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Does Relational Polarization Entail Ideological Polarization? The Case of the 2017 Norwegian Election Campaign on Twitter

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This article investigates different polarizing mechanisms—relational homophily and ideological partisanship—characterizing political communications using Twitter data collected during the 2017 Norwegian election. By combining two computational approches—partition-specific network analysis and quantitative analysis of language polarization—we can examine the linkages between the structure of interactions and political polarization. The results show that the Norwegian political Twittersphere is not made of isolated echo chambers but is structured around crosscutting communities of interaction. There are no signs that communities with higher degrees of polarization are the ones that display higher degrees of homophily. Yet, the degree of ideological polarization differs across communities and topics. Some topics, such as political hate and far right and economy and taxes, are more polarized than others.

Keywords: polarization, social media, Twitter, echo chambers, Norway, election campaign, homophily

Social media platforms such as Facebook and Twitter play an increasing role in election campaigns (Stier, Bleier, Lietz, & Strohmaier, 2018) as they enable candidates to directly communicate with the public, to mobilize potential voters, and to influence the public agenda, as well as allow citizens to actively participate in public debates by voicing their opinions and political preferences. At the same time, there has been a growing concern about social media having contributed to increased political polarization. Cass Sunstein's metaphor of echo chambers (Sunstein, 2018), according to which social media users selectively engage with ideologically like-minded on social media, inducing segregation of the environment for opinion formation, is commonly invoked as the main mechanism linking social media and political polarization. Yet, empirical evidence about the linkage between echo chambers on social media and political polarization is contradictory.

On the one hand, a growing body of research, based on digital traces, has documented the existence of echo chambers on social media in different countries and political contexts (Batorski & Grzywińska, 2018; Bessi et al., 2016; Del Vicario et al., 2016; Del Vicario, Zollo, Caldarelli, Scala, & Quattrociocchi, 2017; Furman & Tunç, 2020; Garimella, De Francisci Morales, Gionis, & Mathioudakis, 2018; Grömping, 2014; Hayat & Samuel-Azran, 2017; Hong & Kim, 2016; Jacobson, Myung, & Johnson, 2016; Lynch, Freelon, & Aday, 2017; Nikolov,

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Oliveira, Flammini, & Menczer, 2015; O'Callaghan, Greene, Conway, Carthy, & Cunningham, 2013; Park, Park, Lim, & Park, 2016; Wieringa, van Geenen, Schäfer, & Gorzeman, 2018; Williams, McMurray, Kurz, & Lambert, 2015; Zollo et al., 2017). There are also several widely cited scientific contributions that have provided support for the linkage between echo chambers and polarization (Aragón, Kappler, Kaltenbrunner, Laniado, & Volkovich, 2013; Barberá, 2015; Conover et al., 2011; Schmidt, Zollo, Scala, Betsch, & Quattrociocchi, 2018). On the other hand, several contributions have provided evidence that question the causal linkage between echo chambers and political polarization, showing that individuals are exposed to more diverse and cross-cutting opinions on social media than in offline settings (Bakshy, Messing, & Adamic Lada, 2015; Barberá, 2014; Barnidge, 2017; Fletcher & Nielsen, 2017).

Yet, exposure to ideologically heterogenous content does not preclude ideological polarization. Exposure to diverging opinions may coexist with polarization when cross-interactions follow the logic of "trench warfare" (Karlsen, Steen-Johnsen, Wollebæk, & Enjolras, 2017), in which opinions are reinforced through contradiction as well as confirmation. Thus, the linkage between the structure of digital network on social media (characterized by echo chambers or ideological homophily or by crosscutting interactions) and the degree of polarization needs to be further investigated to understand how social media may enhance political polarization.

With this backdrop, this contribution proposes to distinguish between two mechanisms leading to polarization—*relational* and *ideological*—and to investigate the following *research question*: Is ideological polarization correlated with relational polarization? To do so, two different computational approches are harnessed. Partition-specific network analysis (Freelon, 2020)—allowing to investigate homophily in digital networks—is combined with quantitative analysis of language polarization (Demszky et al., 2019).

Mechanisms of Political Polarization

As pointed out by DiMaggio, Evans, and Bryson (1996), polarization—the distributional properties of public opinion reflecting the extent of disagreements—is significant to many political issues, political conflict and change, and intergroups relation. Different explanatory mechanisms have been advanced to explain the contribution of social media to polarization (Barberá, 2020; Van Bavel, Rathje, Harris, Robertson, & Sternisko, 2021; Yarchi, Baden, & Kligler-Vilenchik, 2021), including homophily or relational polarization and ideological partisanship polarization.

Relational Polarization Resulting from Homophily

The concept of homophily entails that similar people tend to connect in social networks more often than dissimilar people. A useful distinction proposed by Lazarsfeld and Merton (1954) identifies two types of homophily: *status homophily*—in which similarity is based on ascribed characteristics like race, ethnicity, sex, or age, and acquired characteristics like religion, education, occupation, or behavior patterns—and *value homophily*, which is based on values, attitudes, and beliefs (McPherson, Smith-Lovin, & Cook, 2001). In the political domain, the most common mechanism for political homophily is probably the mechanism of selective affiliation, according to which people tend to select their communication partners among people who share their political beliefs (Bond & Sweitzer, 2018). There is evidence that social network structure affects a wide range of opinions and behaviors, including political ones (Bond et al., 2012; Christakis & Fowler, 2007, 2008). In the political domain, individuals may sort on political *identities* (political party or ideological disposition), according to political *issue positions* (policy issues), or on their levels of *political engagement* (Huber & Malhotra, 2013). The formation of echo chambers may be thought as the direct effect of homophilic tendencies and might be correlated with political polarization (Stroud, 2010) when like-minded people share the same political orientations and are only minimally exposed to challenging opinions. Yet, the link between ideological homophily and echo chambers on the one hand, and polarization on the other hand, is increasingly questioned as, despite the importance of political interactions on social media between like-minded individuals, cross-cutting interactions are also frequent (Barberá, 2020). This entails that polarization may be driven by other social mechanisms than homophily and echo-chambers. There is evidence that polarization might be driven by increased exposure to ideologically heterogenous information: Karlsen, Steen-Johnsen, Wollebæk, and Enjolras 2017 find that the dynamics of online cross-cutting interactions could be more aptly described by the logic of "trench warfare," in which opinions are reinforced through contradiction as well as confirmation.

