Divided Information Space: Media Polarization on Twitter during 2019 Indonesian Election

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Abstract

Nowadays, the understanding of the impact of social media and online news media on the emergence of extreme polarization in political discourse is one of the most pressing challenges for both science and society. In this study, we investigate the phenomenon of political polarization in the indonesian news media network based on the pattern of news consumption patterns of Twitter users during 2019 Indonesian elections. By modeling news consumption patterns as a bipartite network of news outlets-Twitter user, and then projecting to a network of news outlets, we observed the emergence of a number of media communites based on audience similarity. By measuring the political alignments of each news outlet, we shows the politically fragmented Indonesian news media landscape, where each media community becomes an political echo chamber for its audience. Our finding highlight the important role of mainstream media as a bridge of information between political echo chamber in social media environment.

Keywords: network, news media, echo chamber, twitter, community detection

1. Introduction

The outbreak of extreme partisan attitudes in various democratic countries has been the problem of this century [1]. This phenomenon cannot be separated from the rise of digital technology, social media and online news media, which makes it easier for citizens to obtain and discuss political information [2]. On the one hand, digital technology increases the chances of individuals being exposed to information from a variety of perspectives [3]. But on the other hand, mediation and personalization of information by social networks also has the potential to limit exposure to only information that is politically agreed upon [4], giving rise to misperceptions of facts and events [5] and leading to the emergence of increasingly extreme political attitudes [6].

Confirmation bias and selective exposure are two important factors behind the dynamics of information consumption on social media [7]. A number of studies have shown empirically the tendency of social media users to focus on specific narratives, and interact intensively with those who have the same political preferences [8]–[10]. This micro tendency may lead to the emergence of echo-chambers [7], [11] that divide the social media space into politically homogeneous user communities [12]. In each community, users tend to ignore dissenting information and to interact with information adhering to their preferred narrative. The study of digital echo-chamber phenomena is quite challenging [7]–[12]. However, most of research in this area examine fragmentation and polarization in user networks. Meanwhile, empirical works to investigate information segregation due to fragmentation of information sources is constrained by the difficulty of measuring the political tendencies of the news media [13].

In network perspective, the dynamics of information consumption on social media is basically the process of network formation that connects readers and information sources (e.g. web, blogs, online media, etc.) through various means, e.g. browsing, sharing and others. Therefore, in this study, to gain a better understanding about information echo-chamber and its polarization effect, we will explore the anatomy of media network constructed from news consumption activity on Twitter during 2019 Indonesia election. Specifically, we analyzed 667,821 election-related tweets to investigate the phenomenon of polarization of the news media in Indonesia, as well as explore the role of each news outlet in the dynamics of news consumption during the election. This paper is written with the following structure: data and analysis methods will be discussed in sections two and three of this paper, while in section four we discuss the results of the analysis based on the objectives of this study. Conclusions and contributions of the study are discussed at the end of this paper.

2. Data

This study investigates news consumption patterns on Twitter during the 2019 Indonesian presidential and legislative elections. We conducted the data collection process from March 27 to May 19, 2019, covering the campaign period, elections (17 April 2019), the vote recapitulation and announcement period (21 May 2019). We use DMI-Tcat application [14] to extract data from Twitter based on a number of keywords related to the candidates, namely: (i) Candidate I (Prabowo - Sandiaga Uno): prabowo, sandiaga uno ; (ii) Candidate II (Joko Widodo - KH. Maaruf Amin): joko widodo, jokowi, maaruf amin, kiyai maaruf.

In this study we only focused on 667,821 of total 13,990,975 tweets, which contained news links from 559 Indonesian news media, and were shared at least ten times by Twitter users (see Table SI 1). Figure 1 shows 10 most popular media during the election. From this figure we know that mainstream news outlets dominate the Indonesian political news market on Twitter.

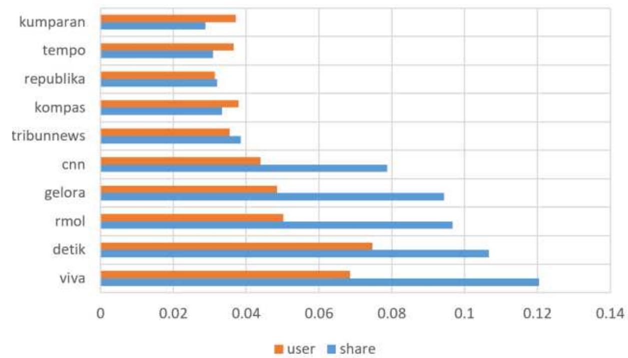

Figure 1 News media with the largest number of shares and readers

3. Method

3.1 Bipartite Network

News consumption activities on social media form patterns of information exposure that can be modeled as a bipartite network between Twitter users and information sources. The user-media bipartite network (S) is composed of two type of nodes, namely user node (n_A = 115,621) and news outlet node (n_B = 559). Each edge (n_e = 466,542) connecting two nodes indicates that user a_i $(a_i \in A)$ consumes news, which is expressed through sharing or retweeting, from outlet b_i $(b_i \in B)$. To explore connectivity patterns among news outlets, we project bipartite network S into news outlet network $\hat{S}$, where edge weight indicates a number of shared audience between these outlets. In this study, we focus on the largest connected component of weighted network $\hat{S}$, which is composed of 559 media nodes and 55,662 edges.

Table 1 shows that the projection network has a fairly dense structure (density = 0.35). Therefore we need to evaluate significance of each edge and filter out random interaction between reader and news source. In this study we use the method proposed by [15], which has been proven effective for investigating bipartite systems in various areas, from biological, financial to social systems. Specifically, we attach p-values at each edge of the projection network, then apply multiple hypothesis testing using a statistical threshold value of 0.01, and then make moderatly corrections using False Discovery Rate method (FDR) [16].

Table 1 Characteristics of Indonesian news media network

Statistics	Pre-filtered network	Final network
# of node	559	528
# of edge	55,662	27,192
Diameter	3	6
ave.path length	1.64	1.953

Density	0.35	0.195

3.2 Community Structure

In this study we use Fast Greedy algorithm [17] to analyze the meso structure of projection network $\hat{S}$. To validate the results, we also implemented the Walk Trap algorithm [18], then compared the results of both algorithm using adjusted rand index method [19]. We find the adjusted rand coefficient is 0.8 , which indicates that two algorithms produces similar result.

