DO COMMENTS ON YOUTUBE DIFFER ACROSS GENRE?

Cliff Loke and Anjan Pal

Nanyang Technological University, Singapore

ABSTRACT

This study examines the differences in online comments between educational videos and entertainment videos on YouTube. By employing content analysis of 2,000 comments, it examines the association between the different comment categories and the two genres of videos. For educational videos, the findings suggest that comments were enriching in terms of requesting further information, recommending videos, expressing opinion, commendation, disagreement, and sharing anecdotes as well as personal information. However, for entertainment videos, comments were enriching in terms of reflecting impression, compliments and expressing general sentiments. The potential implications from theoretical and practical perspectives are discussed.

KEYWORDS

User-Generated Content, Content Analysis, Social Media, YouTube, Video Genre, Interface Design, Entertainment Videos, Educational Videos

1. INTRODUCTION

YouTube has been accessed by over one-third of the Internet population (OmniCore, 2018). The website provides Internet users have become keen to use information from various social media platforms such as Facebook and YouTube. Besides communicating with their online peers, users engage themselves in social media in every aspects of their lives starting from education to entertainment. They tend to plug their knowledge gaps from variety of resources that are readily available for access on the Internet. For instance, they use video source repository YouTube, which ranks 2 in terms of getting website traffic after Google, for procedural learning (Alexa, 2018).

Even though the revolution of cutting edge Internet technologies have turned social media into a public space to seek, search, and share information, the exponential growth of information pose serious challenges in terms of evaluating quality, and usefulness in order to make informed decisions in the selection of resources (Rieh, 2002). During information seeking, people make relevance judgement as they attempt to discern and evaluate the content of resource. To some extent, several paralinguistic affordances such as likes and views on Facebook and YouTube provides superficial signs of content popularity. However, user comments offer more in-depth insights about public perceptions about an online content. Online videos have become a popular information resource. With more than a billion user accounts created, YouTube, an online video platform offers paralinguistic affordances such as likes, dislikes, shares and views to indicate users' preferences. It also allows users to comment on videos. Thus, crowdsourced cues that are socially generated can further influence video seekers in their selection of video resources (Loke et al., 2017) and have been a growing part of Internet resources metadata. Metadata are used for subjective relevance judgement and form a basis of recommendations (Bogdanov and Herrera, 2011). To cope with information overloading, such crowdsource cues are often processed heuristically to evaluate and shortlist resources (Zhang et al., 2014). However, users' comments that are usually presented in a chronological thread format, involve extensive efforts to process, and thus cognitively overloaded.

Video is one of the most common form of media sought on the Internet and the video comments facility produces rich socially generated cues. User commenting is a key facility that leverages on social interconnectivity for communication through the resource. It has the potential to support decision making for video seekers. YouTube, with its huge and diverse user base, has an immense amount of user comments have been generated and can contribute to the video experience (Siersdorfer et al., 2010). Any online videos that

have comments from a wide user base and often result in very varied perspectives. While user comments can influence the selection of video resource, the sheer amount of comments generated can be time consuming and daunting for video seekers to process. To reduce the time and effort in processing the comments, a summarised view of comments could support video seekers in discerning and evaluate the video. The richness of comments had led to research developing an application based on mining opinions in comments to indicate positive and negative responses (Potthast, 2009). This allowed a large number of comments to be summarized and helped users to sort the comments according to its positive or negative connotations. This afforded users to form some basis of evaluation on the resource. Beyond dichotomous levels of positive and negative, the richness of comments can be explored to provide granular levels of opinions and perspectives.

Research on various social media platforms had drawn out general categories of comments and these provide a useful starting point for analysis (Thelwall, 2018, Madden et al., 2013). Categorical schemas for comments emerged from these studies reflected diversity in granularity and context. While these studies have produced important contributions to the understanding of user behavior and comments relationships, there has not been sufficient research to understand how the comments from different video genres such as educational videos and entertainment videos. These vastly different genres can result in how the comments are used to develop interface features and analyzed. A strong classification scheme for YouTube user comments can open up multiple areas of research and improve the understanding of comment behavior and its potential impact.