Ideological Partisanship Polarization

Recording DiMaggio and colleagues' (1996) definition of polarization as affecting the distribution of opinions including bimodality and alignment of opinions, political polarization entails changes in people's political attitudes and alignment of these attitudes along ideological or party divides. Political polarization in the United States, for example, can be traced to increased disagreements about the role of government and a realignment of people attitudes along the party dividing dimension (Hopkins & Sides, 2015). Divisive social media messages, either because they feature the opposition between political ingroup and outgroup or express moral outrage, tend to capture attention and to receive more engagement, contributing to ideological polarization expressed in social media messages (Van Bavel et al., 2021). A way to capture such a tendency toward ideological polarization consists in measuring polarization in partisanship language (Gentzkow & Shapiro, 2010; Gentzkow, Shapiro, & Taddy, 2019). Language partisanship has originally been used to measure the frequency with which newspapers use language that would tend to sway readers to the right or to the left on political issues (Gentzkow & Shapiro, 2010), and, among other things, to investigate the extent to which Wikipedia is polarized (Greenstein & Zhu, 2012), and to quantify the slant of U.S. news channels (Martin & Yurukoglu, 2017). Recently, Gentzkow et al., (2019) have extended this approach by developing a measure of *partisanship polarization* allowing to quantify the magnitude of partisan differences in speech (by specifying multinomial model of speech with choice probabilities that vary by party), to measure trends in party differences in political speech, using data on the text of speeches in the U.S. Congress from 1873 to 2016. Thus, to the extent that attitudinal polarization is reflected in differences of language, attitudinal polarization will be mirrored in the content of social media posts and can be measured as such.

Data and Methods[1]

To investigate these mechanisms—homophilic partisanship and ideological polarization—we require data about the relationships between Twitter users who are engaged with Norwegian politics on Twitter. Here, we summarize the main steps taken to create data about the network representing mentions and interactions.

Data Collection

A list of 1,845 Norwegian political actors with Twitter accounts was made: This comprised all the candidates standing in the 2017 Norwegian general election who had a Twitter account. By querying the open Twitter API, we made another list of all 833,931 Twitter users who followed one or more of the accounts and counted how many of the politicians' accounts they followed. Then, 4.2 million tweets from the Twitter Historical PowerTrack API were acquired, which comprised all tweets that: (i) were coded as Norwegian-language by Twitter; (ii) were posted in the seven months leading up to and including the Norwegian general election in 2017 (March–September 2017); and (iii) were posted by one of the 264,853 accounts in that followed more than one politicians' account.

Based on these tweets and further data about accounts' followers and friends, a selection of accounts that would be the focus of our investigation was made. Using criteria similar to Barberá, Jost, Nagler, Tucker, and Bonneau (2015) accounts that had "bot-like" characteristics or appeared to be inactive (i.e., accounts that: (i) sent < 10 or > 2500 tweets in the election period; (ii) had < 25 followers; OR, (iii) followed < 100 accounts) were removed. Further, accounts that followed fewer than 10 of the politicians accounts were also removed so that ideological coding of the selected accounts could be reliably automated, as explained in the following section. This gave a set of 11,236 users considered to have been actively engaged with Norwegian politics on Twitter in the period between March and September 2017.

Partisanship Assignment

The ideology of social media users has been automatically coded after selection on communication content (e.g., supervised text classification of tweets; Colleoni, Rozza, & Arvidsson, 2014; Conover, Gonçalves, Flammini, & Menczer, 2012; Himelboim, McCreery, & Smith, 2013; Pennacchiotti & Popescu, 2011, 2021) on the basis of endorsement (i.e., the choices of who a user follows are taken to reflect their ideology such that ideology may be inferred; Barberá, 2015; Barberá, Jost, Nagler, Tucker, & Bonneau, 2015; Bond & Messing, 2015). Also based on endorsement, Halberstam and Knight (2014) coded users' ideologies as a function of the known ideologies of the political actors they follow. Following this latter method, we coded our selected users for "party ideology," which is a discrete class (one of the nine parties in the Norwegian parliament) and for "ideology left-right," which is a scalar value between (0–10) that has been normalized for the analysis.

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[1] More details provided in the SI: https://github.com/benjolras/benjolras-Supplementary-information-relational-ideological-polarization

The “party ideology” variable is calculated as the most common party of the political actors (from list P above) that the user follows. The variable “ideology left-right” is computed as the mean average of the values for the parties of the political actors that the user follows. The values used to position the parties on the left-right scale are based on the averaged self-identification of the candidates for each party during the 2013 national parliamentary election based on a candidate survey realized by Hesstvedt and Karlsen (2017).

The Norwegian parties that are represented in the Parliament designed by their English name, Norwegian name and abbreviation in bold: Labor party (*Arbeiderpartiet*, **A**), Conservative Party (*Høyre*, **H**), Progress Party (*Fremskritspartiet*, **FRP**), Center Party (*Senterpartiet*, **SP**), Liberal Party (*Venstre,* **V**), Christian Democratic Party (*Kristelig Folkeparti*, **KRF**), Green Party (*Miljøpartiet de Grønne*, **MDG**), Socialist Left Party (**SV**), and Red Party (*Rødt,* **R**). The analysis includes, in addition to these main parties, an array of minor parties that are not represented in the Parliament but that presented candidates at the 2017 election. These are as follows: The Christian Party (KRISTNE), a Christian right party; the Alliance (ALLI), a nationalist party; Democrats in Norway (DEMN), a right-wing populist/nationalist party; Health Party (HELSE), a single-issue party; Coastal Party (KYST), a national conservatist party; Pirate Party (PIR), promoting “pirate politics”; and the Capitalist Party (LIBS), a liberalistic party. To measure polarization in a multiparty system such as the Norwegian one, we view polarization as the distance from citizens between blocs of multiple parties. Historically, the Norwegian policy space has been well represented by a left-right dimension (Strøm & Leipart, 1993), with the main political divide between the left social democratic bloc and the right conservative bloc. The right bloc comprises the Conservative Party, the Progress Party, the Liberal Party, and the Christian democratic party, whereas the left bloc includes the Labor Party, the Green Party, the Socialist Left Party, the Center Party, and the Red Party.

We validate the estimates by looking at distributions of the ideology estimates on the left-right scale and by party, using the entire set of Twitter users, including the candidates, and consisting 179,377 users. The differences between parties reflect the ideological distribution of party-politics in Norway.

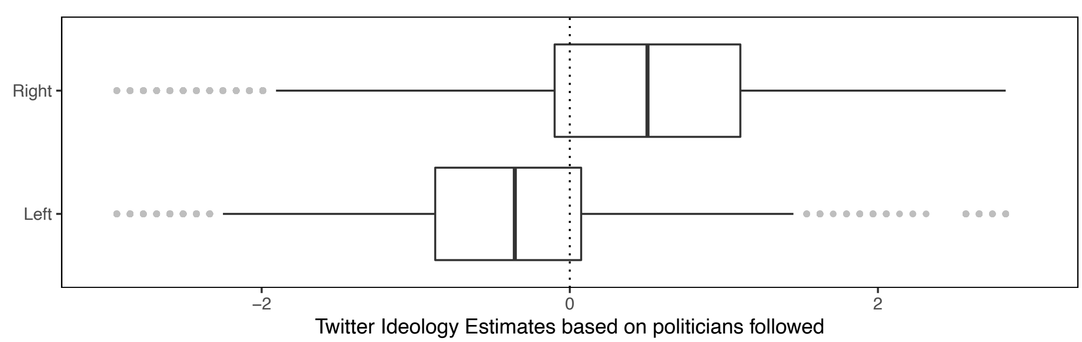


Figure 1. Twitter-based ideology estimates.

