360-MAM-Affect:

Sentiment Analysis with the Google Prediction API and EmoSenticNet

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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 have developed an architecture for 360-MAM-Select, a recommender system for educational video content. 360-MAM-Select will utilise sentiment analysis and gamification techniques for the recommendation of media assets. 360-MAM-Select will increase user participation with digital content through improved video recommendations. Here, we discuss the architecture of 360-MAM-Select and the use of the Google Prediction API and EmoSenticNet for 360-MAM-Affect, 360-MAM-Select's sentiment analysis module. Results from testing two models for sentiment analysis, *SentimentClassifer* (Google Prediction API) and *EmoSenticNetClassifer* (Google Prediction API + EmoSenticNet) are promising. Future work includes the implementation and testing of 360-MAM-Select on video data from YouTube EDU and Head Squeeze.**

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

I. INTRODUCTION

Video and television services have advanced beyond passive viewing, as they have become interactive. The consumption of online video content has become one of the most popular activities on the Internet. In the UK there was an 8% growth in the online video audience and 262% growth in the mobile online video audience in the past year [7]. Europe has experienced a 5% growth in its online video audience and the number of mobile video viewers has increased by 162% since December, 2011 [6]. The sheer volume of video uploaded to the Internet every day means this growing audience has an ever-growing selection of videos to watch, but sorting these becomes a challenge. YouTube alone has 100 hours of video uploaded every minute [28]. On YouTube, videos are sorted by editorial categories, accompanied by manual tags and video titles created by the uploader [28].

We are developing an online recommender system (360-MAM-Select) [9] that uses sentiment analysis and gamification to achieve higher quality video recommendations for users. 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 [17]. 360-MAM-Select will adapt to sentiment expressed by users on videos, whilst gamification will motivate engagement with video content.

Section II discusses related work in recommender systems, sentiment analysis and gamification and Section III the design and architecture of 360-MAM-Select. Section IV discusses results from testing two models, *SentimentClassifer* (Google Prediction API) and EmoSenticNetClassifer (Google Prediction API + EmoSenticNet) for potential use in 360-MAM-Affect, the sentiment analysis module of 360-MAM-Select. Section V examines 360-MAM-Select in relation to other work and Section VI concludes with plans for future work.

II. BACKGROUND AND LITERATURE REVIEW

A. 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 [24]. Recommender systems can reduce time spent searching online, and aid in decision making for large online communities. Recommender system algorithms need to personalise the user experience effectively [21]. This poses a challenge, requiring efficient algorithms to supply high quality recommendations to end users [2]. Faridani [10] trained a recommender model for an online clothes store, using textual and numerical ratings from the OpinionSpace dataset. Hanser et al. [15] developed NewsViz giving numerical emotion ratings to words, calculating the emotional impact of words and paragraphs, which facilitates displaying the mood of the author over the course of online football reports. NewsViz tracks the emotions and moods of the author, which facilitates 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, as shown in Figure 1. Most research has shown that emotions can be influential in making recommendations [29]. Little research has explored,

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'how emotions interact with recommendation algorithms - the usage of emotional variables in the recommendation process' [29, p. 22].

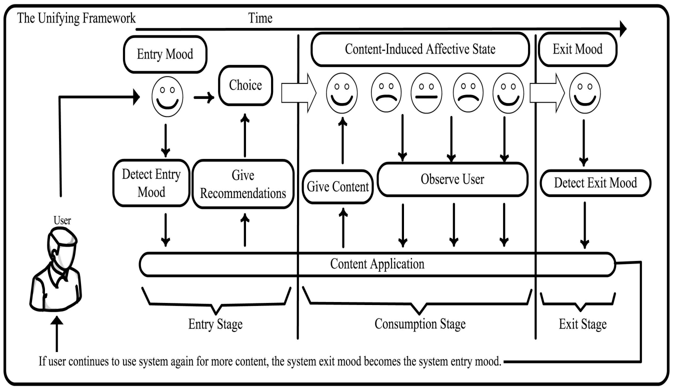

Figure 1. Unifiying Framework (Tkalčič et al. [25])

B. 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 [2]. 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 [18]. Natural Language Processing [3], [23] and Machine Learning [26] techniques are frequently utilised in sentiment analysis.