Building on the premise that different search goals can result in different curating and evaluating processes, this study examines the differences in online comments between educational videos and entertainment videos on YouTube. For this purpose, the framework of Madden et al. (2013) was leveraged.

By understanding the differences between comments found in educational video resources and entertainment video resources can develop a more robust classification scheme. The more robust classification scheme can better support the development of interface features for video retrieval that leverages on the richness of user comments to evaluate and add value to the video content.

2. RELATED LITERATURE

Interactivity is one of the keys to social media platforms. Many social media platforms afforded interactivity through user comments. Interaction with the online content and other users lead to better user engagement. User comments is a form of user-generated content that can evolve like an online conversation, allowing users to express their opinions and emotions that can be analysed to provide value for businesses and information products (Fan and Gordon, 2014, Yang, 2012). Studies from the business domain investigate social media and user-generated content to improve branding and develop new products (Culnan et al., 2010). A prediction model was developed based on the number of users' comments to forecast the expected popularity of articles published by an online newspaper (Tatar et al., 2014). Businesses and organizations leverage on the understanding of social media interactivity to make predictions and create value propositions.

User-generated comment allows richer analysis as compared to other common social media metrics such as Ratings and Number of Likes. The richer analysis stems from the forms of interaction and the qualitative nature of user-generated comments. The interaction in social media, in particular user-generated comments, reveals interactivity in two forms. The interactivity between the users of the social media platform, user-user interactivity, is captured as conversations in user-generated comments while user-content interactivity are the user-generated comments made directly in reference to the social media content (Ksiazek et al., 2016). The analysis of comments allowed business entities to make sense out of leaner metrics such as a rating system (Stringam and Gerdes Jr, 2010). Other potentials from the analysis of comments that have found success include popularity prediction (Tatar et al., 2011), supporting recommendation systems (Li et al., 2010) and ranking metrics (Tatar et al., 2014). The mining and analysis of comments has created opportunities and supported the development of features for better user interaction.

User-generated comments has shown to influence perception and evaluation of the online resource. For example, research investigating the interplay between public service announcements posted in YouTube and its corresponding user comments has found that both supportive and derisive comments had affected the evaluation of the announcement (Walther et al., 2010). Examining user comments as online reviews on hotel room sales, Ye et al. (2009) suggest online consumer-generated reviews had strong influence on the number

of online bookings. These studies suggested that social influence is exhibited through user comments and play a part in decision-making.

Park et al. (2008) explored comments from Digg and del.icio.us and presented categories such as Summary, Additional Information, Impression and Opinion. The categories produced from the study are general and unable to convey the richness of information found in the comments. Jansen et al. (2009) investigated comments on Twitter and produced 23 different comment types. While this study yielded a more granular form of comment classification, they are specific to the context of a marketing study. Content analysis was performed on over 66K of YouTube user comments and derived a more general classification scheme that has ten broad categories and 58 subcategories (Madden et al., 2013). This schema reflects the diversity of comments from the YouTube user base and provides an initial structure upon which other user comment studies can build on.

As one of the largest video platform, researchers are studying YouTube in order to understand video content and usage, video seeking, and user interaction and behavior. Kousha et al. (2012) reviewed the how academics studied YouTube videos across various disciplines and found that there is wide variety of research conducted on YouTube video content. Paek et al. (2014) analysed the content of 365 YouTube videos on e-cigarette and suggested that YouTube videos may play a major role as a promotional medium due to its effective persuasiveness. Madathil et al. (2015) conducted a systematic review on YouTube literature concluded that YouTube is increasingly used as a platform to convey health related information and contains misleading information that could find its way to lay person.

Interaction patterns in YouTube are studied to understand core users and video virality. Abisheva et al. (2014) analysed metrics like view counts, number of comments, favourite markings of the video and set of referrers that led users to the video, in order to understand the factors that impact video popularity. Khan (2017) examined the various motivations for participation and engagement in YouTube. Such studies provide insights to online user behavior and engagement to social metrics.

