Analysing Emotional Sentiment in People's YouTube Channel Comments

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Abstract. Online recommender systems are useful for media asset management where they select the best content from a set of media assets. We are developing a recommender system called 360-MAM-Select for educational video content. 360-MAM-Select utilises sentiment analysis, emotion modeling and gamification techniques applied to people's comments on videos, for the recommendation of media assets. Here, we discuss the architecture of 360-MAM-Select, including its sentiment analysis module, 360-MAM-Affect and gamification module, 360-Gamify. 360-MAM-Affect is implemented with the YouTube API [9], GATE [5] for natural language processing, EmoSenticNet [8] for identifying emotion words and RapidMiner [20] to count the average frequency of emotion words identified. 360-MAM-Affect is tested by tagging comments on the YouTube channels, Brit Lab/Head Squeeze [3], YouTube EDU [28], Sam Pepper [22] and MyTop100Videos [18] with EmoSenticNet [8] in order to identify emotional sentiment. Our results show that *Sad, Surprise* and *Joy* are the most frequent emotions across all the YouTube channel comments. Future work includes further implementation and testing of 360-MAM-Select deploying the Unifying Framework [25] and Emotion-Imbued Choice (EIC) model [13] within 360-MAM-Affect for emotion modelling, by collecting emotion feedback and sentiment from users when they interact with media content. Future work also includes implementation of the gamification module, 360-Gamify, in order to check its suitability for improving user participation with the Octalysis gamification framework [4].

Keywords: 360-MAM-Affect, 360-MAM-Select, affective computing, Brit Lab, EmoSenticNet, gamification, Google YouTube API, Head Squeeze, machine learning, natural language processing, recommender system, sentiment analysis, YouTube, YouTube EDU.

1 Introduction

The consumption of online video content has become one of the most popular activities on the Internet. In the UK, online video audiences continue to grow on all

devices and the number of daily video viewers on mobile devices has increased by 46% between May, 2014 and May, 2015 [15]. YouTube alone has 300 hours of video uploaded every minute and over half the video views come from mobile devices [29]. Recommender systems have proven their ability to improve the decision-making processes for users in situations that often involve large amounts of information, such as the selection of movies to watch online [11].

We are currently developing an online recommender system (360-MAM-Select) [6], [17] that employs sentiment analysis and gamification techniques applied to people's comments on videos to achieve higher quality video recommendations for users. 360-MAM-Select will adapt to sentiment expressed by users on videos, whilst gamification will motivate engagement with video content. Section 2 discusses related work on recommender systems and sentiment analysis and Section 3 the design and implementation of 360-MAM-Select with its sentiment analysis module, 360-MAM-Affect and its gamification module, 360-Gamify. Section 4 discusses results from testing 360-MAM-Affect by tagging comments on the YouTube channels, Brit Lab/Head Squeeze, YouTube EDU, Sam Pepper and MyTop100Videos with EmoSenticNet in order to identify emotional sentiment. Section 5 examines 360-MAM-Select in relation to other work and Section 6 concludes with plans for future work.

2 Background and Literature Review

2.1 Recommender Systems

Recommender systems recommend products and services whilst searching online content and rank products against others for comparison. Improving online decision-making processes, particularly in electronic commerce, then allows online users to cope with large amounts of available information [21]. Recommender system algorithms need to personalise the user experience effectively [14]. This poses a challenge, requiring efficient algorithms to supply high quality recommendations to end users [23]. Faridani [7] trained a recommender model for an online clothes store, using textual and numerical ratings from the OpinionSpace dataset. Hanser et al. [10] developed NewsViz giving numerical emotion ratings to words calculating the emotional impact of words and paragraphs, facilitating the display mood of the author over the course of online football reports. NewsViz tracks the emotions and moods of the author, aiding reader understanding. Tkalčič et al. [25] propose a Unifying Framework for emotion detection and inclusion in recommender systems. This framework has three main phases: (1) entry, (2) consumption and (3) exit [25]. Most research has shown that emotions can be influential in making recommendations [30]. Little research has explored, 'how emotions interact with recommendation algorithms - the usage of emotional variables in the recommendation process' [30, p. 22].

