# Using Objective Words in SentiWordNet to Improve Word-of-Mouth Sentiment Classification

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*To improve the performance of word-of-mouth sentiment classification, this work reevaluates objective sentiment words in the SentiWordNet sentiment lexicon.*

Mining sentiments of opinions from word-of-mouth (WOM) enables consumers to develop buying, switching, and diffusing strategies. A term with a suitable sentiment tag is essential for sentiment classification. SentiWordNet is a public sentiment lexicon that's used to extract sentiments of WOM for sentiment classification. However, most existing sentiment mining models ignore objective words, which comprise more than 90 percent of the words in SentiWordNet. These objective words are often considered useless.

Our research reevaluates objective words in SentiWordNet by assessing the sentimental relevance of objective words and their associated sentiment sentences. We propose two sampling strategies and integrate them with the support vector machines (SVMs) for sentiment classification. According to the experiments, the proposed approach significantly outperforms the traditional sentiment mining approach, which ignores the importance of objective words in SentiWordNet.

The aim of our research is to use the sentiment effect from SentiWordNet's objective words for WOM sentiment classification to obtain improved evaluation performance. Traditionally, WOM is a type of oral communication, whereby an information sender shares his or her own experiences related to a brand, product, or service with an information receiver for noncommercial purposes (for others' efforts in this area, see the related sidebar).

A potential consumer might take advantage of WOM's influence before making a purchasing decision by considering pieces of relevant WOM. A positive WOM usually encourages a potential consumer to make a positive buying decision, whereas a negative WOM usually results in a negative decision. Thus, sentiments within WOM play a crucial role in consumer decision making. Since the advent of the Internet, electronic WOM is diffused more rapidly, broadly, and widely, and without any geographic limitation. The task of mining opinions automatically from electronic WOM has increasingly attracted the attention of both practitioners and researchers.



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## Related Work in Word-of-Mouth Sentiment Analysis

Sentiment analysis of word-of-mouth (WOM) communication provides useful information to potential consumers. Most sentiment analysis research focuses on sentiment classification of review documents. One of the major processes is the discovery of sentimental words.[1] We can accomplish this task more easily by applying a sentiment lexicon. Some affective lexical resources include General Inquirer,[2] WordNet-Affect,[3] SentiWordNet,[4,5] SenticNet,[6] and SenticNet 2.[7]

A sentimental WordNet, SentiWordNet has become a well-known and useful sentiment lexicon due to its high coverage. For example, Bruce Ohana and Brendan Tierney evaluated the function of sentimental scores in SentiWordNet for the automatic sentiment classification of film reviews.[8] Their proposed approach using sentiment value in SentiWordNet slightly outperforms the approach using only frequency of sentimental words.

Bas Heerschop and his colleagues argued that most approaches in sentimental analysis ignore a document's significant structural aspects.[9] According to their experiments, the approach—which integrates rhetorical structure theory—outperforms other approaches without using the discourse structure. Horacio Saggion and Adam Funk applied SentiWordNet to opinion classification of a business-related data source.[10] More complete literature reviews in the field of sentiment mining can be found elsewhere.[11]

Many sentiment-based classification tasks extract sentimental words directly from SentiWordNet to avoid using a manual sentiment lexicon. In previous work, Chihli Hung and his colleagues applied SentiWordNet for tagging sentimental orientations and classifying documents into five qualitative categories.[12] This approach outperforms the traditional information quality approach (in which SentiWordNet isn't used).

In SentiWordNet, 93.75 percent of synonymous sets have a stronger objective sentiment tendency than positive or negative sentiment orientation. This might make the tasks that use SentiWordNet for sentimental tagging suffer from noise for sentiment classification. However, most existing related research tasks ignore the fact that too many objective terms are defined in SentiWordNet. As we describe in the main article, our research focuses on this issue and proposes an approach for improving the performance of sentiment classification by revising the sentiment value and orientation of objective words in SentiWordNet.

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## SentiWordNet

One of the major tasks for WOM sentiment analysis is to classify WOM documents into their sentiment polarities, such as positive and negative.[1] Sentiment extraction of WOM requires the advance identification of sentiment orientations of opinion words.[2] Thus, building or making use of an existing sentiment lexicon is an initial task for sentiment analysis.