Given that the use of YouTube has been widely adopted for various purposes starting from education to entertainment (Khan, 2017, Möller et al., 2018), users' comments on videos also helps to make sense about the perceptions of the online community. While YouTube has been abundantly used for the purpose of entertainment (Khan, 2017, Cheng et al., 2013), it has also become a tool for learning (Choi and Behm-Morawitz, 2017). Eventually, YouTube facilitates different media channels for different genres of video. Regardless of different media channels and genre, the comment function on the platform allows users to express their sentiments and much more even beyond the content of the video per se (Choi and Segev, 2016). From astute, reasonable, and well written, they can also be informal, indiscreet or even nonsensical.

Prior works suggest that users' comment can raise relevant issues that can help content creators in developing their content, and can be deemed as valuables to those planning to create an educational video in order to enhance learning in an innovative way. While the interaction through user comments creates valuable insights and conversations, it can also result in arguments and antagonisms. In this vein, little research has been trained on how comments can be differed across different genre. Currently, the lack of structural organization of user comments has limited the utility of users' perceptions for both consumers as well as creators of those videos.

3. METHODOLOGY

To address the research question, comments were required to be collected for educational videos as well as entertainment videos. First, the video channels were determined, then videos from the channels were selected for the harvesting of comments.

Videos were chosen from the two channels (TedEd – Educational; ExplosmEntertainment - Entertainment) that had comparable subscription numbers during the data collection. There is a need to ensure that subscription numbers were similar as this is indicative of the number of video viewers who are viewers of the channel. (Five videos were selected from each channel. The videos were initially sorted to be within the upload period between 6 to 12 months. This is to ensure that there were sufficient comments for the videos.) Then, comments for those videos were retrieved. Figure 1 shows the overview of data collection.

Figure 1. Overview of data collection

For the two types of videos, 200 comments were randomly selected from each of the videos. This led to a set of 1,000 comments (200 x 5) for each of the two types of videos. Thus, a total of 2,000 comments (1,000 comments for educational videos + 1,000 comments for entertainment videos) were admitted for coding.

The coding scheme was adopted from the prior work (Madden et al., 2013). The category for spamming comments is removed in this study as spams may not be user generated and can cause noise within the data. Two coders were involved in the coding process that was done using two phases. In phase I, a subset of 200 comments from each of the two types of videos (thus, a total of 400 comments) was coded independently to establish for mutual agreement of the coding scheme between the coders. A Cohen's Kappa score of 0.7 was used as a threshold for the inter-coder agreement. Disagreements were resolved through discussion. Thereafter, in phase II, the remaining 1,600 comments (2000 - 400) were divided equally between the two coders to complete the coding process.

For the purpose of data analysis, Chi-square tests were employed. The analysis facilitated the examination of the association between the comment types and each of the video types.

4. RESULTS

Overall, a total of 2,000 comments from two YouTube video channels, educational and entertainment were coded. Chi-square test was conducted to assess whether the comments from the educational videos was different from that of the entertainment videos. The results of the test is reported according to the category scheme proposed by (Madden et al., 2013). Table 1 presents the percentage of each category and the chi-square statistic, comparing the comments for educational and entertainment videos. Table 1 presents the percentage of each category and the chi-square statistic, comparing the comments for educational and entertainment videos.

Comments in the Information category provided or requested objective or factual information about the content and context of the video. In this category, Information Request-type comments indicated significant difference between the two video types. Requesting information ($\chi^2(1, N = 2000) = 19.99, p < 0.001$) appeared more in the comments for educational videos than for entertainment videos. These comments were asked for details in terms of seeking information or explanation of something related to the video.

Comments in the Advice category either requested assistance or prescribed suggestions or recommendations on what to do in a particular situation. These comments were specifically requesting or giving individuals' judgements, and contained modal verbs such as "should" and "could." In this category, comments on requesting advice, giving advice, and recommending another video indicated significant difference between educational video and entertainment video. In particular, while comments on Requesting advice ($\chi^2(1, N = 2000) = 4.36, p < 0.05$) appeared more in the entertainment videos than in the educational videos, Giving advice ($\chi^2(1, N = 2000) = 8.66, p < 0.01$) appeared more in the educational videos than in the entertainment videos. Recommendation of another video ($\chi^2(1, N = 2000) = 19.40, p < 0.001$) were found more in the educational videos than in the entertainment videos. These comments were included under the category of Advice, because such comments can be interpreted as one person giving advice to another about which videos to watch.