Table 2 Descriptive statistics of community partitions using the Fast Greedy algorithm

Statistics	Fast Greedy
# of community	5
Modularity	0.256453
# node in cluster 1	202
#node in cluster 2	313
# node in other clusters	13

3.3 Political stance of online news media

We need to measure political stance of news outlets in order to investigate political polarization that occurs in media networks during the elections. In this study the media stance was identified based on partisan behavior of their audience, assuming that people tended to be selective about information, i.e. only reading and sharing news articles in accordance with their political preferences. Following [20], the process of media classification is carried out in 3 stages, as follow: (i) Hashtag-based user labeling: 1400 political hashtag associated with certain political groups are used to identify the political affiliations of these hashtag users (see Figure SI1). At this stage, we successfully identified 153,990 labeled users, which will then be used as seed nodes for the label propagation algorithm at later stage.; (ii) Network-based user labeling: at this stage we apply Label Propagation algorithm to expand the number of labeled users (see Table SI2) [21], [22]. We have successfully identified political affiliation of 388,253 Twitter users, with prediction accuracy of 98% (see Table SI3); (iii) Media classification: we use polarity rule [12] to identify media stance based on the political affiliation of their audiences. Table 3 shows classification result of 559 news outlets in Indonesia.

Table 3 Descriptive statistics of media stance during election

	# news outlet	# Share	# Users
Pro-Joko Widodo	347	373,932	39,806
Pro-Prabowo	212	404,058	61,966
Total	559	777,990	101,772

4. Analysis

4.1 News consumption patter

The current disintermediated environment composed by a heterogeneous mass of information sources, on the one hand, has reduced the centralization of information, which is a characteristic of information consumption patterns in the previous era [23]. But on the other hand, it may lead to the emergence of audience fragmentation into various groups of information sources [24]. The distribution of readers in Figure 2 shows that people tend to interact with a few news outlets, despite the availability of various alternative news sources. Naturally, this may lead to a wider-but-fragmented landscape of information sources, where news outlets are grouped based on audience similarity.

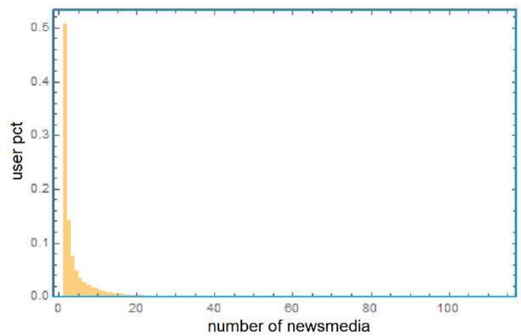

Figure 2 The number of news media consumed by twitter users.

4.2 Segregation in media network

We implement a community detection method on media network to identify media clusters emerged from news consumption activities on social media. The network decomposition process using the Fast Greedy algorithm (see Table 2) revealed the presence of 5 media communities, where there were two very dominant clusters, covering 98% of total news outlets analyzed. Table 4 shows a number of mainstream news outlets in these two dominant communities.

Tabel 4 The mainstream news media in the two dominant communities.
Alexa rank [25] is used as a proxy for credibility of news media

No	Community 1	Media Rating	Community 2	Media Rating
1	tribunnews	42	okezone	22
2	detik	84	liputan6	133
3	kompas	132	grid	148
4	suara	299	sindonews	154
5	kumparan	321	idntimes	323

The media network has a high modularity value (M = 0.25), which is indicates the presence of information sources segregation in the Indonesian media network during the elections. Considering that the grouping of news outlets reflects the preferences of audience over news sources, we need to measure the extent of polarization between the two media communities, as follow [26], [27]:

$$p(u) = \frac{y-x}{y+x} \qquad (1)$$

where y (x) is a fraction of twitter users who share news tweets from outlets in media community $C_1(C_2)$. Figure 3 shows the presence of strong bimodality in the distribution of news audience activity in each community. This indicates that each media community is an echo chamber for their respective audiences, that is a groups of like-minded people cooperating to reinforce a shared narrative.

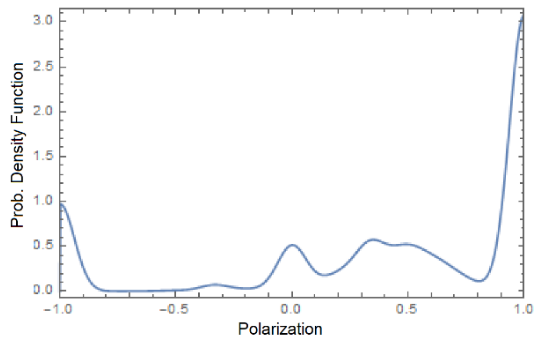

Figure 3 Audience segregation

4.3 Political polarization

To understand the relationship between segregation in media networks and the political alignments of news media during the elections, we elaborate the composition of partisan media in the two dominant media clusters. As shown in table 5, based on the cross reference between the political valence of news outlets in table 3 and the media community in table 4, the composition of the partisan media in each community tends to be politically homogeneous. This fact confirms the occurrence of political polarization in Indonesian media networks. Table 4 also shows that Joko Widodo-leaning media has a stronger tendency to group in the same cluster than Prabowo-leaning media, while news outlets with moderate political stance are relatively small in number and spread evenly in two dominant clusters.

Table 5 Composition of partisan media within each media community

Political allignment	Cluster I	Cluster II
pro-Prabowo	0.837	0.045
Neutral	0.089	0.028
pro-Joko Widodo	0.074	0.927

Figure 4 visualizes the political polarization of Indonesian news media during 2019 Presidential Elections. As seen in the figure, the structure of media network is divided into two dominant clusters, each with a relatively homogeneous political identity. This shows that the pattern of news consumption in 2019 Indonesian elections is not only fragmented, but also forms a political echo-chamber where audiens tend to be exposed to politically homogeneous information coming from news outlet with the same political tendencies.

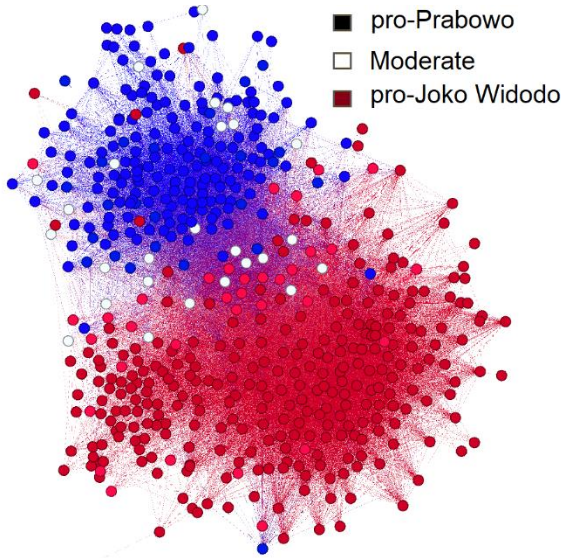

Figure 4 Political polarization in Indonesian news media networks during 2019 Presidential Elections

4.4 Interaction across political communities

We then elaborate on empirical facts about interactions between news media across political affiliations [20]–[22], [26]–[28]. Figure 5 shows the statistical characteristics of interaction between news outlets, intra and inter media communities. In general, the Indonesian news media network shows homophily properties, where news outlets with the same political stance tend to be connected to each other (Joko Widodo-leaning media: median = 0.842, IQR = [0.809, 0.873]; Prabowo-leaning media: median = 0.543, IQR = [0.514, 0.577]). In general, this characteristic is stronger for Joko Widodo-leaning media than Prabowo-leaning media. Furthermore, the interaction tendency from Joko Widodo-leaning media to Prabowo-leaning media (median = 0.045, interquartile distance (IQR) = [0.0023, 0.064]) is much smaller than the opposite (median = 0.306, IQR = [0.273, 0.323]). Meanwhile, interactions tendency from moderate news media partisan media are almost equal (pro Joko Widodo: median = 0.425, IQR = [0.345, 0.527]; pro Prabowo: median = 0.438, IQR = [0.302, 0.538]).

