SEMARAK ILMU PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Identifying Political Polarization in Social Media: A Literature Review

Siti Nurulain Mohd Rum[1,*], Raihani Mohamed[1], Auzi Asfarian[2]

[1] Department of Computer Science, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, Selangor, Malaysia
[2] Department of Computer Science, Faculty of Mathematics and Natural Sciences, IPB University, Indonesia

ARTICLE INFO

Article history:
Received 16 May 2023
Received in revised form 10 August 2023
Accepted 21 September 2023
Available online 26 November 2023

Keywords:

Political opinion polarization; Echo chambers; Filter bubbles; Sentiment analysis; Social network analysis; Opinion mining

ABSTRACT

Online social media platforms are often responsible for the rise of fake news, which can occasionally prevent people from knowing the truth and fuels partisan political conflict. The idea of "echo chambers" and “filter-bubbles” draws attention to how social media is incredibly fragmented, individualized, and niche-focused, all of which serve to further polarize public opinion. These terms have been associated with the referendum of Brexit in the UK and the victory of Donald Trump in 2016's US presidential election. The term “homophily” on the other hand refers to the tendency of people to be in a circle that shares the same thought and interest, that could also contribute to political division in social media. In the positive side, high political polarization demonstrates the freedom of expression, on the other hand it can heighten political tensions and inequalities, which may have an adverse effect on a nation's stability. Determining political division and its origins via social media is therefore a crucial topic for discussion. In this research work, several articles were examined to discover the computing methods and approaches employed by the existing works for identifying political polarization in social media.

1. Introduction

Every day, millions of individuals use social media, generating vast amounts of digital data that can be used to extract useful information about human dynamics and behaviours. The media platform all over the world has experienced dramatic shifts over the past few decades with the growth of the internet, legislative reforms, and the changes of public preference. These developments, particularly in social media have led to substantial changes in the journalism industry, particularly in the reduction of newspaper’s production replaced by the digital news outlet, the emergence of online media, often of a thematic or political bent. The evolution of social media platforms such as Facebook, Instagram and Twitter have driven a significant change in the way the news was interpreted by the whole world, with algorithms that encourage sensational and divisive content. It has gained popularity due to its ability to connect people across the globe and people are

* *Corresponding author.*
E-mail address: snurulain@upm.edu.my

https://doi.org/10.37934/araset.34.1.8089

free to express everything. It also contributes to the increased sharing of news on the internet because of the formation of networks among users.

Scholars pay great attention to the intersection of social media and politics [1-4]. The filter bubbles are a term that is an exhibition arising from the use of social media that refers to groups or people who provide their own views, contributing directly to the polarization of public opinion [3, 5-7]. The reasons why this topic is of increasing interest are due the prevalence and common political content in social media. In fact, 25 percent of the Facebook and Twitter users' report that they have experienced seeing the political news in their daily news update [8] in their personal social media account. Not only in the United States, but throughout the whole world, political polarization is on the rise [9-11]. This can be due to the increase of social media usage. Political polarization can be classified into two types. The first is ideological polarization, which is defined as the difference between political opponents' viewpoints, beliefs, attitudes, and postures. The second is affective polarization, which is based on the research into the function of identity in politics and how the importance of identification within a group (such as a political party) can aggravate enmity across groups [12,13]. Affective polarization measures how much people enjoy their political allies and detest their political opponents [14]. A higher level of polarization may be beneficial for society due to its capacity to anticipate increasing levels of political activity and voter views [15]. On the other hand, can also bring negativity to the democracy, increasing power concentration [16], legislative deadlock [17,18] and dissatisfaction among citizen [19,20]. Social media has been claimed to be the cause of the increase in civic engagement, but such interaction can also turn people away from politics in hyper-partisan situations. Similarly, polarization itself could make politics less interesting to people. On the other hand, the disclosure of misinformation about the news can help in forming support groups to destroy opponents. In politics, the definition of an echo chamber is a metaphorical solution of explaining a condition where the only similar facts and opinions are exchanged [21]. People within the circle of echo chamber can only come across the facts in which they already agree. They also believed that the contents that were fed to them are always true. Under these circumstances, anyone who disagrees with the fact will be said to have been misinformed and the worst will be labelled as naive. Some fear that personalization algorithms on the internet will ease the echo chamber's role by setting the specific contents on the specific target readers to gain more and more support. Some even believed that the discrimination of desire and belief will widen up the gap of those who are knowledgeable about politics and those who are not, could indirectly increase political tensions and political gap differences that could endanger the democracy by suppressing the democratic awareness and communication [21-23]. This could also affect the digital political activity on social media. The structure of the social community of individuals is affected by the phenomenon of homophiles. Homophily is a person's tendency to associate themselves with others who have similar interest and thought [24]. Individual networks tend to be homogeneous in diverse features, such as demographics, socio-economic situation, political beliefs, class and race [24]. As a result, one's tendency may develop based on other people who are like-minded and share common characteristics, that will further narrow down the political news gained from its social environment. The term "filter bubbles "is coined by [25] is another term to describe the state of people in social media that is fragmented resulting from the intelligent personalized algorithm based on the information such as the search history, past-click behaviour on the internet and the location of the user. The alarming features of echo chambers is they may spread the biases or fake news that tend to lead to the lack of original thought, challenging ideas and opposing viewpoints. This phenomenon is concerned for the future of human knowledge, limiting the quality of fact and information from the diversity of content that hinders people from developing understanding on complex issues. Therefore, it is important to identify the echo chambers, homophily and other factors that caused polarization in social media leading to the spreading of disinformation contributed to pressure and the gap in political situation. The main objective of this study is to identify the computation techniques and methodologies used by existing studies to detect political polarization in social media.

