How do Computational Social Science Methods Measure Political Polarization in Discourse? A Scoping Review

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Abstract

The rise of political polarization within western societies has been portrayed by events such as the United States Capitol riot, or the United Kingdom's exit from the European Union. In this context, we argue that computational social science (CSS) methods offer a scalable and language-independent fashion to measure political polarization, enabling the processing of big data. In this vein, this article offers the first scoping review of the application of CSS methods to the analysis of political polarization through text as data. We propose a categorization framework and reflect on the advantages and disadvantages of the different models used in the literature. Additionally, we underline the importance of filling research gaps such as considering the temporal characteristic of political polarization, using a mathematical approach to analyze the use cases, and avoiding location and platform bias. We also provide recommendations for future research.

Keywords: political polarization; computational social science (CSS) methods; text as data; scoping review; Twitter

Introduction

Recent political events, such as the United States Capitol riot, Hungary's prime minister Viktor Orbán publicity doubting that liberal democracies can remain globally competitive, the tensions between Brussels and Warsaw due to incompliance of the rule of law by Poland, or the United Kingdom exit from the European Union are consequences of complex ideological phenomena not always well understood or measured (Scharfbillig et al., 2021). This ideological phenomenon has been named by scholars as political or ideological polarization, which stands for the extent of the difference on political opinions, attitudes, and beliefs. Although such theoretical definition has found some stability in the literature, the different forms of measuring political polarization have not (Gentzkow, 2016).

The increasing use of the term political polarization over the last years (Gentzkow et al., 2019; Jensen et al., 2012) has been justified by the political differences in existing parties, as well as by the establishment of new ones with radical ideological positions (Dimock et al., 2014). This cross ideological environment is known to reinforce diversity and deliberation, creating opportunities to assess different point of views (Nahon & Hemsley, 2014; Shaw & Benkler, 2012). However, within the range of ideologies, the opposing sides can adopt extreme positions, which leads to less engagement with differing ideas and to an increasing number of groups showcasing homophilic behavior, which denies and excludes different ideological stands (Yarchi et al., 2020). The events described in the first paragraph of this introduction constitute attacks on democratic norms and serve as examples of the negative side of political polarization. However, it is unclear if these ideological divisions are being overstated, due to the difficulty of measuring them.

At present, the three main methods to measure political polarization are: 1) value surveys, such as the World Values Survey or the European Social Survey; 2) voting analysis, to understand if the citizen's vote is polarized; and 3) policy views, to investigate whether the distribution of voter preferences on moral or economic issues, for instance, is polarized. However, value surveys show no evident political polarization from 1975 until 2019, voting analysis is highly dependent on candidates' characteristics and the magnitude of the upward polarization trend that is observed is far from previous peaks, and policy views on specific issues, which have been very much studied since 1993, maintain a normal distribution instead of a bimodal polarized one (Ellis & Stimson, 2012; Gentzkow, 2016; Jost, 2006).

The main measure that tends to show consistent evidence for political polarization is the distribution of democrats and republicans on cross party antipathy (Dimock et al., 2014), where it is possible to measure the increasing distance between the consistently liberal and the consistently conservative populations. This evidence goes hand-in-hand with DiMaggio group's theory on inter and intra constrains between electorate ideological groups, which states that as cross-pressure between different ideological groups diminish, they became more internally homogeneous and externally distinct (DiMaggio et al., 1996). This has been consistently happening in the last few years, due to increasing cross party antipathy (Gentzkow, 2016). This explanation is parallel to good clustering criteria, where well defined groups are those more polarized, as well as more cohesive (less constrains internally) and distant (higher cross-pressure intra clusters). The motivation for this work relies in the interception of known statistical models, such as clustering, with political science, to contribute to the consistency in measuring political polarization.

The interception of statistical models, computer science and political science is represented by computational social science (CSS) methods, which offer the specificities for prediction (with algorithms) and for explanation (with research questions and hypotheses) of social phenomena (Wallach, 2018). The CSS field was created in 2006 at the International Workshop on Computational Social Choice, however, its orientation towards machine learning was cemented in 2010 at the workshop Computational Social Science and at the Wisdom of Crowds of the Neural Information Processing Systems (NIPS) annual conference (Mason et al., 2014).

