0.9508	0.9509
SVM	0.9382	0.9381	0.9382

Table 10. P-values-two-tailed-eBook review

Model	P values
Proposed model	**0.0010**
Three-way decision framework	**0.0013**
FFCM	0.0219
SVM	0.0101

5 Conclusion

This paper presents an extended three-way based framework for binary opinion classification. The framework extends semantic rules to select relevant reviews. This framework implies that incorporating relevant semantic rules can be enhanced the model F-measure and provide a promising way to construct an opinion classifier using fuzzy concepts. The experimental results show that our model achieved significant performance compared to all other baseline models. The contribution made by the proposed framework is an innovative feature selection method. The performance of the proposed framework relies on selected semantic frequent tags. It is tough to incorporate all semantic structures into the model. It remains as future work to find efficient implementation on this.

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