2. Identifying Political Polarization in Social Media

One common method to investigate echo chambers and polarizing opinion in social media is through modelling [26,27]. The concepts from the study of dynamics opinion have evolved since the 1970s and many were borrowed from this approach. The establishment of consensus relies on the early models of opinion [28]. In time, the researchers have been diversified into models that encourage multiple opinions to coexist, with the nature of a special case of two opposing opinions (i.e., polarization). These models are focused on either an existing model of consensus or new processes focused on sociological and psychological hypotheses. [27,29,30]. The new polarization models incorporate processes focused on the idiosyncrasies of social media online; for example, the algorithmic bias [31] and re-connection of social ties [9]. The study by [32] investigates whether users were clustered into like-minded groups using an algorithm for community detection [33] to separate users into regular contact groups in each network. The study showed that users of partitions gave high modularity ratings [34] for all the examined networks, indicating a solid group structure. There is ample evidence to conclude that the development of social networks may influence the change of attitudes and behaviours. Peer views are believed to be heavily affected individual perceptions [35]. Online media networks are considered to profoundly affect the perceptions and attitudes in many aspects of human life [25,36]. Research has shown that certain human traits are clustered into social networks [37] such as happiness, obesity, smoking and political opinions. It is assumed that such grouping on social networks ('homophilia') emerges from both a preferential relation to similar individuals when developing or breaking ties, and from peer interaction making related individuals more alike. Though it can be complex to discern which process has worked in observational research to induce homophobia [38], experimental methods were used to show online peer control influencing human habits and attitudes like musical tastes [39], health-related behaviours [40], possibility to vote [41], evaluation of news articles and emotional transfer [42].

2.1 Modeling

One of the most common questions when studying dynamics in the social field is “who influences whom?”. Not only sociologists and psychologists are interested in this question, but it has also attracted many other people specifically in marketing analyst, political scientists, and organizational scientists. The scoring systems are used by many probabilistic models as a framework for the degree of influence, interaction, and other social relationships in social media platform [43-46]. Since the relationships with influence are rarely made explicit, they need to be inferred from other information. Traditionally, influence has been studied by analysing the structural links pattern in the observed networks, such as "friendships" with Facebook and “Follower” in Instagram [47]. Since the level of relationships are rarely made transparent, they must be inferred from other evidence. A personalization algorithm has become a common solution to solving the topic of information overloading. As a result, it could distort the facts and content and hinder the access to the information of important topics. The researchers [48] established a model of opinion dynamics in which individuals are linked through social networks that may affect their decision based on the perspectives to which they are exposed to. They also examined the interplay between those mechanisms and the key features of real networks. The study also revealed that algorithmic filtering affects the information exchange, especially the views and opinions made by others in the cases where information is against the user's pre-existing belief. Figure 1 is an example of the opinion formation model developed by [48]. There are three parts of the opinion forming model. The first part is the fundamental mechanism of the social network that connects users across bonds of friendship. The second is the process of activation that determines the timing of the sharing of information between users via the social network. The third part is the algorithmic filtering process that chooses which data is viewed in the timeline of the user. A study by [49] put forth a model to gauge opinions in which a minority of influential individuals people spread their ideas via social networks. An opinion probability density function is the model's output. To measure how polarised the final distribution is, they devised an index. the suggested methodology used in a discussion on Twitter about the late president of Venezuela, Hugo Chavez. The suggested method able to identify various levels of polarisation based on the network's structure.

