Infodemics on Youtube: Reliability of Content and Echo Chambers on COVID-19

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Abstract

Social media radically changed how information is consumed and reported. Moreover, social networks elicited a disintermediated access to an unprecedented amount of content. The World Health Organization (WHO) coined the term infodemics to identify the information overabundance during an epidemic. Indeed, the spread of inaccurate and misleading information may alter behaviors and complicate crisis management and health responses. This paper addresses information diffusion during the COVID-19 pandemic period with a massive data analysis on YouTube. First, we analyze more than 2M users’ engagement in 13000 videos released by 68 different YouTube channels, with different political bias and fact-checking indexes. We then investigate the relationship between each user’s political preference and her/his consumption of questionable/reliable information. Our results, quantified using information theory measures, provide evidence for the existence of echo chambers across two dimensions represented by the political bias and by the trustworthiness of information channels. Finally, we observe that the echo chamber structure cannot be reproduced after properly randomizing the users’ interaction patterns.

Keywords: Infodemics, Social Media, Youtube, Misinformation

1 Introduction

The case of the COVID-19 pandemic made explicit the critical role of information diffusion during critical events. A relevant example was the massive amount of uncertain information shared by the media to justify the withdrawal of one AstraZeneca vaccine batch, which led to a dramatic lack of trust in it. At the very first stages of the COVID-19 pandemic, the World Health Organization (WHO) defined infodemics as “an overabundance of information - some accurate and some not - that occurs during an epidemic” [1]. Other definitions stressed the element of disinformation spreading rapidly through social media platforms and other outlets [2]. The information ecosystem radically changed with the advent of social media platforms as they implement algorithms and interaction schemes to maximize user engagement. Those algorithms account for users’ preferences and may significantly alter social dynamics and information diffusion [6].

We need to understand how people seek or avoid information and how those decisions affect their behavior [3] when the news cycle — dominated by the disinter-mediated diffusion of content — significantly alters how information is consumed and reported on.

This corresponds to investigate what is called social contagion, i.e., the spread of ideas, attitudes, norms, or behavioral patterns from individual to individual through social influence, imitation, and conformity. Social contagion depends on users’ attitudes, tendencies, and intentionality. In general, users tend to select the information they like the most and ignore statements dissenting from their worldviews [7] [23]. Our attention span is limited [4] [5] and feed algorithms might limit our selection process by suggesting content similar to those we are usually exposed to [13] [15]. Furthermore, users show a tendency to favor information adhering to their beliefs and join groups formed around a shared narrative, that is, echo chambers [7] [16] [17] [18] [19] [20]. Echo chambers are environments in which users’ opinion, political leaning, or belief about a topic gets reinforced due to repeated interactions with peers or sources having similar tendencies and attitudes. Selective exposure [21] and confirmation bias
(i.e., the tendency to seek information adhering to preexisting opinions) play a pivotal role in the emergence of echo chambers on social media [7, 20, 23, 24]. In this work, we follow the definition of echo chambers provided in [6] to understand the users’ attention patterns on YouTube during the COVID-19 pandemic. According to some studies, YouTube is playing a prominent role in the radicalization of opinions [10, 25, 26] and in the diffusion of questionable (i.e., poorly fact-checked) content being one of the most visited online domain and information retrieval platforms. Our dataset contains 10M comments relative to the videos published from 68 prominent information channels on YouTube in a period ranging from December 2019 to September 2020.

In more detail, we analyze users engagement, in terms of comment posted by the users, on videos produced by YouTube channels with a known political bias and fact-checking index. We then investigate the relationship between users political preferences and their consumption of questionable/reliable information. We start by introducing some preliminaries used throughout the article. Then, we explain how we categorize YouTube channels in order to obtain their bias in the political dimension and their reliability in terms of information produced and disseminated. Then, we investigate the relationship between the users political preferences and their consumption of questionable/reliable information. Finally, we analyze the relationship between the preferences of users with respect to those expressed by other users connected to them in the social network finding that echo chambers exist on YouTube across the political and fact-checking dimensions.

