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An Analysis of Interaction and Engagement in YouTube Live Streaming Chat

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Abstract—**Live streaming is a popular social media platform. Most live streaming services allow viewers to interact with each other and the broadcaster via text chat. Thus, exploring user behavior and chat communication within a live streaming context is increasingly important. In this paper, we explore YouTube general live streaming chat. We extracted a corpus in the political domain from Trump's 2020 presidential campaign in the United States. Then, using advanced Natural Learning Processing (NLP) algorithms, we examined users' behavior in live chats. We focused on three elements of YouTube user behaviour: chat content, commentators' behaviour, and user engagement evoking factors. We observed that the chat messages are very emotional. They include a lot of emojis, some of which are domain-depended. Almost all messages express sentiment and the positive sentiment outweighs the negative. Abusive language is very common in the messages. However, while heavy users express more sentiment, the tend to use less abusive language. Although it is difficult to know exactly what was said in the video that caused the engagement of the chat participants, using a topic model, we were able to show that sarcasm evokes involvement.**

1. Introduction

Live streaming is a rising social media medium. The majority of live streaming services enable viewers to connect with one another and with the broadcaster through text chat. Thus, it becomes increasingly important for the Human-Computer Interaction (HCI) community to explore users' behaviour and chat communication in a live streaming context.

There are two types of social live streaming services: general live streaming services which are not limited to any theme, such as YouNow, Facebook live, YouTube live, or IBM's Ustream, and topic-specific live streaming services, such as Twitch (video games), or Picarto (art). Much research and many experiments on topic-specific live streaming services have already been carried out, but there are few scientific studies on general streaming services. Therefore, in this paper, we focus on a general streaming service, YouTube live.

Not much research has been done on YouTube live chat messages. Machine Learning (ML) algorithms for spam detection were applied [1] and in a preliminary study, a clustering method for learning emotional cognition was used [2]. With the growing interest in NLP over the past years, useful and efficient tools have been developed and it is now possible to perform a deeper computational analysis of user behavior in YouTube live chat.

The YouTube corpus that we have collected is political. It consists of videos from Donald's J Trump campaign in the 2020 United States presidential elections. Each speech was an hour in average with an active live chat. We analysed the users behavior in the live chats using advanced NLP algorithms for Name Entity Recognition (NER), sentiment analysis, toxic (a.k.a abusive) comment classification and topic modeling.

We experimented three aspects of YouTube user behavior. First, we examined the chat message content, focusing on main message characteristics features, such as word count, emoji usage, sentiment, and abusive word usage. Second, we analysed the commenting users behaviour and observed that while most of the commentators commented only a few times, there was a small group of heavy users with more than a thousand comments each. Thus, we further investigated the differences between these two groups. Third, we explored possible factors that encourage users to actively participate in the live chat.

Our user behaviour analysis reveals that even though the chat comments are short, they are very emotional. There is a massive use of emojis, some unique to the domain or the platform, and there are almost no neutral comments. The dominant sentiment is positive. However, there are a lot of offensive comments. Generally, the heavy users express more emotional involvement, but use offensive language less frequently. The interaction between the chat participants is very low. Even though, it is difficult to find what in the content of the video evokes more involvement in the chat conversation, the topic models revealed some interesting findings.

This paper is organized as follows: Section 1 is the introduction, in Section 2, we describe related work on topic-specific and general live streaming chat. In Section 3, we describe the political dataset of our use case. Subsequently,

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in Section 5, we detail our results and in-depth analysis. Finally,in Section 6, we summarize the primary findings and suggests future research directions.

2. Related Work

2.1. Topic-specific live streaming chat

Topic-specific live streaming chat has been widely investigated. Most of the studies have been focused on Twitch, one of the largest live streaming platforms for games. Numerous experiments have been undertaken in order to comprehend the use, effect, and challenges of this emerging form of media. Several articles explore the platform's social, cultural, and economic dynamics [3], [4], [5], [6], [7], media and community-based ramifications [8], [9], [10] and language [11], [12]. However, recently, a few publications use Machine Learning (ML) approaches and Natural Language Processing (NLP) techniques to manage chat and engage data automatically [11], [13], [14], [15], [16], [17], [18].