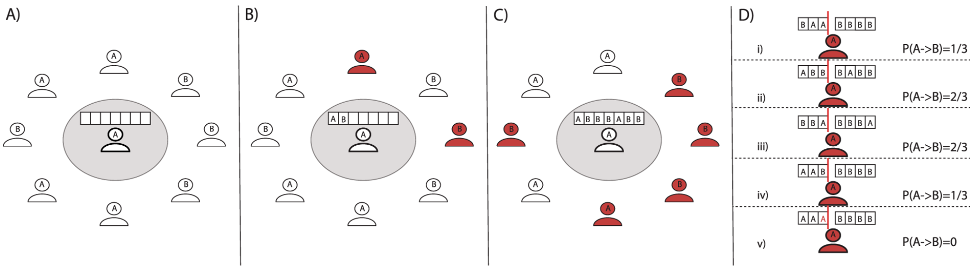

Fig. 1. Schematic representation of opinion dynamic [48]

The study by Wang *et al.,* [50] is another example that suggested a model to replicate the memes spreading on Twitter. The study was performed by modelling the evolution of the language used by people to observe the substance of interaction to detect influence in the form of temporal dynamics [51]. Their model builds on the significant body of sociolinguistic study that suggests, when two people communicate, either orally or in writing, words used by someone on social media can contribute to the possibility of imitation by others. The degree of influence to which it is measured is based on the disparities of interaction and relationships of the observed network. This concept is regarded as linguistic accommodation [52]. Their model is inspired by Blundell *et al.,*'s turn-taking action model [43], which also incorporates the principle of Bayesian language modelling [53].

2.2 Machine Learning

Colleoni [54] in their work used machine learning to define and detect the trends generated from social media data through the intelligent decisions based on empirical evidence. A training set is used to infer a model by using a supervised learning algorithm that is used for mapping data. The training data consists of a text corpus that is classified as political and non-political that is related to the Democrat or Republican political party according to the characteristics of the investigation. The training set is split into two elements. The first element is used to train the algorithm for classification. To evaluate the algorithm, the second part is used to test its ability to accurately identify the unseen instances and the levels of accuracy range from 0 to 1. They were able to define the general political ideology of the users and quantify the levels of political homophilia by classifying all the content shared according to the political orientation. The work also revealed that the frequency of homophilia is higher than in the non-reciprocated network. The research by [55] uses statistical methods to discover the comprehensive dataset of individuals, organizations, incidents, and written texts to establish a rigorous and representative measure of socioeconomic, cultural, and human capital forms to essentially drive institutional impact. Mohale [56] discussed the issue of fake news on social networks through the use of ensemble machine learning in their work. They also give an analysis of the current use of automation to spot fake news on social networks and examine the potential modifications to these strategies. They proposed an ensemble-based paradigm for false news identification. The study by [57] describes a method for identifying the polarisation of social media users during election campaigns marked by the rivalry of political factions, known as IOM-NN (Iterative Opinion Mining using Neural Networks). The method uses a feed-forward neural network-based on automatic incremental process to analyse the postings made by social media users. The study iteratively creates new classification rules starting from a constrained set of classification rules created from a small fraction of hashtags that are well known to support faction. These guidelines are then applied to ascertain how people are strongly identified with a certain faction. The methodology has been evaluated based on two case studies that examine the polarisation of many Twitter users during the 2018 Italian general election and the 2016 US presidential election. The obtained results demonstrate the high accuracy and efficacy of the suggested strategy because they are more accurate than the average of the opinion polls and closely match the actual results. The method to gauge the polarisation of American state legislatures was developed in a study by [58] through an experimental comparison of three different machine learning algorithms. Their strategy is based on open-source software and accessible data sources. The findings imply that when predicting the polarisation of the state House and state Senate legislatures, artificial neural network regression performs better than both support vector machines and ordinary least squares regression. The work by [12] introduces a method called TIMBRE (Time-aware Opinion Mining through Bot Removal), which aims to identify the polarity of social media users during election campaigns marked by the conflict between political factions. This methodology is aware of and depends on the categorization of posts and users based on keywords. Additionally, it recognises and removes data generated by social media bots that try to change the public's perception of political candidates, preventing the dissemination of information that is strongly biased. A case study that examines the polarisation of several Twitter users during the 2016's U.S. presidential election has been used to test the suggested methodology. The findings demonstrate the advantages of both eliminating bots and accounting for temporal factors in the forecasting process, demonstrating the high accuracy. They also examine how the 2016's U.S. presidential election may have affected political discourse by looking at social media bots.