A sentiment lexicon can be built manually, for example, as with the General Inquirer.[3] However, manually building a sentiment lexicon is time-consuming and makes it hard to obtain high coverage. For example, the General Inquirer lexicon defines only about 3,600 entries. This approach also suffers from annotator bias: The same annotator might give the same word different sentiment tags at different times, or different annotators might give the same word different sentiment tags.

We can use a lexical induction approach to identify sentiment orientations. To do this, we build a sentiment lexicon based on manually defined, paired lists of seed words with nonambiguous sentiment polarities. Based on these seed words, we expand the sentiment lexicon by repeatedly searching seed word synonyms and antonyms in an online lexicon such as WordNet.[4] Which and how many seed words to use in a lexicon is difficult to decide in advance, but such choices have a strong effect on the lexicon's coverage.

Based on the well-known WordNet online lexicon and a set of supervised classifiers, researchers have developed *SentiWordNet*,[5,6] a high-coverage sentiment lexicon. SentiWordNet simultaneously defines each synonymous set (synset) with three sentiment tags—that is, positive, negative, and objective. Each tag has its specific value from 0 to 1, and their sum is equal to 1. A word with a stronger positive, objective, or negative sentiment tendency is defined as a positive, objective, or negative word, and a positive or negative word is further defined as a sentiment word. Many WOM classification tasks extract sentiment words directly from SentiWordNet to avoid using a manual or small sentiment lexicon. SentiWordNet version 3 consists of 117,659 synsets, but 93.75 percent of them are objective words whose objective value is greater than it counterparts.[6]

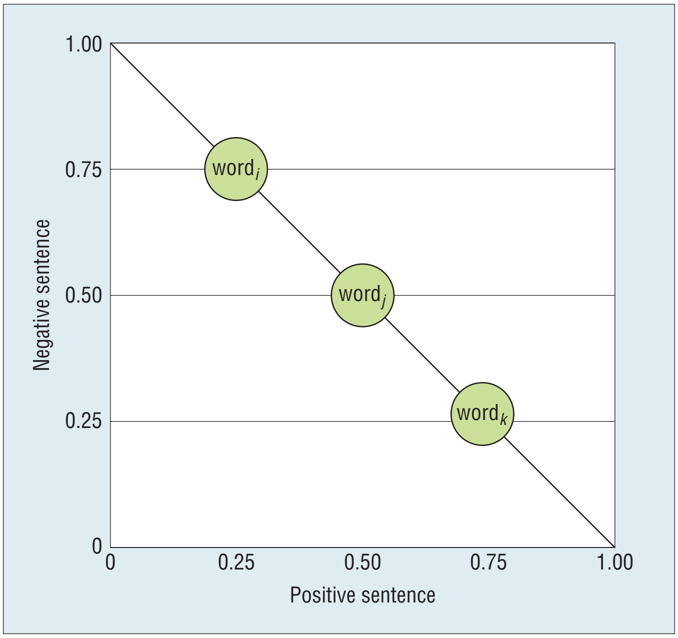


**Figure 1. Relationships between objective words and sentiment sentences, assuming there are two types of sentiment sentences: positive and negative. Words *i*, *j*, and *k* are classified as objective according to SentiWordNet. Here, word *k* has a stronger positive sentiment tendency than words *i* and *j*, and word *i* has a stronger negative sentiment tendency than words *j* and *k*.**

Most existing sentiment classification tasks that use SentiWordNet simply ignore objective words, considering them of little use in providing a cue for a clear sentiment orientation. However, such objective words might have some effects on sentiment classification, because they can be affected by their co-occurring sentiment words. As an example, we'll use two sentences wherein each word contains three sentiment values in brackets—that is, positive, objective, and negative—while looking up SentiWordNet as follows:

- Sentence 1: I (p:0, o:1, n:0) will (p:0, o:1, n:0) read (p:0, o:1, n:0) this (n/a) book (p:0, o:1, n:0) later (p:0, o:1, n:0).
- Sentence 2: Reading (p:0, o:1, n:0) this (n/a) book (p:0, o:1, n:0) is (n/a) happy (p:0.875, o:0.125, n:0).