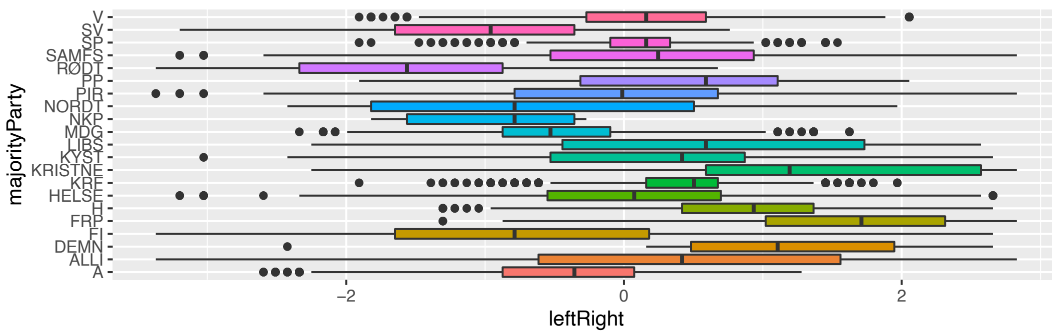


Figure 2. Twitter-based ideology estimates of candidates.

Figure 1 displays the distribution of Twitter-based ideology estimates of candidates on the ideological space according to their position on the left-right political scale computed on the basis of their party-belongings, whereas figure 2 displays this distribution according to their party-belongings. The distribution of ideological estimates according to parties reflects, to a great extent, the party positions on the left-right scale, characterizing Norwegian politics, with the left-wing parties being correctly positioned on the left and the right-wing parties on the right.

Selection of Political Tweets

Since we are interested in political communications between the selected users, we need to classify tweets as political/nonpolitical, where we adopt a broad definition of "political"—much like "political communication," though not necessarily political content. From this viewpoint, communication with political actors would be considered as "political" even if the content is not. A tweet was classified as "political" if: (i) it contained a word, phrase, or hashtag from a precompiled list; or (ii) it mentioned, was sent by, or interacted with the account of a political actor (interactions are replies, retweets, and quoted tweets).

The lists of political terms and political actors were compiled in two steps. First, a list of 28 words, phrases, and hashtags that defined political topics was manually compiled by one of the authors familiar with Norwegian political communication in social media. Further, the list of political actors names comprising the 1,845 accounts from political actors having a Twitter account was included. Then, these lists were expanded in a semiautomated process, similar to Conover and colleagues (2011), using the idea of keyness analysis (Edmundson & Wyllys, 1961). Keyness is a statistic that highlights words that are unusually frequent in one set of texts compared with another set of texts. Here, the comparison was between the tweets that were seen to contain a term from the initial list of terms or to interact with an account from the initial list of actors and the set of remaining tweets. Thus, the list of generated keywords was expected to include good candidates for expanding the initial lists.

By scanning the automatically generated list of the most frequent keywords and examining instances of tweets containing the suggested words, phrases, hashtags, and account names, one of the authors added 677 words, phrases, and hashtags to the list of political terms and 249 further accounts considered to be "opinion leaders" to the list of political actors. Using the expanded lists, we filtered our initial set of 4.2 million tweets according to the presence of a political term or interaction with an account of a political actor, resulting in a set of around 1.5 million "political" tweets. The frequency-led nature of the query expansion process means we are confident that most political tweets were identified, and the use of keyness analysis helps to mitigate researcher bias in the selection of terms and accounts.

The acquired and derived data (i.e., the 11,236 selected users with ideological coding, the lists of their friends/followers, and the tweets classified as "political") were the basis for the preparation of data for the interactions network. *The combined mentions and interactions network*, which is used in the analyses presented here, has weighted directional edges that record how many times user A has mentioned, replied to, quoted, and/or retweeted user B. These counts apply only to tweets that were classified as political. It has 11,061 nodes (not all 11,236 selected users mention or interact with any of the others) and 463,521 edges.

Network Homophily: Community Detection and Assortative Mixing

The Social Network Analysis toolkit includes several techniques for exploring networks' structural characteristics. Clustering algorithms are commonly used tools for detecting the community structure of a network. Such algorithms build on the general principle that members of a community will have more relationships with nodes within their groups than with nodes outside their groups. The most popular of these algorithms involve network modularity maximization (i.e., a process aiming at organizing network's nodes into clusters, within which tie density is as high as possible, and between which tie density is as low as possible). Commonly used network modularity-maximization algorithms include Clauset-Newman-Moore, Wakita-Tsurumi, Newman-Girvan, and the Louvain method (for an overview, see Yang, Algesheimer, & Tessone, 2016). To identify the network's structure, we use a modularity-maximization algorithm: the Louvain algorithm (Clauset, Newman, & Moore, 2004). We retain the top 10 communities (selected according to the number of nodes and edges they represent) for further analysis. We measure the extent to which these communities are characterized by homophily (also referred to as "assortativity") by computing a homophily or "assortativity" coefficient defined as a ratio of the number of outbound ties directed to users who share the same political orientations and the total number of outbound ties. More formally, assortative mixing or "assortativity" (the measure of homophily) is characterized (Newman, 2003) by the quantity e_{ij}, which is defined as the fraction of edges in a network that connect a vertex of type *i* to one of type *j*. The "assortativity" coefficient for the whole network is thus: $= \frac{\sum e_{ij} - \sum a_i\, b_i}{1 - \sum a_i\, b_i}$, where a_i and b_i are the fraction of each type of end of an edge that is attached to vertices of type *i.* On undirected graphs, where the ends of edges are all of the same type, a_i = b_i. This formula gives $r = 0$ when there is no assortative mixing (all nodes link to others of a different type) and $r = 1$ when there is perfect assortative mixing (all nodes link to others of the same type).

