Focused Concept Detection and Polarity Measurement of Web Video Using Social Context

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ABSTRACT
The explosive growth of videos on the Web poses new challenges for the effective visualization of hundreds of videos at once. Given any issue-based query, a search system returns a huge list of ranked results including many different perspectives related to single issues. It would be easier for the user if the search results could be grouped based on the theme or the opinion expressed in the video, and if they were thus presented for browsing. In this paper, we describe our attempt to address the above problems by detecting the focused concept of the video and the polarity of opinion expressed by means of sentiment analysis. Clustering of ranked tags over the initial results can extract thematic sub groups whereas dictionary-based sentiment analysis helps to detect the negative and positive polarity to a certain extent, yet demands more investigation. Evaluation of 500 user comments shows a moderate recall of 45-57% and a precision of 73% on average with SentiWordnet alone, while recall and precision shows an average 7% improvement when the polarity is detected with a combination of contextual word lists.

Keywords
Sentiment analysis, tag ranking, video categorization,

1. INTRODUCTION
Large amounts of news, documentary videos and videos of real-world events are uploaded and shared online. Content creation is not restricted to the professional media and news channels alone, as more and more videos for similar interests and events are also created and republished by users to express their opinions about the event. As a result, a single query fetches thousands of videos with multiple viewpoints but these are unfiltered. It would be ideal if the results were grouped or presented in a way to reflect the focused content and the emotional polarity. For example, a query of “Copenhagen summit on climate change” should reflect which videos have pro-climate change views, which videos express the other side of the divide, and which videos are neutral but focus on related issues concerning the main topic, so that the user will be able to browse efficiently with minimal effort.

Motivated by the above observation we propose to address the problems with two tasks: (1) identifying the focused concept, and (2) measuring the opinion polarity.

The identification of a focused concept is needed because the opinions are normally directed to specific object, people, event or issues. We carried our focused concept detection (FCD) experiment with 500 short videos from YouTube[i] for 10 different queries and polarity detection evaluation with 500 user comments.

Throughout this paper we use polarity measurement and polarity detection interchangeably to mean the same thing. The present work focuses mostly on sentiment polarity detection, with a small overview of focused concept detection.

The rest of this paper is organized as follows. Section 2 describes some work related to sentiment analysis in different domains. Section 3 describes our approach for both tasks. In Section 4 we describe the experimental results followed by our conclusions in section 5.

2. RELATED WORK
Sentiment classification is the task of determining the sentiment of text (product reviews, news, blogs). The scope can be at the document level [4, 5] or it can be directed towards a specific object or entity [6]

A large number of studies in sentiment analysis exist and the majority are focused on the sentiment analysis of reviews [9] (movies, products), news [10, 12], and blogs [11]. Many research studies are geared towards dictionary-based approaches [4] where predefined lists of polarity words are used to annotate the text and decide the document sentiment polarity. Hu et al. [4] started with a list of seed words and extended with Wordnet [5] synonym and antonym relations to create a list of polar words. SentiWordnet [2] is another approach to create a dictionary of polar words for the same purpose, which we are using in our work. Polar words are a good clue, but can be significantly affected by the context. Wilson et al. [7] did phrase-level sentiment classification by extracting features from the word context. To our knowledge, not many studies exist on analyzing the sentiment polarity of videos, except Bermingham et al. [1] who analyzed YouTube data using sentiment analysis and social network analysis in the context of online radicalization. Our work is some way in line with the above study where they explore the sentiment towards some issues such as radicalization, but we combine different information spaces such as tags, descriptions, user profiles in order to detect the perspective of any given issue and their polarity .

Lin’s [2] study focused on visual variation and tag usage to describe the perspective differences among web videos, but we focus on the aggregation of multiple evidences for a video to rank and cluster the perspective view.

