# Sentiment Prediction for User Comments on Home Appliances Products

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**Abstract.** Subjective information in products reviews play vital role in home appliances manufacturing industry. Generally, the comments are trusted worthy since we assume the customers will not make false ones. But in fact, there are cases that ratings and comments are not matched for some products. This paper proposed an approach to detect improper ratings by classifying and predicting the corresponding sentiment expressions in text reviews. To evaluate the effectiveness of the proposed method, we conducted experiments on a dataset which consists of customer reviews in 14 models of home appliances made by Haier. Results show that the sentiment polarity of the reviews can be predicted accurately, and the proposed method can be applied to detect and prevent a product from false rating.

**Keywords:** Sentiment Analysis, Product Review, Continuous Vector Model

## 1 Introduction

With the explosion of Chinese e-commerce, customer reviews have become a key factor in sentiment analysis, such as opinion mining and product recommendation. Reviews not only support customer decision making, but also enable manufacturers to know their customers preferences, and implement continuous iterative improvement [1].

In traditional home appliances manufacturing industry, communication between end-users and organizations often includes too much transferring and waiting, thus a simple feedback information exchange may become a complicated process. Haier has established an innovation platform that creates connection among user community, designers, suppliers and manufactures [2]. It collects the requests, challenges and recommend solutions that are posted and commented by end-users to certain products. Extraction subjective information in these large amount of text materials provides accurate understanding of sentiment expressions and may further bring tremendous business opportunities [3].

Most online shopping sites allow users to give rating (*e.g.* from 1 to 5) to indicate the degree of satisfaction for the product. In addition, users are often required to post comments regarding the products representing their opinion on different aspects of products. Typical consumer reviews contain valuable information about the quality of products, as well as additional recommendations. It has been studied that both ratings and comments carry different weight in decision making [4]. However, ratings and comments are not always emotionally consistent. For example, a user gives 5 stars to a product, but leaves an obvious negative comment corresponding to it. Sentiment analysis can be helpful to solve these unfair

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judgments which are solely calculated by counting the number of likes/dislikes clicks, and therefore prevent a product from falsely gaining/losing its popularity [5].

In this paper, we focus on sentiment prediction on consumer reviews/comments in the domain of home appliance products. A web crawler is used to obtain the comments for product items of a certain category. Automatic sentiment classification approaches are explored and applied to help both manufactures and users analyzing the volume of information from the increasing amount of comments.

The rest of the paper is organized as follows. Section 2 gave a brief review of the state-of-the-art research in natural language processing, opinion mining, and sentiment classification. Section 3 introduced the proposed algorithms. Section 4 presented the datasets and discussed the experiments results, and Section 5 concluded the paper.

## 2 Related Works

One of the basic sentiment analysis is the binary classification problem, *i.e.* to classify a given review's polarity as positive or negative. It plays a vital role in opinion mining for social network [6], document summarization [4], product reviews [7], and *etc.* Usually, this can be done by using either lexicon-based [8] or machine learning approaches [9]. The lexicon-based approach measures the polarity from lexicons derived from various resources which contains the typical semantic words or phrases [10]. Machine learning approaches apply a series of traditional machine learning algorithms on features extracted with vector space model (VSM) [11]. For example, Pang and *et al.* [12] demonstrated standard supervised methods on movies review data, and illustrated that support vector machine (SVM) provided more accuracy as compared to Naive Bayes and maximum entropy classification (ME).

Due to the complexity and ambiguity of sentiment expression, simple words and phrases cannot express the sentiment polarity accurately. Most traditional methods suffer from the high dimensionality and high sparsity problems, and therefore does not show good enough performances in sentiment classification. Recently, document representation methods such as *Doc2vec*[13] where the model is trained to represent a sentence or even a paragraph, have been introduced to solve sentiment classification problems from document level, and it shows higher performance than bag-of-words approaches [14]. It is also noted that deep learning technology has been shown to be effective in a wide range of natural language processing tasks [15].

In this work, continuous vectors [16] are exploited to represent online comments on appliances products from customers, and the SVM is used as the classifier system to increase the performance.

## 3 Continuous Vector Model for Comments Representation

Words or sentences representation is an important procedure in sentiment analysis. The principle underlies continuous vectors representation is that human beings can easily perceive the exact meaning of words in a review, whereas computer does not. Thus, effective comments representation models are required to distinguish different words.

Generally, a comment in text format can be divided into $N$ words, *i.e.* $w_1, w_2, \cdots w_N$. Each $w_i$ is projected to different vectors, and the position in vectors of individual word is unique. These column vectors get together to form the word matrix, as is showed in **Fig.1**.

