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영화 대본에서 감정 및 정서 분석: 사례 연구

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Emotion and Sentiment Analysis from a Film Script: A Case Study

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[요 약]

감정은 서사 생성과 이해 모두에서 중요한 역할을 한다. 본 논문은 플루칙의 감정 모델을 기반으로 영화 대본에서 8가지 감정 표현을 분석하였다. 먼저 각 장면별 수동으로 감정을 태깅하였고, 이 때 8가지 감정 중 분노, 공포, 그리고 놀람이 가장 우세하게 나타났는데, 이는 스릴러 영화 장르를 고려할 때 의미있다고 할 수 있다. 또한, 스토리에서 긴장이 가장 고조되는 클라이맥스에서 다양한 감정이 복합적으로 나타난다고 가정하였고, 대본 상에서 3 부분의 클라이맥스를 확인할 수 있었다. 그 다음으로 파이썬(Python) 프로그래밍 언어 기반 자연어처리 도구인 NLTK (Natural Language ToolKit)의 감성 분석 도구를 이용하여 수동 감정 태깅과 비교한 결과, 분노와 공포 감정에서 높은 일치율을, 그리고 놀람, 기대, 혐오 감정에서는 낮은 일치율을 보임을 확인하였다.

[Abstract]

Emotion plays a key role in both generating and understanding narrative. In this article we analyzed the emotions represented in a movie script based on 8 emotion types from the wheel of emotions by Plutchik. First we conducted manual emotion tagging scene by scene. The most dominant emotions by manual tagging were anger, fear, and surprise. It makes sense when the film script we analyzed is a thriller-genre. We assumed that the emotions around the climax of the story would be heightened as the tension grew up. From manual tagging we could identify three such duration when the tension is high. Next we analyzed the emotions in the same script using Python-based NLTK VADERSentiment tool. The result showed that the emotions of anger and fear were most matched. The emotion of surprise, anticipation, and disgust, however, scored lower matching.

색인어 : 감정 분석, 정서 분석, 영화 대본, 자연어 처리

Key word : Emotion analysis, Sentiment analysis, Movie script, Natural Language Processing

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Ⅰ. Introduction

Storytelling is an intelligent communication between two entities − the author (or the storyteller) and the reader (or the audience). The author tries to deliver his or her story to the reader in an engaging and emotional way. In this vein emotion can play a key role to represent and understand narrative. Quite a few studies have been conducted in order to identify or analyze the emotions that the reader experiences while reading (or viewing) [1][2][3][4][5].

Opinion mining or sentiment analysis refers to computational analysis for the subjective opinions or sentiments expressed in text, with the help of natural language processing, machine learning, or text mining [6]. While approaches of sentiment analysis in text is widely various depending on the purpose and application domain, in general they have processes as follows. First, features related to emotion or sentiment in text are represented using a feature vector; second, using this feature vector, a learning model is constructed and trained; third, based on the constructed model, application systems classify or infer appropriate emotions or sentiments. The feature vector can be constructed either at the sentence level or at the document level. As for the document-level features, context information can be added for better understanding of sentiments expressed in sentences. Typical sentiment analysis features include term presence and frequency, occurring positions in the sentence (e.g., start, middle, end of a sentence), PoS (Part of Speech), negation, document topic, etc. [6][7][8].

Typically sentiment refers to either positive or negative emotional state, mood, or attitude, while emotion has more diverse definitions ranging from discrete emotions to continuos emotional state via distinct dimensions. In this article we focus more on emotions rather than sentiments, and propose a systematic approach to identify and analyze emotions in text.

Ⅱ. Related Work

Emotion is essential for the analysis of narrative. While reading or experiencing narrative, we feel a wide range of different emotions [2][4][5]. This section describes previous studies related to the analysis of emotions and sentiments, particularly in narrative.