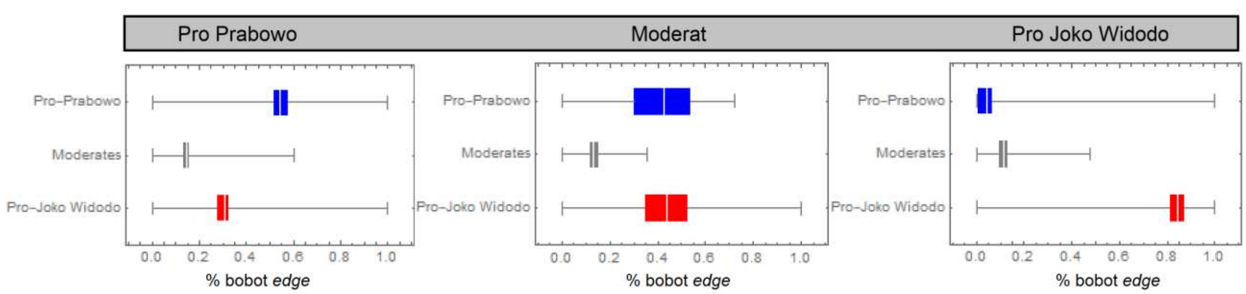

Figure 5 Statistical characteristics of interaction between news outlets, intra and inter political affiliations. White vertical lines are median values, horizontal thick lines are interquartile ranges, and black thin horizontal lines are 10th and 90th percentile values.

The Statistics of interaction between media across political affiliations indicate that information exposure to Joko Widodo's supporters is relatively more homogeneous, coming from news outlets with the same political affiliation, compared to information exposure to Prabowo's supporters. This can be understood by looking at the composition of partisan media in each media community. Moreover, as discussed in previous studies [20], the Prabowo-leaning media is dominated by segmented news media, such as the Islamic news portal (e.g. **eramuslim**, **portal-islam**, **republika**) and opposition media (e.g. **viva**, **rmol**, **gelora** etc.), while mainstream media tends to be neutral or in favor of Joko Widodo. As a result, Prabowo's supporters tend to be exposed to information coming from the pro-Joko Widodo news media, but not vice versa.

4.5 News media centrality

We further investigate the role and position of each news outlet in the information ecosystem during the 2019 Indonesian elections. We use two indicators, namely *within module degree z-score* (z_i) and *participation coefficient* (Pc_i) [29], to measure the role of a news outlet based on its relations with other outlets within or between media communities. The *within module degree z-score* (z_i) measures connectivity of a news outlet in its community internally, as follow:

$$z_i = \frac{k_i - \bar{k}_{s_i}}{\sigma_{ks_i}} \qquad (2)$$

where k_i is the degree of news outlet i within the cluster s_i, $\bar{k}_{s_i}$ is the average degree of all media in cluster s_i, and σ_{ks_i} is the standard deviation of degree k in cluster s_i. The greater the value of z_i, the higher the connectivity of outlet i relative to other outlet in its community. Meanwhile, cross-cluster node connectivity is evaluated using the participation coefficient (pc_i) indicator, as follows:

$$Pc_i = 1 - \sum_{s=1}^{M} \left(\frac{k_{is}}{k_i}\right)^2 \qquad (3)$$

where k_{is} is the number of relation of outlet i to other outlets in cluster s. Value $Pc_i \sim 0$ if outlet i is only connected to the outlet in its group only. Conversely, the value of $Pc_i \sim 1$ if the relation of an outlet is evenly distributed in all clusters.

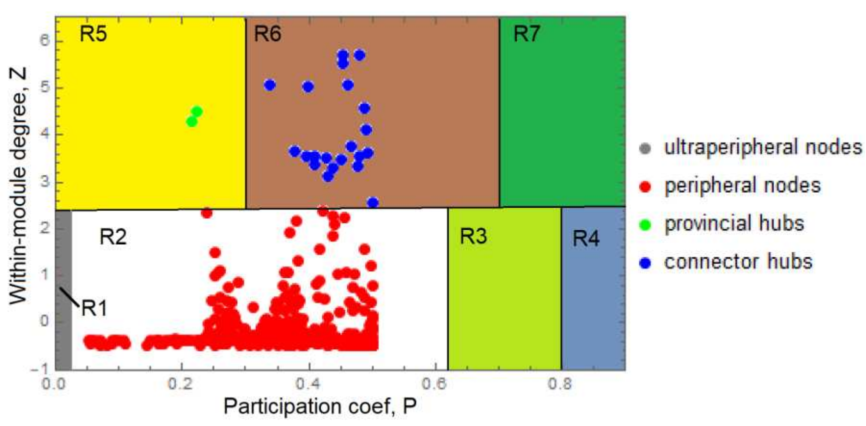

Figure 6 The role of news outlets within the z-P space: (R1) ultra-peripheral nodes ($z < 2.5, P \leq 0.05$); (R2) peripheral nodes ($z < 2.5, 0.05 \leq P \leq 0.62$); (R3) non-hub connector ($z < 2.5, 0.62 \leq P \leq 0.8$); (R4) non-hub kinless nodes ($z < 2.5, 0.8 \leq P$); (R5) provincial hubs ($z \geq 2.5, P \leq 0.3$); (R6) connector hubs: ($z \geq 2.5, 0.3 < P \leq 0.75$); (R8) kinless hubs: ($z \geq 2.5, P > 0.75$).

The combination of the two indicators forms 7 regions of node roles within z-P parameter space, as shown in Figure 6. Based on the position of news outlets in the z-P parameter space it is known that ~96% of news outlets are ultra-peripheral (R1) or peripheral nodes (R2), or low degrees nodes with little or no cross-cluster connection. The remaining media fills the R5 region as a provincial hub (R5), namely news outlets that have high centrality within its own cluster, or as connector hubs in the R6 region, namely news outlets that have high connectivity to all clusters.

