Exploring the latent social space of COVID-19 Twitter elites

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Abstract

Within the context of the COVID-19 Infodemic, popular social media users play a major role, as they have the ability to influence public opinion through their massive reach. We study the network of influential users discussing the pandemic on Twitter, where we consider users as nodes, and following relationships as directed edges. The resulting structure is modeled by embedding the actors in a latent social space where users closer to one another have a higher probability of forming edges, thus producing a “social map” of the COVID-19 Twitter universe. The results suggest the existence of two distinct communities, which can be interpreted as “generally pro” and “generally against” vaccine mandates. We further show that the two groups are not fully homogeneous: the latent space accurately captures the entire spectrum of beliefs between the two extremes, demonstrating how closely the users’ personal opinions tend to be related to who they follow.

Keywords— Polarization, COVID-19, Social media, Network analysis, Latent space models

1 Introduction

The infectious disease known as COVID-19 dramatically affected the lives of billions of people around the globe. Given its massive impact, the pandemic naturally assumed a central role in both private and public discourse, dominating the discussion on- and offline. Social media, in particular, has been massively used to exchange pandemic-related information as well as disinformation, leading to what has been defined as an “infodemic” alongside the pandemic [1–3]. This context saw the emergence of pandemic-related social media elites, accounts with a large number of followers which regularly discuss the pandemic and the issues surrounding it [4, 5]. These actors play a very important role in public communication, as they can shape popular sentiment and public discourse, and thus can potentially influence political decision making [6]. This is especially true in a setting characterized by increasing polarization and historically low trust in mainstream news, which allows politically and financially motivated actors to emerge [7–10]. Because of this, understanding the role that popular social media users play and the ways in which they operate is crucial for tackling the arising challenges in public communication [11]. In this paper we tackle this issue, with the aim of drawing an explanatory map of the network of COVID-19 Twitter elites. We first identify users that are popular in the discussion related to the pandemic on Twitter, and go on to study their (directed) network, where an edge between two actors is present if one of them follows the other. To analyse the resulting network structure we make use of latent space models, which postulate that nodes in the network are embedded in a latent social space, where the probability for two actors to connect is inversely related to their distance within the space [12]. We, in particular, make use of the latent cluster random effects model, which incorporates model-based clustering, allowing to identify cohesive communities in the network, as well as extra nodal parameters to account for actor-specific heterogeneity in the propensity to form edges [13]. The results suggest that the network can be partitioned into two macro-communities. By focusing on a number of exposed users, such as politicians, activists and news outlets, we show how the two communities can be interpreted as “generally pro” and “generally against” vaccine mandates, corroborating recent research on the role of polarization in pandemic-related online conversations [14–17]. But our results also highlight the presence of substantial within-cluster heterogeneity: not all users in the two communities are the same, and not only the two polar opposites are represented. To the contrary, the latent space is able to capture the full spectrum of beliefs between the two poles. In particular, more radical users are positioned towards the extremes of the latent space, while more moderate and neutral actors, such as health ministers and news outlets, are closer to the center. Both group memberships and latent positions are thus informative on the (unexposed) users’ stances on the pandemic and its management. In addition to these results, our analysis demonstrates how, by making use of latent space models, it is possible to accurately map the COVID-19 Twitter landscape by only modeling information on who follows whom within the elite network. This finding highlights the strength and the pervasiveness of echo chamber effects on the platform, and showcases
the power of latent space network models for studying communication on social media.

2 Data and Methods

Identifying the network of COVID-19 Twitter elites

Social media elites can be broadly understood as users with the ability to influence [18]. There are several different ways to operationalize this general characterization. We here choose to identify the most popular users as those who authored the most popular tweets, where the popularity of a tweet is given by the sum of its likes, replies and retweets (including quotes). We will therefore first need to identify popular tweets discussing COVID-19, and then relate those tweets to their authors. For our study we make use the COVID-19 Twitter dataset published by Banda et al. [19], which comprises IDs of tweets containing pandemic-related keywords from January 1, 2020 onward. These keywords were handpicked and continuously tracked to provide a global and real-time overview of the chatter related to the COVID-19 pandemic. The dataset was collected through use of Twitter’s streaming API, which allows free access to a random 1% sample of publicly available tweets in real-time [20]. At the time of the analysis, the full dataset contains about 1.32 billion tweet IDs, representing both tweets and retweets in all languages, 340 million of which are unique (without retweets). Each tweet’s creation time and language are also provided. Using the tweet IDs, we are then able to recover additional information on the tweets, such as the text, the author and metrics such as likes and retweets counts.