C. Gamification

Game mechanics and game design techniques are used to enhance non-game scenarios [8]. Common gamification methods include 'badges', given when a user reaches an achievement, and 'leaderboards', which display the rank of a user in relation to the rest of the community [20]. Field experiment results show that implementing gamification mechanics does not automatically increase activity, but users who actively partake in monitoring their own and others' progress with badges demonstrate increased user activity [14]. Gamification is popular for monitoring and analysing online communities, and enables them to be categorised based on the contributions they make [4]. Increasingly, gamification is used in marketing and product design because it helps to improve user activity [30]. Gartner, a leading information technology company, anticipate that gamification over the next 5 years will be a significant positive trend [11]. Gamification has shown improvement in learning and information retention in education and staff training [19], demonstrating that it is quite flexible in potential applications. Gamification techniques such as "achievements" also improve student engagement with educational material by rewarding the student [5].

III. DESIGN OF 360-MAM-SELECT

Figure 2 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 content, incorporating a module for sentiment analysis and emotion modelling (360-MAM-Affect) and gamification (360-MAM-Gamify), based on the Unifying Framework (Figure 1). 360-MAM-Affect's emotion detection module will collect emotion data from the user during the entry, consumption and exit stages of the Unifying Framework, which will facilitate access to how the user responds emotionally to media content. Emotion data will be collected on two levels, the primary emotion (mood direct experience) and the meta emotion (thoughts and feelings about the mood) [17, p. 102]. Users will choose one of the six emotions they feel represents their present state (with the Emotion Feedback Emoticon Popup shown in Figure 2), and they will identify if they liked (L) or this disliked (D) feeling that emotion. 360-MAM-Affect will harvest user YouTube and Head Squeeze [16] comments on video content and identify the overall reception of that video, providing tailored recommendations for particular users. 360-Gamify will provide incentives to users to interact with 360-MAM-Select by rewarding them for providing primary and meta data feedback on their emotional state or text comments and likes/dislikes.