Quantifying Partisanship Polarization in Tweets

To quantify partisanship polarization in Tweets messages between the language of users labelled "left" and "right" in each network top community, we follow the computational approach advanced by

(Demszky et al., 2019). We first build a vocabulary for each community containing unigrams and bigrams (i.e., words) that occur in a given community's tweets at least 50 times, counted after stemming and stop-word removal. We then apply the estimator of speech partisanship from (Gentzkow et al., 2019) which allows to control for finite sample bias (resulting because the number of words that a Twitter user could choose is large relative to the total amount of words that are observed). Gentzkow and colleagues (2019) define their estimator as "the posterior probability that an observer with a neutral prior expects to assign to a speaker's true party after hearing the speaker speak a single phrase" (p. 9). The estimator consistently estimates partisanship under the assumption that the user's words are drawn from a multinomial logit model with lasso-type penalty (Taddy, 2013). The *partisanship* of a Tweet π between right-wing ($i \in R$) and left-wing ($i \in L$) Twitter users is:

$$\pi = \frac{1}{2}\left(\frac{1}{|L|}\sum_{i \in L} q_i \cdot \rho_{-i} + \frac{1}{|R|}\sum_{i \in R} q_i \cdot (1 - \rho_{-i})\right)$$

where q_i is the vector of empirical words frequencies for tweeter *i*, and ρ_{-i} is a vector of empirical posterior probabilities a neutral observer assigns to $i \in L$ after seeing a word in *i*'s tweet. This estimator captures two components of polarization (Demszky et al., 2019) between-group difference and within-group similarity. If there is no difference in speech usage between the two political blocs (left-right), then this probability is .5 (i.e., we cannot guess the user's political bloc any better after observing a phrase).

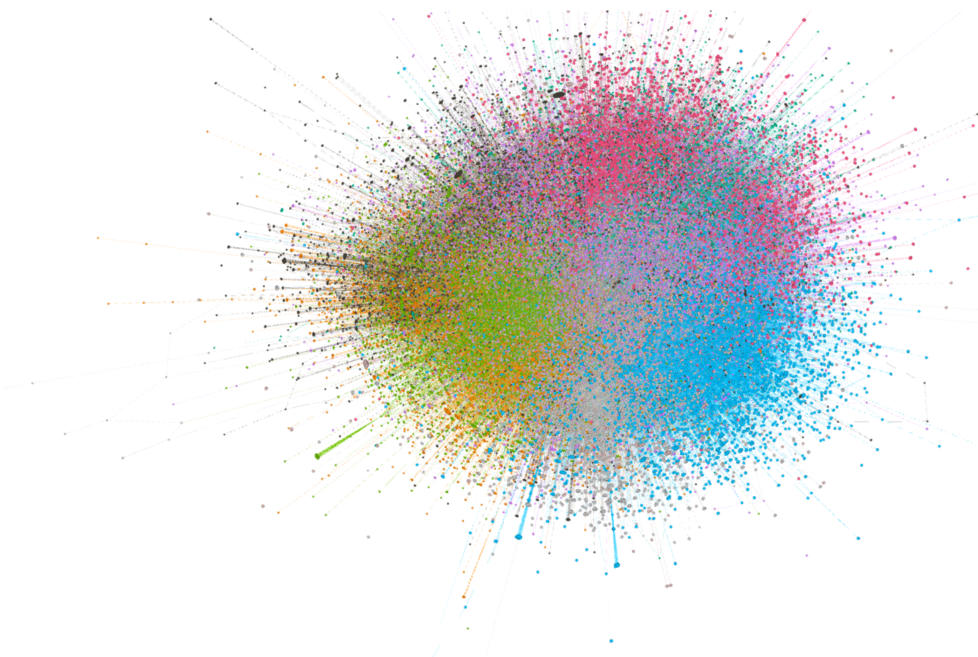
We compute polarization within each community and by topics (within and between topics). Topics are identified, following the approach of (Demszky et al., 2019), by taking advantage of the ability of the vector space model (word embeddings) to represent higher-level semantics. Clustering word embeddings gives similar results as LDA topic modeling, especially when documents are short (e.g., tweets) and the window size of the embedding model is sufficiently wide (Hovy, 2020). We train GloVe embeddings (Pennington, Socher, & Manning, 2014) using the Mittens Python package (Dingwall & Potts, 2018) and cluster the embeddings via K-means to assign all tweet embedding to the centroid to which they are closest to obtain the topics.

Results

The presentation of the results consists of three steps that enable us to investigate the two mechanisms of polarization—relational homophily and ideological partisanship—and to inquire into the extent to which ideological partisanship is related to the structure of the network and to the topics that are the subjects of the interactions on Twitter. First, we look at the structure of the network using community detection algorithms and assess the degree of homophily of the clusters constituting the interactions network. Second, we identify the main topics characterizing the interactions network by combining word embeddings and k-means clustering methods. Finally, we assess the degree of polarization characterizing interactions on Twitter across topics and communities.

Structure of the Network of Interactions

Following the approach advanced by Freelon (2020) we first partitioned the interactions network into subgraphs retaining only the 10 largest communities since the Louvain algorithm generates a few very large clusters and many very small clusters. The top 10 communities of the interactions network represent 98.64% of all nodes and 99.75 % of all edges. Figure 1 presents a visualization of the top 10 communities in the interaction network. The modularity coefficient was of 0.363, indicating relatively dense clusters. The legend of the figure and the descriptive statistics for each community (with the numerical labels produced by the Louvain algorithm) are presented in Table 1. The visualization indicates that there exist interactions between the top 10 communities, as there are many nodes and links joining them. Communities 1 and 13 are the biggest in terms of number of nodes, whereas communities 10 and 4 are the smallest. The assortativity coefficient is close to zero for all the communities, indicating that the network of interactions present a low level of homophily—whether we consider homophily according to party affiliation or according to bloc appurtenance (left-right).



Communities
Left-Right politics
Media
Environment-economy
Radical right
Right-wing politics
Health politics
Oslo
Sport

Figure 3. Top 10 communities in the Interaction-Network.

Table 1. Top 10 Communities' Legend, Number of Nodes, and Assortativity Coefficient.

Community	Color in the figure	Number of nodes	Assortativity coefficient by party	Assortativity coefficient by left-right
13 Left-right politics		5495	0.03	0.04
6 Media, institutions, and interest groups		3606	0.03	0.03
15 Environmental and economic politics		3885	0.04	0.03
1 Radical right/system critics		5648	0.02	0.02
10 National Broadcasting NRK	--	503	0.07	0.07
2 Right-wing politics		2444	0.04	0.04
39 Health politics		2443	0.04	0.04
8 Oslo		1901	0.03	0.13
33 Sport and sport politics		3853	0.03	0.03
4 Media/news	--	364	0.07	0.06

Table 2 presents the results of a more qualitative inspection of these communities, allowing one to identify their main characteristics and to label them. The table displays, for each cluster, the users with the highest in-degree values (i.e., displaying a high number of incoming links), the top hashtags, and the top words characterizing the tweets belonging to these clusters. Considering both the highest in-degree users (where the top users are either political parties or party leaders), the top-hashtags (related to the election campaign), and the top words (mainly top politicians), it appears that community 13 is about political discussions across the left-right divide. Similarly, community 8 is about politics in the Norwegian capital, Oslo. Community 6 is related to a "democratic fare," taking place in the city of Arendal at the beginning of August, called Arendal's week, where politicians, interest groups, and media are meeting with the public. The political debate between party leaders arranged by the National Broadcasting television in Arendal is usually considered as the official start of the election campaign. Community 4 seems to consist mainly of interactions related to the media, while Community 15 is topically oriented toward economic and environmental issues. Community 10 is concerned with the National Broadcasting company NRK, Community 2 appears to be dominated by radical right politics, while Community 39 is thematically oriented toward health politics, and Community 33 is concerned with sport and sport politics.