2-1 Emotion Analysis for Narrative

The reader's emotional responses that can occur while reading a text story can be divided into two types: cognitive interest and emotional interest [2]. Cognitive interest represents the emotions that can occur as cognitive responses mainly due to the narrative structure, involving the emotions such as suspense, surprise, and curiosity. Emotional interest refers to the emotions that the reader can feel when they enter a storyworld, including the emotions such as identification or empathy with characters. Although these two types of literary emotions as the reader's emotional responses to narrative are often intertwined to each other and difficult to make a clear distinction between them, it can be a convenient starting point to address narrative-relating emotions.

While emotion is a complicated human phenomenon including mental, psychological, physiological, and biological activities, most emotion models can be divided into two types. One is distinct or basic emotion models; the other is 2-dimensional or 3-dimensional models. In distinct or basic emotion models, there exist several fundamental emotions (e.g., Ekman's 6 basic emotions − happiness, sadness, anger, fear, disgust, and surprise [9]) that are primitive by nature (regardless of age, gender, or race). In two dimensional (or circumplex) model, a variety of different emotions can be represented via two dimensions − valence and arousal [10]; in three dimensional model via three dimensions − pleasantness (or valence), arousal, and dominance.

In addition to the emotion models mentioned, the OCC (Ortony, Clore, and Collins) emotion model [11] is often employed in computational emotion models. In the OCC emotion model, 22 emotion types are described as valenced reactions of an agent's cognitive appraisal of a given situation. The OCC emotion model can be categorized as a kind of distinct emotion models, but does not differentiate basic or fundamental emotions from compound or complex emotions.

2-2 Sentiment Analysis

In general text analysis for emotion/sentiment analysis can be divided into two categories. One is word-based analysis in which word and emotion is one-on-one matched. Lexicon-based or Bag of Words (BoW) approach belongs to this. The advantage of word-based approach is that its analysis can be made in a simple way when the dataset is ready. The semantic relations between words, however, are difficult to analyze because they focus only on emotion data based on matching words and does not consider the relations between words. The other is sentence-based analysis in which both word-based emotions and the relations between words are analysed. N-gram approach or deep learning algorithm such as Convolutional Neural Network (CNN) can be employed for this kind of text classification [11].

Sentiment analysis can be applied in a wide variety of applications for the analysis of the subjectivity in text - including marketing, product and service reviews [12][13]. In this manuscript we focus on word-based approach in the movie script.

Ⅲ. Our Approach

3-1 Material

As a material for analyzing emotions represented in a movie script, we chose a Korean thriller film named *A Hard Day* (*Kkeut-kka-ji-gan-da*; directed by Kim Seong-hun, 2014). There are two main characters in this film – Go Geon-soo as protagonist ; Park Chang-min as antagonist/villain. Geon-soo is a special crime detective who is trying to cover his accidental hit and run. Chang-min, knowing Geon-soo’s secret, keeps threatening him as the story unfolds. During the movie, while the protagonist Geon-soo keeps talking and shows a variety of emotions, the antagonist Chang-min does not talk much and rarely reveal his emotions.

3-2 Procedure

In order to compare the results, we first manually tagged the script of the film *A Hard Day* (*Kkeut-kka-ji-gan-da)* based on the 8 fundamental emotion types introduced by Plutchick – anticipation, trust, joy, sadness, anger, fear, disgust, and surprise [14]. Two undergraduate students read the script, and then tagged emotions that could describe each scene appropriately, with the intensity range from 1 to 3.

Next, we conducted a sentence-based emotion analysis using Google Translate and NLTK (Natural Language Toolkit). While there exists Korean language corpus for sentiment analysis such as KOSAC (Korean Sentiment Analysis Corpus) [15], in this paper we chose to use Google Translate in order to analyze emotions sentence by sentence in each scene. Google Translate is a web-based free translating service that is most used worldwide, and its accuracy rate is reported up to 80% from non-English to English translation [16].

After translating from Korean to English by using Google Translate, we then conducted preprocessing to remove unnecessary words and expressions (e.g.,) and tag information (e.g., <sync>). Finally the translated script is separated or merged so that each sentence can be represented by a single line, which prevents several sentences from being analyzed as one emotion.