Table 6 Descriptive statistics of the news media role during election. Media rating is based on Alexa rank [25]

Region	News outlets	# of outlet	Political composition (%)	Median rating
1	Kapanlagi, indosport, time, apnews, voanews, thejakartapost, foreignpolicy, cgtn, paperform, historia	56	Joko Widodo: 56.4 Moderate: 1.8 Prabowo: 41.8	1,050,000
2	grid, suara, brilio, kompasiana, bolasport, cnbcindonesia, wowkeren, dream, bola, abc	449	Joko Widodo: 58.4 Moderate: 5.12 Prabowo: 36.5	687,211
5	gelora, rmol	2	Joko Widodo: 0 Moderate: 0 Prabowo: 100	1,070,000
6	Okezone, tribunnews, detik, kompas, liputan6, sindonews, kumparan, idntimes, merdeka, tempo	21	Joko Widodo: 76.2 Moderate: 14.3 Prabowo: 9.6	918

How partisan news outlets populates the R5 and R6 regions reveals differences in the characteristics of information echo-chamber of the two candidates. As shown in table 6, there are only two news outlets in the R5 region, and both are Prabowo-leaning media. This means that gelora and rmol are central outlets within the information echo-chamber of Prabowo's supporter. However, this also implies that Joko Widodo's supporters have diverse sources of information. In general, the Joko Widodo-leaning media, as well as moderate media, dominate the R6 region as a *connector hubs*, which means that these outlets are consumed by supporters of both candidates. The fact that news outlets in the R6 region have low Alexa Rank highlights the important role of mainstream news media as a bridge of information between opposite political sides, especially in heated election.

5. Conclusion

In this study we reveal empirical facts about political polarization in indonesian news media network during 2019 elections. By modeling news consumption patterns as a bipartite network of news outlets-Twitter user, and then projecting to a media network, we observed the emergence of a number of media communites based on audience similarity. By measuring the political alignments of each news outlet, we shows the politically fragmented Indonesian news media landscape, where each media community becomes an political echo chamber for its audience. More specifically we find that, compared to the Prabowo media cluster which tends to be centralized in a small number of outlets, Joko Widodo's supporters have diverse sources of information. However, information exposure to Joko Widodo's supporters is relatively more homogeneous coming from the media with the same political affiliations.

Nowadays, the understanding of the impact of social media and online news media on the emergence of extreme polarization in political discourse is one of the most pressing challenges for both science and society. Our finding highlight the important role of mainstream media as a bridge of information between political echo chamber in social media environment.

Pengakuan

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Supplementary Information

SI 1. Data

Table S1 Descriptive statistics of the 2019 Indonesian Election tweet dataset

Statistics	Count
# of tweets	13990975
# of tweets with a Url	667821
# of hashtags	74515
# of unique users	3958817

SI 2. Hashtag

We manually label 1400 of the total 74515 hashtags recorded in the dataset, which is 700 hashtags for each candidate, and has been used by at least 10 different users. User political affiliation is calculated using the polarity rule as follows [12]:

$$V(u) = 2\frac{\frac{tf(u,C_O)}{total(C_O)}}{\frac{tf(u,C_O)}{total(C_O)}+\frac{tf(u,C_1)}{total(C_1)}} - 1 \qquad (1)$$

where $tf(u, C_o$ is the frequency of users using the hashtag C_o, with the total frequency of hashtag usage is $total(C_o)$. Political valence $V(u)$ is in the range $-1 \leq V(u) \leq 1$. We use a threshold value of ± 0.2, where users are labeled pro-Prabowo if they have a valence score <0.2, while pro-Joko Widodo if a valence score> 0.2.

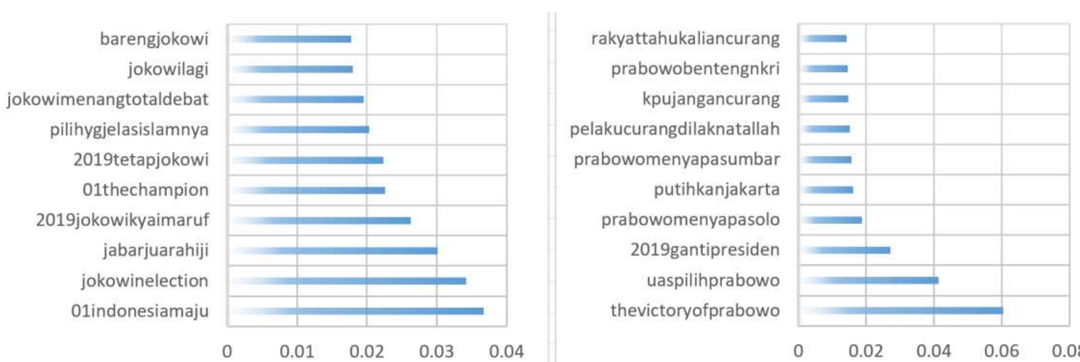

Figure S1: Political hashtags of each candidate: (a) Joko Widodo; (b) Prabowo

SI 3. Retweet network

Table SI2 Descriptive statistics of retweet network

Statistics	Retweet network	Giant component
# of nodes	558801	542243

# of edges	4372893	4372706
Average degree	15.651	16.1282
# componen	16397	1

SI 4. The accuracy of label propagation algorithm

The k-stratified cross (5-fold) validation model is implemented to validate the results of the label propagation algorithms. We use 4/5 of the total seed nodes as training data and evaluate the performance of the algorithm in the remaining 1/5 sections.

Table SI3 Precision & recall scores for the label propagation algorithm

Precision	*Recall*	*Accuracy*
0.984853	0.985031	0.984955

SI 4. Media Classification

We group media scores into 5 groups, as follows:

$$S(v) = \begin{cases} -2 & if\ v \in [-1, -0.6] \\ -1 & if\ v \in [-0.6, -0.2] \\ 0 & if\ v \in [-0.2, 0.2] \\ 1 & if\ v \in [0.2, 0.6] \\ 2 & if\ v \in [0.6, 1] \end{cases} \qquad (2)$$

where $S(v) < 0$ means pro prabowo, $S(v) > 0$ means pro Joko Widodo and $S(v) = 0$ means media v tends to be neutral.