Table 2. Highest In-Degree Users, Top Hastags, and Top Words in Top 10 Communities From Cross-Sectional Partition of Political Interactions on Twitter.

Cluster	Screen Name	In-Degree	Top Hashtags	Top words in tweets
Left-right politics (13)	arbeiderpartiet jonasgahrstore venstre	2718 2590 2442	#nrkvalg, 4700, #valg2017, 3358, '#dax18, 2711,	@erna_solberg @arbeiderpartiet @jonasgahrstore

	hoyre	2276	'#valg17, 1574,	Government
	frp_no	1953	#nrkdebatt, 1324,	@trinesg
	trinesg	1907	#aplm17, 1063,	@audunlysbakken
	sv_parti	1688	'#polkvart, 981,	
	audunlysbakken	1501	#arendalsuka, 935,	
	Krf_norge	1412	#alleskalmed, 707	
	abidraja	1302		
Oslo (8)	ketilso	831	#osby, 566,	@partiet
	raymondjohansen	562	#sykkel, 323,	@sykkelioslo
	lan_marie	470	#nrkvalg, 302,	Bicycle
	oslokommune	262	#valg2017, 297,	@syklistenes
	oslopartiet	236	'#norge, 238,	@aftenposten
	budstikka	210	'#dax18, 228,	@lan_marie
			#oslo, 176,	@bymiljoetaten
Arendalsuka (Arendal's week): Media, institutions and interest groups (6)	konservativ	1752	#arendalsuka, 1226,	School
	aftenposten	2300	#valg201', 652,	education
	Jantoresanner	769	#nrkvalg, 474,	debate
	Lindacat	691	#dax18, 388),	Arendal's week
	arendalsuka	528	#lmnso, 341	
	nhokristin	403		
	NRK	386		
	innovasjonnorge	286		
	unioslo	283		
	forskningsradet	281		
Media/news (4)	tegnehanne	98	#siste, 43,	#nrkdebatt
	norskpsykologf	91	'#dax18, 21,	Political
	dagsnytt18	91	'#snorden, 15,	Politicians
	ntbinfo	90	'#nrksport, 14	Parliament
				The people
				@psteigan
				Trump
				@tyskpolitikk
Environmental and economic politics (15)	vidarhelgesen	839	#arendalsuka, 1593,	@svparti
	nikolaiastrup	646	'#lovese, 1589,	@partiet
	olaelvestuen	492	#nrkvalg, 1431,	@hoyre
	kjellingolf	321	#valg2017, 1094,	@arbeiderpartiet
	Nho_no	319	#elbil', 1090,	@venstre
	abjartnes	283	#verdtåbevare, 1068	Oil
	norskoljeoggass	267		Green
				Renewable
				@zeronorge
				#elbil

National Broadcasting NRK (10)	nrkno nrkrogaland presseforbundet	1654 51 31	#nrkarkiv, 180, #valg17, 169	@vgnett @nrkno #falskenyheter #dax18 #2valg #fakenews
Radical right/system critics (1)	doremusschaffer lysglimt real_frp realdonaldtrump	894 335 316 237	#dax18, 5196), #nrkvalg, 2835, #valg201, 2753, '#valg17', 1206, '#nrkdebatt', 1064	Trump Norway Norwegian @espenteigen (Press Chief Frp) Frp
Health politics (39)	morgenbladet norsksykepleier nrkytring legeforeningen solveighorne helse_og_omsorg ktoppe	385 351 266 263 262 256 252	#valg2017, 720, #pårørende, 686, #arendalsuka, 546, #dax18, 453, #psykisk, 301, '#helsekonf, 276	Health @benthhoyre @kreftforeningen @helsepartiet @norsksykepleier @helsedir @meggelise (Helsepartiet) @legeforeningen
Sport and sport politics (33)	tv2davy rbkfotball nff_info sponsorconsult idrett Nrk_sport	350 157 155 119 109 103	#nrkvalg, 417, '#valg2017, 372, '#valg17, 187, #esnball, 167, #dax18', 150, '#2hockey, 138	Norway Norwegian Money Europe World
(2) Right-wing politics	Senterpartiet Rotevatn kristinclemet Faktisk.no Kjetilba Jasnoen mathildetg Minervanett Ungevenstre ungehoyre	1442 1342 1045 760 640 632 221 204 162 160	#valg2017', 210), ('#norge', 183), ('#dax18', 135), ('#digikonf', 129), ('#nrkvalg', 108), ('#innovasjonstalen', 101), ('#innovasjon', 86), ('#kulturmelding', 74), ('#valg17', 74)),	@venstre Trump @rotevatn @trinesg @erna_solberg Høyre Government @aftenposten

In sum, Table 2 shows that the political Norwegian Twittersphere during the 2017 national election consisted of 10 thematically related communities, interacting around limited political or policy issues. The biggest communities such as community 1 (radical right politics) and 13 (left-right politics) are related to political debates. However, although Community 13 (left-right politics) is characterized by interactions across political lines, involving both right-wing and left-wing political parties and their supporters, Community 1 (radical right politics) and Community 2 (right-wing politics) appear to consist mainly of interactions among like-minded political actors and partisans (the Conservative Party for Community 2 and radical right actors for Community 1). In contrast, the remaining communities are structured around discussion topics, being policy issues, places, or events.

Another dimension of the structure of the interactions network is the linkages between these communities (i.e., the extent and the ways to which the different communities or subgraphs are related to one another). A way to investigate those linkages (Freelon, 2020) is to look at the proximity matrix (adjacency matrices for communities as nodes), which displays the proximity—proportion of shared ties between two clusters—of each community to every other community. Table 3 displays the proximity matrix for our interactions network. Each cell represents the number of ties shared between two communities. Diagonal cells contain internal ties—that is, ties for which both nodes are members of the same community.

Community 13 (left-right politics) is strongly connected with Community 1 (radical right politics), indicating that there exists a significant level of interaction between these two communities that are oriented toward political topics. There are also strong connections between Community 13 (left-right politics) and Community 15 (environmental and economic politics) and Community 2 (right-wing politics). These results show that there are significant interactions between the dominant cross-party political public spheres on twitter during the election campaign (Community 13 left-right politics) and more ideologically segregated communities, such as Community 1 (radical right politics) or Community 2 (right-wing politics), confirming that the political Twittersphere during this election campaign did not exhibit strong homophily or the existence of echo-chambers.

Table 3. Proximity Matrix for Cross-Sectional Partition (Count of Common Edges, i.e., Received or Sent).