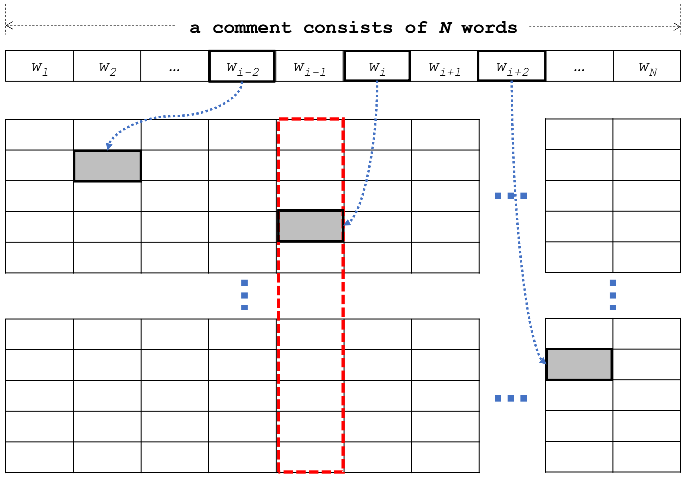



**Fig. 1** Word matrix for comment representation.

A neural network (NN) is employed to automatically predict a target word $w_i$ from its neighbors $w_{i-2}$, $w_{i-1}$, $w_{i+1}$, $w_{i+2}$. As shown in **Fig.2a**, this NN consists of three layers: input layer, hidden layer and output layer. In practice, the word matrix that consists of all input candidates are used as inputs, and the column vector into which $w_i$ is projected becomes the output.

Define the input vector as:

$$[x_1, x_2, \cdots, x_K]^T \tag{1}$$

which is a $K \times 1$ column vector determined by word. And the customer comment containing several words can be denoted as:

$$c = [w_1, w_2, L, w_N]^T . \tag{2}$$

The word matrix that contains all input vectors can be represented as:

$$[\cdots, \mathbf{v}_j, \mathbf{v}_{j+1}, \cdots]_{K \times M}, \quad 1 \le j \le M , \tag{3}$$

where $M$ is the given dimension of the vector. The weights connect input vector, hidden layer, and the output layer are defined respectively as:

$$\Omega_{K \times V} = [\omega_{ij}]_{K \times V}, \quad \Omega'_{V \times K} = [\omega'_{jl}]_{V \times K} , \tag{4}$$

where $V$ is the number of the nodes in hidden layer. The input of a node in the hidden layer is calculated using the following formula:

$$\sum_{j=1}^{V} \omega_{ij} x_i . \tag{5}$$

And outputs of hidden layer are worked out using sigmoid function:

$$h_j = \frac{1}{1+\exp(-\sum_{j=1}^{V}\omega_{ij}x_i)}, \tag{6}$$

where $h_j$ represent the whole hidden layer:

$$\mathbf{H} = [h_1, h_2, \cdots, h_V]^T. \tag{7}$$

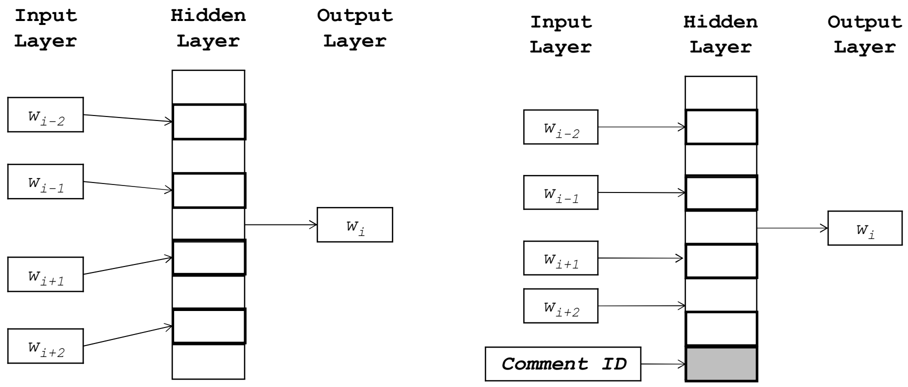
The *softmax* function is used to get final output vector:

$$y_l = \exp\left(\sum_{j=1}^{V}\omega'_{jl}h_j\right)\Big/\sum_{m=1}^{K}\left[\exp\left(\sum_{j=1}^{V}\omega'_{jm}h_j\right)\right], \tag{9}$$

where $1 \le l \le K$, and the output layer can be represented by:

$$[\mathrm{y}_1, \mathrm{y}_2, \cdots, \mathrm{y}_K]^T. \tag{10}$$

The cross-entropy function is exploited to evaluate error, and the stochastic gradient descent algorithm and back propagation algorithm is adopted to update $\Omega_{K\times V}$ and $\Omega'_{V\times K}$ .Considering potential contribution of the entire comment, the comment ID information is added into NN, as shown in **Fig.2b**. Similar training process can be applied.