The use of CSS methods for the analysis of real-life and online political polarization, both by the political elite and the civil society, is increasing in the literature (Web Of Science, 2022), showing high-performance metrics within the field (Kursuncu et al., 2019; Peterson & Spirling, 2018; Shaw & Benkler, 2012). In this scoping review, we focused on text as data, which enabled us to encompass both real and online environments, as well as both players involved in political polarization: the political elite, composed by political party members; and the civil society, composed by civilians belonging to a specific country or political system (Lee, 2013). Despite increasing interest, CSS categorization methods are inconsistent, making it difficult to identify advantages and disadvantages for each problem use case, within the wide range available (Cantini et al., 2020; Esteve Del Valle et al., 2021; Serrano-Contreras et al., 2020). This scoping review aims to fill this gap by collecting and analysing existing publications, structuring the methodologies used, sharing lessons learned, and making recommendations for future research.

Method

To access literature focused on measuring political polarization quantitatively using text as data, we applied the following five-stage framework: 1) identifying the research question; 2) gathering data; 3) selecting relevant papers; 4) charting the data; and 5) collating, summarizing, and reporting the results (Arksey & O'Malley, 2005). Bearing in mind the research question "What are the CSS methods used to measure political polarization on text?", we created a four-part query focused on the main topics: political, polarization, measurement (CSS methods), and text. The first part of the query aimed at distinguishing papers on political issues, including the keywords: 'politic*'; 'political ideology'; 'political partisanship'. The second part focused on the polarization topic, including the keywords: 'polariz*'; 'polaris*'; 'extrem*'; 'radical*'. The third part of the query aimed at finding papers using quantitative methods, mainly CSS methods, including the keywords: 'quantit*'; 'measur*'; 'model*'; 'method'. The last and forth part focused on the text as medium, including the keywords: 'narrative'; 'discourse'; 'text analysis'; '*grams'; 'nlp'; 'natural language processing'; 'communication'; 'terms'; 'transcripts'. Since the topic of political polarization has been studied across different fields, we decided to conduct our search in eight different databases: Scopus, Web of Science, Academic Search Complete, SAGE Premier, PsycINFO, Psychology and Behavioural Sciences Collection, and PsycARTICLES.

This query retrieved 258 papers at the date of 11/11/2021, whose abstracts were read, resulting in the inclusion of 26 papers in the scoping review according to five criteria: must be an article on politics; must be an article on polarization; must use quantitative measures on text; must be published from 2010 onwards; and must be in English, Spanish, or Portuguese. The 26 papers were fully read by the three authors and further analyzed, resulting in a final selection of seven papers and in the addition of four papers through references. The final set of 11 papers was qualitatively categorized according to (1) polarization model type, (2) polarization function definition, (3) pre-processing techniques, (4) domain knowledge, (5) text source, (6) disadvantages, (7) advantages, (8) part of a bigger model, and (9) political model. All this process is represented in Figure 1.

[INSERT FIGURE 1 HERE]

We also created and applied a second query to compare the trend in the number of publications in the same field of research. This second query is referred as 'text analysis' and it was only run on the Scopus database, because it has multiple fields and presents the same distribution in number of works for each field (Stahlschmidt et al., 2020). The keywords were the same as the third and fourth part of the main query. Using both queries, we divided the results into trend over time and space (Figure 2 and Figure 3).

The second query retrieved 186 170 papers (Figure 2 and Figure 3), at the same date of 11/11/2021. More general selection criteria were used: must be published from 2010 onwards; and must be in English, Spanish, or Portuguese. No further reading of the papers was performed as we were interested only on the general trend in the field. The queries used, the data for Figure 2 and 3, and the table with the papers coded can be find here: https://osf.io/4qsb9/.

[INSERT FIGURES 2 AND 3 HERE]

Results

The results of the scoping review are structured into three parts: two general analyses, one on quantitative and another on qualitative analysis, and a categorization proposal based on the literature named *Categorization Framework*.