Sentence 1 is an objective sentence because it doesn't contain any sentiment words. Sentence 2 is a positive sentence because the sum of positive values is greater than that of negative values. Initially, the words in sentence 1 are of no use for sentiment classification, because these words have no clear sentiments. However, *read* and *book* in sentence 1 have a positive tendency because these two words appear in a positive sentence—that is, sentence 2. In Figure 1, suppose that there are two types of sentiment sentences: positive sentences and negative sentences. Suppose that words *i*, *j*, and *k* are objective words according to SentiWordNet. The task of our research is to reassign a proper sentiment value and tendency for such objective words in a specific document collection.

In Figure 1, word *k* has a probability of 0.75 shown in a positive sentence. Word *i* has a probability of 0.75 shown in a negative sentence. Word *j* has the equal probability in both sentiment sentences. Therefore, word *k* has a stronger positive sentiment tendency than words *i* and *j*, and word *i* has a stronger negative sentiment tendency than words *j* and *k*. Consequently, the relationship between a sentiment sentence and an objective word provides a useful hint for sentiment classification.

Based on this concept, our work reevaluates the sentiment value and tendency for objective words that have some relationships with sentiment sentences. According to the experimental results, our proposed approach obtains a better classification performance than the method that uses the traditional SentiWordNet lexicon.

## Traditional Sentiment Classification Using SentiWordNet

The traditional sentiment classification approach, which classifies documents based on SentiWordNet, is divided into two modules, as Figure 2 illustrates.

### WOM Document Preprocessing

The first module is for preprocessing WOM documents. This occurs using a traditional text-mining process that contains sentence segmentation, part-of-speech tagging and filtering, lemmatizing, and stop-word removal. A WOM document might contain several sentences, and a sentence usually

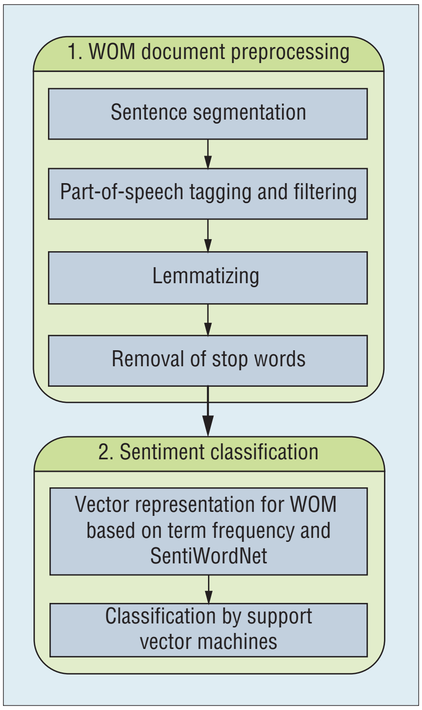


**Figure 2. The traditional sentiment classification approach. The first module is a word-of-mouth (WOM) document preprocessing, and the second module is WOM document sentiment classification.**

expresses a specific sentiment tendency. Hence, we treat a sentence as a processing unit. A WOM document is divided into several sentences based on punctuation, such as a semicolon, exclamation point, question mark, or period. However, the full stop (the period) becomes a valid sentence segmenting punctuation only if it's followed by a space and an initial capital letter or it is the end of the sentence.

Similar to WordNet, SentiWordNet includes only *open-class words*—that is, nouns, verbs, adjectives, and adverbs. The second step in this module is to choose a proper part-of-speech tag for a word due to its ambiguity. A word with a different part-of-speech tag might have a different sentiment value or even sentiment orientation. We use the Brill tagger to search a proper part-of-speech tag for a word. We chose this tagger because it's well known and its accuracy is acceptable in the field.

A word usually has some morphs, for example, *Happy*, *HAPPY*, *happy*, *happily*, or *happiness*. Because only base forms of words are stored in SentiWordNet, the third step in this module lemmatizes each word into its base form. Finally, we use a 598-word-stop list to remove insignificant stop words that contain no semantic or sentiment concepts.

## Sentiment Classification

This module includes two steps: vector representation for WOM and classification by SVMs.