In the scenario text data, after preprocessing, only necessary information remains - including audio, visual, behavior instructions and dialogues. Using Python-based NLTK, we extracted sentiment (3 types – positive, neutral, and negative) scores sentence by sentence in which the scores range from 0 to 1. As development environments, we employed Python version 3.5.1 and NLTK VADER(Valence Aware Dictionary and sEntiment Reasoner)Sentiment 2.5. Fig.1 describes overall work flow of our approach.

Ⅳ. Results and Discussion

4-1 Results of Emotion Analysis by manual tagging

We first analyzed tagged emotion data manually. The overall matching rate of scene-based emotion tagging between two human taggers was 80.0% without considering the intensity of emotions, including no emotion cases. It should be noted that the matching rate is rapidly decreasing when including emotion cases only (that is, when at least one tagger specifies at least one emotion in the scene). In that case, the most matched emotion was sadness (66.7%), and then fear (59.6%), surprise (57.4%), anger (56.9%). Compared to negative emotions, positive emotions were relatively matched low – joy (30.0%), anticipation (12%), and trust (0%), in which the emotion of trust is tagged only once by one tagger. Table 1 shows the overall matching rate between the taggers.

The most dominant emotions in the script were found out as surprise, fear, and anger. In Fig.2 three kinds of emotion distribution were normalized and represented in different color: the blue line represents overall emotion range scene by scene ; the orange characterizes the overall emotion range expressed by the protagonist Go Geon-soo; the green shows the overall emotion range expressed by the antagonist Park Chang-min. As the graph

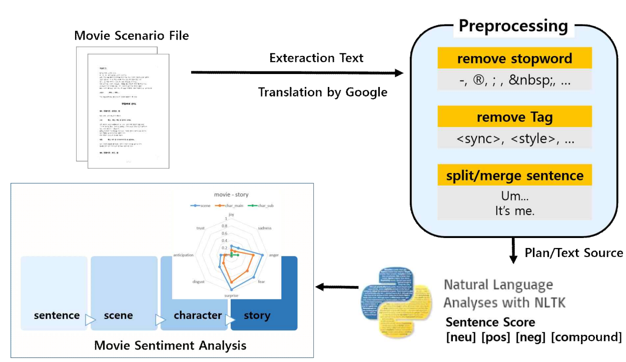

Fig. 1. Work Diagram of Our Approach

in Fig.2 shows, the shape of overall emotions by each scene is almost identical to that of overall emotions by protagonist, though there are slight differences in intensity. It may be mainly because the contrasting characteristics of two characters − emotionally expressive protagonist and emotionally non-expressive villain.

In traditional narrative structure, climax plays an essential role in which rising actions are in its highest point with greatest tension [17]. Based on this notion of climax, we posit that the negative emotions will be accumulated around the climax. In our scene by scene emotion analysis, there exists three climax duration: scene 53 to 55, 62 to 68, and 72 to 74, where the last climax includes ‘twisted surprise.’ Fig. 3 shows the emotion analysis graph in the second climax of the script.

4-2 Sentence Analysis

We also analyzed the sentiment of the translated scenario text data using *VADERSentiment* tool in NLTK. We first calculated compound sentiment value of each sentence, and then select representative emotion that is closet to the compound value of each emotion in Plutchik’s wheel of emotions. Next we merged the emotions scene by scene and compared those with the results of manual emotion tagging. As there was difference in tagging scheme between manual tagging (where intensity of each emotion is ranged from 1 to 3) and NLTK VADERSentiment (where intensity of each emotion is set to 1, and the sentiment value is accumulated depending on the frequency of emotional sentences), direct comparison is difficult. Thus we compared the differences between the average value of human tagging emotions and the accumulated emotion values from NLTK VADERSentiment. Overall the complete matching rate (that is, zero difference) was 42.6% (average of positive emotions:38.2%; average of negative emotions: 47.0%), and the differences less than 2 (that is, differences from zero up to 1) was 68.3% (average of positive emotions: 61.0%; average of negative emotions: 75.6%). Table 2 shows the matching rate between human tagging and NLTK VADERSentiment for each emotion.