The quantitative analysis of the results shows an increasing trend reflected on both queries (Figure 2), which might be correlated with an increasing interest on the analysis of growing division within societies, as well as on computational methods applied to societal issues (Pew Research Center, 2021). The studies focusing on political polarization measurement on text data are a subfield of the text analysis within CSS methods, and as expected the first follow the trend of the second (Figure 2). Our analysis by region has considerable bias towards the US region on both queries. This follows the disproportion we can find in research between countries, where western societies are overrepresented (Figure 3). An interesting new 'region' appears in the works selected by this review – English-online – which is a digital region defined by language, instead of country. Such a 'region' can be quite useful when exploring online platforms but hinders the possibility of correlating digital findings with offline parameters such as location.

The qualitative analysis of the results points out to five general topics: the type of environment (real life or online), the online data contamination, the type of platform, the timeframes commonly selected, and the language dependence.

Delving into the type of environment, the 11 papers selected for this scoping review can be split between in-real-life (IRL) speech (Mathew Gentzkow & Shapiro, 2010; Matthew Gentzkow et al., 2019; Jensen et al., 2012; Peterson & Spirling, 2018; Sloman et al., 2021) and online discourse (Cantini et al., 2020; Esteve Del Valle et al., 2021; Jiang et al., 2020; Kursuncu et al., 2019; Makrehchi, 2016; Marchal, 2021; Serrano-Contreras et al., 2020). Four papers use US congress speech, being the congress transcripts the majority of IRL data text, and three works use Twitter data. Peterson and Spirling (2018) analyze the British parliament discourse, being the only paper on IRL speech outside the US.

The online data contamination is a crucial topic for online environments, such as YouTube, Reddit, and blogs, which are text medium sources in the use cases analyzed in different papers. In the online environment there is the possibility of contamination by fake accounts or bots, for this reason a pre-selective choice of the users within the online platform is needed. Only two of the papers selected perform data cleaning, removing data lineage derived from bots or other AI agents (Kursuncu et al., 2019; Makrehchi, 2016).

The type of platform affects the users' interactions, ranging from hashtags, retweets, reddits, posts, comments, etc., and might affect the polarization of the shared text. No cross-platform analysis was done in political polarization with text as data, to date and from our knowledge, as none of the papers is focused on one topic through more than one platform.

Regarding the timeframe, dates collected range between one year and one month, depending on the amount of input data researchers are dealing with, as well as on their aims. One common feature to collect text data is picking a specific period before and after the event of interest. Only one paper deals with the time dependence on possible polarized terms (Jiang et al., 2020).

Finally, although text analysis models are language dependent, they can also be replicated in other languages according to the same procedure. When dealing with dictionaries, this dependence can be overpassed if researchers build their own dictionary. Serrano-Contreras et al. (2020) showcase higher dependence because it uses sentiment analysis, which performs better in English than in any other language.

Categorization Framework

The Categorization Framework here detailed was built based on patterns found in the literature with the aim to easily identify the best model type for each problem use case in the context of political polarization, using text as data. The models of interest are the ones which measure the extent of political polarization, although not all the papers focus solely on that. From the ones selected, five measure political polarization specifically (Belcastro et al., 2020; Gentzkow & Shapiro, 2010; Gentzkow et al., 2015; Jensen et al., 2012; Peterson & Spirling, 2018), while the rest present a polarization model as part of a bigger model. The latter type of models aim at predicting election results (Belcastro et al., 2020), finding communication factors affecting polarization (Marchal, 2021), understanding the interaction between polarization and participation (Serrano-Contreras et al., 2020), determining if people can detect ideology through expressions (Sloman et al., 2021), predicting extremist text content (Kursuncu et al., 2019), understanding interaction between covid-19 and polarization in online discourse (Jiang et al., 2020), and predicting political conflicts (Makrehchi, 2016).

This Categorization Framework groups model types against nine features. We based our definition of model types on the overview of text models from Grimmer and Stewart (2013), which follows the machine learning algorithms classification. One extra category was added to cover techniques which precede machine learning, named Statistical and Parametric Models. The models are then divided into five types: 1) Statistical and Parametric, which are empirical frameworks based on text analysis problems, where assumptions are made on the words frequency probability distribution and which are explicitly built for each problem; 2) Classification, which considers models where text is classified according to poles, factions, or ideologies and where this task is supervised because the model contains text examples divided by class/ideology (hand coded or through word dictionaries); 3) Timeseries, which encompasses frequency analysis of the words and usually appears ensembled with other techniques, mainly clustering ones; 4) Clustering, which is a type of unsupervised machine learning technique where the classes are not known a priori and are found through difference in patterns; and 5) Scaling, which maps actors to ideological spaces (latent space with words belonging to a specific topic) and can be applied to word scores or through a generative approach called word fish. We chose one work representative of each model type and analyzed them according to the nine features defined in this study: 1) polarization model type; 2) part of a bigger model; 3) political model; 4) text source; 5) polarization function definition; 6) domain knowledge; 7) pre-processing techniques; 8) disadvantages; and 9) advantages.