2.3 Sentiment Analysis

Traditional sentiment analysis techniques rely either on collection of rules based on semantic and affective data or on supervised approaches to machine learning where the accuracy depends heavily on the size and significance of a pre-labelled text sample training set. The social media monitoring on voter opinion allows political strategists to forecast a party or political candidate's success and improvise their vulnerabilities well before the real elections. Blogs, chats, debates, and interviews about the future of political parties and politicians flood the social networks during the election season. The amount of data produced is important for research use, analysis and drawing of inferences using the recent techniques. The study by [59] introduces the development of a computational method utilizing Natural Processing Language (NLP) revealed that two of the most consequential and changing trends of contemporary political life are strongly linked (large-scale of misinformation and philanthropy initiatives). Conover *et al.,* [60] in their work discussed how the networked public domain is formed by social media and promotes contact between groups of various political orientations. Six weeks before the 2010's U.S. congressional midterm elections, they analyse two political network interactions made up of more than 250,000 tweets. By using manually annotated results and network clustering algorithms, their result shows that there is a strongly divided partisan structure in the network of political retweets, that restricted ties between left- and right-leaning users. But this is not the case with the user-to-user network, which is dominated by a single group of heterogeneously politicized users where ideologically divided communication at a higher rate than the retweet network. They claimed that people with the political motive influenced people through promoting dialogue by injecting biased content into information outlets whose main audience are those ideologically opposed with the intention to slowly erase their pre-believed opinions and eventually agreeing with the content. Their hypothesis is supported with statistical evidence. Haselmayer *et al.,* [61] in their work proposed a method for gathering the fine-grained sentiment ratings by crowd coding to create a dictionary of negative feelings in a language and for a domain of preference. The analysis of large text that requires resource intensive hand coding is enabled by dictionary. They measure the expression tonality from dictionary terms and verify these calculations with manual coding data. Their results show that the crowd-based dictionary provides an effective way for measuring the sentiment. Their findings also indicate that the crowd-based dictionary offers accurate and true emotion calculation. A graph-based technique was developed in the work by [62] to create three representations of patterns to gather linguistic cues that reveal different aspects of written language. They then measure the prevailing degree of echo chamber activity on Facebook accounts by identifying the echoing contact between a post and its associated comments. Two content-based features are structured to allow such detection; the first helps position representation of feedback on a discussion topic, and the second focuses on the form and strength of emotion elicited by a topic. To extract certain traits from social media data, their study uses semi-supervised, data-driven methodologies. To capture implicit linguistic cues that signal various features of written language, this study has developed a graph-based technique to generate three pattern representations. An approach for extracting elements that include both target posture and emotion traits has also been suggested to better categories echoing behaviour.

3. Conclusion

Over the years, many attempts have been made by scholars to better understand the usage of social media that has changed the political landscape towards people's attitudes and behaviour. Many studies revealed that social media is one of the major contributors to the growing number of echo chambers that play a significant role on political polarization. In the presence of echo chambers, their beliefs are amplified through communication within the closed system and been protected from objection. Access to the information that are contrary to the interests of individuals or groups maybe limited with the presence of echo bubbles and homophily. This will create the tendency for people to be in the circle that only associate themselves with others that have similar interest and thought. Most of them are also interested in getting news for just a short period of time and do not actively seek out online news on a regular basis, resulting in important disparities in news use. Echo chambers, homophily, filter bubbles, and the connection between news consumption, media use, and different types of polarization must be understood in the context of media environments that are increasingly digital, mobile, and platform dominated. Political polarization through social media can sometimes benefit society in terms of practising democracy, however, on the other hand, it can also result in increased political tensions and divisions, which can ultimately affect the stability of a country. Considering these facts, developing methods and techniques for detecting political polarization patterns in social media is a crucial subject. In this paper, we have identified the approaches used by researchers to detect the polarization in political opinion. The methods can be categorized into three as presented in Table 1. From the standpoint of text analytics and natural language processing, the echo chamber, homophily, filter bubbles, and the connection between news consumption can be directly related to the online communications studies, social network studies, sentiment analysis, and studies in natural language processing (NLP). It is crucial to have a reader-centric approach when evaluating the echo chamber effect through text. The interpretation of the posted messages by users requires subjective positions and viewpoints perceived by the message. This interpretation represents the context, awareness, and level of interest of readers in reading the text. Articulation and acceptance of emotional support relies on the communication skills and emotional competence of interlocutors in online communications.

