# Mining Emotions in Short Films: User Comments or Crowdsourcing?

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## ABSTRACT

Short films are regarded as an alternative form of artistic creation, and they express, in a few minutes, a whole gamma of different emotions oriented to impact the audience and communicate a story. In this paper, we exploit a multi-modal sentiment analysis approach to extract emotions in short films, based on the film criticism expressed through social comments from the video-sharing platform YouTube. We go beyond the traditional polarity detection (i.e., positive/negative), and extract, for each analyzed film, four opposing pairs of primary emotions: joy–sadness, anger–fear, trust–disgust, and anticipation–surprise. We found that YouTube comments are a valuable source of information for automatic emotion detection when compared to human analysis elicited via crowdsourcing.

**Categories and Subject Descriptors** : H3.3 [**Information Search and Retrieval**]; K.4 [**Computer and Society**]

**General Terms** : Human Factors, Experimentation

**Keywords**: Sentiment Analysis; Social Media Analytics; YouTube

## 1. INTRODUCTION

The large amount of user generated content available in YouTube [8], represents a valuable source of real opinions and discussions which can be exploited to track the emotions evoked by the uploaded videos, in particular, our goal in this work is to explore the emotions experienced by users while watching short films. To this end, we consider two directions, on one hand we study the comments posted by the users on short films available on YouTube and on the other hand we use crowdsourcing to gather insights on the polarity and emotions a person associates to a short film. By doing so, we address two questions: (i) can YouTube comments alone provide enough information to detect the different emotions and polarity of a short film? and (ii) is it necessary to explicitly ask the users to provide their opinions on how emotions are associated to a short film?. Like a full-length movie, a short film tells a story and makes people identify and feel with the characters, however, the main difference between them is that the short film has only a few minutes to enable the audience to follow the plot and understand the story being told. Automatically detecting in short films emotions such as joy, sadness, fear, anger, and surprise, has several practical applications, for instance, classifying or recommending certain short films to a user who looks forward to experience a given emotion.


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## 2. EMOTION DETECTION APPROACH

Our approach for emotion detection in short films is based on a multi-modal sentiment analysis algorithm introduced in [2], and it comprises the following steps:

1. create a *profile* for each short film,
2. extract the terms from the profile,
3. associate to each term an *emotion* and *polarity*,
4. compute the *emotion vector* and *polarity* for each short film.

First, we build a *profile* for each of the short films. The profile consists of all the comments collected for the corresponding short film. After building the profiles, we perform part-of-speech tagging on each of them, using LingPipe [1] and MorpAdorner [4], in order to extract the *nouns* and *adjectives*. Part-of-speech tagging is necessary because the same word can act as a different part-of-speech depending on the context of the sentence. Then, we use a term-based matching technique to associate each term with emotion and polarity values. To this end, we used in our study the NRC Emotion Lexicon (EmoLex) [3], a large set of human-provided word emotion annotated according to Plutchik's psychoevolutionary theory [5], which considers that there are eight primary emotions, which form four opposing pairs, joy–sadness, anger–fear, trust–disgust, and anticipation–surprise. In addition, EmoLex also includes positive and negative sentiments associated to the words.

Finally, we define the emotional vector, $e_p$, for short film $p$ as follows: Let $T_p$ be the set of terms extracted from the short film's profile $p$, and $T_m$ the set of all terms in EmoLex annotated with emotion $m$, where $m \in M$; $M := \{$*joy, sadness, anger, fear, trust, disgust, anticipation, surprise*$\}$, i.e., Plutchik's eight basic emotions. Then, the $m^{th}$ dimension of emotional vector $e_p \in \mathbb{R}^{|M|}$ is given by:

$$e_p[m] := \sum_{t \in T_p} \mathcal{I}_m(t)$$

where $\mathcal{I}_m(t)$ is an indicator function that outputs 1 if the term $t \in T_p$ is associated to emotion $m$, and 0 otherwise. In the case of comments we perform an additional processing step by using term frequency–inverse document frequency weighting scheme. Finally, we normalize vector $e_p$ to produce a probability vector $\hat{e_p} = \frac{e_p}{N_M}$, where $N_M$ is a normalization constant that corresponds to the total number of terms $t \in T_p$ associated to an emotion.