SI 5. Indicators

Table 4 shows the value of within module degree z-score (zi), participation coefficient (pci), community membership and political alignment of each news outlet

Table S4 News outlets indicators: political alignment (<0: pro prabowo; >0 pro Jokowi); community membership, participation coefficient and within module degree z-score

News Outlet	Political alignment	Community membership	Participation coefficient	within module degree z-score
portalsatu	2	0	0	-1.30453
pembawaberita	-2	0	0.316828	1.097838
melekpolitik	2	3	0.128419	1.802476
idntimes	1	3	0.467108	1.831165
gzeromedia	2	3	0.235537	-0.75089
riauonline	-2	0	0.293934	1.321788
kata	-2	0	0	-1.36561
acehsatu	-2	0	0.375	-1.32489
antaranews	1	3	0.472066	2.11806
rakyatrukun	2	3	0.30839	-1.05213

klikmerdeka	-2	0	0.239198	-0.75484
suaraislam	2	3	0.24716	-0.19144
indonesiasatu	2	3	0.159272	0.654896
militermeter	-2	0	0.32	-0.08299
qureta	2	0	0.252401	-0.44945
lampungpro	0	3	0.369846	-0.76523
islambuzzer	-2	0	0.260355	-0.93807
lassernewstoday	-2	0	0.29591	-0.18478
infosurabaya	2	3	0	-1.2673
jawapos	1	3	0.478617	1.759442
allannairn	2	3	0.165289	-1.15254
koransulindo	2	3	0.1472	-0.3062
tribunnews	1	0	0.483432	2.136151
zonasatunews	-2	0	0.228532	-0.71412
indoharian	-2	0	0.31148	-0.44945
magik	2	3	0.18	0.253243
harianjogja	2	3	0.481859	-0.22013
cgtn	2	0	0	-1.36561
jurnalpolitik	2	3	0.362812	-1.06647
narasi	2	3	0	-1.12385
businesstimes	2	3	0.375	-0.86565
agusyudhoyono	-2	0	0.165289	-0.97879
pemilihindonesia	2	3	0.42	-1.09516
rri	2	3	0.32626	0.870067
tangerangnews	-1	3	0.375	-1.25295
pepnews	2	3	0.21875	-1.19558
suara-islam	-2	0	0.289627	1.097838
panturapost	2	3	0.183768	0.339312
alif	2	3	0.110727	-1.06647
abadikini	1	0	0.474368	-0.06263
benderranews	2	0	0.46875	-1.28417
galamedianews	2	3	0.154238	1.199997
islami	2	3	0.073964	-0.93737
abc	2	3	0.260355	-0.9804
kicknews	2	3	0.336735	-0.82261
blokbojonegoro	2	3	0.178414	0.009383
sukabumiupdate	2	3	0.154848	1.343444
infodesaku	-2	0	0.263114	-0.06263
katadata	2	3	0.157104	2.060681
radardepok	2	3	0.154337	1.042204
setkab	2	3	0.112638	1.630339
matanasional	-2	0	0.301783	-0.04227
thejakartapost	2	3	0	-1.1382
idcinema	2	3	0.130502	0.984825
kontan	2	3	0.168155	2.075026
dakta	-2	0	0	-1.0195
situasinews	-2	0	0.331426	-0.38837
hetanews	2	3	0.192841	0.597517
goaceh	-1	0	0.285932	-0.02191
validnews	2	3	0.408163	-1.22427
portal-bangsa	-2	0	0.232988	0.446348
gesuri	2	3	0.138221	1.902889
kabargolkar	1	3	0	-1.2673
satuharapan	2	3	0.228532	-0.34924
nusakini	2	3	0	-1.23861
waspada	1	3	0.382041	-0.55006

law-justice	-2	0	0.306992	1.403224
analisadaily	2	3	0	-0.86565
nerdfitness	2	3	0.187695	0.296278
radarluwuraya	-2	0	0.3848	-0.63268
riau1	-2	0	0.404997	0.324194
rancah	2	3	0.342653	-0.83696
porosnews	-2	0	0	-1.1213
portal-islam	-2	0	0.270993	1.993637
suaramuslim	0	0	0.42	0.039167
keprinews	-2	0	0.348188	-0.61232
rmol	-2	0	0.24806	1.973278
suara	0	0	0.483961	1.973278
providencemag	2	3	0.336735	-1.1382
poskotanews	2	3	0.159783	1.54427
bantenhits	-1	0	0.375	-0.16442
riau24	-2	0	0.38875	0.202039
babe	2	0	0.498992	1.219993
cekfakta	2	3	0	-1.28164
pikiran-rakyat	2	3	0.133386	0.927446
jabarekspres	2	3	0.176855	-0.63613
sumbartime	-2	0	0.135634	-0.61232
muslimoderat	2	3	0.173817	0.72662
visimuslim	-2	0	0	-1.0195
wartaekonomi	0	3	0.467355	1.558615
netralnews	2	3	0.35503	-1.15254
alinea	2	3	0.157903	0.827033
metrojambi	-2	0	0.292078	0.40563
era	2	3	0.152778	0.597517
kanalaceh	-2	0	0.193762	-0.55125
rappler	2	3	0.244898	-0.77958
radarjawatengah	2	3	0.131863	0.769654
voa-islam	-2	0	0.282689	0.894248
harianpijar	-1	0	0.497489	-0.00155
suarasurabaya	2	3	0	-1.25295
batamtoday	0	0	0.30839	-1.03986
obsessionnews	2	3	0.223537	-0.80827
danum	2	3	0.163234	0.597517
koranindonesia	2	3	0.140362	0.798344
sorot	2	3	0	-1.28164
konten	-2	0	0.41701	-0.99915
opini	1	3	0.160245	0.640552
rmoljakarta	-2	0	0.271383	0.40563
beritagar	2	3	0.430604	0.210209
kitakini	-2	0	0.301783	0.40563
bolasport	2	3	0.166528	0.267588
hariansib	2	3	0.201446	-0.73654
radarkontra	2	3	0	-1.23861
santrinews	1	3	0.047591	-0.7222
hidayatullah	-2	0	0.372854	0.40563
mojok	2	3	0.131984	1.142618
jpnn	0	0	0.484208	1.769688
chanelbanten	2	3	0.150337	0.956136
indiemedia	-2	0	0.079861	-0.91771
keepo	1	3	0.283165	-0.80827
pajak	2	3	0.167574	0.396691
channelnasional	-2	0	0	-1.26381