2.2 Sentiment Analysis

Sentiment analysis is the process of recognising negative, positive and neutral opinions [27]. The advantage of sentiment analysis, when compared with traditional methods of opinion collecting, such as surveys, is that sentiment analysis can provide a larger sample for a lower cost than traditional survey methods. Customer surveys can be very limited and costly for organisations to conduct [19]. The challenge faced by sentiment analysis is the sheer variety of data on the Internet, and that it is available in so many different forms. This information is not static, as new information is uploaded almost constantly, and most of it can be edited and changed over time [12]. Natural Language Processing [1], [19] and Machine Learning [26] techniques are frequently utilised in sentiment analysis. Lerner et al. [13] found emotions to be powerfully influential on decision-making and proposed a model of decision-making called the Emotion-Imbued Choice (EIC) model, which synthesises their findings. The EIC model takes into account emotions in two ways, firstly through the decision maker's prediction of their expected emotions as a result of the outcome of their decision and secondly, through the current emotions of the decision maker, which traditionally have been excluded from rational choice models [13].

3 Design and Implementation of 360-MAM-Select

Figure 1 shows the architecture of our recommender system for media asset management (360-MAM-Select) for monitoring and engaging users during the selection and viewing of media content, incorporating a module for sentiment analysis and emotion modelling (360-MAM-Affect) based on the Unifying Framework [25] and EIC model [13]. The gamification module, 360-Gamify, is based on the Octalysis gamification framework [4, p.815] which displays the various gamification techniques used in applications to motivate users in different ways [4]. 360-MAM-Affect's emotion modelling module collects emotion data from the user during the entry, consumption and exit stages of the Unifying Framework, facilitating access to how the user responds emotionally to a video. Emotion data is collected on two levels, the primary emotion (mood direct experience) and the meta emotion (thoughts and feelings about the mood) [16, p.102]. Users will choose one of the seven emotions they feel represents their present state with the Emotion Feedback Emoticon Popup shown in Figure 1, and they will identify if they liked or disliked feeling that emotion. Recommender systems are employed to aid decision making and emotions have been found to be key in decision making [13], and hence we plan to further aid decision making by understanding users' emotions with 360-MAM-Select. The EIC model will be implemented in 360-MAM-Affect to collect data on current user emotions and expected emotion outcomes, in order to gather information about users' decision making on choosing media content. 360-MAM-Affect's sentiment analysis module harvests user YouTube comments on video content and identifies its overall reception. A collection of comments on a video aids its rating within 360-MAM-Select, in order to provide tailored recommendations for particular users. 360-Gamify provides incentives to users to interact with 360-MAM-Select by rewarding them for

providing primary and meta data feedback on their emotional state or their text comments and likes/dislikes.