The papers from Belcastro et al. (2020), Gentzkow and Shapiro (2010), Gentzkow et al. (2019) and Jensen et al. (2012) fit into the Statistical and Parametric models. Belcastro et al. (2020) being the least sophisticated paper in this category, where partisanship is measured based on the number of Twitter posts supporting each party, after manual coding of the posts. This technique is not scalable, and the class attribution is manual. However, it still showcases the basic principle applied on more advanced techniques: political polarization measurements derive from the proportion of supporting terms (or posts or hashtags) for each ideology pole. Advances in this version comprehend techniques for automatic (statistical) class attribution, bias correction, and validation. Gentzkow et al. (2019) represent well this category. This study develops an empirical framework as a specific model for political polarization in a biparty system, which has four steps: data pre-processing; parameter estimation; bias correction; and validation. The text source chosen is the transcripts of congressional speech. The data is transformed into bigrams after removing stop words, punctuation, low frequency words, and applying the stemming porter technique. This means that all the speech transcripts were transformed into bigrams such as 'tax.increas', which have two terms concatenated and where the word 'increase' is stemmed to its root 'increas' so it can be matched with 'increasing', 'increases', etc. The speech used from the congress has its speaker identified, and this allowed the authors to collect the bigrams for each Democratic or Republican party, according to its speaker. Words spoken by both Republicans and Democrats have low polarity, because they are cross party, although those only spoken by Democrats are highly polarized towards -1 in the ideology axis (left), and the words only spoken by Republicans are polarized towards 1 (right) in the same axis. The model is parametric, dependent on the bigrams counts for each speaker per session in congress. It is assumed that these follow a multinomial distribution (the probability each bigram being said by a particular speaker is independent and identically distributed). Since the empirical framework is well defined, no domain knowledge is needed to apply this model. One of its main advantages is the bias correction. This bias is observed in finite samples, and 'tend to arise for any measure of group differences that uses observed choices as a direct approximation of true choice probabilities' (Gentzkow et al., 2019, p. 1315). The authors of this paper suggest a leave-out estimator and a penalized estimator to correct it. This is an intuitive solution, based on these authors' work ranging from 2012 to 2019, which has been highly validated in big datasets, and is one of the most robust polarization measures found in this scoping review. The only drawback that can be identified is its parametric nature. The need to build an empirical framework is becoming unusual within the machine learning circle, because it needs to fit the problem and to have the parameters defined explicitly.

The Classification models identified in this scoping review have their class attributed manually (Marchal, 2021; Peterson & Spirling, 2018) or indirectly through sentiment analysis towards ideological topics (Serrano-Contreras et al., 2020). We will focus on the Bayesian Estimation Framework proposed by Marchal (2021) and used as a classification model for political polarization. This model is part of a bigger one applied to Reddit's replies to determine whether a chosen text corpus (reply) is affectively and politically polarized, and which communication factors are involved in the process. In this paper, the ideological leaning of a Reddit user has a neutral *a priori* distribution, updated by the number of comments posted to liberal subreddits and number of comments posted for conservative subreddits. Although no political system is assumed, as the accounts are selected based on English language criteria and not on a region or country location criteria, the work uses the same ideological axis with left/right poles as the biparty system. The main advantage of Marchal's (2021) paper is the approach taken to build the ideology labels. The coding of the ideology of replies is done manually in the first part of the pre-processing phase and extended to a more advanced technique in the second part of the same phase. This reduces the error in ideology coding in the first part and enables to scale it in the second part. In the latter, the ideological coding was examined using a semantic clustering spaCy, to fetch similar words of "liberal" and "conservative," such as "libs," "dems," and "cons". This created a bigger dataset of replies classified as democratic or liberal, which enabled the use of the Bayesian Estimation Framework classification model, which means less manual work. One of the disadvantages of this paper comes from the use of accuracy metric to find the ideological polarization. The higher the accuracy, the better a term defines an ideology (Peterson & Spirling, 2018), although its correlation with polarization might not be clear, as this leads to find orthogonal terms, and polarization can happen in the same terms (parallel terms).