As a global platform, Twitter is host to speakers of many different languages, which induce the formation of largely separate communities. Since our goal is to map the latent space of COVID-19 elites, we chose to limit our analysis to a single language, as doing otherwise would return a fragmented map mostly shaped by language. In principle, it is possible to work with any single language. We here opt for using tweets in German. Apart from computational burden, the choice is motivated by the combination of two facts: firstly, German is predominantly spoken by people from Germany, and to a smaller extent from Austria and parts of Switzerland, thereby guaranteeing a good degree of geographical homogeneity. This prevents the estimated latent positions of the actors (and the resulting clusters) to be primarily driven by their geographical locations. Secondly, German is used by a relevant proportion of the Twitter user base, allowing for a more than sufficient sample size. As the first COVID-19 vaccines started to be available to the public towards the very end of 2020, and given that one of the points that we are most interested in investigating is attitude towards vaccination, we limit our sample to 2021 only, spanning from January 1 to December 31. Considering all tweets in German from 2021 results in a total of 1.51 million unique tweets from 184,406 accounts. The data, sketched in Table 1, allows us to pinpoint popular users by looking at the authors of tweets with the highest interaction metrics. More specifically, we classify a user as elite if they authored a tweet which achieved a popularity score of at least 2000, where we define popularity as the sum of likes, replies and retweets (including quotes) gathered. This threshold results in a total of 1024 popular tweets spanning all months of 2021, each month represented by 53–156 tweets. Those 1024 tweets were produced by 372 users, 31.7% of which were granted verified status by Twitter, meaning that the platform deemed them as both authentic and of public interest [21]. In contrast, only 2.4% of the user base in the initial sample was verified. This confirms that more notable accounts and public figures are, on average, more central to the discussion, as we would expect. The bar plot in Figure 1 depicts the number of tweets authored by the ten most popular users in our sample.

| Tweet ID | Author   | Likes | Replies | Retweets |
|----------|----------|-------|---------|----------|
| 138712... | AnikaBlub | 1,162 | 61      | 53       |
| 135224... | goetzegblatt | 1    | 2       | 1        |
| 140697... | galottom  | 1     | 0       | 0        |
| 146632... | 1_FCMT   | 171   | 26      | 35       |
| 135269... | covid_watch | 0    | 0       | 0        |

Figure 1: Number of tweets authored by the ten most popular users in our sample.
and establish that a (directed) edge from actor $i$ to actor $j$ is present if, at the time of the analysis, $i$ follows $j$. The resulting network, after removing the only 9 users with no connections, is composed of 363 nodes connected by a total of 12182 edges, and is visualized in Figure 2. From the plot, it is immediately apparent that the network is quite dense: In fact, 9.2% of all possible edges are observed. Given that the network is composed of users who produced popular tweets about the same topic, the fact that many of them follow each other makes intuitive sense. From the graph representation, laid out using a variant of the Yifan Hu force-directed graph drawing algorithm [22], the network also seems to be approximately split into two main groups of different sizes. This already gives a first impression of the two main poles that are present in the network, which will be investigated in more detail in the Results section.

**Latent space models for social network data**

To model the network data, we make use of the latent cluster random effects model for social networks [13]. This model is part of the general family of latent space models, originating from the latent distance model proposed by Hoff et al. [12]. Latent space network models postulate that each actor has an unobserved position in a $d$-dimensional Euclidean latent social space, and that the probability for two actors to form an edge is inversely related to their distance in the space. This family of models is particularly suitable for social networks, in which mechanisms such as homophily and triadic closure often play a major role [23]. Handcock et al. [24] added the idea of model-based clustering to the original latent distance model, allowing for the actors’ positions in the latent space to come from a mixture of normal distributions, where each mixture component represents a cluster. Krivitsky et al. [13] further extend this by adding nodal random effects, to control for actor-specific heterogeneity in the propensity to form edges. More precisely, without the inclusion of nodal or edgewise covariates, the model specifies the probability of an edge $y_{ij}$ between nodes $i$ and $j$ through:

$$
\logit(\Pr(y_{ij} = 1|\beta_0, Z, \delta, \gamma)) = 
\beta_0 - \|z_i - z_j\| + \delta_i + \gamma_j
$$

where $Z = (z_1, ..., z_n)$ are the latent positions of the nodes in the $d$-dimensional latent space, $\beta_0$ is an intercept, and $\delta = (\delta_1, ..., \delta_n)$ and $\gamma = (\gamma_1, ..., \gamma_n)$ are node-specific sender and receiver effects, that account for the individual users’ propensity of following or being followed, respectively. Here the latent positions $Z$ are assumed to originate from a finite spherical multivariate mixture of independent normal distributions, and the random effects $\delta$ and $\gamma$ are assumed to be drawn independently from normal distributions with mean 0 and variances $\sigma_\delta^2$ and $\sigma_\gamma^2$, respectively. The model is estimated through a Bayesian routine based on the use of a Markov chain Monte Carlo algorithm implemented in the R package latentnet [25].