patriotnkri	2	3	0.249851	-0.79392
fajar	1	3	0.428826	1.400823
realitarakyat	1	3	0.341797	-0.57875
suarapemred	-2	0	0.317198	0.018808
kabardaerah	2	3	0.5	-1.2673
faseberita	-2	0	0.28875	-0.71412
kliksamarinda	2	3	0.140362	0.798344
cakaplah	-2	0	0.309642	0.934966
bataraonline	2	3	0	-1.23861
dprd-kaltimprov	2	3	0.130502	0.984825
hersubenoarief	-2	0	0.281348	0.711016
netz	1	3	0.159838	0.497104
kbr	2	3	0.221718	-0.50703
rmolbengkulu	2	3	0.255	-0.32055
eramuslim	-2	0	0.263024	2.034355
koranntb	-1	3	0.5	-1.28164
monitor	2	3	0.249851	1.214341
gelorabangsa	2	3	0	-1.08082
geotimes	-1	0	0.359001	0.873889
suarasosmed	2	3	0.204142	-0.96606
matanurani	2	3	0.201891	-0.29186
torajadaily	2	3	0.205516	-0.20579
topbuzz	2	3	0.265261	1.314755
gomuslim	2	3	0.176381	0.42538
alumni212	-2	0	0.273719	0.487066
jpost	2	3	0.160245	0.640552
alexanews	2	3	0.178557	0.138485
breakingnews	2	3	0.126581	0.870067
eastasiaforum	2	3	0.5	-1.2673
sketsanews	-2	0	0.339801	0.303835
djournalist	2	3	0.148101	0.669241
kaltimkece	2	3	0.1298	0.99917
kolomwarta	-2	0	0	-1.26381
investor	2	3	0.149684	0.482759
manadopostonline	2	3	0.158099	0.066762
kuninganmass	-2	0	0.289085	0.242758
konfrontasi	-2	0	0.276461	1.484661
indopos	1	3	0.442328	0.740965
opera	1	3	0.476371	-1.09516
okezone	2	3	0.482334	2.103715
beritahati	2	3	0.169922	0.368001
mediaumat	-2	0	0.408163	-1.28417
inilah	0	3	0.484429	1.142618
riautrust	0	0	0.244898	-1.26381
beeoneinfo	2	3	0.41701	-1.02344
beritabersatu	2	3	0.173568	0.324967
kompasiana	2	3	0.204544	0.568828
garudaonline	2	3	0.401235	-0.92303
themuslim500	2	3	0.183257	-0.03365
pdiperjuangan	2	3	0.265928	-0.83696
jurnalintelijen	2	3	0	-1.2673
darirakyat	2	3	0.396694	-0.95172
tribunsantri	2	3	0.117188	-0.86565
senyumperawat	-2	0	0.18	-0.65304
ujungjari	2	3	0.18115	0.497104
bataranews	-2	0	0.339444	-0.42909

kolomnasional	-2	0	0	-1.28417
jurnas	2	3	0.224766	-0.52137
medanbisnisdaily	2	3	0.250575	0.45407
mediaoposisi	-2	0	0	-1.16202
muslimobsession	2	3	0.184929	-0.048
indonesiakininews	2	3	0.34875	-0.8513
inibalikpapan	2	3	0.130926	-0.34924
mercinews	0	3	0.431872	0.167175
tabloidbintang	2	3	0.137845	1.199997
smh	2	3	0.382612	0.769654
liputanislam	2	3	0	-1.25295
swararakyat	-2	0	0.309256	-0.26622
islampos	-2	0	0.358533	0.079885
matamatapolitik	2	3	0.145429	1.214341
tempo	1	0	0.484978	1.769688
kawalpemilu	0	0	0.333841	1.342147
seputarpresiden	2	3	0.209751	-0.76523
newmandala	-1	0	0.341797	0.140962
siagaindonesia	2	3	0.182495	0.353657
mediaharapan	-2	0	0.172336	-0.61232
kincir	2	3	0.148451	0.827033
jokowidodo	2	3	0.145635	1.54427
seruji	-2	0	0.311842	0.568503
radarbandung	-2	0	0.352653	-0.83627
vertanews	2	3	0.154449	0.884412
saudagarnews	2	3	0.149014	0.654896
indonesiaberita	2	3	0.274449	-0.49268
redaksiindonesia	2	3	0.247847	-0.44965
elshinta	2	3	0.182868	0.855723
mediamadura	-2	0	0.274449	0.894248
indosport	2	3	0	-1.28164
klikaktifis	2	3	0.182706	0.224554
gatra	1	3	0.475309	1.54427
radarnonstop	-2	3	0.5	-1.23861
hariannusa	2	3	0.48	-1.2673
faktakita	-2	0	0.290657	-0.81591
selidiknews	2	3	0.277778	-0.86565
kelung	-2	0	0.315263	-0.55125
ngopibareng	2	3	0.133281	1.30041
pribuminews	-2	0	0.054012	-0.6734
time	2	0	0	-1.28417
smartcitymakassar	2	3	0.358533	-0.77958
ajnn	-2	0	0.32	-0.49017
indovoices	2	3	0.35695	-0.82261
kabarsinjai	-2	0	0.258034	-0.59196
inisiatifnews	2	3	0.163379	0.740965
gonews	-2	0	0.288234	1.790047
sinarharapan	2	3	0.162441	0.755309
inilahkoran	-2	0	0.375	1.179275
kapanlagi	2	3	0	-1.09516
swamedium	-2	0	0.249132	1.952919
stv	2	3	0.109519	-0.13406
1news	2	3	0.150497	-0.49268
kabarpolitik	-2	0	0.418958	-0.28658
faktabanten	-2	0	0.261621	0.059526
potretnews	-1	3	0.499055	-1.1382

solopos	2	3	0.160686	1.673373
inapos	-2	0	0.31148	-0.44945
suarakalimantan	2	3	0.150702	0.468415
pollingkita	-1	0	0	-1.36561
centerofrisk-sia	-2	0	0.27258	0.079885
moeslimchoice	-2	3	0.491782	-0.66482
fokusjabar	1	3	0.197531	-1.18123
inews	2	3	0.470817	1.615994
beritaterkini	-1	0	0.24013	-0.63268
beritajogja	-2	0	0.362812	-0.40873
rmollampung	-2	0	0.408163	-0.97879
indonesiakita	-2	0	0.286678	1.525379
indonesiainside	-2	0	0.269381	1.810406
linikota	2	3	0.14456	0.72662
buff	-1	0	0.304688	-0.85663
wartaplus	2	3	0.368828	-0.8513
balicitizen	-2	0	0.350303	-0.55125
nusantara	-2	0	0.152778	-1.16202
jakartaglobe	2	3	0	-1.22427
riaumandiri	-2	0	0.426903	-0.42909
katasandi	-2	0	0	-1.0195
infonews	-2	0	0.188366	-0.34766
dream	0	0	0.440331	0.120603
daulatdesa	2	3	0.399524	-0.99475
aksi	-2	0	0	-1.34525
riausky	2	3	0.411357	-0.52137
rmolbanten	-2	0	0.383831	0.711016
pdiperjuangan-jatim	2	3	0.265928	-1.06647
radartegal	2	3	0.151955	0.927446
pks	-2	0	0.274592	0.996043
kurio	2	3	0.444444	-0.9804
suarapantau	-2	0	0.32	-0.97879
jarilangit	-2	0	0.185493	-0.85663
nahimunkar	-2	0	0.31148	-0.44945
jokoway	2	3	0.12327	1.343444
pkb	2	3	0	-1.16689
paperform	-2	0	0	-1.28417
kedaipena	-2	0	0.299712	1.240352
mongabay	2	3	0	-1.16689
tarbawia	-2	0	0.216814	0.344553
sumselsatu	2	3	0.172902	0.468415
klikkabar	2	3	0.225652	-0.62179
ksp	2	3	0.164069	0.296278
suarabmi	2	3	0.117188	-1.08082
bisnis	2	3	0.403865	1.974613
indoprogress	2	3	0.1376	0.669241
ayojalanterus	-2	0	0.33099	-0.69376
partaiperindo	2	3	0	-1.28164
pasundanekspres	2	3	0.18447	0.081106
utamanews	1	3	0.090703	-1.00909
beritahub	-2	0	0	-1.28417
arrahmah	-2	0	0.250865	-0.20514
mattanews	2	3	0.1298	0.99917
detik	1	0	0.47621	1.423583
senayanpost	2	3	0.19996	0.511449