Barbieri et al. [14] explored two main tasks unique to the Twitch platform: emote (emoji-like images) prediction and trolling detection. kobs et al. [11] examined the suitability of emotes as emotional markers to perform sentiment analysis on Twitch comments and Reis [13] developed a rule-based sentiment analysis model to interpret user chat messages.

Nakandala et al. [15] examined how the gender of streamers is associated with the nature of conversation over one billion Twitch chat messages. They found that female streamers receive significantly more objectifying comments while male streamers receive more game related comments. Geo et al. [16] demonstrated an online chat room for offensive expression detection. They employed transfer learning from Twitter to video live streaming posts on Twitch and filtered out offensive expressions via three modes: hide, replace, and alert. Additional efforts were made by Ringer ell al. [17] who introduced a large-scale live stream chat dataset with a case study analysis of word vector methods applied to the dataset.

Last year, an ECML-PKDD discovery challenge 2020, called Chat Analytics for Twitch (ChAT) was introduced. Koos et al. [18] defined the task of subscription prediction for Twitch as follows: "Given the chat messages of a user in a channel on Twitch (including metadata such as timestamps and the currently streamed game), predict whether or not the user is subscribed to the channel". Four teams submitted their systems. All of them applied ML algorithms, but modeled the input data differently.

2.2. General live streaming chat

In 2016, Scheibe et al. [19] recognized the lack of studies on general live streaming services. They used YouNow as a case study to apply analysis regarding information behavior on social media to general social live streaming services.

Since then, little research has been done on general live streaming platforms in relation to what has been done on topic-specific live streaming platforms. Lykousas et al. [1] investigated the creation and distribution of adult content in two famous live streaming services, LiveMe and Loops Live, which have millions of users and produce large volumes of video content on a regular basis. Two large datasets were created by crawling the social graphs of these platforms and broadcasters of adult content were identified using a pre-trained deep learning model. Lykousas et al. findings show that existing moderation mechanisms are inefficient at suspending those users' accounts.

Later, Lykousas and Patsakis [20] discovered predatory behavior and grooming on chats that eluded LiveMe's moderation mechanisms. In addition to conventional text approaches, they examined the use of emojis in this context, and also user interactions through LiveMe's gift mechanisms. Lykousas and Patsakis research revealed the risk of grooming of minors and demonstrated the scope of the issue on those platforms.

2.2.1. Youtube live. Pires and Gwendal [21] introduced a dataset that can help researchers gain a clearer understanding on the behavior of user generated content live streaming videos services. They compared Twitch and YouTube and pointed out differences between them. However, while Twitch attracted a lot of research attention in recent years, less research has been carried out on YouTube live.

Guo and Fussell [2] conducted a preliminary study on emotional contagion in live streams using archived YouTube live video transcripts and associated live chat messages. They discovered that sentiment in live video oral transcripts and text chat between viewers is related to sentiment in subsequent viewer comments. The association between viewers' chat messages and subsequent chat is greater than the association between oral messages in the video and subsequent chat. In certain live streams, however, negative sentiment in the live video is accompanied by less negative chat.

Recently, in order to explain spammers' behavior, Yousukkee et al. [22] explored YouTube live streaming comments. They examined seven users behavior features and message characteristic features and found that, the relevant score, the time spent in live chat and the number of messages per user performed best in terms of run time and classification efficiency. Yousukkee et al. concluded that the best ML method for real-time classification is a decision tree.

A year ago, Munger and Phillips [23] recognized that there exist little quantitative social science research on the political content on Youtube and suggested a "supply-and-demand framework" for analyzing politics on YouTube. They first addressed a variety of novel technological capabilities of YouTube as a platform and as a compilation of videos. Then, they described an extensive quantitative information on the supply and demand of alternative political content on Youtube and showed that the number of people watching far-right videos peaked in 2017.

In this paper, we analyse user behaviour in YouTube live chat using NLP methods. The domain of our chats is political. For compatibility, we also provide valuable quantitative information presented in previous works.