A word in SentiWordNet usually contains several senses. Each sense has its own sentiment value in three sentiment orientations. We pick up the first sense for a word in its assigned part-of-speech tag in SentiWordNet, because this sense is generally the most common usage.[7] We can then obtain a word's sentiment value from SentiWordNet, and the sentiment value of a sentence can be accumulated by words.

Each synonymous set in SentiWordNet contains three sentiment tags in positive, negative, and objective orientations, respectively. For word $i$, $posW_i$ indicates the sentiment value in positive orientation, $negW_i$ indicates the sentiment value in negative orientation, and $objW_i$ indicates the sentiment value in objective orientation. Thus, the sum of $posW_i$, $negW_i$, and $objW_i$ for word $i$ equals 1. A word whose sentiment value is the greatest in positive, negative, or objective orientation is defined as a positive, negative, or objective word, respectively.

Because the SVM has performed effectively for classification in the literature, we use SVM for WOM sentiment classification. More specifically, we use the sequential minimal optimization algorithm with a poly kernel for SVM due to its efficiency.

A document vector **j** is represented as $D_j = [W_1, W_2, \ldots, W_m]$, where $m$ indicates the total number of words in the dataset and $W_i$ is the weight value of word $i$. Such words are filtered by the document preprocessing module and shown in SentiWordNet.

The weight value of a positive word is equal to its term frequency ($TF$ in Equation 1) multiplied by its positive score. The weight value of a negative word is equal to its term frequency multiplied by its negative score and then multiplied by (–1). The remaining objective words are assigned 0, as Equation 1 shows.

$$W_i = \begin{cases} TF_i \times posW_i, & \\ \quad where\ W_i \in [positive\ words] & \\ TF_i \times negW_i \times (-1), & \\ \quad where\ W_i \in [negative\ words] & \\ 0,\ otherwise. & \end{cases} \quad (1)$$

## Reevaluating Sentiment Influence for Objective Words

SentiWordNet has become a useful sentiment lexicon for sentiment classification, but 93.75 percent of its entries are objective words. We revise the sentiment value and tendency of objective words that have a strong relationship with sentiment sentences. As Figure 3 shows, our approach consists of three modules: WOM document preprocessing, modification of objective words in SentiWordNet, and sentiment classification. The first and last modules are the same as those we described earlier. Here, we focus on the second module, which is the modification of objective words in SentiWordNet.

This module consists of four steps:

- determining sentiment orientation and value for words and sentences,
- conducting negation processing,

- calculating the relevance of an objective word and its associated sentiment sentences, and
- adjusting sentiments for objective words.

After the WOM document preprocessing module, only nonstop words exist in their base forms in each sentence. So, using our previous example sentences, sentence 1 contains only two words (*read* and *book*), and sentence 2 contains three words (*read*, *book*, and *happy*). The first step in this module is to determine the sentiment orientations and values in both word and sentence levels. In terms of the word level, we propose to reassign a new sentiment value and orientation to such words. For sentence *j*, $posS_j$ indicates the sentiment value in positive orientation and $negS_j$ indicates the sentiment value in negative orientation, as Equations 2 and 3 show, respectively.

$$posS_j = \sum_{i=1}^{n} posW_i \tag{2}$$

$$negS_j = \sum_{i=1}^{n} negW_i, \tag{3}$$

where $n$ is the number of sentiment words in sentence $j$ and $word_i \in sentence_j$. A sentence becomes a positive or negative sentence due to its greatest sentiment value in positive or negative orientation, respectively, which Equation 4 shows.

$$Sentence_j with \begin{cases} positive\ sentiment\ tag, \\ \quad if\ posS_j > negS_j \\ negative\ sentiment\ tag, \\ \quad if\ posS_j < negS_j. \end{cases} \tag{4}$$

The second step in this module is negation processing. A sentence's sentiment orientation will become inverse when it contains a negative modifier. We treat *no*, *not*, *but*, and *however* as negative modifiers. For example, sentence 2, *reading this book is not happy*, becomes a negative sentence.