kabartoday	-2	0	0.26692	1.097838
koranperdjoeangan	-2	0	0	-1.18238
kabarkampus	2	3	0.166528	0.267588
rmoljabar	-1	0	0.489464	0.059526
lampost	2	3	0.186919	0.18152
infopresiden	2	3	0.212669	0.267588
indotelko	-2	0	0.386621	-0.75484
matamata	-1	0	0.493827	-1.28417
metrobatam	-2	3	0.265928	-0.83696
rmolsumut	0	3	0.41701	-1.02344
ngelmu	-2	0	0.237188	0.018808
beritamuslim	-2	0	0.097304	-0.63268
kirijatim	-2	0	0.331426	-0.38837
saifulmujani	2	3	0.20843	0.095451
infonawacita	2	3	0.142012	-1.12385
republika	-1	0	0.49321	1.93256
pwmu	-2	0	0.28932	0.527785
beritacenter	2	3	0.172336	1.156962
daulat	2	3	0	-1.23861
instingjurnalis	-2	0	0.329112	0.711016
wartabromo	2	3	0.145161	0.884412
inspiratormedia	-2	0	0.24013	-0.63268
idtoday	-2	0	0.293367	0.487066
monitorday	2	3	0.110727	-0.83696
pojokfakta	-2	0	0	-1.26381
onanhiroshi	-2	0	0.336735	-0.49017
jurnaljatim	2	3	0.166424	0.411036
kabarnusa	2	3	0.176635	0.554483
repelita	-1	0	0.403989	1.219993
jitunews	1	3	0.494524	0.066762
tagar	2	3	0.255489	2.189784
celebestopnews	2	3	0.222725	-0.11972
trendolizer	0	3	0	-1.28164
wartakota	2	3	0.473373	-1.18123
suaranasional	-2	0	0.295431	0.466707
harianbatakpos	2	3	0.195159	-0.36358
joglosemarnews	2	3	0.251947	0.109796
popnesia	2	3	0.073964	-0.93737
pemilu	2	3	0.154579	0.72662
menitpertama	2	3	0.280897	-0.44965
indonews	2	3	0.215858	-0.47834
faktajabar	2	3	0.15936	0.353657
pikiranumat	-2	0	0.29145	0.222399
radaraktual	-2	0	0.333267	-0.24586
seruindonesia	2	3	0.124444	0.310622
shoecarnival	2	3	0.210539	-0.13406
seword	2	3	0.131569	1.716407
serikatnews	2	3	0.2688	-0.99475
sangpencerah	-2	0	0.222149	-0.40873
harianterbit	-2	0	0.30884	0.772093
mediamuslim	-2	0	0.250865	1.566097
jatimnet	2	3	0.268011	-0.46399
dinamikajambi	2	3	0.182956	0.095451
liputan6	2	3	0.470285	2.290197
jogjainside	2	3	0.244898	-1.20992
portalmakassar	-2	0	0.281528	-0.38837

zonasultra	-2	0	0.425244	-0.3273
military-today	2	3	0.197531	-0.03365
duta	-2	0	0.332777	1.28107
turnbackhoax	2	3	0.396694	-0.95172
kabarriau	-2	0	0.444444	-0.81591
detikbanten	2	3	0.134702	1.085239
setneg	2	3	0.226843	-0.14841
caping	0	0	0.307643	-0.08299
rmoljatim	-2	0	0.31444	0.039167
cakrawalamedia	2	3	0.13031	0.798344
jatimpos	2	3	0.187574	0.052417
radarbangsa	2	3	0.139898	1.156962
strategi	2	3	0.140488	0.970481
beritaterkinionline	-2	0	0	-0.81591
pelitaekspres	2	3	0.375	-1.12385
beritakini	-2	0	0.336735	-0.49017
harianindonesia	-1	3	0	-1.23861
dailyadvent	1	0	0.32699	-0.83627
infomenia	2	3	0.064444	-0.87999
gosumbar	-2	0	0.285932	1.342147
deliknews	-2	3	0.499241	-0.7222
kiblat	-2	0	0.226843	-0.57161
koran-jakarta	2	3	0.126799	0.669241
barometerjatim	2	3	0.227608	-0.24882
halloindo	-2	0	0.447811	-0.51053
voanews	2	3	0	-1.23861
kumparan	0	0	0.496313	1.973278
harianmerdeka	-2	0	0.297521	0.263117
harapanrakyat	-2	3	0.197531	-1.06647
lensaindonesia	-2	0	0.418669	1.199634
sindonews	1	3	0.477041	2.11806
metropolitan	-1	0	0.439817	-0.71412
harianindo	1	3	0.328181	-0.96606
baskomnews	2	3	0.153837	0.42538
jurnalislam	-2	0	0	-0.71412
jiromedia	-2	0	0.05551	-0.69376
tentik	-2	3	0	-1.2673
teraslampung	-1	3	0	-1.28164
medcom	2	3	0.132169	2.075026
radarbogor	-2	3	0.377415	-0.19144
posmetro	0	3	0.375	-1.28164
teropongsenayan	-2	0	0.293589	2.075074
nusanews	-2	0	0.492865	1.952919
portal-rakyat	-2	0	0.310002	-0.18478
detiksumsel	2	3	0	-1.1382
beritalima	0	0	0.493511	-0.49017
Indonesia	-2	0	0.228532	-0.04227
kompas	1	0	0.472662	1.749329
teras	0	0	0.483237	-0.53089
krjogja	1	3	0.499635	-1.03778
wps	-1	0	0.352653	-0.83627
telusur	0	3	0.491295	1.042204
brilio	2	3	0.131984	1.142618
rakyatku	2	3	0.354564	0.669241
kanalkalimantan	2	3	0.288234	-0.55006
dutaislam	2	3	0.266805	-0.3062

