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Polarization of the vaccination debate on Facebook

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Background: Vaccine hesitancy has been recognized as a major global health threat. Having access to any type of information in social media has been suggested as a potential influence on the growth of anti-vaccination groups. Recent studies w.r.t. other topics than vaccination show that access to a wide amount of content through the Internet without intermediaries resolved into major segregation of the users in polarized groups. Users select information adhering to theirs system of beliefs and tend to ignore dissenting information.
Objectives: The goal was to assess whether users' attitudes are polarized on the topic of vaccination on Facebook and how this polarization develops over time.
Methods: We perform a thorough quantitative analysis by studying the interaction of 2.6 M users with 298,018 Facebook posts over a time span of seven years and 5 months. We applied community detection algorithms to automatically detect the emergence of communities accounting for the users' activity on the pages. Also, we quantified the cohesiveness of these communities over time.
Results: Our findings show that the consumption of content about vaccines is dominated by the echo chamber effect and that polarization increased over the years. Well-segregated communities emerge from the users' consumption habits i.e., the majority of users consume information in favor or against vaccines, not both.
Conclusion: The existence of echo chambers may explain why social-media campaigns that provide accurate information have limited reach and be effective only in sub-groups, even fomenting further opinion polarization. The introduction of dissenting information into a sub-group is disregarded and can produce a backfire effect, thus reinforcing the pre-existing opinions within the sub-group. Public health professionals should try to understand the contents of these echo chambers, for example by getting passively involved in such groups. Only then it will be possible to find effective ways of countering anti-vaccination thinking.

1. Introduction

Despite the scientific consensus that vaccines are safe and effective, unsubstantiated claims doubting their safety still occur to this day. Perhaps the most famous case is the multiple times disproved [1–3] myth that the MMR vaccine causes autism. However, outbreaks and deaths resulting from objections to vaccines continue to happen [4,5], with the anti-vaccination movement gaining media attention as a result. Mandatory vaccination policies only seem to foment the controversy [6]. Although vaccine hesitancy may have many causes, a lack of confidence is certainly a prominent one [35].

Since 2013, the World Economic Forum has been listing massive digital misinformation among the main threats to our society [7]. Recent studies outline that misinformation spreading is a consequence of the shift of paradigm in content consumption induced by the advent of social media. Indeed, social media platforms like Facebook or Twitter have created a direct path for users to produce and consume content, reshaping the way people get informed [8–13]. Since misinformation influences individuals' beliefs (e.g. risk perceptions), it may also influence the attitude towards vaccination [36]. It has frequently been discussed that social media play a role in the formation of vaccine hesitancy [37].

Like for other misinformation campaigns, Facebook provides an ideal medium for the diffusion of anti-vaccination ideas. Users can

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access a wide amount of information and narratives and selection criteria are biased toward personal viewpoints [14–16]. Online users select information adhering to their system of beliefs, tending to ignore dissenting information and form the so-called echo chambers i.e., polarized groups of like-minded people who keep framing and reinforcing a shared narrative [17–19]. The interaction with content dissenting from the shared narrative is mainly ignored and might even foment users segregation, heated debating and, thus, burst opinion polarization [20]. Such a scenario is not limited just to conspiracy theories, but applies to all issues that users perceive as "critical", such as geopolitics or health topics [21] and facilitates the emergence of polarized groups [12] i.e., clusters of users with opposing views that rarely interact with one another.

In this paper, we perform a quantitative analysis to study the evolution of the debate about vaccines on Facebook, taking into account two groups (communities) with opposing views, anti- and pro-vaccine. Considering the liking and commenting behavior of 2.6 M users, we analyze the evolution of both communities over time, taking into account the number of users and pages, and their cohesiveness. Our findings confirm the existence of two polarized communities. Additionally, we find evidence that selective exposure plays a pivotal role in how users consume content online. The two communities display different rates of engagement, with the users of the anti-vaccine community being generally more active than those active in the pro-vaccine community.

2. Methods

2.1. The Facebook platform

Facebook is an online social networking website where people can create profiles or pages to connect with other people and share information such as life events, photos, videos and articles. As of the fourth quarter of 2017, Facebook had 2.2 billion monthly active users. Users on Facebook can interact with posts (i.e., textual content, videos, photos, or links pointing to external documents) from other people or public pages by adding comments or giving a thumbs up (like). More specifically, users' actions allowed by Facebook interaction paradigm are *likes*, *shares*, and *comments*. Each action has a particular meaning [38]: a like represents a positive feedback to a post, a share expresses a desire to increase the visibility of a given information, and a comment is the way in which collective debates take form around the topic of the post.