Homophily and triadic closure are generally prevalent phenomena in social media, and particularly so on Twitter and between popular accounts [26, 27]. Those mechanisms often lead to the formation of sub-groups of actors based on shared beliefs or other characteristics. Identifying such clusters can be helpful in understanding the drivers of polarization and, more in general, grouping behavior. The general task of identifying assortative, tightly knit groups in networks is a large area of research, known under the umbrella term of “community detection” [28]. Notable examples of such methods include modularity maximization algorithms [29] and stochastic blockmodels [30]. Classical community detection techniques are well suited for finding group-structures, but they have the drawback of only returning a discrete partition of the network into clusters, where the connectivity behavior of each actor is fully described by its group label. This has the consequence that two nodes in the same group are considered to be exactly the same in all aspects. This is generally quite simplistic for social networks, in which cohesive groups often do exist, but where members of each group can also be very different from one-another. Within a single group, for example, some nodes might be more “extremist” and isolated from all other communities, while others might be more central to the full network, and still have many connections to other groups. We expect this to be the case in our network of COVID-19 Twitter elites: While we can assume polarization and grouping behavior to be present, we also expect the social positioning and political beliefs of the actors to be more accurately described through a continuous, multidimensional spectrum rather than with discrete labels. Because of that, we are not only interested in the clear-cut grouping of nodes, but also in uncovering the (continuous) social positioning of the users relative to one-another. The chosen latent cluster random effects model is therefore particularly well suited for our application, as it combines clustering and latent position modeling, thereby enabling us to simultaneously capture polarization and grouping behavior as well as the positioning of the actors relative to each other in the socio-political spectrum.
3 Results

We fit the latent cluster random effects model to our data, setting both the number of clusters \( k \) and the number of dimensions \( d \) to 2. The choice of two clusters is backed by the approximated Bayesian Information Criterion for data-driven model selection proposed by Handcock et al. [24]. Moreover, since much of the literature concerns itself with investigating polarization in the online discussion revolving around the COVID-19 pandemic, and given that polarization suggests the existence of two sub-groups [31], setting \( k = 2 \) appears to be the natural choice from a substantive perspective. With regards to the choice of \( d \), while dimensionality for latent space network models is generally an open question, setting \( d = 2 \) is considered to be the standard for applications in which interpretability of the positions is central, as it simplifies the visualization and description of social relationships [32]. We also experimented with different values of \( d \), and observed that using higher dimensionality did not have a big impact on the cluster assignments. Note that data and code for the analysis are openly available on our GitHub repository.

The results of the model fitting are visualized in Figure 3. The axes correspond to the two latent dimensions \( Z_1 \) and \( Z_2 \), respectively, and the estimated community memberships are indicated by the color of each node. More specifically, the posterior probabilities for each user of belonging to the one or the other cluster are represented by the node-specific pie charts. Node sizes are scaled by each actors’ total degree within the network. Note that, as defined by the model, two nodes which are closer to one another have a higher probability of forming an edge, i.e. of following each other. At a first glance, we see that the two communities are distributed along the horizontal axis \( Z_1 \), with the more numerous blue community occupying the left and center parts of the figure, and the orange one being located towards the right-hand side. Moreover, from the posterior membership probabilities we can see that group memberships are fairly clear for the majority of the nodes. Nonetheless, significant uncertainty can be observed for a non-negligible proportion of the actors, which lie in-between the two clear communities in the space.