**(a)** NN for continuous bag of word **(b)** NN with Comment ID

**Fig. 2** Neural network (NN) for continuous bag of word and the Comment ID.

## 4 Experiments and Discussions

We have collected 84000 items of online customer reviews from 14 models of refrigerators manufactured by Haier. The source of the product review data is crawled from www.jd.com which is a popular E-commerce website in China. As is shown in **Table.1**, all comments are semi-automatically mapped into three polarities, *i.e. positive*, *neutral* and *negative*, based on the corresponding ratings. Comments with 5 and 4.5 stars are classified as positive items, those with stars between 2.5 to 4.5 are mapped to neutral category, and the rest are considered as negative comments. To obtain a balance dataset, 2000 items are taken from each polarity, and all these selected comment items are mixed together in a random order. It is helpful to balance positive and negative documents so that we focus on the efficiency of proposed framework rather than other factors which may affect the performance of classifiers.

The utility of *Doc2vec* was used to calculate the vector representations of comments by implementing the proposed NN. The polarity is used as the comment ID to learn the representation of each review. To test classification performance, all vectors are sent to SVM classifier, and results are evaluated based on the testing features.

**Table 1** The size and distribution of the dataset.

| No. | Type | Rating | Preprocessing | Polarity | Number of Comments |
|---|---|---|---|---|---|
| 1 | BC-93TMPF | 5 Stars | | Positive | 2000 |
| | | 4 Stars | | | |
| | | 3 Stars | | Neutral | 2000 |
| | | 2 Stars | | | |
| | | 1 Star | | Negative | 2000 |
| ⋮ | | | | | |
| 14 | BCD-642WDVMU1 | 5 Stars | | Positive | 2000 |
| | | 4 Stars | | | |
| | | 3 Stars | | Neutral | 2000 |
| | | 2 Stars | | | |
| | | 1 Star | | Negative | 2000 |

Among the 2000 comments items of each type of refrigerators, training set and validation set are divided with a ratio of 1:1 Commonly used indicators in sentiment analysis are used to evaluate the effectiveness of our proposed method, and the prediction accuracy can be defined as follows:

$$accuracy = \frac{tpos + tneu + tneg}{tpos + tneu + tneg + fpos + fneu + fneg}, \tag{11}$$

where *tpos*, *tneu*, *tneg*, *tpos*, *tneu*, *tneg* denote "true positive", "true neutral", "true negative", "false positive", "false neutral" and "false negative", respectively.

**Fig.3** shows the accuracy of the classified reviews with different length of comment vectors. The sapphire dots are worked out according to Equation (11). The black line is the curve fitting of accuracy. It is supposed that the error of accuracy obeys Gaussian distribution, and then the lower and upper bounds are ±3%. It demonstrates that almost all sapphire dots fall into the area closed by two red dot lines.

Apparently, the accuracy increases fast when vector dimension increases from 20 to 100. That means the prediction accuracy improves as the vector dimension increases. However, when vector dimension is greater than 100, the accuracy does not show appreciable development.

The experimental results show that our proposed sentiment prediction model and the classifier succeed to classify more than 75% of the reviews correctly and can be effective to correct those mis-marked comments/reviews.

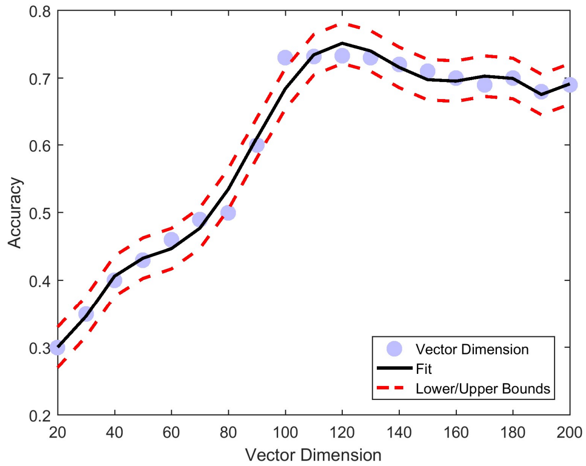



**Fig. 3** Sentiment prediction accuracy curve.

## 5 Conclusion

In this paper, we presented a study on classifying the product reviews using continuous vectors from balanced review datasets. SVM is applied as the classifier. Based on the experiment results, we believe that the proposed method can be helpful to identify and detect those fake reviews which are probably mismarked by users. We are still in the process of investigating the possibilities to integrate the sentiment analysis with other key modules of manufacturing industry, to enhance the performance of the value chain.

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