3. Use Case: Political Domain

As mentioned before, our work was done in the political domain. In the recent years, political promotions through YouTube became more and more popular as the social impact YouTube can cause became evident. Our corpus was taken from Donald's J Trump campaign in the 2020 United States presidential elections. we have collected around 280 videos from Trump's official YouTube channel featuring Trump's promotional speeches. Each speech was an hour in average with an active live chat. We took the chat's text with a total of 7,861,920 words and the speech transcription generated by YouTube's voice recognition feature. The corpus is publicly available in https://bit.ly/YouTubeLiveStreamingChat

4. NLP Methods used in this research

Our main objective in this research is to demonstrate the use of NLP methods on a general live streaming service. These methods are used in order to solve different problems when analysing raw text.

4.1. Name Entity Recognition (NER)

NER as its name suggests, is the problem of recognizing name entities such as people names, places, organizations and quantities in the text. For example, in the following sentence: "Robert drove his car from the new US Embassy in Jerusalem to his home" the name entities are "Robert", "the US Embassy" and "Jerusalem". Each of these entities is classified as a person name, an organization and a location respectively. The NER problem is actually composed from two sub-problems. The first step is to recognize the name entities in the text and the second step is to classify them. In our research we wished to find the dominating entities in the comments. The tool we used to solve this problem is called "spaCy" [1] and it uses a machine learning statistical model.

4.2. Sentiment analyses

Sentiment analyses is the problem of recognizing and categorizing feeling and emotions in text. Specifically, we wanted to classify the live chat comments as positive or negative. To achieve that, we used a pre-trained model - "distilbert-base-uncased-finetuned-sst-2-english" [24] from Hugging Face's open-source framework Transformers[2]. The model returns a score for each of the comments from 0 to 1. A score close to 0 is very negative, and a score near to 1 is very positive.

1. https://spacy.io
2. https://huggingface.co/transformers/quicktour.html

4.3. Abusive content identification

Another problem we needed to solve is the identification of abusive/toxic comments in the live chat. For this problem as well we used Hugging Face's open-source framework Transformers[3]. We used a model built by Laura Hanu[4] at Unitary[5]. The model predicts how much the comment is 'toxic', 'severe toxic', 'obscene', 'threat', 'insult' and 'identity hate', giving each a probability percentage grade. However, we used a binary threshold such as any comment with a score higher than the threshold will be considered offensive.

4.4. Topic modeling

Topic modeling is another well known subject in the NLP field. The purpose of a topic model is to identify the abstract topic for a given raw text. The model is suppose to divide the given text into topics by clustering similar repeating words into different groups. Therefore, for example, words such as "virus", "vaccine" and "pandemic" are expected to appear in comments about COVID-19, thus the model should categorize those comments as the same topic. In our research, we used the LDA (Latent Dirichlet allocation) model [25]. Using the Gensim[6] [26] python library for topic modelling, we trained an LDA model. Given raw text, the model outputs groups of words which we can recognize as different topics.

5. YouTube Live-chat

In this section, we examine three aspects of YouTube users behavior: the content of the chat message, the commentators behaviour, and the factors that evoked the viewers engagement.

5.1. Chat content

To give a clear picture on our data, we first detail the main message characteristics features. On average, there are 5.45 words per message. 34.84% of the messages are mostly written in upper case letters, probably to attract the eye of other participants and/or to indicate strong feelings.

We examined whether there was any interaction between the chat participants during the broadcast by counting the *@mention* number of appearances in the messages. Only 1.21% of the messages included mentions of participants. This implies that the discourse between the participants was either limited or implicit.

To check whether there was a discussion on a particular person that may have been present or mentioned in the

3. https://huggingface.co/unitary/toxic-bert
4. https://laurahanu.github.io
5. https://www.unitary.ai
6. https://radimrehurek.com/gensim

video, we used NER. 425,970 mentions of persons were recognized. We illustrated the prominent ones by a word cloud[7] in Figure 1. Unsurprisingly, the presidential candidates, Joe Biden and Donald Trump, are the most frequently mentioned persons in the chats. But, other politicians, such as, Nancy Pelosi, Mike Pence, Kamala Harris and Hillary Clinton, are frequently mentioned too. Additional highly refereed persons are Biden's son Hunter as well as the billionaire philanthropies, Bill Gates and George Soros.