As our task is of unsupervised nature, we do not have a set in stone “ground truth” with which to compare the model-based labeling and the estimated positions of the actors. To interpret the results, we therefore need to dig into the data and consider the emerging patterns. As the network is limited in size, and thanks to the naturally high propensity of elite users to voice their opinions, it is fairly straightforward to identify some of the more prominent actors and gauge their views on pandemic-related governmental interventions based on public information. Through this process, we can appreciate how the latent position of each actor in the network is strongly associated with their public stances on government mandates. More specifically, despite substantial within-cluster heterogeneity in stances (and their intensity) on several issues, users in the blue community hold views which can be summarized as “generally for” interventions and vaccine mandates. The opposite is true for actors in the orange community, which can be described as “generally against” such measures. Moreover, the positioning of nodes within communities is also informative on the actors’ beliefs, capturing the within-cluster heterogeneity mentioned. Specifically, more central (external) positions in the overall latent space are associated with more moderate (extreme) stances. To showcase these patterns, we highlighted and labeled some of the exposed users in Figure 3, where each user is indicated with their Twitter username. The very center of the space is occupied by the most popular actors, most of whom, despite having connections to both groups thanks to their “elite among elites” status, reside firmly in the blue camp: A prime example is Karl Lauterbach, the current health minister of Germany from the Social Democratic Party (SPD). He is known to be a strong proponent of vaccination and mandatory vaccination for all [33]. Two other prominent exponents of this group are Christian Drosten (c_drosten), a prominent virologist who has been described by major media outlets as “the country’s real face of the coronavirus crisis” and “the nation’s corona-explainer-in-chief” [34], and Melanie Brinkmann (BrinkmannLab), another well-known virologist who was among the proponents of the No-COVID strategy [35]. Moving a bit further left in the space, another very popular user in the network is Flying_Doc, a medical doctor who has been outspoken in his support for policy proposals such as a vaccine mandate for all adults, and allowing access to events only to people who are both fully vaccinated and tested (“1G+” in the German political jargon). If we look even more towards the left on the \( Z_1 \) dimension, we encounter positions that are increasingly more in the direction of decisive government interventions. Examples of this are dr_heartbreaker, a medical professional who has expressed his support for hard lockdowns and the aforementioned No-COVID strategy, and NavonDienst and Doktor_Freakout, two anonymous medical doctors who also vehemently voiced their dissent for what they deemed to be bland policy making, and vouched their support for stronger restrictions. To conclude our outlook on the blue community, we also labeled two more peripheral, less Twitter-popular nodes. On the bottom-left of the plot we find DanZickler, an intensive care doctor who also expressed his support for more decisive action by the government, while on the top left we find MuttiveFaschos, who tweeted at the hashtags #ZeroCovid and #harterLockdownJetzt (“harder lockdown now”). All in all, our analysis highlights how users categorized in the blue group generally tend to openly support governmental efforts to contain the pandemic, and that the estimated dimension \( Z_1 \) is associated with the intensity of the actors’ voiced stances on policy.

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1https://github.com/gdenicola/latent-space-covid-twitter-elites
Figure 3: Latent positions of the actors in the network of COVID-19 Twitter elites estimated via the latent cluster random effects model. A number of prominent users are highlighted. The axes correspond to the two latent dimensions $Z_1$ and $Z_2$, while the estimated posterior probabilities for each user to belong to the "pro vaccine mandates" (blue) or "anti compulsory vaccination" (orange) cluster are depicted through the node-specific pie charts. Major German media outlets are found in between the two communities.

We now shift our focus to the orange community, which is composed of actors who have, on average, significantly less followers within this elite networks, and tend to more or less strongly oppose pandemic-related government mandates. We start our overview with DrPuerner, who is the user with the highest number of popular tweets in our dataset. A medical doctor, Pürner rose to prominence during the pandemic for his stark criticism of COVID measures and opposition to government mandates. While not downplaying the dangers posed by COVID-19, he attracted following and praise from conspiracy theorists and from the populist right-wing party “Alternative for Germany” (“AfD”), notorious for its anti-system beliefs [36]. Closer to DrPuerner in the latent space we can also find wolff_ernst, a self-described journalist and writer, who has openly associated himself with COVID-related and general conspiracy theories [37]. We also labeled two more peripheral nodes in this cluster, namely users Zukunft37 and Whereismymodel3, anonymous accounts who openly voice their vaccine skepticism and opposition to government mandates. Two prominent members of the aforementioned AfD, Alice_Weidel (joint party head) and JoanaCotar (member of the German parliament), are also part of the orange community. Unsurprisingly, the two are close to one another in the latent space, reflecting their similar policy stances. Perhaps more surprisingly, their estimated latent positions are not far from that of Sahra Wagenknecht (Swagenknecht), former parliamentary leader of “The Left” (“Die Linke”) party. Despite being on the other end of the political spectrum, she also opposes general vaccination mandates [38]. She is located more towards the middle of the plot, and has substantial uncertainty in her community membership, with a posterior probability of approx. 75% to belong to the orange community. Another actor whose community membership is uncertain is Christian Democratic Union (CDU) politician and former health minister Jens Spahn (jensspahn). He is not far in the space from his successor Karl Lauterbach, but lies a bit more on the right: He’s classified in the blue community, but has a posterior probability of approximately 25% to belong to the orange one. This is in line with the fact that, while he is a proponent of widespread vaccination, he is opposed to the idea of compulsory vaccination for all [39]. To conclude our overview of the space, we highlight some other notable accounts located in-between the two clusters, namely those belonging to prominent news outlets. Given that we expect them to have a diverse following due to their authority status, their central positioning makes intuitive sense. But even between media outlets, the model is able to draw a distinction: zeitonline and tagesschau, generally reputable news sources, are closer to the center of the space, and, although with substantial uncertainty, la-
beled as blue. On the other hand, BILD, the most prominent German boulevard newspaper, is located more towards the right, and has a higher probability of belonging to the orange group.