	1 Radical right	**2 Right-wing politics**	**4 Media/news**	**6 Interest groups**	**8 Oslo**	**10 National Broadcasting NRK**	**13 Left-right politics**	**15 Environmental and economic politics**	**33 Sport and sport politics**	**39 Health politics**
1 Radical right	191663	30684	486	15231	19734	2854	75587	24156	14010	19922
2 Right-wing politics	30684	17900	153	6190	4387	573	26178	10267	3599	4390
4 Media/news	486	1837	1837	139	168	42	1288	172	33	59
6 Interest groups	15231	6190	139	31687	3318	446	19384	7628	1852	7328
8 Oslo	19734	4387	168	3318	34376	364	9325	12459	2189	2383
10 National Broadcasting NRK	2854	573	42	446	364	849	1263	561	386	505
13 Left-right politics	75587	26178	1288	19984	9325	1263	75999	31558	7767	18996
15 Environmental and economic politics	24156	10267	172	7628	12459	561	31558	62443	2093	4344
33 Sport and sport politics	1401	3599	33	1853	2189	386	7767	2093	18331	1679
39 Health politics	19922	4390	59	7328	2383	505	18996	4344	1679	40284

Another aspect of the structural characteristics of the interactions network is the presence of nodes that receive large numbers of ties from multiple communities or clusters. In interactions networks, such nodes help bringing ideologically opposed clusters together and offer common ground for cross-cutting debate. Freelon (2020) suggests two such criteria for identifying such nodes: They should rank highly on one measure of network prominence such as in-degree and substantial proportions of their incoming ties must be distributed fairly evenly across two or more communities.

Table 4 displays the five most prominent intermediary nodes that bridge several communities. The four columns of the table contain, respectively, the screen names, in-degrees, list of the 10 communities, and the number of ties linking the intermediary node with each community. The five most prominent intermediary nodes are either top politicians (party leaders) or political parties. In most cases, these intermediary nodes span bridge several of the most politically oriented communities, such as Community 13 (left-right politics), Community 1 (radical right politics), Community 15 (environmental and economic politics), and Community 2 (right-wing politics).

Table 4. Five Most Prominent (Highest In-Degree) Intermediaries.

Screen Name	In-Degree	Cluster	Ties
erna_solberg	16319	13	5893
		1	4500
		15	1656
		39	1414
		2	1026
		6	923
		33	452
		8	332
		4	61
		10	32
venstre	12969	13	3504
		1	3232
		15	2128
		2	1994
		39	613
		6	575
		8	563
		33	318
		4	26
		10	9
arbeiderpartiet	12802	13	3992
		1	3637
		15	1668
		39	1188
		6	843
		2	792

		8	315
		33	314
		4	48
		10	11
Partiet (MDG)	11721	15	4874
		1	3104
		13	1154
		8	1152
		2	616
		39	395
		6	211
		33	165
		10	34
		4	16
jonasgahrstore	11305	13	3986
		1	2770
		15	1537
		39	992
		2	829
		6	685
		8	219
		33	214
		4	55
		10	18

Topics: GloVe Embeddings and k-means Clustering

Following Demszky and colleagues' (2019) approach, we assign topics based on words embedding by clustering the trained sentence embeddings (GloVe) using the k-means clustering algorithm to assign the tweets embeddings to eight clusters (topics). Topics are constituted of words that cooccur within the corpus (i.e., the tweets) and are labeled based on the inferred meaning of the top words constituting them. Table 5 presents the results of this assignment with each cluster being assigned a subjective label based on the top words characterizing each cluster. The first topic (cluster 0) is related to political events, the second (cluster 1) to polls, the third (cluster 2) to profiled politicians, the fourth (cluster 3) regroups argumentative expressions and indicates exchanges of opinions, the fifth (cluster 4) relates to the green transformation in the wake of the climate crisis and the necessary innovations it entails, the sixth (cluster 5) to the issue of hate speech and the far-right, the seventh cluster (cluster 6) is about the economy and tax policies, while the last topic (cluster 7) seems to aggregate common words and does not really constitute a topic.

Table 5. Clusters, Topics, and Words.

Cluster	Topic	Top words	Proportion
0	political events	Moss, hour, evening, saturday, morning, stage, summer, week, Trondheim, Thursday, Sarpsborg, weekend, event, #redningshund, visits	0.18
1	polls	citizen, barrier limit, majority, krf, sp, left, measurement, mandate, sv, mdg, red green, v, ap, vote, voter, voter, frp, h, party, red	0.10
2	politicians	Listhaug, Sylvi, Solberg, she, her, Erna, Prime Minister, cnn, Hareide, Siv, Teigen, pronunciation, salmon, critic, Northug, Amundsen, Gahr	0.07
3	argumentative expressions	like, maybe, know, whatever, something, yes, difficult, thought, beautiful, own, one, a little, say, actually, should, always, find, sure, points	0.23
4	innovation and transformation	conversion, digitalization, technology, health industry, digital, ICT, innovation, health data, sustainability, student housing, instruments, internationalization, #conversion, competence, mobility, renewable, ecological, #climate, climate cuts, #education	0.13
5	political hate and far right	abuse, circumcision, violence, neo-Nazi, experienced, free speech, London, terror, Muslim, Jew, killed, Islam, harassment, far right, civil, condemnation, monopoly, san, Nazism, sexual	0.05
6	economy and taxes	pay, billion, subsidy, million, richest, income, earn, housing, wealth tax, make, save, tax, cost, billion, emissions, krone, owner, co2, tax, cut	0.125
7	other	Not, I, one, them, just, believe, are, were, what, do, then, somebody, from, come, will, know, self, completely, a lot, see	0.08

Figure 3 displays the distribution of topics by community. Although most of the topics are fairly equally distributed across communities, there are exceptions. Topic 0 (political events) is overrepresented in Community 4 (media/news) and, to a certain extent, in Communities 33 (sport) and 10 (National Broadcasting NRK). Topic 4 (Transformation and innovation) is overrepresented in Community 6 (Arendal), Community 15 (environmental and economic politics), and Community 39 (health politics). Topic 3 (argumentative expressions) is overrepresented in Community 1 (radical right), Community 8 (Oslo), and Community 33 (sport), indicating that these communities are characterized by exchanges of arguments. Topic 6 (economy and taxes) is overrepresented in Community 8 (Oslo) and Community 15 (environmental and economic politics). In sum, the distribution of topics by community makes sense given the main orientation of these communities.