Table 1. Percentage of comments for each category across video genres and Chi-square statistic

		Video Genres		N = 2000 df = 1	
		Edu	Ent	χ^2	Cramer's V
Information	Request***	3.60	0.70	19.99	0.10
	Make comparison	0.90	1.50	1.52	0.03
	Give (video content)	2.30	2.60	0.19	0.01
	Give (video context)	3.40	2.20	2.65	0.04
	Give (General)	4.90	6.90	3.60	0.04
Advice	Requesting	1.60	3.00	4.36	0.05
	Giving	7.00	4.00	8.66	0.07
	Recommending another video***	2.20	0.10	19.40	0.10
Impression	General***	0.90	6.10	40.03	0.14
	Positive	4.20	2.00	8.06	0.06
	Negative***	3.60	10.50	36.33	0.14
Opinion	Request ***	8.20	1.00	59.07	0.17
	Give (General)***	18.6	9.80	31.78	0.12
	Give (Positive)***	2.90	0.80	12.14	0.08
	Give (Negative)***	7.60	1.20	48.69	0.16
	Give (Mixed)	2.90	3.60	0.78	0.02
	Insult	2.30	1.20	3.52	0.04
	Compliment***	3.80	8.30	17.81	0.09
	Criticism	7.40	6.00	1.57	0.03
	Tribute	0.30	0.20	0.20	0.01
	Speculate	4.40	7.10	6.73	0.06
Responses	Agree	1.30	0.50	3.59	0.04
	Confirm	0.20	0.70	2.79	0.04
	Disagree***	3.10	0.50	19.12	0.10
	Challenge	0.80	0.90	0.06	0.01
Expression of personal feelings	General***	0.40	4.20	32.13	0.13
	Positive	2.30	2.40	0.02	0.01
	Negative	6.20	3.50	7.90	0.06
General conversation	Greetings	0.10	0.30	1.00	0.02
	Thanking***	2.70	0.40	17.33	0.09
	Joke	3.20	5.60	6.85	0.06
	Apology	0.08	0.10	5.47	0.05
	Reference to offsite communication	1.10	2.60	6.20	0.06
	Status description	2.10	0.40	11.71	0.08
	Anecdote***	8.10	0.60	67.60	0.18
	Random off-topic exclamation	1.20	0.10	9.34	0.07
	Request personal information	0.30	0.20	0.20	0.01
	Give personal information***	2.50	0.10	22.45	0.11
	Express plans/desires/wishes	4.60	3.10	3.04	0.04

***p < 0.001

Comments in the Impression category includes expressing short immediate that has positive, negative or general sentiment. These comments often contains paralinguistic features like emoticons and interjections such as “Yay!” and “Wow!”. Positive impressions appeared more in educational videos ($\chi^2(1, N = 2000) = 8.06$, $p < 0.01$) while negative impressions ($\chi^2(1, N = 2000) = 36.33$, $p < 0.01$) were mostly associated with entertainment videos. General impressions ($\chi^2(1, N = 2000) = 40.03$, $p < 0.01$) appeared more in the entertainment videos than the educational videos.

Comments in the Opinion category make request or offer viewpoint on a video, person, object or topic. Opinion comments do not encourage actions and contain explicit and subjective value judgements. Opinion requesting comments ($\chi^2(1, N = 2000) = 59.07$, $p < 0.001$) are more prevalent in educational videos. Opinion giving comments (general, positive and negative) appear more in educational videos while more compliments ($\chi^2(1, N = 2000) = 17.81$, $p < 0.001$) and speculations ($\chi^2(1, N = 2000) = 6.73$, $p < 0.05$) are found in entertainment videos.

Comments in the Responses category are comments that agree, confirm with evidence, disagree, or challenge with evidence the video content. Responses that disagree ($\chi^2(1, N = 2000) = 19.12, p < 0.001$) appear more frequently in educational video than entertainment video. No other responses differed significantly between the two types of videos.

