Product improvement based on online reviews from product designer’s perspective

To cite this article: Shugang Li and Jiali Kong 2018 IOP Conf. Ser.: Mater. Sci. Eng. 423 012114

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Product improvement based on online reviews from product designer's perspective

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Abstract. With the popularity of online shopping, the number of online reviews has greatly increased. Online reviews have become a major factor influencing consumer shopping behaviour and have become one of the references for product designers to improve their products. It is difficult for product designers to obtain useful information for improving products from mass reviews. From the perspective of product design, the article establishes a product improvement model. First, in order to filter noise effectively, this paper uses word2vec and cosine distance to convert words into emotional word vectors innovatively. Then the emotional vector is used as the input of the GRU (Gated recurrent units) neural network for emotional classification. Finally, we propose a product improvement strategy from a product designer's perspective combined with a joint analysis model. In addition, we conducted case studies using new methods in Disneyland’s online reviews. Case studies show the effectiveness of the method.

1. Introduction
The rapid development of online reviews has created opportunities for companies to help them find useful customer preference information and improve product effectiveness. For enterprises, the user's online commentary information includes not only consumer experience, feelings and experiences, but also dissatisfaction and expectation of the product. This is the power source for continuous improvement and innovation of the company's products.

However, due to the massiveness and complexity of online reviews, it makes sense to filter the noise in the network comments to extract valuable customer opinions. Opinion mining, also known as sentiment analysis, Hu and Liu [1] explored the characteristics of the products in which customers expressed their opinions, and whether their opinions were positive or negative. Turney [2] offered a simple unsupervised learning algorithm for classifying comments. He used PMI to calculate the semantic direction of the extracted phrase. However, this traditional method of sentiment analysis relies heavily on the poor scalability of word bags and manually specified rules.

In order to solve the above problems, we designed a product improvement strategy model based on the product designer's perspective. First, we took online reviews as our data source. Then we asked the product designer to construct the attribute lexicon and seed lexicon. See the first part in Figure 1.

Secondly, in order to solve the problem of data quality and noise, we use word2vec to train words into word vectors, and use Euclidean distances to map words into emotional dimensions innovatively. It can effectively eliminate noise and reduce the dimension of the word vector. Then, we use the emotional vector as an input to the GRU (Gated recurrent units) neural network and divide the comments into two categories based on emotional characteristics. See Part 2 in Figure 1.
Finally, conjoint analysis model analysis model used for product improvement. See Part 3 in Figure 1. We used Disney's data to conduct a case study of this method. Case studies show the effectiveness of the proposed method.

Figure 1 Research framework

2. Method

2.1 Word vector
In this paper, word2vec[3] model is used to map each word into k-dimensional vector. By setting the depth of context, we can get a deeper feature representation of text. The k-dimensional vector not only includes the potential semantic relationship between words, but also avoids the dimension disaster. This paper selects the CBOW model in word2vec. The CBOW model is used for predicting target words using words in a given sliding window. Online reviews are trained by the word2vec model to get dictionary \( D = \{(d_1, w_{2v_1}), (d_2, w_{2v_2}), \ldots, (d_n, w_{2v_n})\} \). Among then, \( d_i(i=1,2,\ldots,n) \) represents a set of words and \( w_{2v_i}(i=1, 2, \ldots, n) \) represents the word vector of \( d_i \).

2.2 Emotional word vector
In order to extract online comments more quickly and efficiently, we further convert word vectors into emotional vectors. Firstly, product designer is invited to choose words with strong sentimentality in the dictionary D as seed words and determine its weight. For example, "like", "quiet" and "recommended" are positive emotion seed words, "nausea", "noisy" and "bad" are negative emotion seed words. The seed word set is denoted as \( E = \{(e_1, w_{2v_1}), (e_2, w_{2v_2}), \ldots, (e_k, w_{2v_k})\} \), where \( e_j(j=1,2,\ldots,k) \) is the seed words, and \( w_{t_j}(j = 1, 2, \ldots, k) \) is the emotional weight corresponding to \( e_j \), \( w_{2v_j} \) is the word vector.

Then we use the similarity between each word \( e_j \) in E and each word \( d_i \) in D to calculate the emotional distribution of \( d_i \). The emotional distribution of \( d_i \) is achieved by cosine distance: \( F = \text{sim}_{i,j} = \text{sim}(d_i, e_j) \). Then we can obtain the set of emotional vector features \( \text{Senti2vec} = \{(d_1, [\text{sim}_1])^{1*}, (d_2, [\text{sim}_2])^{1*}, \ldots, (d_n, [\text{sim}_n])^{1*}\} \). Such as, the similarity between the word "Disney" and the vocabulary of the seed word set {"clean", "recommended" "very good", ..., "expensive", "noisy", "bad", ...} is {0.23, 0.52, 0.41, ..., 0.62, 0.02, 0.12,...}. It expresses the weight of the word "Disney" on these emotional vectors.
expressions and realizes an abstract representation of the emotions of the words \( d_i \) to achieve a better effect of affective calculations. The construction process is shown in Figure 2.

![Figure 2 Emotion vector construction](image)

2.3 Emotional classification

Senti2vec represents the weight of "Disney" in these emotional expressions and realizes the abstract representation of \( d_i \) to achieve the effect of better realization of emotional calculation.

In order to overcome the problem that RNN cannot handle distance dependence well, LSTM is proposed [4]. Gated recurrent units [5] are a more novel variation of LSTM networks. GRU maintains the effect of LSTM while making the structure simpler, so it is also very popular. The model combines the forget and input gates into one update gate and merge the hidden state and cell state into one state.

