

Activists preserving the (Digital Media) Environment – Advocacy Coalitions of Lützerath

Keywords: climate protest, digital network analysis, topic modelling, advocacy coalitions

Extended Abstract

The changing media environment and the establishment of smartphones intertwined offline and online protest actions. Via digital media, anyone can receive real-time news updates, pictures and videos of ongoing climate protest actions, such as anti-coal-activists barricading themselves in tree houses in the German village of Lützerath. The protest received a lot of media attention and highlighted the social cleavages between supporters of the climate protests and political antagonists: Through a triangulation of automated network and content analyses, we show that these cleavages are reflected in advocacy coalition networks – and their backlash – on Twitter and Telegram.

Digital media feature networks of advocates but also of antagonists who do not share the political goals of the advocates of the climate movements. Based on these digital networks, which discuss and share similar topics with a common perspective, conclusions can be drawn about advocacy coalitions [1] and online-counterpublics [2]. The digital platforms' properties and affordances have an influence on the structure of these networks and their interaction. Yarchi et al. [3] found clear differences between Twitter, Facebook and Whatsapp regarding formation and polarization of user networks. Distinctions between Twitter and Telegram may be attributed to differences in the user group itself, as users banned from mainstream social media sites such as Twitter migrated to less moderated platforms such as Telegram. Since it is primarily extreme and anti-establishment actors that are 'deplatformed' [4], it should be easier for political antagonists to form counterpublics on Telegram than on Twitter. With regard to the protest actions in Lützerath, we therefore derive the following research questions: *To what extent can coalitions of advocates and antagonists in relation to the protest actions in Lützerath be found on Twitter and Telegram? How do these coalitions differ on Twitter and Telegram regarding user interaction, network structure, and disseminated content?*

Our data collection combined two sources, covering posts from January 5–18, 2023: (1) We accessed Twitter's Academic Research API (academictwitteR; [5]), resulting in posts of 170,918 individual users. (2) On Telegram, we collected data from 388 public channels and groups via the Telegram API. We used a snowball sampling approach to collect data, starting with 26 protest related seed channels. Channels/groups that did not use a climate protest-related term at least once during the specified period were excluded.

In order to capture 'advocacy coalitions', we first looked at the overall discourses on Telegram and Twitter from a network perspective [6] and uncovered community clusters [7] based on amplifications of specific posts as structures of retweets (Twitter) and shared group activity (Telegram). In order to uncover topical and ideological differences between the communities within the debate, we applied BERTopic [8] per sub-network, a pre-trained, transformer-based topic modeling approach that combines word embeddings, UMAP (Uniform Manifold Approximation & Projection), HBDSCAN (Hierarchical Density-Based Spatial Clustering), and c-TF-IDF (combination of term frequency and inverse document frequency) approaches. In both media environments, network structures are separable along ideological poles. For each platform, we found an isolated sub-community in opposition to more densely interconnected and diverse mainstream communities. An analysis of the content per network cluster showed, however, that roles were reversed per media environment: While the Twittersphere's structure

is divided into a mainstream of climate protest advocates and a fairly large, yet less diverse, antagonist cluster, the supporters and organizers of the Lützerath protests were isolated from the overall debate on Telegram, being formed around conservative, right-wing and conspiracy groups. The question of which topics were being discussed depends on the (ideological) positioning of the users within in the sub-network – no matter the platform: The protesters' advocacy coalitions criticised police violence, capitalism, and mobilized resources, while their antagonists focused primarily on oppositional figures such as Greta Thunberg and framed protesters as violent leftwing-extremists and terrorists.

Despite these ideologically-driven similarities of content and network dissemination across different platforms, there were clear differences: The protesters' advocacy coalition on Twitter was composed of an internal cluster, talking about organisational issues and first-hand experiences during protests such as police violence, and an external cluster of advocates that amplified the protesters' policy goals and argued against critics. This indicates that protesters were much more successful in spreading their content to a wider, supportive audience on Twitter, while Telegram mainly represented an organizational tool for them. Additionally, the protesters' antagonists were composed of much more diverse networks on Telegram that also promoted a diverse range of ideological stances and conspiracy myths. The critics of climate protests on Telegram therefore formed a mainstream "Alliance of Antagonism" [2], with users of diverse ideologies and worldviews joining forces against the protesters as a common enemy. The networked inversion of mainstream and counterpublic per platform may not only be the result of distinct platform affordances, but also of very different ideological user types.