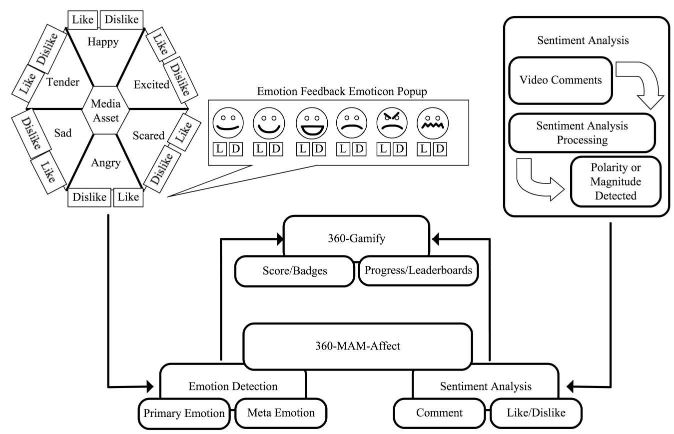

Figure 2. Archiecture of 360-MAM-Select

IV. SOFTWARE ANALYSIS FOR 360-MAM-SELECT

As we move towards implementation of 360-MAM-Select we have conducted software analysis on selected software tools we intend to employ. Using the Google Prediction API [13] we created two sentiment analysis prediction models, (1) *SentimentClassifer* model and (2) *EmoSenticNetClassifer* model, and discuss the results on testing these models. First, we manually created a text file containing fictional arbitrary English sentences that were similar to YouTube comments, labelled as positive, negative or neutral in terms of sentiment. In total 39 sentences were used, 13 positive, 13 negative and 13 neutral. The *SentimentClassifer* model was trained with the Google Prediction API and it identified 3 numberLabels (examples of Positive, Neutral or Negative sentiment) and predicted a classificationAccuracy of 61%. We then queried *SentimentClassifier* with 10 arbitrary sentences not present in the training data to see if *SentimentClassifer* identified them as positive, negative or neutral. *SentimentClassifer* had no difficulty identifying the sentiment of straightforward sentences such as sentences 1 and 2 (Table I). When processing more ambiguous sentences such as sentences 4 and 5 *SentimentClassifer* failed to identify the correct sentiment (Table I). However, accuracy can be improved with a larger training data set. The Google Prediction API documentation [13] explains that for the best results, the training data should be of similar length to the expected queries. Using long text strings for training and short text strings in the queries (vice versa) can potentially alter the results. Our training data and queries were of similar length, so we do not believe it caused distortion in the results (Table I).

TABLE I. TESTING SENTIMENTCLASSIFER WITH ARBITRARY SENTENCES

SentimentClassifer Model				
Sentence Number	*Queried Sentence*	*Emotion outputLabel*		
		Positive	*Negative*	*Neutral*
1	There are five birds on the overhead cables.	0.00	0.00	1.00
2	I am so excited for this event tonight.	1.00	0.00	0.00
3	I can say that I do not like apples, but I do love pears.	1.00	0.00	0.00
4	Not like I care about what happens to you.	1.00	0.00	0.00
5	I hate you more than you will ever know.	0.63	0.37	0.00
6	Got to love this guy but I really hate the situation they place him in, they are just not fair.	0.99	0.01	0.00
7	Hate this film it is just a terrible squeal.	0.77	0.22	0.00
8	I bought ten chickens for dinner, and only 2 carrots.	1.00	0.00	0.00
9	This car park can hold twenty-four cars.	0.00	0.00	1.00
10	Your videos have been getting worse over time, it is not up to the standard that it once was. I think I will unsubscribe.	0.35	0.65	0.00

We conducted a second test (*EmoSenticNetClassifer* model) with the Google Prediction API, using EmoSenticNet [12]. EmoSenticNet is provided in an XLS format as a lexical resource that assigns six WordNet-Affect [1] emotion labels to SenticNet concepts and can be applied to sentiment analysis and other forms of opinion mining [12]. The format of EmoSenticNet data is shown in Table II. The values denote *Concepts* that relate to associated emotions: *Anger, Disgust, Joy, Sad, Surprise* and *Fear*. The value 0 means a given emotion is not associated with a given concept, and the value 1 means the emotion is associated with a given concept. For example, the concept *Absence_Light* is associated with *Sad* and *Fear*, but not associated with *Anger, Disgust, Joy* or *Surprise*.

TABLE II. EMOSENTICNET EXAMPLE VALUES [13]

Concept	Associated Emotions					
	Anger	*Disgust*	*Joy*	*Sad*	*Surprise*	*Fear*
Absence_Light	0	0	0	1	0	1
Turmoil	1	0	0	0	0	0
Self-Esteem	0	0	1	0	0	0
Despair	0	0	0	1	0	0
Shudder	0	0	0	0	0	1
Demoralisation	0	1	0	0	0	0
Daze	0	0	0	0	1	0

We converted EmoSenticNet into a CSV (Comma Separated Values) text file that is a suitable format for the Google Prediction API. The *EmoSenticNetClassifer* model was then trained on the EmoSenticNet data. The concepts from EmoSenticNet [12] are features and the emotions from EmoSenticNet are labels. The numbers were replaced by the text for *Anger, Disgust, Joy, Sad, Surprise* and *Fear*. For example, previously *Absence_Light* would have been displayed as *Absence_Light*, "0,0,0,1,0,1" which was then converted into two separate lines *Absence_Light*, *Sad* and *Absence_Light*, *Fear*. In total, there were 15,033 EmoSenticNet concepts, 3,236 of these concepts are duplicate entries of the same concepts related to more than one emotion. 11,786 of the concepts were only related to one out of the 6 emotions and there was no overlap with other emotions. We found 13 concepts to be unrelated to any of the 6 emotions, and therefore neutral. No concept was found to possess all 6 emotions, the most found was 5 and the least found was 0. Table III shows the frequencies of instances where a concept in EmoSenticNet was associated with one emotion.