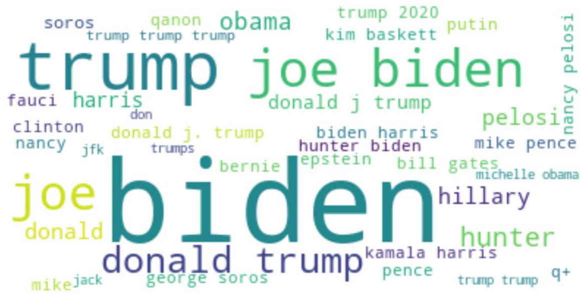

Figure 1. a word cloud of the prominent personalities in our dataset

Next, we analysed the emotional involvement of the users in the chat. There is a massive use of emojis in our dataset. On average, each video consists of 1024.37 messages with at least one emoji. The average number of emojis per video is 6765.37. Most of the messages with emojis include more than one. Since emojis are often used to express feelings, we calculated their distribution in the chat messages. Table 1 shows the ten most frequent emojis in our dataset.

TABLE 1. THE TEN MOST FREQUENT EMOJIS IN OUR DATASET

Image	Emoji	Frequency
❤️	red_heart	245184
💙	blue_heart	129240
❤️	red_heart_selector	127762
👍	thumbs_up	76072
🙏	folded_hands	43206
😂	face_with_tears_of_joy	38553
👏	clapping_hands	38309
🤮	face_vomiting	31600
🌊	water_wave	30186
❤️	heart_suit_selector	28606

Compared to frequent emojis in other social media platforms, such as Twitter [27] and Facebook [28], some of the slightly unusual emojis in our dataset are the 'face vomiting' emoji and the 'water wave' emoji. After looking at word clouds around the 'face vomiting' emoji it seems this emoji is directed mostly toward Biden expressing disdain. Looking at the word cloud around references of Biden also resulted in 'face vomiting' being the dominant association. However, the 'water wave' emoji was caused by some users spamming the emoji, with the intention to support Trump when the meaning was along the lines of "Ride the Trump wave". Also, The three most frequent heart emojis were mostly directed towards Trump. Obviously, since this is a dataset of Trump's campaign, these results are not so surprising.

We also classified the polarity of chat messages aiming to examine whether the expressed sentiment in the message is positive, negative, or neutral. We observed that 54.2% of the messages are positive, 45.69% are negative and the rest (0.11%) are neutral. It is impossible to deduce the prevailing political opinion from the data since the content can refer to political opponents. However, without any doubt, the content is very emotional.

Even though, YouTube provides ways to weed out irrelevant, inappropriate, or offensive comments, it seems that in our dataset none of the precautions were taken. The first way to avoid offensive comments is to assign moderators. moderators can interact with the viewers, remove offensive comments, and flag, hide, or put users into timeout. Another way is to create a block word list. Comments with those word will not show up in the chat. The last feature YouTube provides is to identify potentially offensive messages and to hold them from the chat until the broadcaster will view them and decide whether to approve or not. From the amount of the offensive comments we detected, it seems non of those methods were used. Figure 2 shows the percentage of abusive messages in our dataset for different thresholds. The algorithm classified 25.1% of the messages as abusive using its score threshold for binary classification (0.5). But, even if we tighten the classification criterion and require a higher score (0.9) in order to classify a message as offensive, we will still have 21.5% messages with offensive content.

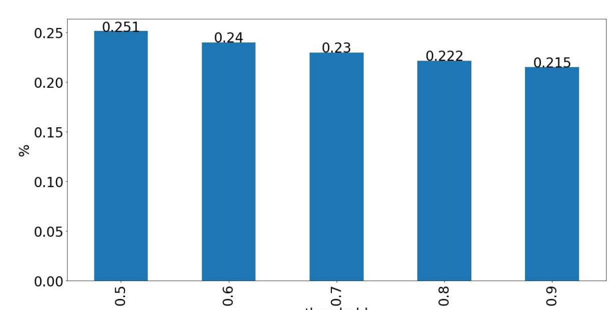

Figure 2. The percentage of abusive messages in our dataset for different thresholds.