References

- [1] Guo, C., & Saxton, G. D. (2014). Tweeting social change: How social media are changing nonprofit advocacy. *Nonprofit and voluntary sector quarterly*, 43(1), 57-79.
<https://doi.org/10.1177/0899764012471585>
- [2] Kaiser, J., & Puschmann, C. (2017). Alliance of antagonism: Counterpublics and polarization in online climate change communication. *Communication and the Public*, 2(4), 371-387. <https://doi.org/10.1177/2057047317732350>
- [3] Yarchi, M., Baden, C., & Kligler-Vilenchik, N. (2021). Political Polarization on the Digital Sphere: A Cross-platform, Over-time Analysis of Interactional, Positional, and Affective Polarization on Social Media. *Political Communication*, 38(1-2), 98-139.
<https://doi.org/10.1080/10584609.2020.1785067>
- [4] Rogers, R. (2020). Deplatforming: Following extreme Internet celebrities to Telegram and alternative social media. *European Journal of Communication*, 35(3), 213-229.
<https://doi.org/10.1177/0267323120922066>
- [5] Barrie, C., & Ho, J. C.. (2021). academictwitteR: an R package to access the Twitter Academic Research Product Track v2 API endpoint. *Journal of Open Source Software*, 6(62), 3272. <https://doi.org/10.21105/joss.03272>
- [6] Bastian M., Heymann S., Jacomy M. (2009). Gephi: an open source software for exploring and manipulating networks. In *Proceedings of the international AAAI conference on web and social media* 361-362. <https://doi.org/10.1609/icwsm.v3i1.13937>
- [7] Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment*, 2008(10), 1-12.
- [8] Grootendorst, Maarten (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794*.
<https://doi.org/10.48550/arxiv.2203.05794>