The third and fourth steps in this module calculate the relevance of an objective word and its associated sentences. The basic concept is that a positive or a negative sentence has some sentimental influence on its associated objective words. A positive sentence contains greater positive value and usually has more positive words than negative words. Thus, a positive sentiment tag is assigned to an objective word when this word appears in a positive sentence more often than in a negative sentence, and vice versa. Thus, the sentiment value of the revised word can be assigned based on the concept of pairwise mutual information from two words being extended to a word and its associated sentence.

For convenience, *posSen* indicates a positive sentence, *negSen* indicates a negative sentence, and probability (Pr) indicates the relationship between a word and its associated sentence. The sentiment value of an original objective word *i* is modified

- (as Equation 5 shows) for a revised positive word when this objective word appears in a positive sentence more often than in a negative sentence; and
- (as Equation 6 shows) for a revised negative word when this objective word appears in a negative sentence more often than in a positive sentence.

An original objective word is unchanged when its appearance in both sentimental orientations is equal. For example, an objective word *i* is shown in positive, negative, and objective sentences six, two, and two times, respectively. This objective word is reassigned as a positive word with a positive value of 0.6 because Pr(*posSen*, *Word*$_i$) (= 6/10) is greater than Pr(*negSen*, *Word*$_i$) (= 2/10).

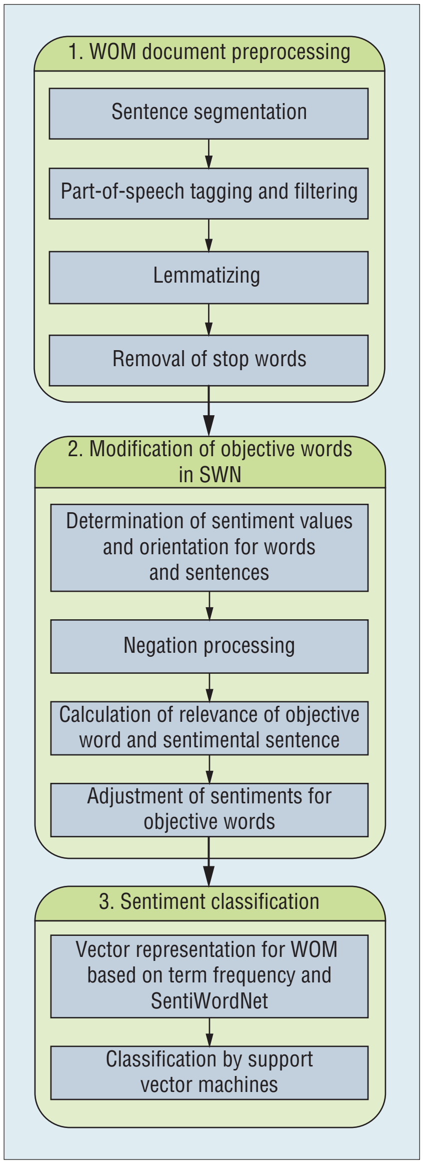


**Figure 3. Architectural overview of the proposed approach. The first module is WOM document preprocessing, the second is modification of objective words in SentiWordNet, and the final module is sentiment classification.**

$$\begin{cases} posW_i = \Pr(posSen, Word_i) = \dfrac{ps_i}{fr_i} \\ negW_i = 0 \\ objW_1 = 1 - posW_i, \end{cases} \tag{5}$$

Table 1. Confusion matrix of accuracy evaluation criteria.

| | | Predicted sentiment orientation | |
|---|---|---|---|
| | | **Positive review** | **Negative review** |
| **Actual sentiment orientation** | **Positive review** | True positive | False negative |
| | **Negative review** | False positive | True negative |

where $\Pr(posSen, Word_i) > \Pr(negSen, Word_i)$, $ps_i$ indicates the frequency of word $i$ in a positive sentence, and $fr_i$ indicates the frequency of word $i$ in a dataset.

$$\begin{cases} negW_i = \Pr(negSen, Word_i) = \dfrac{ns_i}{fr_i} \\ posW_i = 0 \\ objW_i = 1 - negW_i, \end{cases} \tag{6}$$

where $\Pr(negSen, Word_i) > \Pr(posSen, Word_i)$, $ns_i$ indicates the frequency of word $i$ in a negative sentence, and $fr_i$ indicates the frequency of word $i$ in a dataset.