5.2. Chat users

In our live chat dataset of 278 videos, there were 156,300 commentators. The average commentators and messages per video were 918.53 and 5095.66, respectively (one comment

7. word cloud is a visual representation of words that give greater prominence to words that appear more frequently.

per 1.38 seconds). For comparison, the average number of live viewers per video is 46,481.66.

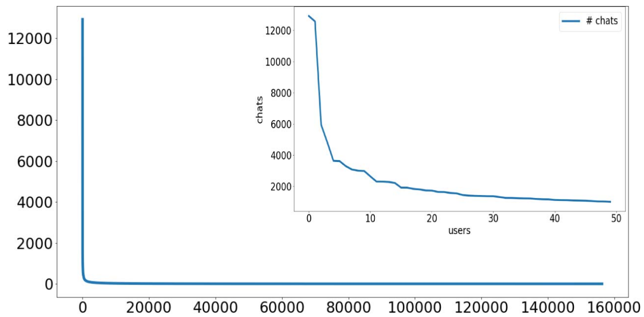

Figure 3. The number of comments per commentator sorted by the comments number.

Figure 3 shows the number of comments per commentator sorted by the comments number. Most of the commentators commented only a few times and there are just a few heavy commentators. The small inner graph presents the same information on the heavy commentator group of the top-50 commentator with more than 1,000 comments in the datset. The trend in the inner graph is similar to that of the general graph. While the average comments per user in general is 9.22 (the median is 2), the average in the heavy users group is 2,312.48 (the median is 1508).

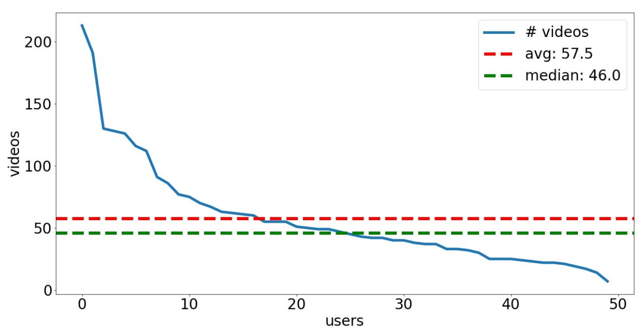

Figure 4. The number of videos each of the top-50 commentators commented on.

Next, we analysed the heavy users behavior. In Figure, 4 we present the number of videos that each of them commented on. The most active user commented on 213 of the videos (76% of the videos) with 12,980 comments!

We tested whether the heavy commentators behaved differently than the other commentators based on the message characteristic features that we identified in the previous section. Table 2 summarize our main findings. An asterisk indicates a statistically significant difference according to the two-sided population proportions test at the 0.01 level.

The heavy commentators use more emojis and uppercase letters. They tend to mention more names of persons and generally express more positive emotion. Abusive language is less common in the heavy commentators group. Perhaps their frequent use of the platform makes them more aware of what is allowed and what is not allowed to be expressed on the social network.

TABLE 2. A COMPARISON BETWEEN THE TOP-50 COMMENTATORS WITH THE REST OF THE COMMENTATORS

Feature	Top-50 (%)	Others (%)
Comments with Emojis *	27.64	19.45
Uppercase comments *	43.51	34.09
Comments with @*mention*	1.23	1.21
PERSON name entity (NER) *	32.78	29.83
Negative comments (Sentiment Analyzer) *	42.42	45.98
Abusive comments *	17.7	21.82

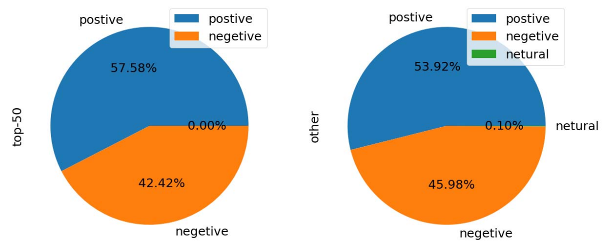

Figure 5. A comparison between the sentiment distributions of the top-50 commentators with the rest of the commentators

Figure 5 illustrates the differences between the sentiment distributions of the heavy users and the rest of the users. Even though, the shape of the distribution is similar, the proportion of the positive comments in the top-50 group is significantly higher than the proportion of the positive comments in the other group.