Table 1
Methods for identifying political polarization on social media

Methods	Description
Modelling e.g., Social Network Analysis, Hawkes Model [43,45,46,48].	For simulating the formation of social networks, mathematical random graphs were utilized to describe how users interact as they join the network. Random graphs are generated by adding nodes to the graph one by one and adding random edges between nodes in accordance with a probabilistic law
Machine Learning e.g., Natural Language Processing [55,60,63]	Computational algorithms that automatically improve and develop through experience. It is used as a branch of artificial intelligence. The algorithms build a model using sample data, referred to as "training data," to make predictions or judgments without being explicitly programmed.
Sentiment Analysis/ Opinion Mining [64,65]	The analysis of emotion relates to the use of natural language processing, computational linguistics, text analysis and physiological characteristics to systematically extract and define. The affective states and subjective data are measured and studied.

Acknowledgement
This work has been presented at the International Symposium Computer Science for Smart Agriculture, Education and Medical (CSSAEM).

References
[1] Barnidge, Matthew. "Exposure to political disagreement in social media versus face-to-face and anonymous online settings." *Political communication* 34, no. 2 (2017): 302-321. https://doi.org/10.1080/10584609.2016.1235639
[2] Bright, Jonathan. "Explaining the emergence of political fragmentation on social media: The role of ideology and extremism." *Journal of Computer-Mediated Communication* 23, no. 1 (2018): 17-33. https://doi.org/10.1093/jcmc/zmx002
[3] Kitchens, Brent, Steven L. Johnson, and Peter Gray. "Understanding Echo Chambers and Filter Bubbles: The Impact of Social Media on Diversification and Partisan Shifts in News Consumption." *MIS quarterly* 44, no. 4 (2020). https://doi.org/10.25300/MISQ/2020/16371
[4] Macafee, Timothy. "The Interplay between Social Media Politics and Offline Political Participation." *American Communication Journal* 20, no. 1 (2018).
[5] Sasahara, Kazutoshi, Wen Chen, Hao Peng, Giovanni Luca Ciampaglia, Alessandro Flammini, and Filippo Menczer. "Social influence and unfollowing accelerate the emergence of echo chambers." *Journal of Computational Social Science* 4, no. 1 (2021): 381-402. https://doi.org/10.1007/s42001-020-00084-7
[6] Terren, Ludovic, and Rosa Borge-Bravo. "Echo chambers on social media: A systematic review of the literature." *Review of Communication Research* 9 (2021): 99-118. https://doi.org/10.12840/ISSN.2255-4165.028
[7] Othman, Zakirah, Noor Hidayah Abu, Shafini Shafie, Nur Badriyah Kamarul Zaman, Emmy Farha Alias, and Wan Ahmad Jaafar Wan Yahaya. "Challenges of Social Media Marketing in Digital Technology: A Case of Small Traders of Agricultural Products in Malaysia." *Journal of Advanced Research in Applied Sciences and Engineering Technology* 28, no. 3 (2022): 312-319. https://doi.org/10.37934/araset.28.3.312319
[8] Duggan, Maeve, and Aaron Smith. "The political environment on social media." (2016).
[9] Rekker, Roderik. "The nature and origins of political polarization over science." *Public Understanding of Science* 30, no. 4 (2021): 352-368. https://doi.org/10.1177/0963662521989193