Comments that express personal feelings include positive, negative and general emotional response or personal feeling that are neither positive nor negative. The chi-square test revealed significant difference for having more general responses ($\chi^2(1, N = 2000) = 32.13, p < 0.001$) in entertainment videos while education video garnered more negative personal feelings ($\chi^2(1, N = 2000) = 7.90, p < 0.01$). No significant difference was found between the two types of video for comments that expressed positive personal feeling.

Comments in the form of general conversation encompasses a wide range of comment types that initiate, maintain and terminate conversations. The results showed that educational videos have more comments than entertainment videos comments for thanking ($\chi^2(1, N = 2000) = 17.33, p < 0.001$), describing current status ($\chi^2(1, N = 2000) = 11.71, p < 0.01$), sharing anecdote ($\chi^2(1, N = 2000) = 67.60, p < 0.01$), providing personal information ($\chi^2(1, N = 2000) = 22.45, p < 0.01$) and moving into random off-topic exclamations ($\chi^2(1, N = 2000) = 9.34, p < 0.01$). On the other hand, entertainment video comments appeared more frequently than educational video comments that are joke ($\chi^2(1, N = 2000) = 6.85, p < 0.01$), apologies ($\chi^2(1, N = 2000) = 5.47, p < 0.01$) and refer to offsite communications ($\chi^2(1, N = 2000) = 6.20, p < 0.01$). There were no significant differences for greeting, request for personal information and expressing desire.

5. DISCUSSION

The following findings can be gleaned from this research. For educational videos, comments can be enriching in terms of requesting further information, recommending videos, expressing opinion, commendation, disagreement as well as sharing anecdote and personal information. Comments on educational videos requested more information compared with those on entertainment videos

To plug knowledge gaps, people tend to request or continue for more information until their need is satisfied (Peterson and Merino, 2003). This is evident in *Information Request-type* comments, which showed a significance difference across the genre of videos comments examined. Comments on educational videos shared more related resources compared with those on entertainment videos. When viewing a video with the intention to learn, sharing related resources for further information suggested more meaningful learning behavior (Barak and Rafaeli, 2004). In addition, comments on educational videos were more opinionated, both positive and negative, compared with those on entertainment videos. This suggested that the educational video comments tend to be more expressive. More perspectives on videos were sought, suggesting that educational video viewers are more open to initiate further discussion. Educational videos were used to convey information and for learning. Furthermore, possible discrepancy in educational videos had led to emergence of comments that disagreed with the content. Comments on educational videos tended to exhibit higher level of politeness and gratitude compared with those on entertainment videos. The comments found in educational video had shown to be more cordial and respectful. This study also suggested that educational video viewers were more willing to share personal information as well as content related information.

For entertainment videos, comments were enriching in terms of reflecting impression, compliments and expressing general sentiments. Comments on entertainment videos had more reflection of general and negative impression compared with those on educational videos. Viewers of entertainment videos expressed more impression formation and complimentary comments than those of educational videos. This suggested the appreciation of entertainment value for such videos. Entertainment videos are able to invoke more affective comments than educational videos. In summary, fourteen of the categories of comments showed statistical differences between the two genres of videos. This suggested that the different genres of videos garner different comments for specific comment categories.

6. CONCLUSION

This study examines differences in online comments between educational videos and entertainment videos on YouTube. By employing content analysis, it points out differences between comments for the two types of videos. The findings suggest that comments can be enriching in terms of requesting further information, recommending videos, expressing opinion, commendation, disagreement as well as sharing anecdote and personal information for educational videos. Furthermore, comments can be enriching in terms of reflecting impression, compliments and expressing general sentiments for entertainment videos.

This study has some limitations. The size of the dataset is limited to the randomly selected comments. The volume of comments needs to be increased substantially to facilitate greater generalizability. This study examined comments for two types of video resources obtained from two specific channels. Future investigation could include a list of possible channels to offer a more holistic treatment on the nature of the comments. The study is also limited by the inability to consider cultural differences between the video commenters as the profile of commenters is not captured.

This study has at least two implications. First, it extends the existing literature by distinguishing the video comments' categorical differences across the two genres. This calls further investigation of other video genres such as Sports, Virtual Reality, and News to refine the categorical framework for video comments on YouTube. Second, from the practical perspectives, this study can inform interface design strategies for the YouTube comment section across the different video genres.

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