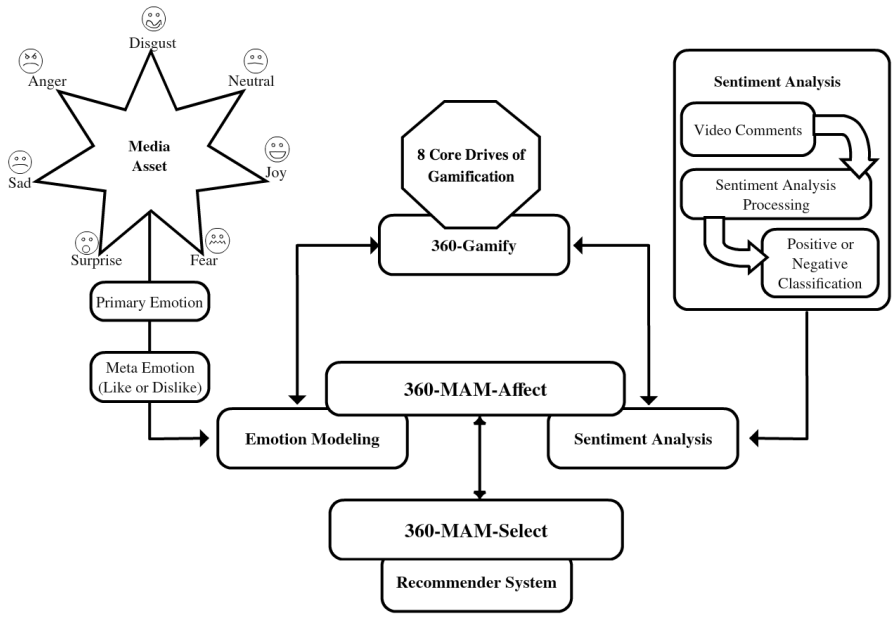

Fig. 1. Architecture of 360-MAM-Select

We implemented 360-MAM-Select's sentiment analysis module, 360-MAM-Affect using Google's YouTube API [9] for YouTube data, GATE [5] for natural language processing, EmoSenticNet [8] for identifying emotion words and RapidMiner [20] for counting the average frequency of emotion words identified. Specific YouTube channel video URLs were harvested using Google's YouTube API [9]. We then used the Google YouTube API to reap the 100 most recent user comments from each video URL. This returned a separate plain text file for each URL, with each comment collected separated by a new line.

4 Results on Analysis of YouTube Channel Comments

We gathered comments from four different YouTube Channels as shown in Table 1. Two of these channels contained mostly science and educational videos (Brit Lab [3], YouTube EDU [28]), the third was a Vlogger's Channel called Sam Pepper [22] which contained a variety of video genres and the fourth, "MyTop100Videos" [18], was collected from a playlist containing a selection of the most disliked videos on YouTube which varied in genre from education to music and Vlogs.

Table 1. YouTube Channel video URLs harvested

YouTube Channel	*Format*		*Number of URLs Reaped*
	Playlist	*Channel*	
Brit Lab/Head Squeeze		✓	490
YouTube EDU	✓		389
Sam Pepper	✓		128
MyTop100Videos	✓		426
Total			1,433

We tagged the reaped YouTube comments with emotions associated with specific concepts [17]. The plain text files reaped by the YouTube API containing YouTube comments were tagged with one or more of the relevant emotions (*Anger, Disgust, Joy, Sad, Surprise, Fear* or *Neutral*) for each concept found. This was achieved with EmoSenticNet which assigns six WordNet-Affect [24] emotion labels to SenticNet concepts and can be applied to sentiment analysis and other forms of opinion mining [8]. The natural language processing and text engineering tool, GATE, was utilised for tagging words with associated concepts from EmoSenticNet using its ANNIE Gazetteer for text information extraction [5]. The ANNIE Gazetteer was manually modified to include lists of concepts linked to emotions from EmoSenticNet [8]. These tagged text files containing YouTube comments were then processed by RapidMiner [20] in order to identify the frequency of tagged emotions within each separate URL from each YouTube channel. We reaped up to 100 of the most recent comments from each of the 1,433 videos and calculated the average frequency of tags for *Anger, Disgust, Joy, Sad, Surprise*, *Fear* and *Neutral* across all of the YouTube channels, as shown in Figure 2.