The sentiment influence of a word or a sentence is positively proportional to its sentiment value. A sentence or a word containing a small sentiment value wouldn't have a great influence on its associated objective words. Thus, the adjustment of sentiments for an objective word might not be meaningful when the sentiment value of its associated sentences or words is not great enough. Thus, we set two sentiment thresholds, one for a sentence and the other for a word.

A sentiment sentence threshold evaluates the average sentence sentiment (see Equation 7). A sentence with a smaller average sentiment value implies that its influence on objective words is less than a sentence with a greater sentiment value. On the other hand, a revised objective word doesn't change its objective state if its revised sentiment value in objective orientation, $objW_i$, is greater than or equal to 0.5. That is, the modification could be meaningful if either $posW_i$ or $negW_i$ is greater than 0.5. Thus, an objective word's revised sentiment value is evaluated by a sentiment word threshold, as Equation 8 shows.

$$\frac{\left|posS_j - negS_j\right|}{n} \geq thresholdS, \tag{7}$$

where $|\cdot|$ means an absolute value function, and $n$ belongs to a natural number group and is the number of sentiment words in sentence $j$.

$$\frac{\max(ps_i, ns_i)}{fr_i} > thresholdW, \tag{8}$$

where $\max(\cdot)$ means a maximum function, $ps_i$ indicates the frequency of word $i$ in a positive sentence, $ns_i$ indicates the frequency of word $i$ in a negative sentence, and $fr_i$ indicates the frequency of word $i$ in a dataset.

## The Experiment's Design

To evaluate the performance of this proposed approach, we use a movie review dataset, Internet Movie Database (IMDb), which includes 27,886 movie review articles. Among this review dataset, 1,000 articles have a preassigned positive sentiment tag, 1,000 articles have a preassigned negative sentiment tag, and others have no preassigned sentiment tag. Because the proposed approach to evaluating the sentiment influence for objective words is an unsupervised method that is independent of preassigned sentiment tags, we use the entire IMDb dataset (except for the 2,000 pretagged articles) to reevaluate the sentiment influence for objective words. Hence, we extract sentiments on the word and sentence levels in 25,886 articles and reassign a proper sentiment value and orientation to objective words in the IMDb dataset.

Due to a document classification task, the preassigned labels are necessary for training classifiers and evaluating the classification performance. Thus, we treat these 2,000 articles with a preassigned sentiment tag as a dataset for the sentiment classification task. The strategy of 10-fold cross validation is used to obtain more general results.

We use the traditional classification criterion of accuracy, as Equation 9 shows. For convenience, we present the accuracy evaluation criterion for classification in a confusion matrix (see Table 1). True positive (TP), true negative (TN), false positive (FP), and false negative (FN) are the four different possible outcomes of a single prediction for SVM. True positive means that a review is classified to a positive class when this review really belongs to the positive class. True negative means that a review is classified to a negative class when this review belongs to a negative class. Both true positive and true negative are correct classifications. False positive means that a review is incorrectly classified to a positive class when this review belongs to a negative class. False negative means that a review is incorrectly classified to a negative class when this review belongs to a positive class.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}. \tag{9}$$

We executed several initial experiments to determine some proper parameters. For example, a set with a sentiment sentence threshold 0.6 and sentiment word threshold 0.5 achieves the highest accuracy in initial experiments. Thus, based on these two sentiment thresholds, we use two sampling strategies—random sampling without replacement, and segmenting documents based on position—to evaluate the difference between the proposed revised objective words in SentiWordNet and the traditional SentiWordNet-based classification approaches.

Because we have 2,000 pretagged movie review documents, the first sampling strategy is to use 30 sub-datasets, which are formed by random sampling without replacement to produce 1,000 review documents for each sub-dataset. Therefore, we can use a statistically significant test to evaluate the proposed sentiment classification approach. On the other hand, different parts of a movie review document might contain different numbers of sentiment words and powers of influence. The second sampling strategy is to divide a document into five equal parts sequentially. Thus, there are five sub-datasets, and each dataset contains 2,000 reduced review documents.