TABLE III. EMOSENTICNET CONCEPTS ASSOCIATED WITH ONE EMOTION

Concepts With Single Emotions						Total Concepts
Anger	*Disgust*	*Joy*	*Sad*	*Surprise*	*Fear*	11,786
257	595	8,821	1,283	330	500	

Figure 3 shows frequencies (%) of instances where a concept in EmoSenticNet was associated with 2 emotions. In these instances all concepts related to 2 of the emotions, and therefore overlap with other emotions. For example, there were 65 occurrences of *Anger* & *Disgust* labelled concepts, 762 concept labels associated with *Joy* & *Surprise.* However, only 3 were associated with *Anger* & *Surprise*. From Figure 3 it can be observed that the emotions *Fear* or *Disgust* often accompanied concepts that were associated to *Anger*. *Joy* was most often associated to *Surprise* and vice versa.

Figure 4 shows concepts that contained three emotion labels. There were 404 concepts associated with three emotion labels, which is 2.69% of the total 15,033 EmoSenticNet concepts.

Disgust, Fear and *Anger* represented a total of 340 of the 404 triple labelled concepts.

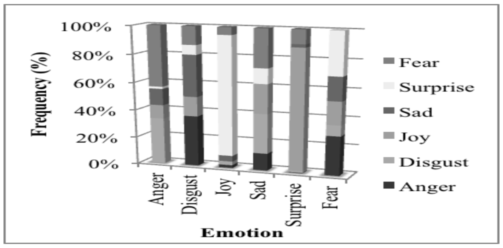

Figure 3. Frequencies (%) of 2 emotions per concept

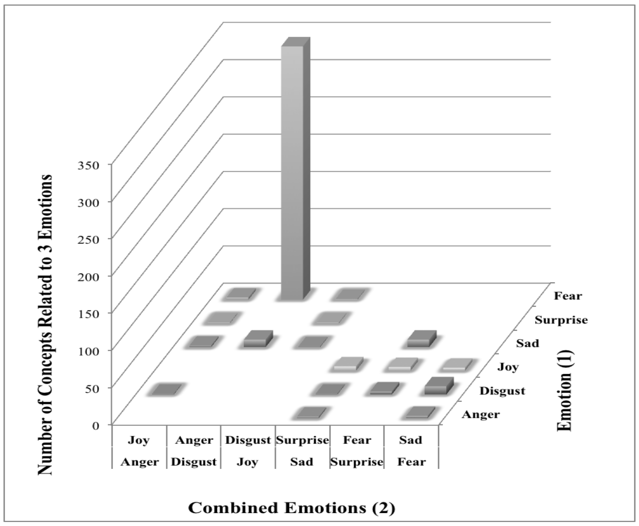

Figure 4. Combination of 3 emotions per concept

Here, we have not included results for concepts that contained four or more emotion labels due small data sizes. A total of 20 concepts contained 4 emotion labels and only 4 concepts contained 5 emotion labels. No concept was found to contain all of the 6 emotion labels.

Using the Google Prediction API, we trained an *EmoSenticNetClassifer* model with the modified EmoSenticNet text file containing 15,033 EmoSenticNet concepts (289.81 KB). It returned 7 numberLabels (*Anger, Disgust, Joy, Sad, Surprise, Fear* and *Neutral*) with a classificationAccuracy of 59%. We queried the *EmoSenticNetClassifer* model with 12 common arbitrary words as well as two concepts (*Rotten Fruit* and *Alcoholism*), which were present in the training data file. Out of the 12 queries, *Joy* was labelled the "outputLabel" for 7 of the 12 queries (see Table V). The results were reasonably accurate with 5 concepts being highest rated in the expected emotion label. However, 7 concepts failed to return the highest rating in the expected emotion label. The two queries (*Rotten Fruit* and *Alcoholism*), which were present in the training data file were expected to be highly rated in *Anger, Disgust* and *Sad*, but on both (*Rotten Fruit* and *Alcoholism*) instances *Joy* was still highly rated in comparison to earlier queries. This may be explained by the fact that *Joy* had the highest frequency of entries in the training data.