2 Related Works

The spread of misinformation and disinformation online is one of the most studied topics of the last few years. In general, the issue has been investigated on multiple platforms, both mainstream ones (e.g. Twitter) and niche ones (e.g. Gab) [7, 8, 9, 13]. A 2018 study [11] limited to Twitter claimed that fake news travels faster than real news. However, a multitude of factors affects information spreading on social media platforms. Online polarization, for instance, may foster misinformation spreading [7, 12]. The range of topics covered when investigating the study of misinformation is also vast, including politics, science, and medicine, among other societal issues. Very few studies investigated the problem of misinformation diffusion on YouTube and mostly in recent times. Indeed, research on online social systems disregarded YouTube concerning other social media platforms (such as Facebook or Twitter) despite its general use by the general audience [41]. Among the possible reasons for this underestimation (especially in the scientific literature), users’ potential anonymity (especially for what concerns comments below videos) and the impossibility to retrieve friendship networks and, to some extent, interaction networks.

One of the main aims of scientific research concerning YouTube is devoted to understanding such a platform’s role in exacerbating users’ opinions through its algorithm of video recommendations. This strand of research was fueled by several news articles that were claiming the radicalizing role of YouTube and its role in disinformation spreading [32, 33, 34]. However, despite the presence of an algorithmic effect, that is common in many social media platforms [9], the role of YouTube in creating rabbit holes, i.e., loops of extreme/questionable contents reinforced by the algorithm and by individual choices in a sort of vicious circle, is still strongly disputed [35, 36, 37, 38, 39, 40]. Nonetheless, regardless of the algorithmic bias, recent work found evidence of political polarization [13], hate [47] and echo-chambers [10] on YouTube, thus confirming, to some extent, the fact that users tend to aggregate and reinforce common opinions concerning polarizing topics.

Another relevant strand of research involving YouTube concerns its role in the diffusion of health-related information and the consequences that disinformation may pose for people’s health. The medical community has therefore conducted several studies on relevant topics such as vaccines [44], cancer [45] and also COVID-19 [42, 43]. However, such studies suffer from limitations related to shallow volumes of analyzed data, which is very limited in providing a detailed picture of online information consumption patterns. Differently, a recent work [15] investigated the problem of the infodemic (at its early stage), including YouTube among other platforms using a representative sample of 7M comments, finding that YouTube amplifies questionable sources less than the other mainstream platforms.

So far, no studies have provided evidence about echo chambers on YouTube concerning medical issues and especially about the COVID-19 pandemic.
3 Preliminaries and Definitions

In this section, we introduce our dataset and some operational definitions used in the analysis.

3.1 Dataset

We consider more than 10M comments of more than 2M users on 13000 videos published by 68 YouTube channels directly linked to news outlets. Table 1 contains a breakdown of the dataset. We collected videos using the official YouTube Data API, searching for videos that matched a list of keywords, including the terms (coronavirus, nCov, corona virus, corona-virus, covid or SARS-CoV).

An in-depth search was then performed by crawling the network of related videos as provided by the YouTube algorithm. We filtered the videos that matched our set of keywords in the title or description from the gathered collection. Finally, we collected the comments received by those videos.

| Users | Videos | Channels | Comments | Period (y/m/d) |
|-------|--------|----------|----------|---------------|
| 2092817 | 12933 | 68 | 10968002 | 2019/12/2 - 2020/9/5 |

Table 1: Data breakdown of the dataset.

Using the data provided by Media-Bias-Fact-Check (MBFC), an independent fact checking agency, we assigned a Political leaning index and a Fact-checking index to each YouTube channel. MBFC provides such indexes for news outlets and we assume that they are inherited by their official YouTube channels. The first index provides a score for the channel’s bias in the political dimension (i.e., its political leaning), while the second represents the factual reporting level of the news published from it. For instance, considering the YouTube channel of Breitbart (a popular far-right news outlet), MBFC assigns to it a political leaning corresponding to Extreme right and a Factual reporting index corresponding to Mixed. Specifically, we assign the values reported in Table 2 and Table 3.

| Label | Extreme left | Left | Left-center | Center | Left-right | Right | Extreme right |
|-------|--------------|------|-------------|--------|------------|-------|---------------|
| Political leaning | -1 | $-\frac{1}{3}$ | $-\frac{1}{3}$ | 0 | $\frac{1}{3}$ | $\frac{2}{3}$ | 1 |

Table 2: Political bias indexes associated to each channel using MBFC.

| Factual reporting | Very low | Low | Mixed | Mostly factual | High | Very high |
|-------------------|----------|-----|-------|----------------|------|-----------|
| Fact-checking     | 0        | 0.2 | 0.4   | 0.6            | 0.8  | 1         |

Table 3: Fact-checking indexes associated to each channel through MBFC.