4 Discussion

In this paper, we identified and modeled the network of users leading the conversation revolving around the COVID-19 pandemic on Twitter. More specifically, we made use of the latent cluster random effects model to map these elite users into a two-dimensional euclidean social space, in which users that are closer to each other have a higher likelihood to connect, i.e. to follow each other. The results suggest the emergence of a natural partition of the network into two dense macro-communities, which are only loosely connected with their opposing counterparts. By focusing on a number of exposed users, such as politicians, activists and news outlets, we show how those two communities can be interpreted as “generally pro” and “generally against” vaccine mandates. This finding confirms recent research demonstrating the polarized nature of pandemic-related online discourse [14–17]. A deeper inspection of the latent space further reveals that users within communities are not fully homogeneous in their stances. To the contrary, the model is able to uncover a nuanced, continuous spectrum of pandemic-related beliefs and policy positions, ranging from demanding radical containment measures all the way to vaccine skepticism and COVID-denying conspiracy theories, covering everything in between those two extremes. In this context, neutral actors, such as mainstream news outlets, have been found to be positioned in between the two clusters, which makes intuitive sense given their authority status. From the latent positions of the politically exposed users in the network, we can also appreciate how attitudes toward governmental interventions tend to follow political inclination, with left and right-wing respectively corresponding to more favourable or unfavourable positions towards restrictions and vaccine mandates. This finding echoes recent research showing how ideology can shape trust in scientists and attitudes towards vaccines [40, 41].

A particular feature of the employed methodology is the ability to combine “classical” community detection, which alone would be insufficient to gain a proper understanding of the network at hand, with more refined, continuous latent space modeling. This allows to map the underlying latent social space with the necessary nuance, while simultaneously returning a partition of the network into sub-groups, which can be useful, e.g., for classification purposes. The results of the modeling thus allow us to obtain a clearer picture of the network as a whole, and can be used for garnering insight on single (unexposed) users.

One point that we would like to bring up is that the studied network is fairly small, as a result of the relatively restrictive popularity threshold we chose for defining a popular tweet: It would thus be possible to decrease the threshold to obtain a larger network. We note, though, that using a lower value somehow “loosens” the definition of elite, as users that are less popular on average would make it into the network. Experimenting with the threshold, we also observed that using different values almost only impacts the size of the periphery of the network, and does not change the overall picture. We also note that, as we here only model the behavior of elites, we cannot a priori assume our results to be valid for the overall discussion. While, given the (well documented) strong influence of popular users in the conversation, it is reasonable to believe that many of the results could extend to the general Twitter population, further research would be needed to confirm this.

Another aspect that we would like to discuss is the fact that our analysis does not include any element of natural language processing. While it would most certainly be possible to make use of the tweets’ text content to obtain further insight on the users, we explicitly choose to focus solely on the network component, and thus to only use information on who follows whom. By doing so, we demonstrate how tightly the users' personal networks are intertwined with their beliefs. Given that the latent positions of the actors are estimated by the model solely using their follows and followers within the network, it is quite remarkable how consistently actors neighboring each other in the estimated latent space are also near in their stances on COVID-19 and its management, and how closely the space is able to track the belief spectrum. The echo chamber effect is well documented in the literature: Users tend to follow those who hold ideas similar to theirs, and are thus rarely exposed to opposing views. This, in turn, leads the users’ beliefs to become self-reinforcing, thereby resulting in further polarization [42, 43]. Our analysis showcases the pervasive nature of this phenomenon on the platform. The fact that following behavior is so closely related to beliefs and attitudes is indeed what opens the door for latent space models as powerful tools for drawing maps of social media landscapes, which can in turn be used to increase our understanding of the underlying social and behavioral structures. Indeed, while we here applied the methodology to map the discussion revolving around COVID-19, it is, in principle, possible to perform similar types of analysis on any topic. Given its explanatory and predictive power, we believe latent space modeling of elite social media networks to have great potential for improving our general understanding of the online landscape, ultimately aiding policymakers in their quest against the spread of misinformation worldwide.

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