Supplementary Material

Network Analysis

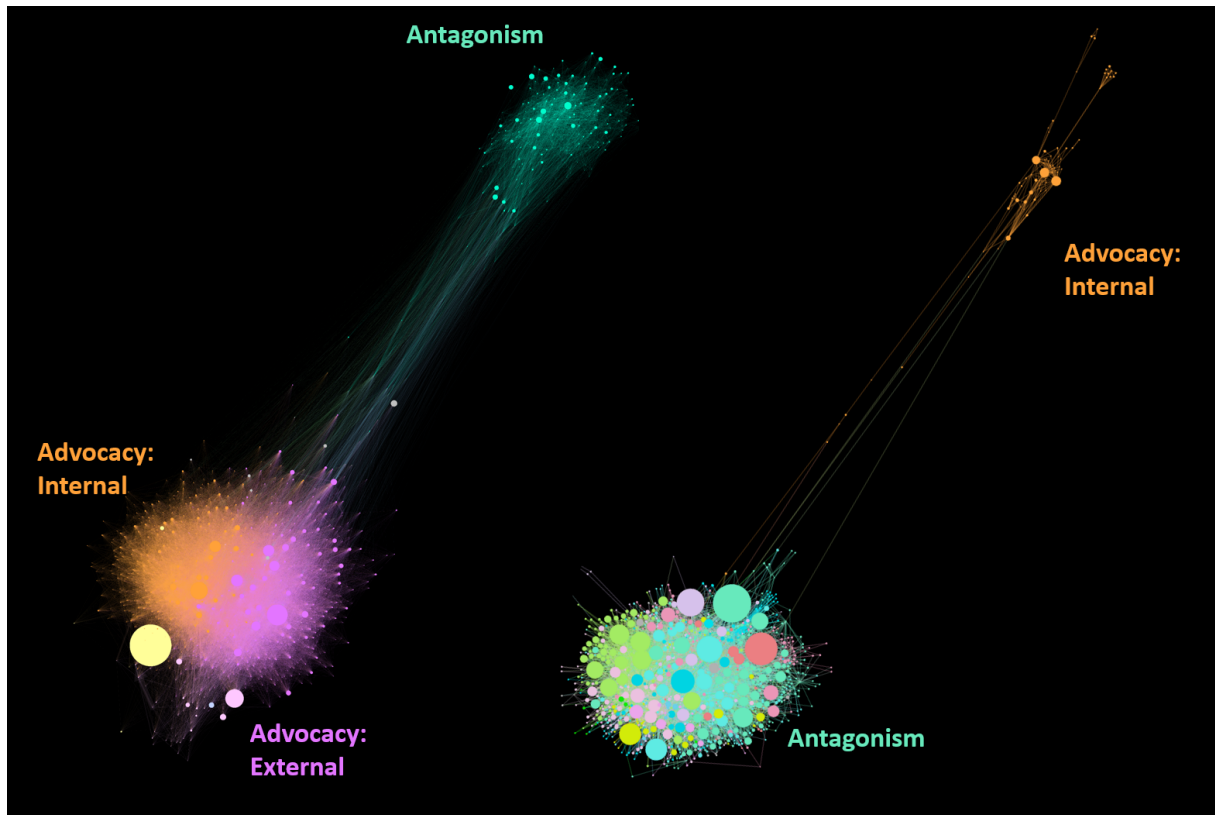


Figure 1. Comparison of community structures of debates on Twitter (left, filtered by k-core 6) and Telegram (right, filtered by k-core 2). Higher degree of filtering was applied to the Twitter user-network to create comparability with Telegram's group- and channel-network. Colouring is based on community modularity.