[10] Kubin, Emily, and Christian von Sikorski. "The role of (social) media in political polarization: a systematic review." *Annals of the International Communication Association* 45, no. 3 (2021): 188-206. https://doi.org/10.1080/23808985.2021.1976070
[11] Singer, Daniel J., Aaron Bramson, Patrick Grim, Bennett Holman, Jiin Jung, Karen Kovaka, Anika Ranginani, and William J. Berger. "Rational social and political polarization." *Philosophical Studies* 176 (2019): 2243-2267. https://doi.org/10.1007/s11098-018-1124-5
[12] West, Emily A., and Shanto Iyengar. "Partisanship as a social identity: Implications for polarization." *Political Behavior* 44, no. 2 (2022): 807-838. https://doi.org/10.1007/s11109-020-09637-y
[13] Mason, Lilliana. *Uncivil agreement: How politics became our identity*. University of Chicago Press, 2018. https://doi.org/10.7208/chicago/9780226524689.001.0001
[14] Druckman, James N., and Matthew S. Levendusky. "What do we measure when we measure affective polarization?." *Public Opinion Quarterly* 83, no. 1 (2019): 114-122. https://doi.org/10.1093/poq/nfz003
[15] Wagner, Markus. "Affective polarization in multiparty systems." *Electoral Studies* 69 (2021): 102199. https://doi.org/10.1016/j.electstud.2020.102199
[16] Lee, Frances E. "How party polarization affects governance." *Annual review of political science* 18 (2015): 261-282. https://doi.org/10.1146/annurev-polisci-072012-113747
[17] Weber, Till. "Negative voting and party polarization: A classic tragedy." *Electoral Studies* 71 (2021): 102335. https://doi.org/10.1016/j.electstud.2021.102335
[18] Wolak, Jennifer. *Compromise in an age of party polarization*. Oxford University Press, 2020. https://doi.org/10.1093/oso/9780197510490.001.0001
[19] Charalambous, Giorgos, and Direnç Kanol. "Political Dissatisfaction and Decline of Party Identification: Societal Depoliticisation in the Republic of Cyprus (2006–2012)." *Comparing Strategies of (De) Politicisation in Europe: Governance, Resistance and Anti-politics* (2019): 103-129. https://doi.org/10.1007/978-3-319-64236-9_5
[20] Voogd, Remko, and Ruth Dassonneville. "Are the supporters of populist parties loyal voters? Dissatisfaction and stable voting for populist parties." *Government and Opposition* 55, no. 3 (2020): 349-370. https://doi.org/10.1017/gov.2018.24
[21] Guo, Lei, Jacob A. Rohde, and H. Denis Wu. "Who is responsible for Twitter's echo chamber problem? Evidence from 2016 US election networks." *Information, Communication & Society* 23, no. 2 (2020): 234-251. https://doi.org/10.1080/1369118X.2018.1499793
[22] Dubois, Elizabeth, and Grant Blank. "The echo chamber is overstated: the moderating effect of political interest and diverse media." *Information, communication & society* 21, no. 5 (2018): 729-745. https://doi.org/10.1080/1369118X.2018.1428656
[23] Ksiazek, Thomas B., Edward C. Malthouse, and James G. Webster. "News-seekers and avoiders: Exploring patterns of total news consumption across media and the relationship to civic participation." *Journal of broadcasting & electronic media* 54, no. 4 (2010): 551-568. https://doi.org/10.1080/08838151.2010.519808
[24] Dehghani, Morteza, Kate Johnson, Joe Hoover, Eyal Sagi, Justin Garten, Niki Jitendra Parmar, Stephen Vaisey, Rumen Iliev, and Jesse Graham. "Purity homophily in social networks." *Journal of Experimental Psychology: General* 145, no. 3 (2016): 366. https://doi.org/10.1037/xge0000139
[25] Pariser, Eli. *The filter bubble: What the Internet is hiding from you*. penguin UK, 2011. https://doi.org/10.3139/9783446431164
[26] Dandekar, Pranav, Ashish Goel, and David T. Lee. "Biased assimilation, homophily, and the dynamics of polarization." *Proceedings of the National Academy of Sciences* 110, no. 15 (2013): 5791-5796. https://doi.org/10.1073/pnas.1217220110
[27] Flache, Andreas, and Michael W. Macy. "Small worlds and cultural polarization." In *Micro-Macro Links and Microfoundations in Sociology*, pp. 146-176. Routledge, 2014. https://doi.org/10.1080/0022250X.2010.532261
[28] DeGroot, Morris H. "Reaching a consensus." *Journal of the American Statistical association* 69, no. 345 (1974): 118-121. https://doi.org/10.1080/01621459.1974.10480137
[29] Malarz, Krzysztof, Piotr Gronek, and Krzysztof Kulakowski. "Zaller-Deffuant model of mass opinion." *arXiv preprint arXiv:0908.2519* (2009).
[30] Nyczka, Piotr, and Katarzyna Sznajd-Weron. "Anticonformity or independence?—Insights from statistical physics." *Journal of Statistical Physics* 151, no. 1-2 (2013): 174-202. https://doi.org/10.1007/s10955-013-0701-4
[31] Sîrbu, Alina, Dino Pedreschi, Fosca Giannotti, and János Kertész. "Algorithmic bias amplifies opinion fragmentation and polarization: A bounded confidence model." *PloS one* 14, no. 3 (2019): e0213246. https://doi.org/10.1371/journal.pone.0213246
[32] Williams, Hywel TP, James R. McMurray, Tim Kurz, and F. Hugo Lambert. "Network analysis reveals open forums and echo chambers in social media discussions of climate change." *Global environmental change* 32 (2015): 126-138. https://doi.org/10.1016/j.gloenvcha.2015.03.006

