Sentiment Analysis in movie reviews using Word Embedding: A Case Study

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워드 임베딩 기법을 기반으로 한 영화 리뷰 감성 분석: 사례연구

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요 약

People search, transfer and generate information about various services and goods online. As such network-based living platforms are activated, online reviews have on consumers are becoming more and more influential. Consumers write online reviews not just based on objective values of the commodities or services, but also include subjective views and emotions. However, sentiment analysis of online reviews conducted so far have focuses mainly on positive, negative and neutral aspects of articles. Therefore, this research expands the scope of sentimental polarities to multi-dimensional sentiment analysis using online reviews. For this research, movie reviews were collected, and a sentiment word dictionary having 511 sentiment words with 8 sentimental categories were constructed. Then, word2vec, a machine learning technique for text embedding, was used to project sentimental words onto a 200-dimensional vector space. The dimensionality of the embedded data are reduced to 2-dimensional vectors. We also calculated the center coordinates of 8-sentimental categories to identify a emotional model, geometric properties and spatial relations among the categories. This result can provide a new sentiment model of a movie review domain. We reiterate the suggested model can overcome the limitation of genre-based recommendation by providing a new way of recommendations based on consumer sentiments.

1. Introduction

Online reviews are written in a natural, personal manner, and often openly conveys the writer's opinions and thoughts. As a result, consumers often use products and services after viewing other users' reviews or recommendations. Therefore, there is an increasing number of attempts to find improvements or make decisions in products and services through online review analysis. As computing technologies collecting and processing unstructured data evolves, researches of analyzing the sentimental texts are conducted in various fields.

Sentiment analysis aims to analyze product reviews and identify the polarity and degree of emotion[1]. Therefore, it is important to use emotional dictionaries that accurately reflect the emotional polarity of words[2].

Various types of sentimental analysis are being proceeded in various domains. However, until now, major research streams either analyzing a simple sentimental polarity - negative and positive, or comparing the performance of text mining algorithms. Thus little research has been conducted to analyze multi-faceted emotional words.

The purpose of this study is to suggest a framework for sentiment analysis considering multi-faceted aspects of emotional words and to perform a case study of analyzing online reviews of movies using the framework. This study is composed as follows: Chapter 2 covers previous research of online reviews and emotional analysis; Chapter 3 presents a framework for sentiment analysis; in Chapter 4, a case study of the movie review using the framework and the results of the study are illustrated; finally, in chapter 5 we discuss conclusions and future research directions of this study.

2. Related Works
2.1 Emotional Model

Many research have conducted to analyze human languages expressing human emotion and have aimed to build conceptual models of emotional words structure. One approach of finding an emotional model is building a hierarchical structure of words—a few basic and primary emotions with many subsequent and secondary emotions[3]. Although various primary emotional categories have been suggested in the previous research, a few common words like anger, fear, pleasure and sadness is considered as basic emotions.

![A Wheel of Emotion](image)

Table 2. Center coordinates of 8 emotional categories

<table>
<thead>
<tr>
<th>Stimulant</th>
<th>Perception</th>
<th>Felt</th>
<th>External</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss of a loved one</td>
<td>Left alone</td>
<td>grief</td>
<td>Crying</td>
<td>Obsession over the subject of loss</td>
</tr>
<tr>
<td>Unexpected occurrence</td>
<td>What is this?</td>
<td>amortment</td>
<td>Pause</td>
<td>Buying time to perceive</td>
</tr>
<tr>
<td>Danger</td>
<td>Danger</td>
<td>terror</td>
<td>Fleeing</td>
<td>Safety</td>
</tr>
<tr>
<td>Support of the same group</td>
<td>Friend</td>
<td>admiration</td>
<td>Dressing up</td>
<td>Mutual Support</td>
</tr>
<tr>
<td>Acquisition of a valuable object</td>
<td>Ownership</td>
<td>ecstasy</td>
<td>Acquiring / Repeating</td>
<td>Resource Acquisition</td>
</tr>
<tr>
<td>New territory</td>
<td>Explore</td>
<td>vigilance</td>
<td>Draw a map</td>
<td>Knowledge on territory</td>
</tr>
<tr>
<td>Obstruction</td>
<td>Enemy</td>
<td>rage</td>
<td>Attack</td>
<td>Destruction of obstruction</td>
</tr>
</tbody>
</table>

2.2 Online Review

Before purchasing of a product, consumers usually gather and compare a lot of information for better decision making. One way of acquiring information is considering e-WoMs(electronic Word-of-Mouth), online reviews or experiences posted by other consumers[5]. Consumers trust online reviews as much as personal recommendations. Positive reviews make potential consumers trust qualities of products or services while negative ones make people hesitate to purchase. As reviews on products and services are posted on the web, massive amount of online reviews are being rapidly shared and delivered[6]. As a result, online review has been recognized as an critical factor for consumer in purchase decision making as well as for corporate customer management[7]. Online reviews are available for most products sold on/offline, including clothes, daily supplies, home appliances, movies and travel products. Attempts have been made to use online reviews to identify improvements in products or services or to use them in corporate decision making[8]. Kim et al., proposed a methodology for analyzing online customer reviews by introducing the concept of text mining technology and market segmentation[9]. Sung et al., conducted a study to find out the correlation between the emotional polarity of online review, the characteristics of information and purchase intention[10].