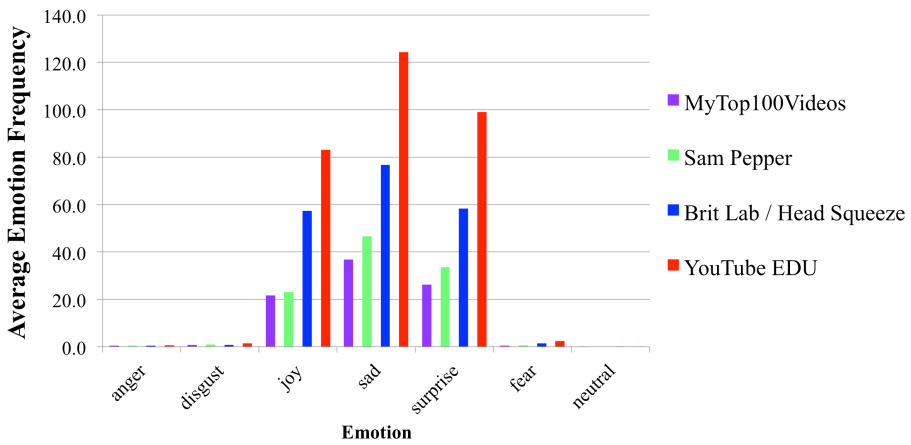

Fig. 2. Average emotion frequencies across YouTube channels

These averages were calculated by arithmetic mean:

$$(A = \frac{S}{N})$$

A = average emotion frequency, S = total sum of given tagged emotion and N = total number of video URLs for given channel. Three (*Sad, Surprise* and *Joy*) of the seven emotion tags were above 20 for average emotion frequency, which have previously been found to be more frequently related to concepts from EmoSenticNet [17]. *Anger, Disgust, Fear* and *Neutral* were considerably lower with none of these four emotions being higher than 3 for their average emotion frequency. However, this could be attributed to fewer concepts in EmoSenticNet being linked to these emotion tags [17]. The least common emotion was, *Neutral,* with an average emotion frequency of only 1, though this was not unexpected due to the low number of concepts in EmoSenticNet that were found to be neutral [17]. It is surprising that the channels, *MyTop100Videos* and *Sam Pepper* do not appear to have a higher average number of emotion tags for *Anger, Disgust, Sad* or *Fear*, considering the playlist chosen from *MyTop100Videos* includes some of the most disliked videos on YouTube. *Sam Pepper* has incurred a huge degree of criticism online for abusive and harassing actions in his videos [2]. Hence, it was expected that more negative emotions would have been found in comments on his videos. It is noted that both *MyTop100Videos* and *Sam Pepper* scored much lower in *Joy* and *Surprise* on average than the two educational YouTube channels, *Brit Lab/Head Squeeze* and *YouTube EDU*.

5 Relation to Other Work

Previous work has identified the importance of recommender systems [21] and their ability to personalise experiences [14] to provide high quality recommendations [23]. Emotion [16] has been identified as an important factor in improving recommender systems [25]. It is expected that by utilising both emotion detection and sentiment analysis, 360-MAM-Select will advance recommender systems by providing an improved user experience. Identifying sentiment towards online videos and user emotions in order to aid user decision making will improve the recommendation of online video content.

6 Conclusion and Future Work

The hypothesis of this research is that sentiment analysis, emotion detection and modelling and gamification will improve online recommendation of media assets. The sentiment in user comments on YouTube channel videos will help to identify higher quality content. Here, we discussed the architecture of 360-MAM-Select, our recommender system for media assets, including its sentiment analysis module, 360-MAM-Affect and its gamification module, 360-Gamify. We discussed the implementation of 360-MAM-Affect, employing the YouTube API, GATE for natural language processing, EmoSenticNet for identifying emotion words and RapidMiner for counting the average frequency of those identified emotion words. We discussed results from testing 360-MAM-Affect by tagging YouTube channel comments with EmoSenticNet in order to identify emotional sentiment. Future work includes further implementation and testing of 360-MAM-Select using the Unifying Framework [25]

and Emotion-Imbued Choice (EIC) model [13] within 360-MAM-Affect for emotion modelling, by collecting emotion feedback and sentiment from users when they interact with media content. The gamification module, 360-Gamify, will also be implemented and tested with the Octalysis gamification framework [4].

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