For example, an emotional vector for a short film over dimensions [joy, sadness, anger, fear, trust, disgust, anticipation, surprise], can correspond to : [0.08, 0.18, 0.14, 0.21, 0.15, 0.17, 0.03, 0.04]. The components of the probability vector add up to 1, and each of them is a positive number between 0 and 1. Similarly as in the case of emotions, we compute the polarity tuple (*positive, negative*), which is appended to the emotional vector. Note that while this work focuses on short films, this multi-modal sentiment analysis algorithm is applicable to other scenarios using other types of textual resources, such as tweets, blog posts or users reviews.

## 3. EXPERIMENTAL EVALUATION

In this section we describe our dataset and experiments.

**Dataset.** Using YouTube's Data API, we collected a total of 270 short films along with the available metadata (i.e., number of views, likes, dislikes, uploader) and up to 10,000 most recent comments that are posted for each short film. We collected the films from two different short film festivals openly available in YouTube: *Tropfest* [6] and *Your Film Festival* [7]. In this analysis, we considered only those short films which have at least three comments, giving us a total of 235 short films. The average length of the films is 6 and 11 minutes for *Tropfest* and *Your Film Festival*, respectively.

**Experimental setup.** We represent each short film by two vectors of emotions, one built from YouTube comments, as described in Section 2, and one from crowdsourced annotations.

To build the emotion vector via crowdsourcing, we designed 235 human intelligence tasks (HITs), one per short film, using the commercial crowdsourcing platform Amazon's Mechanical Turk (AMT). Our goal is to have workers annotate each short film according to the emotions they perceived to be associated to it. For instance, in the HITs we included questions like: *How much would you associate this short film with the emotion joy? (for example, happy and funny scenes are strongly associated with joy)*, and in a similar fashion for all the remaining emotions.

*Gold Standard.* We asked 12 experts (moviegoers from our research group) to carefully extract the emotions from 10% of the dataset (24 short films). Each video in this subset was analyzed by at least 3 different experts, and differences in the judgments were resolved by majority voting. The experts annotated the short films using the same HITs design but on AMT's sandbox, an environment specially designed for development which allows workers to complete HITs knowing they will not receive a monetary reward.

*Performance metric.* Our aim is to measure how similar are the emotional vectors automatically extracted from the social comments and via crowdsourcing annotations, to the one elicited from the expert judgments. To measure similarity, we use Cosine Similarity, which for two vectors $A$ and $B$, is defined as follows: cosine-similarity$(A, B) = \frac{A \cdot B}{\|A\|\|B\|}$.

**Results.** Figure 1 shows the average cosine similarity between the emotional vectors built from expert judgments and the ones built (i) through crowdsourcing using AMT, and (ii) automatically using YouTube comments. One can observe that the emotional vectors automatically extracted from the comments are approximately 75% similar to the expert's ones, whereas crowdsourcing-based emotional vectors exhibit a similarity of 68%.

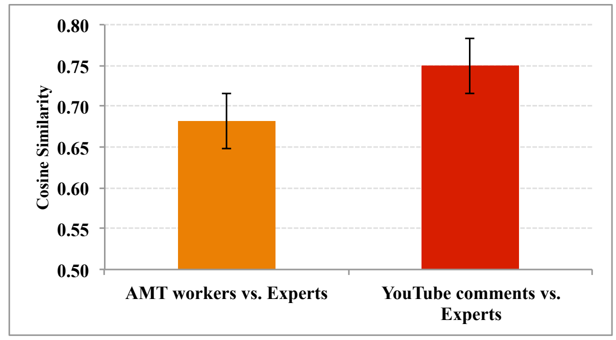


**Figure 1: Cosine similarity between the emotional vectors built from expert judgments and the ones built (i) through crowdsourcing using AMT, and (ii) automatically using YouTube comments.**

## 4. CONCLUSION

In this work we showed an approach for tracking emotions in short films by taking two different directions: (i) analyzing user created content, specifically YouTube comments and (ii) using the wisdom of the crowd to explicitly annotate short films according to the emotions experienced while watching the videos.

According to our results, we conclude that YouTube comments alone indeed provide the information required to automatically extract emotions associated to short films, and crowdsourcing, although providing explicit annotations and useful answers to purpose specific questions, is not vital to achieve this particular objective. However, crowdsourcing can help us to complement our automatic approach, e.g., in cases where no comments have been yet posted for short films. An interesting future direction would be to consider a hybrid approach, which includes crowdsourcing interaction on demand that complements the automatic extraction.

Our study reveals the possibility of automatically and in real time, mining emotions associated to short films. As future work, we plan to extend our approach to the tasks of emotion-based film recommendation and classification.

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