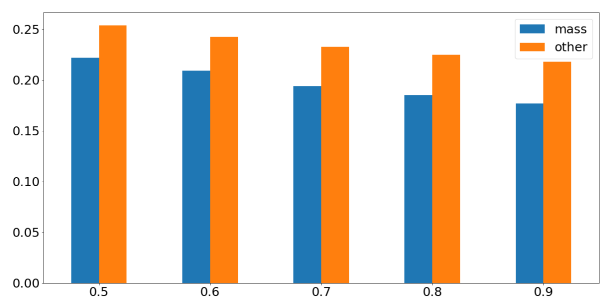

Figure 6. A comparison between the sentiment distributions of the top-50 commentators with the rest of the commentators

Figure 6 shows a comparison between the detected abusive comments of the two examined groups. There is a notable gap between the groups for all the tested thresholds. The gap increases as we raise the threshold value and require the algorithm to get a higher abusive score in order to classify a comment as abusive. As we mentioned before, this difference is a statistical significance.

5.3. Users engagement in chat

After modeling the data into a graph featuring the number of chat comments per time frame, we were interested in discovering what aroused the spikes on the graphs. Figure 7 is an example of such a graph for a single video.

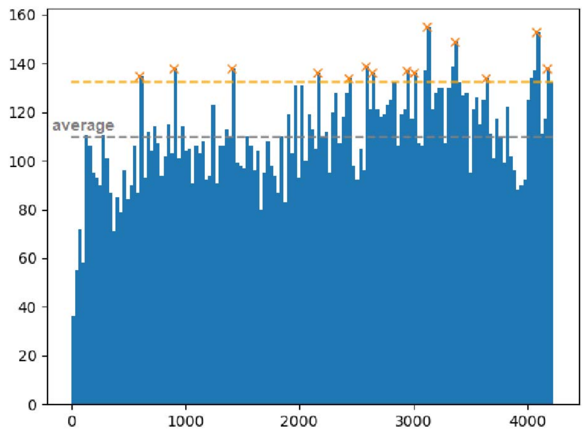

Figure 7. The number of chat comments per time frame (for a single movie).

At first, we searched for special tags in the transcriptions such as [applause] or [music] generated by YouTube's voice recognition and looked for increased activity in the chat around the same time frame. After comparing it to the normal average we have concluded that the result's significance level was not particularly high. Our next step to find the arousing causes was to identify the spikes in the graph and then to use topic models to compare the speech transcription at those peaks to the rest of the corpus.

We ran the LDA topic model on the peaks' speech transcriptions with $k=10$ (number of topics). Figure 8[8] illustrates the algorithm's results. Even though, we asked for ten topics, there are actually only three distinct topics.

We repeated the same procedure for the complete dataset and observed four distinct topics, as presented in Figure 9. Thus, we concluded that there are hot topics which are more attractive and make the participants more involved.

To better visualize the topics, we re-ran the topic model with $k=3$ and $k=4$ for the peaks' speech transcriptions and the complete dataset, respectively. Whereas, the four topics of the complete dataset were not coherent, the topics of the peaks' transcriptions were much better. Figure 10 illustrate the topics and their word clouds. Topic 3 is unique to the peaks' transcriptions. Joe Biden is dominant in topic 3, but does not appear in any of the word clouds of the complete dataset. It implies that when you mention your opponent, it evokes a reaction. It can be noticed that the surrounding words of Biden are positive, e.g., great, right, and well. Apparently, it is a kind of sarcasm. Trump said good words on Biden but meant the opposite of what he said. Using an NLP tool, we were able to recognize that sarcasm evokes user engagement.