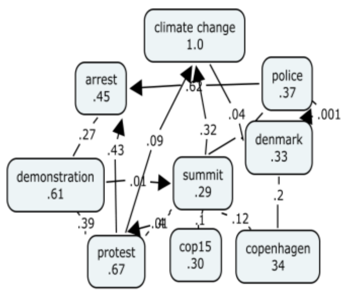
3. OUR APPROACH
The goal of the FCD is to facilitate the thematic grouping of search results and to identify the target object to which the

opinions are directed. Identification of a focused concept has been performed with semantic analysis of rich contextual cues available around the video, whereas identification of opinion polarity is achieved with a combined approach of user profile and sentiment analysis techniques. We collected a dataset of 500 videos from YouTube for 10 queries using focused concept detection.

3.1 Focused Concept Detection (FCD)

We treat FCD as document topic detection where a video is represented by a bag of words including its title, tags, descriptions and other related contextual metadata such as time, place, user details, and thematic group details. For topic identification, we create a local tag graph for each video where the nodes are the tags and the weighted link between two nodes is the co-occurrence distance between two tags. The nodes weights are the sum of the contributions from its neighbor nodes and links. The most-connected node gets a higher rank. Figure 1 (a) illustrates a video and its raw sources of information whereas 1 (b) shows the tag graph with weights. These ranked results in 1 (c) are ultimately used to group the search results to give a new perspective. Details of the ranking and clustering of the ranked results for thematic grouping is outside of the scope of this paper.

Climate change
summit
Copenhagen
protest
arrest
demonstration
Denmark
cop15
police



(a) (b)

Climate change
protest
demonstration
arrest
police
Copenhagen
Denmark
cop15
summit

(c)

Figure 1. (a) Video with its original tags, (b) a subset of the tag graph with weights, (c) the ranked tags

We select the first tags as the concept indicator. The number can be empirically set or follow a threshold function to decide it automatically.

Experimental results of 10 different recent issues (climate change, Google-China dispute, etc.) show that most issue-based queries come with multiple user perspectives and the opinion is both for and against the issues. The example in Figure 2 illustrates the point. It shows a global tag (top right) cloud of 100 results for the query "climate summit in Copenhagen". This result list carries three major subgroups such as "protests by African countries", "protests and demonstrations outside the conference" and a group related to "US president / other leader's speech".

Figure 2. Global tag cloud and three perspectives within it

3.2 Sentiment Polarity Measurement

We adopted a two-mode approach to detect the polarity of video content from its tags and descriptions (reflecting the sentiment of its creator) and the polarity of user opinions towards the video content from the comments. We experimented with two different setups: (1) with SentiWordnet alone, and (2) in combination with a contextual word list and rules of negation.

3.2.1 SentiWordnet

This is a lexical resource for opinion mining. Each synset of Wordnet is assigned a triple polarity score i.e., a positivity, negativity and an objective score. The sum of all the scores equals 1. It was created using a combination of statistical and linguistic approaches. Many studies have used the lexicon for various opinion mining tasks. For example, Devitt et al. [12] have used it for polarity detection in financial news.

3.3 Polarity Measurement with SentiWordnet

In SentiWordnet, each word has three polarity scores: positive, negative and objective scores. Each word may have multiple senses and multiple polarity scores. Since there is no disambiguation involved in SentiWordnet, we need to normalize the word sense scores for each word. The approach we followed is a two-stage approach: word polarity and comment polarity. The word polarity is calculated as following.

1. Each comment is broken down into a list of words after removing the stop words.
2. For each word if the word is an adjective, noun or verb we extract the three polarity scores for each of the senses. For example, the word wonderful has one sense with a polarity triple of {0.875, 0.0, 0.12} whereas "terrific" has three senses (in Table 1 below). In such a case, the word (w) polarity score pl(w) is the average of all senses {0.35, 0.29, 0.31} and is calculated with:

   a. $Pl(w_{pos}) = \sum_{i=1}^{n} \frac{score_{pos}(w)}{n}$

   b. $Pl(w_{neg}) = \sum_{i=1}^{n} \frac{score_{neg}(w)}{n}$

   c. $Pl(w_{obj}) = 1 - \left(Pl(w_{pos}) + Pl(w_{neg})\right)$

   where n is the number of senses of the word w.
3. The polarity securing the highest value is taken as the word polarity (in the above case, it shows that the word can be used either as positive or negative polarity, but in the absence of other information it may always be considered as positive.)

