Collaborative Learning in YouTube: Under Which Conditions Can Learning Happen or Fail to Happen?

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Abstract: *The present proposal presents two studies aiming to examine the conditions under which user engagement with YouTube videos related to climate change supports learning. Study I examined the context of interaction within the platform – threaded comments vs. independent comments. Study II, using machine learning, examined video content characteristics and presenters. Results showed that both video content characteristics and the context of interaction are related with learning. Threaded comments included more counterarguments and knowledge claims, compared with independent comments. Videos with scientists as presenters were more effective compared with videos with politicians or celebrities. Also, videos containing suggestions and solutions were the most effective, whereas videos containing blame for whose fault climate change were the least effective. Our findings show that YouTube has the potential to create communities of shared interest, with a shared commitment to solve a problem, making YouTube a promising platform to promote CSCL but also responsible citizenship.*

Social media tend to become the dominant mean of interaction. Yet, less is known on whether and under which conditions learning is taking place in the context of social networks in the wild. In two studies we examined popular videos on Climate Change (CC) and the comments posted publicly on YouTube. In study I we investigated whether there is evidence of discussion moves that have been associated with learning, such as counterarguments, as well as evidence of learning. In Study II, using machine learning, we examined which characteristics of the video – focusing on content and presenters – elicit discussions which promote learning.

Study 1

We examined comments of a popular video on CC ("Dear Future Generation: Sorry"), comparing comments posted independently with comments posted in the context of a thread. Each comment was coded by two coders regarding its function and its content (see Iordanou & Kuhn, 2020) to examine effective argumentive moves.

Results

The majority of the threaded comments, 86%, were interacting with other comments in the discussion. In the independent comments we found a statistically lower engagement in constructing a counterargument (4%) compared to the threaded comments (29%) (X^2 (1) = 6.250, p = .023). Regarding the content of the comments, the threaded comments included more knowledge claims that have not been presented in the video, (81%) and that were about solutions, compared with the independent comments (Fisher's Exact Test, $p < .05$).

Study 2

Study 2 involved an automated analysis of social-media video's impact on viewers' knowledge, beliefs, and behaviour. Previous metrics for this analysis, such as video virality, number of views and likes/dislike are limited indicators of this impact on viewers attitudes, knowledge and behaviour. Our methodology employed Natural Language Processing (NLP) and machine learning (ML) on thousands of comments to YouTube videos on CC. We focused on explainable methods which could shed light on the features that promote learning.

The dataset included 168 YouTube videos on CC, which had at least 100 comments/replies in English. The commenters' usernames were anonymised during data analysis. Metadata was automatically acquired, indicating whether a comment related to the video or was a reply to another comment and the number of likes on the replies to the comment. A label of *effective* or *ineffective* label was assigned for each video, where one is ineffective, two is neutral and three is effective. This label computation was based on popularity scores, i.e. likes/dislikes numbers, the number of replies it induced, and detection and ranking of topics mentioned in the video's comment An *effective* label induced agreement with the negative effects and dangers of CC and/or expressed the need for change in human behaviour. An *ineffective* video objected to CC or its effects, did not address the topic of CC or did not express an opinion on the topic. A *neutral* video label was assigned when comments did not clearly agree nor disagree that the effects of CC are real and/or on the need for human behaviour change. An independent manual coding of a sample from the comments validated the reliability of the labels.

NLP and sentiment analysis algorithms transformed the raw comments data to a structured form that channels the analysis to words in the sentence which are likely to carry pertinent information. The structured text was processed into features for the ML, from textual/semantic, i.e. n-grams - sets of n consecutive words, to numeric, i.e. number punctuation marks and emojis. A logistic-regression ML classifier was trained and predicted effective or non-effective videos labels the test (unseen) dataset. The training and test sets, 755 and 25% of the dataset, respectively, were balanced to include a similar distribution of ineffective and effective videos. The prediction evaluation included accuracy and F1-Score.

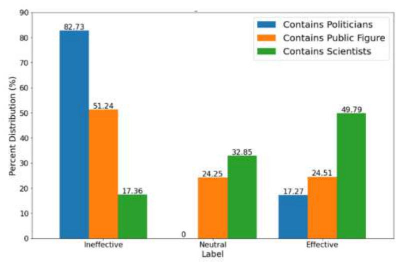
A preliminary explanatory analysis on the attributes of the videos included three-categories coding for videos presenters: politicians, high-profile public figure - business leaders (i.e. Bill Gates), social media personalities, and scientists, and three-categories coding of video styles: videos explicitly *blaming* an entity, i.e. a political party or country, videos suggesting *solutions* to the problem, and videos stating the *effects* of CC. The frequencies of the videos in each category for the effective and ineffective labels were calculated.

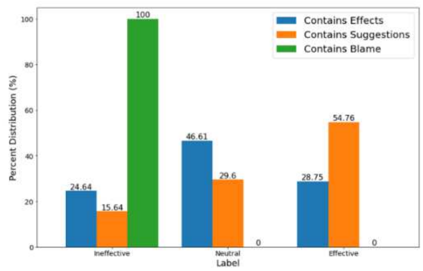
Results

The ML yielded an accuracy of 78.57% and an F1-Score of 78.46% for prediction of effective and ineffective labels. Fig. 1 depicts the distributions of the two video attribute types in effective, neutral and ineffective videos. The classification accuracy indicated a feasibility to automatically study effectiveness of online videos in an explainable manner. Fig. 1a suggests that scientists are more effective presenters and politicians the least effective presenters. Fig. 1b suggests that blame in the videos is not effective, and that videos containing suggestions for solutions to the problem are more effective than videos containing only narration on the effects of CC.

Figure 1

a. Distribution of politicians, public figures and scientists on video effectiveness, b. Distribution of effects, suggestions and blame on video effectiveness.





Discussion

Our results showed that both video characteristics and the context of interaction in YouTube are related with learning about CC. Social interaction taking place in threads is a more facilitative condition for learning, compared with individual comments. Regarding *video attributes*, videos of politicians were ineffective, whereas videos of scientists were the most effective ones. Regarding video content, videos containing direct blame for whose fault CC is, were ineffective, whereas videos containing suggestions and solutions yielded a 54.76% effectiveness.

This novel, yet preliminary study shows the potential of YouTube platform to promote CSCL, especially on a topic of global concern, such as CC, and at the same time points to the need for further research to examine the conditions under which learning can happen or fail to happen in social networks.

References

Iordanou, K. & Kuhn, D. (2020). Contemplating the opposition: Does a personal touch matter? Discourse Processes. 57(4), 343-359.