[33] Blondel, Vincent D., Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. "Fast unfolding of communities in large networks." *Journal of statistical mechanics: theory and experiment* 2008, no. 10 (2008): P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008
[34] Newman, Mark, Albert-László Barabási, and Duncan J. Watts. *The structure and dynamics of networks*. Princeton university press, 2011. https://doi.org/10.1515/9781400841356
[35] Girvan, Michelle, and Mark EJ Newman. "Community structure in social and biological networks." *Proceedings of the national academy of sciences* 99, no. 12 (2002): 7821-7826. https://doi.org/10.1073/pnas.122653799
[36] Shareef, Mahmud Akhter, Bhasker Mukerji, Yogesh K. Dwivedi, Nripendra P. Rana, and Rubina Islam. "Social media marketing: Comparative effect of advertisement sources." *Journal of Retailing and Consumer Services* 46 (2019): 58-69. https://doi.org/10.1016/j.jretconser.2017.11.001
[37] Liu, Dong, and W. Keith Campbell. "The Big Five personality traits, Big Two metatraits and social media: A meta-analysis." *Journal of Research in Personality* 70 (2017): 229-240. https://doi.org/10.1016/j.jrp.2017.08.004
[38] Shalizi, Cosma Rohilla, and Andrew C. Thomas. "Homophily and contagion are generically confounded in observational social network studies." *Sociological methods & research* 40, no. 2 (2011): 211-239. https://doi.org/10.1177/0049124111404820
[39] Salganik, Matthew J., Peter Sheridan Dodds, and Duncan J. Watts. "Experimental study of inequality and unpredictability in an artificial cultural market." *science* 311, no. 5762 (2006): 854-856. https://doi.org/10.1126/science.1121066
[40] Centola, Damon. "The spread of behavior in an online social network experiment." *science* 329, no. 5996 (2010): 1194-1197. https://doi.org/10.1126/science.1185231
[41] Bond, Robert M., Christopher J. Fariss, Jason J. Jones, Adam DI Kramer, Cameron Marlow, Jaime E. Settle, and James H. Fowler. "A 61-million-person experiment in social influence and political mobilization." *Nature* 489, no. 7415 (2012): 295-298. https://doi.org/10.1038/nature11421
[42] Kramer, Adam DI, Jamie E. Guillory, and Jeffrey T. Hancock. "Experimental evidence of massive-scale emotional contagion through social networks." *Proceedings of the National academy of Sciences of the United States of America* 111, no. 24 (2014): 8788. https://doi.org/10.1073/pnas.1320040111
[43] Blundell, Charles, Jeff Beck, and Katherine A. Heller. "Modelling reciprocating relationships with Hawkes processes." *Advances in neural information processing systems* 25 (2012).
[44] Farajtabar, Mehrdad, Yichen Wang, Manuel Gomez Rodriguez, Shuang Li, Hongyuan Zha, and Le Song. "Coevolve: A joint point process model for information diffusion and network co-evolution." *Advances in Neural Information Processing Systems* 28 (2015).
[45] Latapy, Matthieu, Tiphaine Viard, and Clémence Magnien. "Stream graphs and link streams for the modeling of interactions over time." *Social Network Analysis and Mining* 8 (2018): 1-29. https://doi.org/10.1007/s13278-018-0537-7
[46] Simma, Aleksandr. *Modeling events in time using cascades of Poisson processes*. University of California, Berkeley, 2010.
[47] Miller, Daniel. "The ideology of friendship in the era of Facebook." *HAU: Journal of Ethnographic Theory* 7, no. 1 (2017): 377-395. https://doi.org/10.14318/hau7.1.025
[48] Perra, Nicola, and Luis EC Rocha. "Modelling opinion dynamics in the age of algorithmic personalisation." *Scientific reports* 9, no. 1 (2019): 7261. https://doi.org/10.1038/s41598-019-43830-2
[49] Morales, Alfredo Jose, Javier Borondo, Juan Carlos Losada, and Rosa M. Benito. "Measuring political polarization: Twitter shows the two sides of Venezuela." *Chaos: An Interdisciplinary Journal of Nonlinear Science* 25, no. 3 (2015). https://doi.org/10.1063/1.4913758
[50] Weng, Lilian, Alessandro Flammini, Alessandro Vespignani, and Fillipo Menczer. "Competition among memes in a world with limited attention." *Scientific reports* 2, no. 1 (2012): 335. https://doi.org/10.1038/srep00335
[51] Guo, Richard Fangjian, Charles Blundell, Hanna Wallach, and Katherine A. Heller. "The bayesian echo chamber: Modeling influence in conversations." *stat* 1050 (2014): 11.
[52] West, Richard L., Lynn H. Turner, and Gang Zhao. *Introducing communication theory: Analysis and application*. Vol. 2. New York, NY: McGraw-Hill, 2010.
[53] Hawkes, Alan G. "Point spectra of some mutually exciting point processes." *Journal of the Royal Statistical Society Series B: Statistical Methodology* 33, no. 3 (1971): 438-443. https://doi.org/10.1111/j.2517-6161.1971.tb01530.x
[54] Colleoni, Elanor, Alessandro Rozza, and Adam Arvidsson. "Echo chamber or public sphere? Predicting political orientation and measuring political homophily in Twitter using big data." *Journal of communication* 64, no. 2 (2014): 317-332. https://doi.org/10.1111/jcom.12084
[55] Powell, Walter W., and Paul J. DiMaggio, eds. *The new institutionalism in organizational analysis*. University of Chicago press, 2012.