In Figure 1 displays some general features of our dataset.

3.2 Methods

An echo chamber can be defined as an environment made up of users sharing a similar opinion, belief, or political leaning. The views of each user get reinforced due to the repeated interactions with users sharing the same ideas. We quantify the strength of the preferences of YouTube users by means of their engagement (specifically their comments) on videos. Consider a user $i$ commenting a number $n_i$ of videos, each of them having a particular political leaning $b_i$ inherited by the channel that has published it. We define the political bias of user $i$ as

$$p_i \equiv \frac{1}{n_i} \sum_{j=1}^{n_i} b_j .$$

(1)

This index represents an average of the channel’s political leanings on which user $i$ comments and therefore provides information about the user’s political preference/bias.
Figure 1: (a) statistics about the political bias of the channels, (b) statistics about the factual reporting of the channels, (c) density of comments per user (only users with at least 10 comments were considered), (d) density of videos per channel.

Similarly, each video has a fact-checking index $f_i$ inherited by the channel that has published it. Therefore, we define the persistence index of user $i$ as

$$c_i = \frac{1}{n_i} \sum_{j=1}^{n_i} f_j$$

Also (2) has an interpretation similar to the previous one. In particular it is an average of the channel’s fact-checking indexes on which user $i$ comments and therefore gives information about the user’s persistency in commenting videos characterized by a certain trustworthiness. Finally, note that $p_i \in [-1, 1]$, while $c_i \in [0, 1]$.

To study the relationship between the two indexes $p_i$ and $c_i$, we constructed a bipartite network $G$ users/channels in which two nodes $i, j$ are connected if and only if the user $i$ commented at least one video published from the channel $j$. We decided to follow the network approach since it allows us to introduce relational indexes and study the social dynamics typical of social networks, such as YouTube.

4 Experiments

In this section we employ what previously introduced to investigate the relationship between the two indexes, $p_i$ and $c_i$. Since it has been reported a link between the political leaning of users and their tendency to consume high/low fact-checking news [31], we compare the political leaning and the persistence index of each user to verify if a relation exists. Then, we try to detect echo chambers using the topology of $G$ while characterizing the relationship between users using the two indexes of political bias and factual reporting.
4.1 Relation between political bias and persistence

A relation between users’ political bias and their tendency to consume pro vs. anti-science news has been reported in Twitter [31]. To verify if a similar relation was present on YouTube during the COVID-19 pandemic, we constructed a 2D-density plot confronting the political bias and each user’s persistency index. In particular, to obtain Figure 2, we decided to consider the users with at least ten comments to improve the plot’s visibility.

Figure 2: Relation between the political bias of users with at least 10 comments and their persistency index. It is clear that the users with a leaning far from the center tend to consume information from less fact-checked source. In particular, users with a Left leaning have more than one behavior: a part of them consume more fact-checked news, while the others tend to get information through less reliable channels.

Figure 2 shows the results, in which we may note that the users with political leaning far from the center tend to consume less fact-checked news. Interestingly, users with a political leaning skewed towards Left display more than one behavior with a minor part of them having a higher persistency score. Simultaneously, the majority shows lower values of it, indicating that Left political leaning users consume, in a somewhat segregated manner, information from both reliable and questionable sources.