Jiang et al. (2020) provide a good example of the Timeseries model by analysing the polarization of online discourse regarding covid-19, looking for correlations between pandemic events and political polarization on Twitter according to geolocation and social network parameters. For the classification of political ideology, the American liberal and democrat classification is used, as all comments are from the US. The distinction between liberal and democrat comments is made through an initial manual coding of keywords, which then serve as input. The model of interest for political polarization is the first step of these authors' work, which focus on grouping terms through its similarities through time, being the main contribution of the work. This technique is divided into two parts. Firstly, temporal clustering was applied, using a recent time series clustering, which is able to ingest multidimensions, named dipm-SC (Ozer et al., 2020). This technique was used to create time windows with the hashtags per political party pre-selected. Secondly, a Louvain community detection algorithm was applied on each time window to fetch sub semantic clusters with similar terms. This approach provides a methodology to look for further polarized terms on Twitter and takes into consideration the dynamic characteristic of political polarization, inputting the time dimension.

Sloman et al. (2021) showcase both the Clustering and Scaling models. The political polarization model is part of a bigger question to investigate whether socially conditioned variation in speech is a factor to identify others based on their political identity. Sloman et al. (2021) apply a two-step polarization measure. First, it is calculated the logarithmic probability of words being spoken by a democrat or a republican, defining the log odds, which are positive for republican words and negative for democratic. Second, it is calculated the partial Kullback-Leibler divergence (PKL), which is a measure that combines the log odds with the word's probability of occurrence. This first part fits in the empirical framework category, and the second part fits into the clustering category, where the authors found significantly opposing pairs of words. For that analysis the authors map the words in a distributional semantics model, a scaling model type named word2vec, where each word is projected into a common lower dimension space, being possible to measure the distance between them. Having that, the words found in the first step with the highest PKL for republicans and democrats are projected to the same space with word2vec. Having the words within the same dimension, it is possible to apply a clustering algorithm which calculates words' distance using a cosine similarity. This builds the bridge between the advantages of empirical frameworks to classify text according to partisanship, and the advantages of scaling and clustering in finding close or distant words to assess polarity.

The Categorization Framework for all the 11 papers used in this scoping review is available online at: https://osf.io/4qsb9/.

Discussion

This scoping review aims to contribute to a higher consistence within the field of political polarization and CSS methods, by proposing a Categorization Framework which groups and analyses relevant studies. The categorization presented in this scoping review is not mutually exclusive, meaning that we can find multiple model types ensembled into one model. Sloman et al. (2021) and Jiang et al. (2020) show how the scaling and clustering models fit into classification and empirical models, improving the results by their combination.

Besides intending to reach a consistent definition for the theoretical terms used, three main research gaps are identified: 1) the dynamic characteristic of political polarization; 2) the mathematical approach to the use cases; and 3) the location and platform bias found in the literature. Regarding the first gap, the contribution of Jiang et al. (2020) for the analyzes of political polarization within text on social media is quite remarkable, as it is the only selected paper that considers time as a variable, taking into consideration the dynamic characteristic of discourse and polarization. Other papers relate polarization to conflict events (Makrehchi, 2016) or look at polarization throughout a period of time (Jensen et al., 2012). Only Sloman et al. (2021) circumvent the second gap by following a mathematical approach familiar to CSS methods, which comprises the definition of political polarization into independent, dependent, and cofactor variables. Finally, none of the papers included in this coping review avoid the third gap, as none analyze one topic through different online platforms, which would contribute to the mass polarization research field, as Jensen et al. (2012) contribute to elite polarization research by analyzing congress speeches' transcripts and Google Books corpus. Lastly, the CSS methods on political science are highly biased towards biparty environments and within USA (Figure 3), multiparty environments and European analysis of political polarization should, and can, also be done. In this scoping review we have included studies with data from UK, Spain, Iran and the Netherlands, besides the English-online and the USA data.