cakrawala	2	3	0.159272	0.654896
wartajakarta	2	3	0.127066	1.056549
gelora	-2	0	0.201446	1.790047
mediavalid	-2	0	0.301065	-0.30694
kemenag	0	0	0.18	-1.20274
balipost	2	3	0.165289	0.568828
faktualnews	0	0	0.451172	-0.53089
radarcirebon	2	3	0.205761	0.554483
arenapublica	-2	0	0.359862	-0.59196
akurat	2	3	0.339722	1.759442
riauaktual	-1	0	0.375	-1.08058
pojoksatu	2	3	0.405482	1.54427
medianasional	2	3	0.194099	-0.00496
suarakarya	2	3	0.248375	0.138485
rilis	1	3	0.292346	0.296278
2019gantipresiden	-2	0	0.304052	0.649939
palapapos	2	3	0.303644	-0.42096
piee	2	3	0.444444	-1.18123
beritasatu	2	3	0.449001	2.318887
historia	2	3	0	-1.23861
grid	2	3	0.318861	1.128273
batamnews	2	3	0.260355	-0.9804
moslemcommunity	-2	0	0.188366	-1.03986
energyworld	-2	0	0.2952	-0.55125
rmco	2	3	0.131415	1.343444
pinterpolitik	2	3	0.336735	-0.66482
wowkeren	0	3	0.455389	0.855723
mediaindonesia	2	3	0.140037	2.204129
tintahijau	1	0	0	-1.36561
teddygusnaidi	2	3	0.274956	-0.34924
merahputih	2	3	0.36549	1.329099
jatimtimes	2	3	0.459184	-1.16689
hitamputih	1	3	0.23858	-0.49268
rizkidwika	-2	0	0.28875	-0.71412
aktual	-2	0	0.301189	1.219993
pemiluupdate	0	0	0.104938	-1.03986
wartatera	-2	0	0	-1.26381
inikata	2	3	0.171423	0.898757
jatimnow	2	3	0.149447	1.458202
suaramerdeka	1	3	0.477158	0.984825
demokrat	-1	0	0.467682	-0.63268
arahjaya	-2	0	0.296843	1.464302
lamanberita	2	3	0	-1.23861
apnews	2	3	0	-1.25295
jurnalsulbar	2	3	0.173568	0.324967
gontornews	-2	0	0	-1.32489
cyberpancasila	2	3	0.375	-0.86565
infosatu	2	3	0.139332	0.640552
kontenislam	-1	0	0.2877	1.219993
antarafoto	2	3	0.188366	0.167175
bola	2	3	0.155128	-0.52137
lombokita	2	3	0.260355	-0.9804
maribacaberita	2	3	0.459184	-1.16689
cumicumi	2	3	0.202908	-0.07669
harianmedan	-2	0	0.362812	-1.06022
rakyatmediapers	-2	0	0.279641	0.62958

kemenpora	2	3	0.204765	-0.09103
beritaterheboh	2	3	0.264514	-0.06234
ayobandung	-2	0	0.416322	0.507425
nusamerdeka	0	0	0.439156	-0.79555
terkini	-1	0	0.340265	0.079885
sinjaiterkini	1	3	0.5	-1.16689
cendananews	-2	0	0.309256	0.85353
tarbiyah	-2	0	0.303153	0.303835
redaksikota	2	3	0.257117	-0.89434
infopublik	2	3	0.177743	-0.37793
beritajatim	2	3	0.134426	1.458202
nusantaranews	1	3	0.316044	-0.5931
hukumonline	2	0	0.489796	-1.30453
akuratnews	-2	0	0.261853	1.05712
bentengsumbar	2	3	0.249132	-0.70785
jerami	-2	0	0.161975	-0.55125
beritaislam	-2	0	0.240651	1.993637
tirto	2	3	0.461376	1.902889
heraldmakassar	-2	0	0.353299	0.120603
voaindonesia	2	3	0.168038	1.515581
islamedia	-2	0	0.259644	1.199634
prfmnews	-1	3	0	-1.28164
rmolsumsel	2	3	0.369846	1.357789
goriau	-2	0	0.416484	1.912201
politiktoday	-2	0	0.298632	0.344553
cnbcindonesia	1	0	0.481807	1.464302
laduni	2	3	0.169447	0.095451
bidikdata	2	3	0	-1.22427
haksuara	-2	0	0.190131	-0.53089
viva	-2	0	0.499871	1.830765
presidenri	2	3	0.157756	0.525794
merdeka	0	0	0.488498	1.973278
bantennews	2	3	0.367612	-0.1771
beritapagi	-1	3	0.112274	-0.39227
thediplomat	2	3	0.277778	-1.22427
kuwera	2	3	0.35124	-1.05213
minews	2	3	0.162866	0.310622
arrahmahnews	2	3	0.298763	-0.20579
foreignpolicy	2	3	0	-1.28164
gardaindonews	-2	0	0.321663	0.955325
pantau	2	3	0.384886	1.070894
timesindonesia	2	3	0.173391	1.54427
biografiku	2	3	0.226843	-0.14841
kanigoro	-2	0	0.35811	0.283476
islamic-center	2	3	0.165289	0.568828
bonepos	-2	0	0.301783	-0.49017
gosumut	-2	0	0.298929	1.342147
hajimakbul	-2	0	0.312765	-0.28658
satuindo	0	0	0.467127	-0.38837
apahabar	2	3	0.204765	-0.09103
nu	2	3	0.271194	-0.47834
radartasikmalaya	-2	0	0.21875	-0.95843
globalwitness	2	3	0.304688	-0.92303
tribunrakyat	2	3	0.375	-1.20992
sulselekspres	2	3	0.224403	0.353657
covesia	2	3	0.145429	1.214341

partainasdem	2	3	0.375	-1.20992
fakta	2	3	0.32	-0.60744
ansorjateng	2	3	0.254195	-0.23448
jokowibekerja	2	3	0.131415	0.023727
itoday	-2	0	0.5	-1.36561
metrotvnews	2	3	0.153423	1.529926
bekasimedia	-2	0	0.117188	-0.7752
kominfo	2	3	0.149014	0.654896
jatengtoday	2	3	0.33241	-1.08082
teropongnews	2	3	0.144361	0.898757
prokal	2	3	0.133914	1.286065
harianhaluan	1	3	0.362812	-1.06647
bizlaw	0	0	0.290657	-0.81591
detakkaltim	2	3	0.1364	0.870067
rmoljateng	2	3	0.143457	1.085239