Content Analysis

Twitter

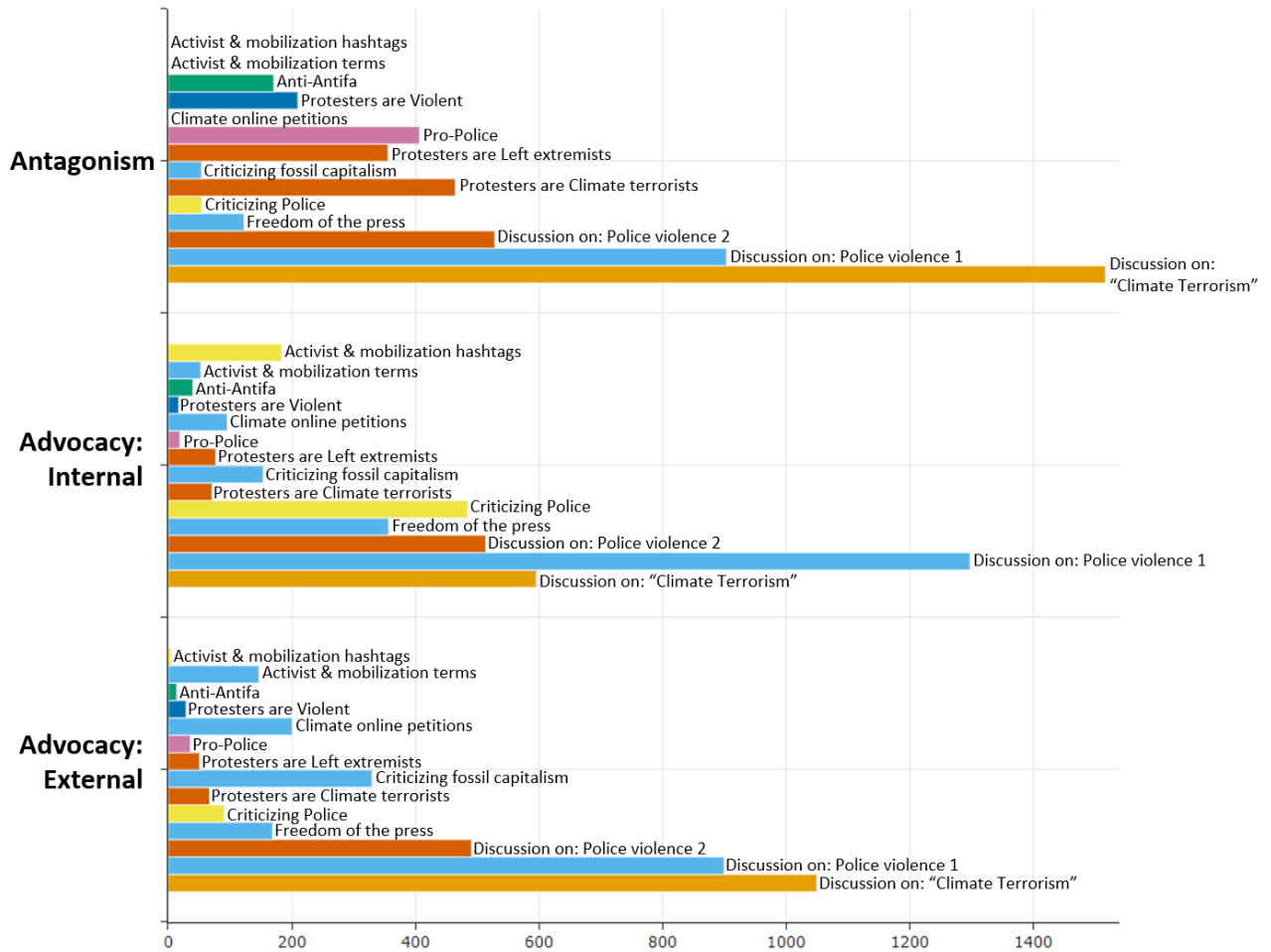


Figure 2. Topics of tweets within the three main community clusters of the Twitter debate. Only the topics (of top 50) with the greatest relevance or variance between clusters were considered.

Telegram

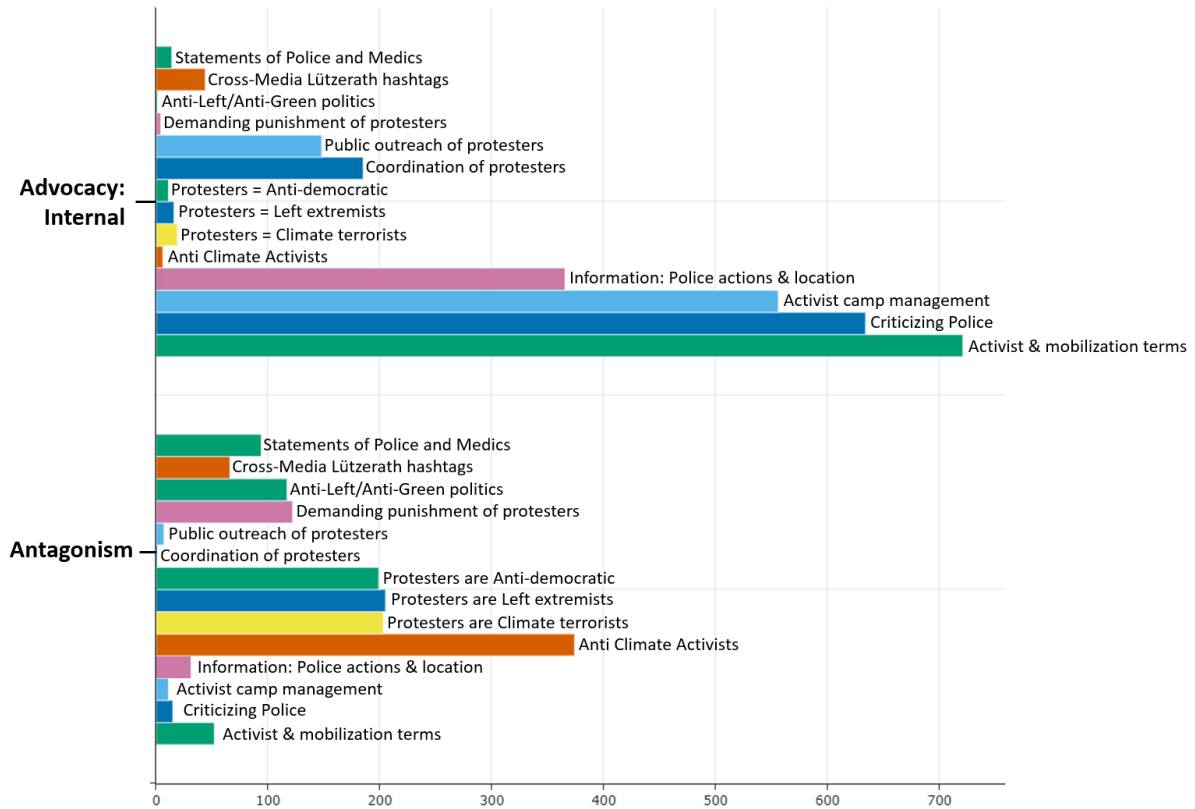


Figure 3. Topics of posts disseminated within all communities of the Telegram debate. For clarity, the content of all “antagonist” clusters was merged. Only the topics (of the top 200) with the greatest relevance or variance between clusters were considered for visualization, as there were many others referring to (extreme) right-wing and conspiracy ideologies.