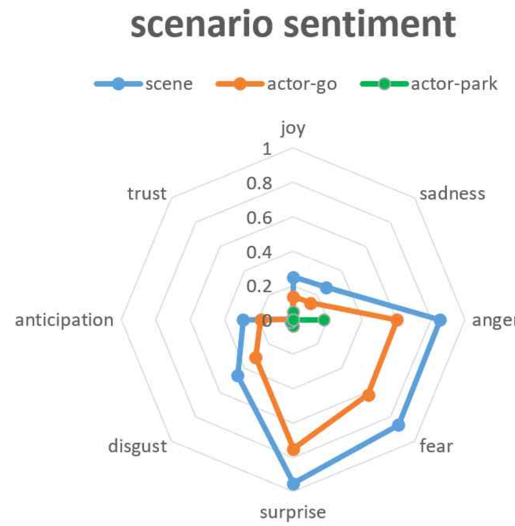

Fig. 2. The ratio of Plutchik’s 8 emotion types occurred in the script overall.

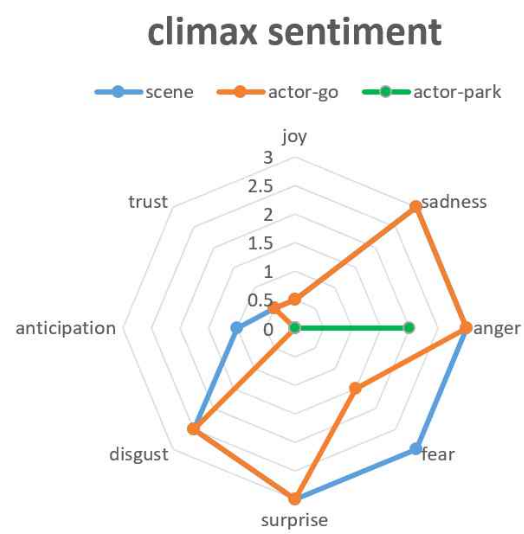

Fig. 3. The ratio of Plutchik’s 8 emotion types occurred in the climax of the script

Table 1. Overall matching rate between two human taggers for Plutchik’s 8 emotion types (without considering the intensity and including neutral emotions)

Positive emotions			Negative emotions				
Joy	Anticipation	Trust	Sadness	Anger	Fear	Disgust	Surprise
.829	.732	.988	.939	.756	.89	.512	.756

Table 2. Overall matching rate between manual tagging and NLTK sentiment analysis for Plutchik’s 8 emotion types (without considering the intensity and frequency of emotions)

Diff	Positive emotions			Negative emotions				
	Joy	Anticipation	Trust	Sadness	Anger	Fear	Disgust	Surprise
0	.488	**.268**	.390	.354	**.622**	**.585**	.317	**.244**
1	.659	**.463**	.707	.646	**.927**	**.890**	.561	**.598**

Ⅴ. Conclusion

In this article we analyzed the emotions represented in a movie script based on 8 emotion types in the wheel of emotions by Plutchik. First we conducted manual emotion tagging scene by scene. The most dominant emotions by manual tagging were anger, fear, and surprise. It makes sense when the film script we analyzed is a thriller genre. We assumed that the emotions around the climax of the story would be heightened as the tension grew up. In manual tagging we could identify three such duration when the tension is high. Next we analyzed the emotions in the same script using NLTK VADERSentiment tool. The result showed that the emotions of anger and fear were most matched. The emotion of surprise, anticipation, and disgust, however, scored lower matching.

While our work has contributions in that we conducted a study on emotion analysis of a film script by using manual tagging and automatic tagging based on Plutchik's emotion model, it has limitations in the number of human taggers and script material. As future work we plan to conduct studies with more script materials and human taggers, adopting machine learning algorithms.

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