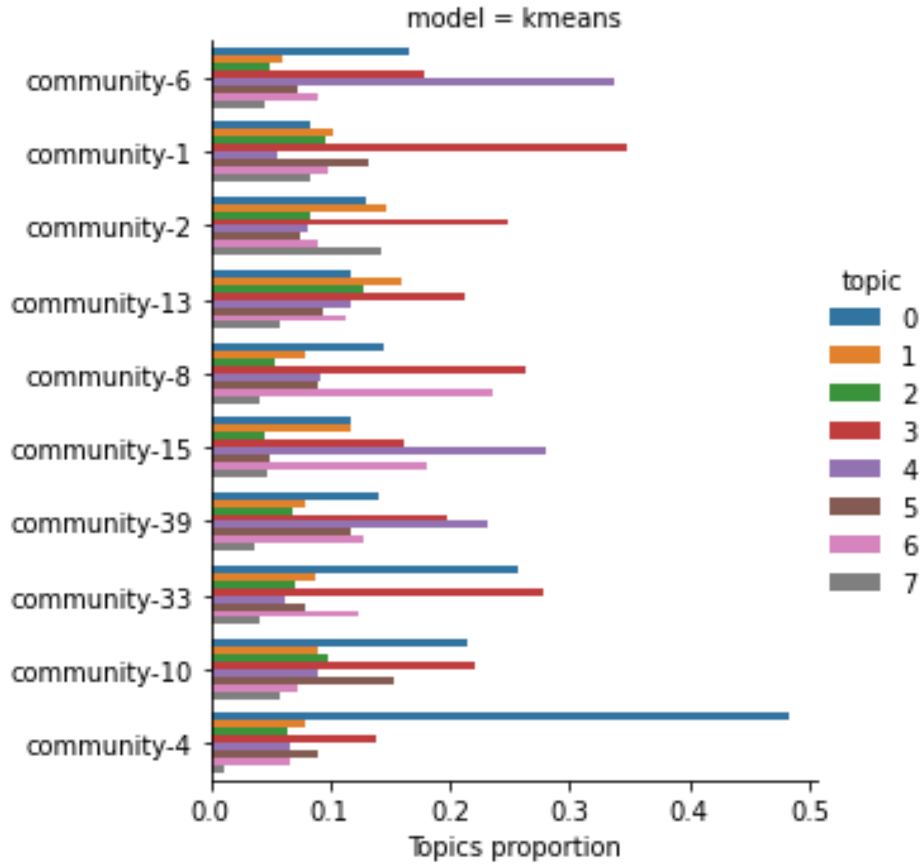


Figure 3. Topic distribution by community.

Polarization Measured Through Tweets' Content

After having characterized both the structural features of the interactions network (community partition and degree of homophily) and the main topics contained in tweets, we can now proceed to the presentation of the estimations of the degree of partisanship polarization measured through the tweets' content. We first consider the overall degree of polarization in each community. Next, we look at the overall degree of polarization by topic and examine the extent to which polarization is driven by the choice of topic (between-topic polarization) or is internal to the topic (driven by partisanship within a topic).

Figure 4 displays the overall degree of partisanship polarization by community compared with the degree of polarization that would occur by randomly assigning ideological appurtenance. Keeping in mind that π is the posterior that a neutral observer expects to assign to a Twitter user true party bloc after seeing a single word from the vocabulary, and that (Gentzkow et al., 2019) report a π of about 0.502–0.504 for the 1870–1990 period in the U.S. Congress, which later increases to about 0.510. We can assess the degree of partisanship polarization by community with the U.S. Congress as benchmark. The degree of across-bloc polarization in Twitter communities lies between 0.502 and 0.503 for Communities 2 (right-wing politics), 8 (Oslo), 10 (National Broadcasting NRK), 33 (sport), and 39 (health politics). In contrast, communities 1 (radical right politics), 4 (media/news), 13 (left-right politics), and 15 (environmental and economic politics) lie between 0.501 and 0.502. The degree of polarization on the Norwegian Twittersphere during the 2017 national election is, thus, comparable to the level that used to characterize the U.S. Congress in the 1990s.[2]

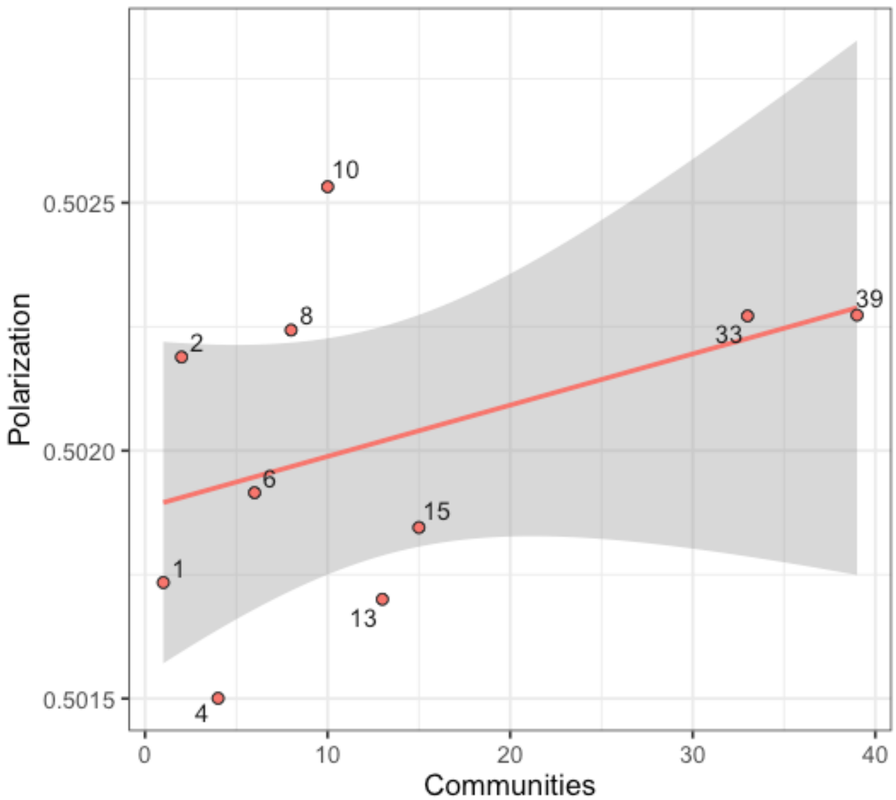


Figure 4. Overall polarization by community—actual value versus random value.

Figure 5, displaying the log odd ratio that left and right partisans choose a topic, shows that the degree of partisanship polarization also varies by topic: Polls and green transformation are more likely to be discussed by Twitter users belonging to the right bloc and hate speech; economy and taxes and politicians are more likely to be discussed by Twitter users belonging to the left bloc across communities.

[2] The degree of polarization in the U.S. Congress prior and posterior to 1990 offers a benchmark for both relatively low and high levels of partisanship polarization.