[56] Mohale, Potsane, and Wai Sze Leung. "Fake news detection using ensemble machine learning." In *European Conference on Cyber Warfare and Security*, pp. 777-XVI. Academic Conferences International Limited, 2019.
[57] Belcastro, Loris, Riccardo Cantini, Fabrizio Marozzo, Domenico Talia, and Paolo Trunfio. "Learning political polarization on social media using neural networks." *IEEE Access* 8 (2020): 47177-47187. https://doi.org/10.1109/ACCESS.2020.2978950
[58] Mersy, Gabriel, Vincent Santore, Isaac Rand, Corrine Kleinman, Grant Wilson, Jason Bonsall, and Tyler Edwards. "A comparison of machine learning algorithms applied to american legislature polarization." In *2020 IEEE 21st International Conference on Information Reuse and Integration for Data Science (IRI)*, pp. 451-456. IEEE, 2020. https://doi.org/10.1109/IRI49571.2020.00075
[59] Calonico, Sebastian, Matias D. Cattaneo, Max H. Farrell, and Rocio Titiunik. "Regression discontinuity designs using covariates." *Review of Economics and Statistics* 101, no. 3 (2019): 442-451. https://doi.org/10.1162/rest_a_00760
[60] Conover, Michael, Jacob Ratkiewicz, Matthew Francisco, Bruno Gonçalves, Filippo Menczer, and Alessandro Flammini. "Political polarization on twitter." In *Proceedings of the international aaai conference on web and social media*, vol. 5, no. 1, pp. 89-96. 2011. https://doi.org/10.1609/icwsm.v5i1.14126
[61] Haselmayer, Martin, and Marcelo Jenny. "Sentiment analysis of political communication: Combining a dictionary approach with crowdcoding." *Quality & quantity* 51 (2017): 2623-2646. https://doi.org/10.1007/s11135-016-0412-4
[62] Calderón, Fernando H., Li-Kai Cheng, Ming-Jen Lin, Yen-Hao Huang, and Yi-Shin Chen. "Content-based echo chamber detection on social media platforms." In *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, pp. 597-600. 2019. https://doi.org/10.1145/3341161.3343689
[63] Farrell, Justin. "The growth of climate change misinformation in US philanthropy: evidence from natural language processing." *Environmental Research Letters* 14, no. 3 (2019): 034013. https://doi.org/10.1088/1748-9326/aaf939
[64] Bodrunova, Svetlana S., Ivan S. Blekanov, and Mikhail Kukarkin. "Multi-dimensional echo chambers: Language and sentiment structure of Twitter discussions on the Charlie Hebdo Case." In *HCI International 2018–Posters' Extended Abstracts: 20th International Conference, HCI International 2018, Las Vegas, NV, USA, July 15-20, 2018, Proceedings, Part I 20*, pp. 393-400. Springer International Publishing, 2018. https://doi.org/10.1007/978-3-319-92270-6_56
[65] Wollebæk, Dag, Rune Karlsen, Kari Steen-Johnsen, and Bernard Enjolras. "Anger, fear, and echo chambers: The emotional basis for online behavior." *Social Media+ Society* 5, no. 2 (2019): 2056305119829859. https://doi.org/10.1177/2056305119829859