GRU contains two gates: an update gate \( z \) and a reset gate \( r \). The data flows and operations are illustrated in Figure 3.

![Figure 3 GRU neural network](image)

2.4 Product Improvement Model

From 2.3, we get the emotional orientation of each attribute in each comment. This article will be divided into 10 attributes (specifically introduced in 3.2). Zhang Z [6] has proven that conjoint analysis can be used to establish an effective product improvement model. Considering the score of each comment as the feeling of the consumer’s perception and text as a consumer utility, our model is:

\[
y = \alpha + \sum_{j=1}^{10} (\mu_j^{pos} x_j^{pos} + \mu_j^{neg} x_j^{neg})
\]  

(1)
Where $y$ is the customer's rating of the product based on his own perception and $x_{j}^{pos}$ represents a consumer having a positive sentiment for attribute $j$ and $x_{j}^{neg}$ having a negative sentiment. If the attribute $j$ obtains $a\mu$ is a coefficient .

3. Evaluation

3.1 Data preprocessing
Due to anti-crawling restrictions, we crawled 23,493 reviews of Disney on xiecheng.com and Dianping.com.

Figure 4 Typical online reviews in China

Part A is text, and it is also the actual comment posted by the consumer. Part B is the consumer’s score on the product as consumers’ utility.

3.2 Establishment of Attribute Words and Seed Words
We invite product designers to determine product attributes. A total of ten categories of attributes are included by the product designer's classification contain 189 words: traffic, price, admission convenience, food, queuing time, amusement items, show, service, facility and surroundings. Since Disney's emotional stage is specific, therefore, the sentiment-based seed thesaurus is constructed in Table 1. A sentiment dictionary containing 72 words was constructed.

| Sentiment          | Emotional intensity | Number of words |
|--------------------|---------------------|-----------------|
| Positive seed words| Very satisfied      | 13              |
|                    | Quite satisfied     | 29              |
| Negative seed words| Very dissatisfied   | 21              |
|                    | Quite dissatisfied  | 9               |

3.3 Emotion analysis
We use the emotional word vector as input to the GRU model. The ratio of training set to test set is 8:2. The experiments in this article are based on LSTM and word2vec. The classification results are shown in Table 2. The main indicators for evaluating text classification are accuracy rate, recall rate and F1 value. By comparison we can find the best accuracy of the models using senti2vec and GRU.

|                     | Precise | Recall | F1 value  |
|---------------------|---------|--------|-----------|
| Word2vec+LSTM       | pos     | 0.872414 | 0.916667 | 0.893993 |
|                     | neg     | 0.807531 | 0.722846 | 0.762846 |
| Senti2vec+LSTM      | pos     | 0.895009 | 0.926916 | 0.910683 |
|                     | neg     | 0.828452 | 0.764479 | 0.795181 |
| Word2vec+GRU        | pos     | 0.912069 | 0.893581 | 0.90273 |
|                     | neg     | 0.736402 | 0.77533 | 0.755365 |
| Senti2vec+GRU       | pos     | 0.931034 | 0.89701  | 0.913706 |
|                     | neg     | 0.740586 | 0.815668 | 0.776316 |

3.4 Product improvement strategy
We put the result of the emotional classification and the user's score on the product into the conjoint analysis model. The coefficient table is shown in Table 3. In the table, we can find that for the attribute of food, the positive and negative sentiment coefficients are negative, and the negative emotional...
strength is stronger than the positive emotional. This shows that the attribute is a variety of evaluations for consumers, for these attributes, enterprises should focus on, which is conducive to obtaining potential consumers. For attributes such as price, equipment and queuing time, the positive sentiment tends is negative and the negative sentiment is positive. This shows that consumers are not satisfied with such properties, Disney should attract consumers through measures such as price reduction promotions or adding entertainment devices. For entertainment, performance, and environmental attributes. The consumer’s assessment is positive and Disney should continue to maintain. Finally, consumers’ sentiments are complex with respect to attributes such as transportation, convenience of access, and services. Disney should pay attention to these attributes, because these attributes can provide Disney consumers with loyalty.

| Attributes         | Emotional tendency | coefficient | Attributes         | Emotional tendency | coefficient |
|--------------------|--------------------|-------------|--------------------|--------------------|-------------|
| traffic            | pos                | 0.047       | food               | pos                | -0.002      |
|                    | neg                | 0.050       |                    | neg                | -0.016      |
| Admission          | pos                | 0.060       | service            | pos                | 0.002       |
|                    | neg                | 0.022       |                    | neg                | 0.006       |
| price              | pos                | -0.021      | show               | pos                | 0.002       |
|                    | neg                | 0.001       |                    | neg                | -0.005      |
| Amusement items    | pos                | 0.010       | facility           | pos                | -0.003      |
|                    | neg                | -0.002      |                    | neg                | 0.003       |
| Queuing time       | pos                | -0.001      | surroundings       | pos                | 0.022       |
|                    | neg                | 0.014       |                    | neg                | -0.018      |

4. Conclusion
This article presents a product improvement model from the perspective of a product designer. This model helps manufacturers find useful information and improve products in mass online reviews. The contributions of this paper mainly include the following two points. First of all, this paper proposes an effective text classification model. It maps word vectors to weighted emotional intervals and uses popular GRU neural networks for sentiment classification. It reduces the computational time complexity by reducing the dimension and achieves higher accuracy. Secondly, the article proposes a product improvement model that proposes improvements to Disneyland effectively.

Acknowledgments
This work was supported by the Chinese National Natural Science Foundation (No. 71272232).

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