TABLE IV. RESULTS OF EMOSENTICNETCLASSIFER MODEL

Query	Emotion Labels						
	Anger	***Disgust***	***Joy***	***Sad***	***Surprise***	***Fear***	***Neutral***
Good	0.139	0.138	0.175	0.137	0.136	0.138	0.133
Bad	0.108	0.107	0.227	0.106	0.239	0.107	0.103
Sad	0.139	0.138	0.175	0.137	0.136	0.137	0.133
Terrible	0.139	0.138	0.175	0.137	0.136	0.138	0.133
Happy	0.189	0.187	0.175	0.188	0.086	0.087	0.084
Horrible	0.139	0.138	0.175	0.137	0.136	0.138	0.133
Bland	0.139	0.138	0.175	0.137	0.136	0.138	0.133
Sweet	0.139	0.138	0.175	0.137	0.136	0.138	0.133
Funny	0.139	0.138	0.175	0.137	0.136	0.138	0.133
Smile	0.139	0.138	0.175	0.137	0.136	0.138	0.133
Rotten Fruit	0.108	0.107	0.227	0.239	0.105	0.107	0.103
Alcoholism	0.189	0.184	0.182	0.184	0.086	0.088	0.084

Figure 5 shows Table IV. in graph form and *Joy* shows consistently higher ratings compared to other emotions labels.

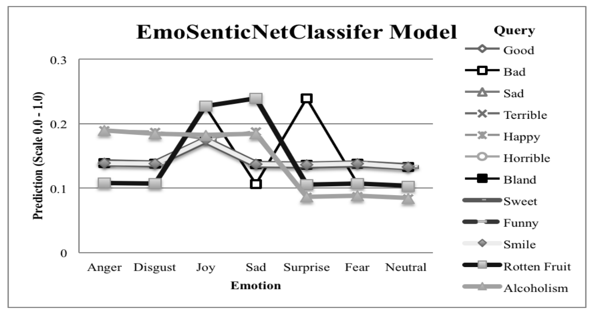

Figure 5. EmoSenticNetClassifer prediction results

V. RELATION TO OTHER WORK

Previous work has identified the importance of recommender systems [24] and their ability to personalise experiences [21] to provide high quality recommendations [2]. Emotion [22] has been identified as an important factor in improving recommender systems [25]. It is expected that by having an emphasis on multiple forms of input and output [25] such as gamification, emotion and sentiment analysis, 360-MAM-Select will advance recommender systems by providing an improved user experience.

VI. CONCLUSION AND FUTURE WORK

This paper discusses the use of the Google Prediction API in developing models for 360-MAM-Affect, the sentiment analysis module of 360-MAM-Select, a recommender system for media assets. The architecture of 360-MAM-Select has been discussed and results from testing two models for sentiment analysis, *SentimentClassifer* (Google Prediction API) and *EmoSenticNetClassifer* (Google Prediction API + EmoSenticNet) are promising and show potential for application within 360-MAM-Affect. However, in training models it is important that balanced examples of each type of sentiment are provided, otherwise results may be skewed (as was seen in Figure 5 for *Joy*). 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 and Head Squeeze [16] videos, should help to identify higher quality content. Gamification will facilitate encouragement of user interaction with 360-MAM-Select, through using leaderboards and badges, by encouraging users to interact with digital content. Future work includes further investigation of how sentiment analysis and gamification can be utilised in order to improve user participation, video retrieval and implementation and testing of 360-MAM-Select.

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