8. Figures were generated using https://pyldavis.readthedocs.io/

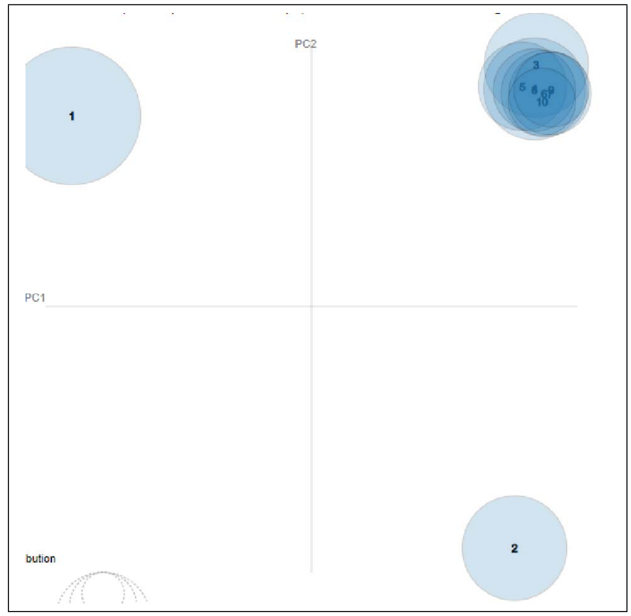

Figure 8. LDA topic model on the peaks' speech transcriptions with $k=10$.

Figure 9. LDA topic model on the complete dataset with $k=10$..

6. Conclusions and Future Work

YouTube can be a rich source for ML and NLP studies. As the second most visited site in the world, with a staggering amount of content uploaded every hour in a variety of contents, YouTube holds the potential to be a source for much more research. We have shown different approaches to use NLP tools to analyse and deduce results. Specifically

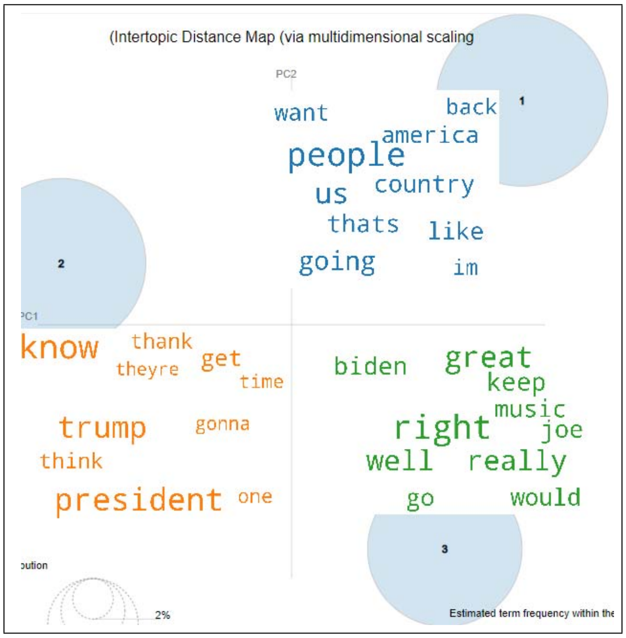

Figure 10. LDA topic model on the peaks' speech transcriptions with *k=3*, including word clouds.

in our dataset, at the comments content domain we have seen the dominating entities, the lack of discourse deduced from the lack of *@mention* tags, the viewers emotional attitude towards each of the competitors (red hearts signaling love towards Trump and vomiting faces signaling disdain towards Biden), and the heavy use of uppercase letters to draw attention. At the commentators behavior area, the sentiment analysis showed that the absolute majority of the commentators are very emotional, and that more then fifth of the commentators with a threshold of 0.9 are offensive.

We have also seen the differences between the heavy commentators and the rest of the commentators. Specifically, we found at a 0.01 significance level that the heavy users use more emojis, uppercase letters, mention more people's names, and that they are generally more positive and less offensive. In search for what evokes the users reactions, we used the LDA model to find the differences between topics at the peaks of the comments per time frame graph, and the complete dataset. Our results implies that mentioning opponents tends to evoke reaction from the viewers.

We believe more work can be done in this field and specifically in our dataset. We plan to investigate the live chat topics as well with the LDA model, and compare it to the topics found in the transcriptions to extract new results. We are also interested in investigating the heavy users specifically, to detect more specific behavior patterns that we might be able to predict.

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