3. A Research Framework

Figure 2 shows a research framework of this study.
After purchasing products or experiencing services, customers create review comments on the web. These online reviews including emotional expressions about products or services can be automatically scraped by a customized programming code. To overcome the previous research, focusing merely on sentimental polarity like positive/negative sentiment, we extend the emotion categories extracted from related works to enrich emotional expressions of the customers. Since heterogeneous and large volume of gathered data should be stored in huge repositories and accessible through networks, we suggest that the data is stored in a cloud service for ubiquitous access to shared pool of configurable system resources. Big data consists of review texts, an extended senti-word dictionary and a product/service category database. The senti-words defined in the dictionary are collected in previous studies and classified into eight extended emotional dimensions.

After filtering the emotional words of reviews listed in the dictionary, we embed the emotional words in 200 dimensional vector space using Word2Vec. Word2vec is a word embeddings model. This model reconstructs linguistic contexts of words using two-layer neural networks. Word2vec allocates a large corpus of text to points in a vector space, typically of several hundred dimensions. Therefore each unique word in the corpus are assigned a corresponding vector in the given space.

Dimension reduction is needed to understand similar emotional words instinctively. t-SNE(t-Distributed Stochastic Neighbor Embedding), a technique for dimensionality reduction that is particularly well suited for the visualization of high-dimensional datasets with minimum loss of information, is used.

A dataset with high dimensionality can be projected onto a two or three dimensional simple dataset. We can calculate the coordinates of clusters’ centers and visualize the clusters positions. The outcomes of clustering, 8 clusters, is compared to psychological emotional model –Plutchik’s 8 emotional model.

### 4. Results

We selected one of the most famous Internet Movie Database website, IMDB.com, for the scraping source of data. IMDB provides movie information such as movie descriptions, genres, actors, star ratings, box office revenues, and movie reviews. We collected movie review texts from the top 200 popular movies in 23 movie genres, a total of 4,600 movies with duplications. We limited the release of the movie from the years 2001 through 2017. Since movies can belong to multiple genres (e.g., comedy and romance), we removed duplicated movies and used 240,338 review articles for this research.

We use Plutchik’s emotional wheel for classifying emotional words. 8 dimensions can contain multiple mental words and we use senti-word dictionary having 511 emotional words. After extracting emotional words listed in the dictionary from movie reviews, we embedded the words in 200-dimensional vector space.

Since we cannot understand a dataset projected onto 200-dimensional vector space, we reduced the dimensionality of the dataset using t-SNE and converted to 2-dimensional vector space with minimum loss of dataset information. The converted dataset could be visualized easily by identifying clusters’ center coordinate. Table 2 denotes the center coordinates of 8 emotional categories.

**Table 2** Center coordinates of 8 emotional categories

<table>
<thead>
<tr>
<th>Emotion</th>
<th>x</th>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>admiration</td>
<td>2.009239854</td>
<td>-3.336770294</td>
</tr>
<tr>
<td>amazement</td>
<td>-2.850721851</td>
<td>-5.681100742</td>
</tr>
<tr>
<td>ecstasy</td>
<td>6.68647556</td>
<td>-4.118373713</td>
</tr>
<tr>
<td>grief</td>
<td>6.360177632</td>
<td>3.563493325</td>
</tr>
<tr>
<td>loathing</td>
<td>-1.60211901</td>
<td>1.682726146</td>
</tr>
<tr>
<td>rage</td>
<td>-1.138211451</td>
<td>2.840940061</td>
</tr>
<tr>
<td>terror</td>
<td>-6.700435099</td>
<td>8.556412443</td>
</tr>
</tbody>
</table>

Figure 3 shows the 8 emotional dimensions and their locations. The size of circle means the frequency of emotional words in each emotional dimension. The identified emotional model is different from Plutchik’s emotional wheel since movie reviews reflect movie reviewers’ feelings from the movie and these feeling is different from general psychological emotions. Rage and Loathing is very close and not common emotions in movie reviews. Ecstasy and Terror, however, are quite common and opposite emotions.
Rage and Terror are relatively close emotions in the above emotional model while opposite emotions in Plutchik's model. This result implies the necessity of a domain-specific emotion model. Ecstasy is a quite common emotion in movie review domain. As it is shown in the above figure, Grief is not opposite emotion of Ecstasy. Many movie audiences feel ecstasy while enjoying some sad movies.

5. Conclusion and Future Research Directions

In this study, a framework for sentiment analysis was presented and a case study was conducted to build a domain-specific emotional model. The results of this study provide the following implications:

First, we need a domain-specific emotional model inferred from emotional word data. Second, emotions in movie reviews may provide some new clues to movie recommendation. We can recommend a movie that feels similar feelings by complementing genre-based movie recommendations.

The proposed method has limitations in that the proposed method is useful only in the area where reviews on experience goods are accessible. In the future, we expect this study will spur further extensions of combining sentiment analysis and word embedding for product recommendation.

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References