Table 1. Word sense and its polarity score in SentiWordnet

	Positive	Negative	Neutral
Terrific (1)	0.25	0.25	0.5
Terrific (2)	0.875	0.0	0.12
Terrific (3)	0.0	0.625	0.375
	0.35	**0.29**	**0.31**

4. After detecting the polarity of the word level we calculate the comments' level of polarity by taking into account of all the word polarities.
5. The comment polarity is decided by majority voting.
6. Document polarity can be an aggregation of comment polarity and the polarity score of the textual content, but on examination of the results we believe that we need to improve the comment polarity accuracy before using it as a feature for document polarity.

3.4 Hybrid Approach

Web 2.0-specific user-generated content defies the conventional grammar rules of language and adopts many user-specific terms due to their popularity. These include terms expressing feeling and opinions, for example, "nope" is used to express a negative impression, whereas "china rockzzz" is used to express positivity.

Examining the results of using SentiWordnet to detect polarity from user views, we have decided to create a list of context words to refine the detection process. The manually-created list includes phrases such as "great idea! +1" as a positive, "little truth -1" as a negative, etc. In this process, if the SentiWordnet detection is in conflict with the contextual pattern the contextual score is given the preference. We also used the rule of negation, for example, the word "good" has a positive score in SentiWordnet but if the word appears in a near context of "good", e.g. "not so good", the polarity score reverses. The contextual list is not an exhaustive list but a manually-selected word contextual pattern from the text under study and still needs to be refined and evaluated extensively. This hybrid approach showed a 7% improvement of recall score.

4. EVALUATION/DISCUSSION

The objective of the evaluation is to examine the coverage of efficient polarity measurement of the videos from the user comments. As part of our test, we took 500 user comments from five different query videos where there are 200 positive comments, 150 negative comments and 150 neutral or other kinds of unclassified comments. For evaluation, we manually labeled them to be used as gold standards. Polarity detection is performed at two levels, first at the word level and secondly at the sentence level.

Table 2. Recall and precision with SentiWordnet

	Recall	Precision
Positive	57%	65%
Negative	45%	69%
Neutral/Others	54%	73%

Out of 500 user comments including 200 positives, 150 negatives and 150 neutral comments, 112 positives are true positives whereas others are classified as either negatives or neutral comments. The proportion of true positives is highest in case of "neutral and other" comments, but still more than one third are misclassified

Table 3. Recall and precision with combined approach

	Recall	**Precision**
Positive	66%	74%
Negative	49%	70%
Neutral/Others	63%	73%

The recall on average are low, ranging from 45%-57% (table 2), whereas the precision is around 65-73%. The reasons for the low recall can be many: user comments are noisy, words are implicit in intention, fuzzy and vague. Many polar words are missed out on due to their non-conventional nature and are not part of Wordnet. Our combined approach of using negation rules and manually-created contextual patterns improves the recall by 7 % (table 3) but still leaves a lot room for improvement.

One interesting observation is that user profiles and their network structures are a great indicator of opinion polarity which can be exploited for better categorizations and presentation of video in search results. We tried to explore whether the intention of the creator in any way influences the comments pattern. It has been noticed anecdotally that video creators with a negative bias mostly get comments conforming to their views when compared to the other two classes. However, the number of test items is too small for any claim of this sort to be formalized, so we need some further investigations to study this pattern.

The application of the present approach can primarily be useful in the areas of search result visualization, recommendation and personalization of videos. Categorization in multiple dimensions enables the user to have a faster and more satisfying browsing experience which is lacking in present frameworks.

5. CONCLUSION AND FUTURE WORK

In order to organize the video search results efficiently, the present paper explores ways to extract the focused concept of a video from various sources of information available. It also explored sentiment polarity based on user comments and user profiles. Evaluation showed that the mere application of traditional sentiment analysis will not suffice to detect the document polarity level. We need to combine this with other fine-grained sentiment detection techniques. We will improve the word context lexicon to be more reliable in detecting the sentiment expressed.

6. ACKNOWLEDGMENTS

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