Conclusion

As political polarization increases, the methods of CSS are important tools which allow us to scale to big data analysis, in a cross-national and language independent fashion. The use of text as data for this analysis is quite remarking, as it enables the intersection between real life environments, with speech transcripts, and online environment, through social media platforms analysis.

This work contributes to the CSS and political science field through the categorization done and the identification of gaps, mainly the dynamic characteristic of political polarization, the mathematical approach to the use cases, and the location and platform bias found in the literature. This scoping also builds the bridge between the advantages of empirical frameworks to classify text according to partisanship, and the advantages of clustering and scaling in finding close or distant words to assess polarity.

A possible future research path might come from the latest studies on text classification which can also be extended to polarization measurement. A common first step in the papers analyzed by this scoping review is the partisanship classification of text. Within this field Ho and Quinn (2008) use machine learning techniques as logistic regression and support vector machines to classify text according to ideology. Additionally, Iyyer et al. (2014) use deep learning techniques such as semi-supervised recursive autoencoders. The latter's recursive method has in consideration the sequence of words in sentences, which is a novelty in the field. All these techniques might be explored outside classification, into prediction of magnitude of each class, to find polarization, bearing in mind that polarization also happens in non-orthogonal terms.

Research on CSS intercepts the real and digital worlds, trying to understand correlations between the phenomena happening on both environments. Nevertheless, one should not forget that the findings of use cases using social media represent the online world, which might not translate into real life, even if both might merge in the future (Boullier, 2018).

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Appendix. Articles used in the current study

Authors	Title	Year	Journal	Doi
Belcastro, L., Cantini, R., Marozzo, F. **et al**	Learning Political Polarization on Social Media Using Neural Networks	2020	IEEE Access	10.1109/ACCESS.2020.2978950
Jensen, J., Kaplan, E., Naidu, S., & Wilse-Samson, L.	Political Polarization and the Dynamics of Political Language: Evidence from 130 Years of Partisan Speech	2012	Brookings Papers on Economic Activity	www.jstor.org/stable/41825364
Gentzkow, M., & Shapiro, J. M.	What Drives Media Slant? Evidence From U.S. Daily Newspapers	2010	Econometrica	https://doi.org/10.3982/ecta7195
Gentzkow, M., Shapiro, J. M., & Taddy, M.	Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech	2019	Econometrica	https://doi.org/10.3982/ecta16566
Peterson, A., & Spirling, A.	Classification Accuracy as a Substantive Quantity of Interest : Measuring Polarization in Westminster Systems	2018	Political Analysis	https://doi.org/10.1017/pan.2017.39
Marchal, N.	Be Nice or Leave Me Alone: An Intergroup Perspective on Affective Polarization in Online Political Discussions	2021	Communication Research	10.1177/00936502211042516
Serrano-Contreras, IJ., Garcia-Marin, J. & Luengo, O. G.	Measuring Online Political Dialogue: Does Polarization Trigger More Deliberation?	2020	Media And Communication	10.17645/mac.v8i4.3149

Sloman, S. J., Oppenheimer, D. M., & DeDeo, S.	Can we detect conditioned variation in political speech? Two kinds of discussion and types of conversation	2021	PLosONE	https://doi.org/10.1371/journal.pone.0246689
Kursuncu, U., Gaur, M., Castillo, C., **et. al**	Modeling islamist extremist communications on social media using contextual dimensions: Religion, ideology, and hate	2019	Proceedings of the ACM on Human-Computer Interaction	arXiv:1908.06520
Jiang, JL., Chen, E., Yan, S.; Lerman, K. & Ferrara, E.	Political polarization drives online conversations about COVID-19 in the United States	2020	Human Behavior And Emerging Technologies	10.1002/hbe2.202
Makrehchi, M.	Predicting political conflicts from polarized social media	2016	Web Intelligence	10.3233/WEB-160333
Del Valle, ME.; Broersma, M. & Ponsioen, A.	Political Interaction Beyond Party Lines: Communication Ties and Party Polarization in Parliamentary Twitter Networks	2021	Social Science Computer Review	10.1177/0894439320987569