2.2. Ethics statement

The data collection process was carried out using the Facebook Graph API [22], which is publicly available. The pages from which we downloaded data are public Facebook entities and can be accessed by anyone. Users' content contributing to such pages is also public unless users' privacy settings specify otherwise, and in that case it is not available to us.

2.3. Data collection

The dataset was generated using the Facebook Graph API to search for pages containing the keywords *vaccine*, *vaccines* or *vaccination* in their name or description. We then cleaned the raw Facebook results. Inclusion criteria were language (English), a minimum level of activity on the page (at least 10 posts), date of the posts (between 1st January 2010 to 31st May 2017), and relation of the page to the topic of vaccination. This last step was essential, since having one of the keywords in the description does not necessarily mean the page's topic is about vaccines. False positive search results are, for example, the pages *The Vaccines* (an UK music band) or *Arthur D'vaccine* (a comedian).

From the resulting set of Facebook pages, we used the Graph API to download all the posts as well as all the related likes[1] and comments. Considering the narrative of the pages and the content of the posts, all the Facebook pages were also manually classified by two raters into two main groups: 145 *pro-vaccine* with 1,388,677 users and 98 *anti-vaccine with* 1,277,170 users. The Cohen's kappa inter-agreement between both raters is 0.966, showing nearly perfect agreement. All the authors approved and verified the final classification. The complete list of the Facebook pages with their respective community label and a breakdown of the dataset are reported in the Appendix (see Table A1).

2.4. Preliminaries and definitions

In network theory a *bipartite network* is a graph whose vertices can be divided into two disjoint and independent sets. The likes (or comments) given by users to the posts of different Facebook pages form a *bipartite network*. This *bipartite network* is formed by a set of users and a set of pages where links only exist between a user and a page if the user liked (or commented) anything on that page.

We can represent the bipartite network with a matrix where each column is a user and each row is a page, and the content of each cell equals 1 if the user liked a post of that page, and 0 otherwise. If we multiply the matrix by its transpose, we get the *projection of the bipartite network*. This new matrix will have a row and column for each page, and the content of each cell will represent the number of common users between the 2 pages that define that cell, that is, the number of users who liked any post on both pages. The same method can also be applied considering the matrix formed by the users' comments.

For illustration, Fig. 1 visualizes a simplified example of a bipartite network with 5 users and 4 pages and the corresponding projection.

Once we have the network of pages linked by their common users (Fig. 1b), we can apply different community detection algorithms to detect *communities*, groups of pages that are strongly connected (Fig. 1c). To do this we apply five well known community detection algorithms: FastGreedy[2] [23], WalkTrap[3] [24], MultiLevel[4] [25] and LabelPropagation[5] [26]. Different algorithms are used as they allow for unsupervised clustering i.e., no human intervention, and they each have different approaches to detecting of communities in the networks. To compare the communities detected with the various algorithms we use standard methods that compute the similarity between different community partitions by considering how the algorithms assign the nodes to each community [27]. Due to its speed and its lack of parameters in need of tuning, the FastGreedy algorithm will be the main reference to compare against the partitions resulting from the application of other com-

[1] Since Facebook started introducing reactions (love, haha, wow, sad, angry) in February 2016, only the likes were considered for the whole period.

[2] It optimizes the modularity score in a greedy manner to calculate the communities. The modularity is a benefit function that measures the quality of a particular division of a network into communities. A high modularity score corresponds to a dense connectivity between nodes inside a cluster and sparse connections between clusters. This algorithm takes an agglomerative bottom-up approach: initially each vertex belongs to a separate community and, at each iteration, the communities are merged in a way that yields the largest increase in the current value of modularity.

[3] It exploits the fact that a random walker tends to become trapped in the denser parts of a graph i.e., in communities.

[4] It uses a multi-level optimization procedure for the modularity score. It takes a bottom-up approach where each vertex initially belongs to a separate community and in each step, unlike FastGreedy, vertices are reassigned to a new community.

[5] It uses a simple approach where each vertex is assigned a unique label, which is updated according to majority voting in the neighboring vertices. Dense node groups quickly reach a consensus on a common label.