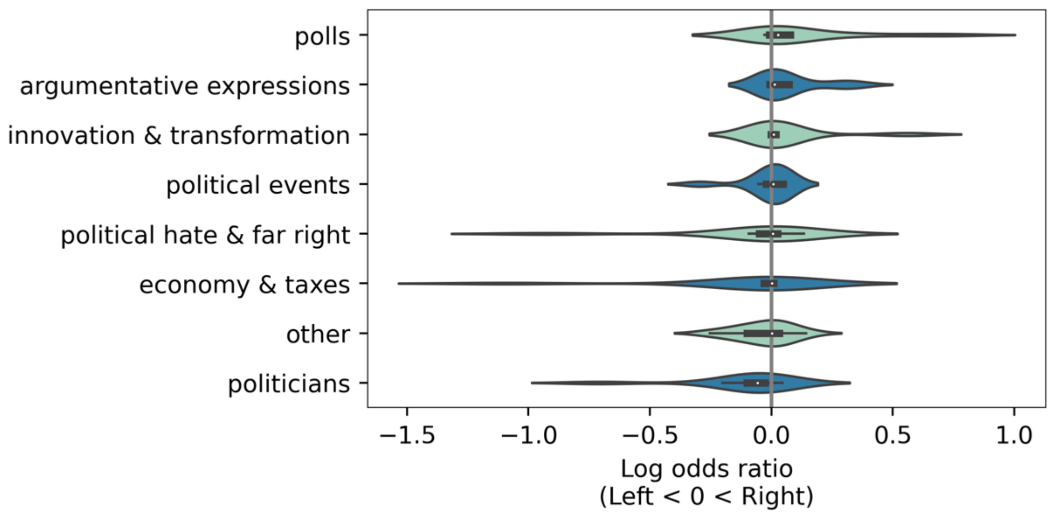


Figure 5. Overall polarization by topic.

To measure within-topic partisanship for a particular community, the degree of across-bloc polarization by topic is calculated, following the procedure developed by Demszky and colleagues (2019), by using only tweets categorized to that topic. Then, overall within-topic partisanship for a community is the weighted mean of the estimated polarization coefficient by topic, with weights given by the proportion of tweets categorized to each topic within each community. Between-topic partisanship is the expected posterior that an observer with a neutral prior would assign to a user's true bloc after learning only the topic (not the words) of a user's tweet. This value is estimated by replacing each tweet with its assigned topic and by computing the polarization coefficient (π) with this data.

Figure 6 shows that for Community 33 (sport) and Community 39 (health politics), within-topic polarization is higher than between-topic polarization, indicating that, if the choice of topic plays a role in determining the degree of polarization, partisanship polarization is more pronounced within the topics. It is the opposite for Community 4 (media/news) and Community 10 (National Broadcasting NRK), entailing that the choice of topic is polarizing in itself (the topics are polarized topics). For the other communities, there are no important differences between within and between topic polarization.

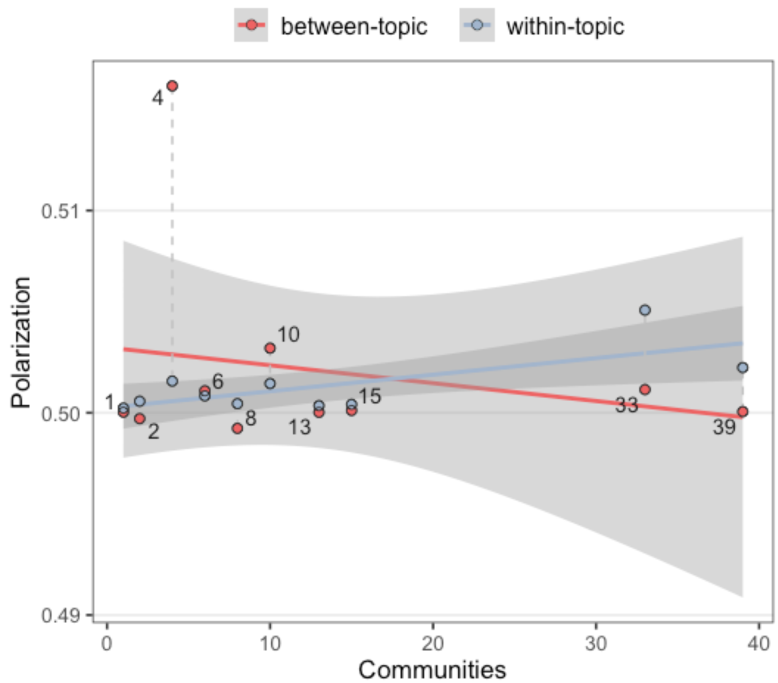


Figure 6. Polarization between and within topic by community.

Discussion and Conclusion

There is a widespread concern that social media contribute to increased political polarization and are thus detrimental to democracy. A popular argument from Barberá (2020) is that social media foster the development of echo chambers, where like-minded citizens reinforce their political views without being exposed to challenging views. Within such an informational environment, the argument goes, individuals become increasingly segregated along partisan lines and tend to radicalize their political views. An alternative argument would be that political polarization is not a consequence of the spreading of social media but has socioeconomic and political causes and is reflected in the political communication taking place on social media.

The results presented in this article show that the Norwegian political Twittersphere is not made of echo chambers isolated from each other but is structured around ideologically crosscutting communities of interaction that are linked to each other. There are, additionally, no signs that the communities characterized by higher degrees of polarization are the ones that display the higher degree of homophily (as measured by their assortativity mixing coefficient), indicating that homophily or partisan selection is not the main mechanism behind polarization on the Norwegian Twittersphere.

Nonetheless, polarization on the Norwegian political Twittersphere appears as a differentiated phenomenon as degrees of polarization differ across communities and vary according to the way they are measured (ideological polarization measured in terms of retweets and in terms of content). The degree of ideological polarization (expressed in tweets messages) between the two main political blocs (left and right) structuring Norwegian politics is varying across these communities, but lies within the range that used to characterize Congressional politics in the United States before 1990 (Gentzkow et al., 2019). However, some topics, such as political hate and far right and economy and taxes, are more polarized than others.

Our findings challenge the conventional wisdom according to which social media systematically fosters polarization and indicate that polarization in social media is contextual (Urman, 2019) and topically related. In fact, social media may contribute to decreased polarization when, as it is the case for the Norwegian political Twittersphere, individuals are embedded in ideologically diverse networks and exposed to challenging information (Barberá, 2014). The intensity of polarization on social media seems to vary in different political contexts (Urman, 2019) and depends on socioeconomic, cultural, and political (such as the type of political system) factors. Indeed, the electoral system in Norway is based on proportional representation leading to a differentiation of the party system (as opposed to majoritarian electoral and bipartisan systems), entailing that, at present, nine parties are represented in the Norwegian Parliament. This plural party landscape entails the need for coalition governments, including several parties that promote a culture of dialog and cooperation, and despite the existence of two political blocks (right and left), there is a culture of cross-ideological cooperation on major issues. Additionally, the media landscape is much less ideologically polarized, partly because of the prominence of the Public Service Broadcaster (NRK) that plays a central role in providing an arena for cross-ideological communication. All these features of the Norwegian political institutions and culture may contribute to fostering cross-ideological interactions and to limiting polarization on social media.

Yet, the relatively high degree of polarization characterizing the community thematically structured around radical-right politics as well as the relatively high degree of polarization of the topic "political hate and far right" indicates that there exists a division, a confrontation, and a tendency toward polarization on the Norwegian Twittersphere between mainstream politics on the one hand and radical-right politics on the other.

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