4.2 Echo Chambers

The echo chamber concept translates into a topology property of the users’ network, in which a user \( i \) (with a given \( p_i \) and \( c_i \)) is surrounded by users with similar index values. Those concepts can be quantified by defining, for each user \( i \), the average political leaning and persistency index of its neighbors:

\[
p_i^N = \frac{1}{k_i} \sum_j A_{ij} p_j \quad (3)
\]

\[
c_i^N = \frac{1}{k_i} \sum_j A_{ij} c_j \quad (4)
\]

where \( k_i \) is the degree of node \( i \) and \( A_{ij} \) is the adjacency matrix of the users bipartite projection obtained from \( G \). Specifically, \( A_{ij} = 1 \) if and only if user \( i \) and user \( j \) commented at least one common video.
Figure 3: (a) relation between the political bias of users and the average political bias of their neighborhood. (c) relation between the persistence index of users and the average persistence of their neighborhood. (b) and (d) are obtained in the same fashion of (a) and (c) but in a randomized network. Plots (a)-(c) clearly shows the presence of echo-chambers from both the political and the questionable/reliable dimension. Plots (b)-(d) confirm that echo-chambers don’t arise from random behaviour.
Figure 3 shows the results of the analysis. The color represents the density of users: the lighter, the larger the number of users. The plots (a), (c) show clearly the presence of echo chambers in the political dimension and the fact-checking dimension. To understand if echo chambers represent a peculiar feature of the empirical network that we are taking into account, we randomized the links of the initial bipartite network [10], employed to obtain the co-commenting network, with $2 \times 10^8$ iterations and performed the same analysis on the randomized user network. The results are shown in (b), (d) of Figure 3 in which we may note that the echo chamber effect disappears. In particular, users with a specific value of $p_i$ and $c_i$ have contact with users with different values of those indexes thus resulting in a distribution with little variation on the y axis.

To give a quantitative description of our results, we compute the joint entropy of the distributions shown in Figure 3. The joint entropy for two discrete random variables is a measure associated with their degree of uncertainty. Consider two random variables $X, Y$. The joint entropy is defined as

$$H(X, Y) = - \sum_{x \in X} \sum_{y \in Y} P(x, y) \log_2(P(x, y)).$$

(5)

where $X$ is the range of $X$, $Y$ is the range of $Y$ and $P(x, y)$ is the joint probability of those values. If $P(x, y) = 0$ we assume that also $P(x, y) \log_2(P(x, y)) = 0$.

The interpretation of (5) relies on the concept of information content: entropy measures the average amount of information carried by the outcome of a trial to predict future outcomes and how “surprising” the outcome is. The distribution with the highest entropy is the uniform distribution, since there is no way to predict the future outcomes and it assumes the value $\log_2(n)$, where $n$ is the number of possible couple $(x, y)$. On the other hand, the distribution with the lowest entropy value ($H(X, Y) = 0$) is $P(x, y) = \delta(x_0, y_0)$, since it is possible to predict exactly what the next outcome is.

We computed (5) for the joint distributions showed in Figure 3, comparing them with their random counterparts. To compute the joint probability we employed a quantization of the space using a grid with steps of 0.01 used to sampling the frequencies of the distributions. We created a matrix of frequencies for each distribution. Since $p_i \in [-1, 1]$ and $c_i \in [0, 1]$ the matrices corresponding to the political distribution had size $200 \times 200$, while the matrices relative to the persistency distribution had size $100 \times 100$. The values were then normalized by their maximum value $\log_2(n)$. The results are showed in Table 4 and Table 5.

|                | $H(X, Y)$ |
|----------------|-----------|
| Political bias | 0.3863    |
| Random political bias | 0.2914 |

Table 4: Joint entropy computed for the distributions in Figure 3 (a)-(b).

|                | $H(X, Y)$ |
|----------------|-----------|
| Persistency    | 0.4297    |
| Random persistency | 0.3338 |

Table 5: Joint entropy computed for the distributions in Figure 3 (c)-(d).

The computed values show that the random counterparts of the real distributions have lower values of entropy. Therefore, the echo-chamber behavior is more unexpected than their random counterpart. This can be explained by noticing that the randomization process leads to distributions centered (approximately) in one point, resulting in a reduced entropy.

5 Conclusions

This paper addresses information diffusion during the COVID-19 pandemic period with massive data analysis on YouTube. First, we analyze more than 2M users’ engagement in 13000 videos released by 68 different YouTube channels, with different political bias and fact-checking indexes. We then investigate the relationship between each user’s political preference and her/his consumption of questionable/reliable information. Our findings show that, during the COVID-19 pandemic, echo chambers
exist on YouTube across the political and the fact-checking dimensions. Furthermore, a substantial difference between the echo chambers behaviour and the random behaviour has been highlighted.

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