## Experiment Results

Our experiment results are based on the two sampling strategies (see Tables 2 and 3). Table 2 contains 30 sub-datasets using random sampling without replacement. According to the experiments, the average accuracy is 71.89 percent for the traditional, nonrevised SentiWordNet and 76.02 percent for the proposed, revised SentiWordNet. We can use the standard deviation to measure models' generalization. The traditional, nonrevised SentiWordNet and the proposed, revised SentiWordNet models have 0.0170 and 0.0158 standard deviations, respectively.

Based on the average accuracy and standard deviation, the proposed, revised SentiWordNet model achieves a higher and more stable classification performance. In terms of each sub-dataset, the revised SentiWordNet outperforms the nonrevised SentiWordNet evaluated by the criterion of accuracy in all sub-datasets (see Table 2). We use a *t*-test to check whether a difference between the two models achieves statistical significance. According to the *t*-test result, the revised SentiWordNet is significantly better than the nonrevised approach, as shown by its 0.000 *p*-value result.

**Table 2. Experiment's results comparing traditional and proposed approaches using random sampling without replacement.**

| Subset | SentiWordNet (%) | Revised SentiWordNet (%) |
|---|---|---|
| 1 | 71.1 | 75.3 |
| 2 | 74.4 | 77.7 |
| 3 | 74.1 | 78.4 |
| 4 | 68.9 | 75.7 |
| 5 | 71.8 | 74.0 |
| 6 | 72.0 | 76.0 |
| 7 | 69.4 | 73.5 |
| 8 | 72.0 | 78.3 |
| 9 | 72.7 | 76.7 |
| 10 | 73.3 | 75.2 |
| 11 | 73.2 | 78.2 |
| 12 | 74.8 | 77.1 |
| 13 | 69.9 | 74.3 |
| 14 | 72.9 | 74.3 |
| 15 | 71.1 | 75.3 |
| 16 | 71.4 | 77.0 |
| 17 | 73.5 | 74.8 |
| 18 | 75.1 | 77.4 |
| 19 | 68.8 | 75.5 |
| 20 | 72.1 | 76.7 |
| 21 | 70.5 | 73.0 |
| 22 | 73.5 | 78.5 |
| 23 | 71.0 | 75.5 |
| 24 | 69.0 | 75.5 |
| 25 | 71.5 | 76.5 |
| 26 | 72.6 | 78.4 |
| 27 | 71.0 | 74.6 |
| 28 | 72.3 | 77.3 |
| 29 | 71.9 | 75.8 |
| 30 | 71.0 | 74.1 |

**Table 3. Experiment's results comparing traditional and proposed approaches using a segmenting document based on position.**

| Subset | SentiWordNet (%) | Revised SentiWordNet (%) | Improvement (%) |
|---|---|---|---|
| 1 | 73.40 | 78.00 | 4.60 |
| 2 | 74.10 | 77.90 | 3.80 |
| 3 | 73.75 | 78.15 | 4.40 |
| 4 | 74.13 | 77.68 | 3.55 |
| 5 | 74.05 | 78.20 | 4.15 |
| Average | 73.89 | 77.99 | 4.10 |

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Table 3 compares the performance of the revised SentiWordNet and the nonrevised SentiWordNet approaches based on individual parts of documents. The revised SentiWordNet outperforms the nonrevised SentiWordNet approaches in all experiments. The final sub-dataset, which is extracted from the final part of documents, appears to achieve greater accuracy. This approach takes advantage of small dimensionality and maintains similar classification accuracy to that of the approach using the full-length documents. According to these two sampling strategies, performance is improved for all experiments if the proposed revised SentiWordNet is used.

Our work directly extracts the first sense of a word in its assigned part-of-speech tag in SentiWordNet because this usage is generally the most common. Thus, for possible future work, the technique of word sense disambiguation could be applied before the extraction of SentiWordNet. Sentiment extraction from linguistic or semantic viewpoints is another possible direction. For example, the technique of document summarization based on sentence, paragraph, or document levels could be used for further development. Finally, our work uses SVM techniques; a further research direction might focus on using various classification algorithms—such as ensemble learning—for sentiment classification.



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