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Discourse Polarization Index - Analysis Of Top-Down And Ground-Up Political Discourses in Portugal

Catarina Trindade Pereira

Master in International Studies

Supervisor:
PhD Raquel da Silva, Integrated researcher,
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SOCIOLOGIA
E POLÍTICAS PÚBLICAS

History Department

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Catarina Pereira

Abstract
An increasing number of events across the world have been a warning for democracy stability in established democratic countries. Events such as Hungary's prime minister Viktor Orbán publicity doubting that liberal democracies could remain globally competitive, and the increasing voting share of anti-establishment parties in European member states are consequences of the political polarization phenomenon which endangers our democracy. To understand if we are becoming more polarized, literature has been focusing on measuring political polarization through surveys and voting data, without consistent evidence for any trend. Although the theoretical definition of political polarization has found stability in the literature, the different forms of measuring it have not. The measurement of political polarization needs to be more robust and extended to mass society besides elite society, enabling a comparison between the two, and within the real life and the digital. This dissertation answers this need, measuring political polarization, using text-as-data and computational social science methods, in an effective way independent of manual tasks, language, survey or pooling, polarization's actors, and environments. It uses an empirical framework applied to parliamentary discourses and Twitter data to create a Discourse Polarization Index (DPI) which enables the assessment of the evolution of political polarization in discourse, considering its state and process. Portugal is used as use case, showing an increase in political polarization from 2015 to 2021, for the elite and the mass society, with similar behaviour between the two groups. A semantic validation is done, and research future steps are given.

Keywords: political polarization; computational social science; natural language processing; social media; Twitter; parliament; text as data

Resumo

Diversos acontecimentos mundiais põem em causa a estabilidade democrática nos países democráticos. Destacando-se o comentário do primeiro-ministro húngaro, Viktor Orban, que declarou que as democracias atuais podem não ser competitivas globalmente, justificando a inclinação por uma autocracia, assim como o número crescente de partidos antissistema na Europa ocidental. Ambos os eventos são consequência da polarização política, um fenómeno que tem vindo a pôr em risco as democracias ocidentais. Para perceber a tendência, a literatura tem-se focado na medição quantitativa da polarização política através de questionários e sondagens, sem nenhuma tendência identificada. A quantificação da polarização política precisa de ser mais robusta e estudar também a polarização da massa publica, para além da elite, sendo possível assim a comparação da polarização entre os dois grupos, mas também entre os ambientes em que interagem, na vida real ou no digital. Esta dissertação responde a essa necessidade, medindo a polarização política, usando texto e métodos de ciências sociais computacionais, independente da língua, dos questionários, das sondagens e de tarefas manuais. A dissertação usa um modelo matemático empírico aplicado ao discurso parlamentar e a dados retirados do Twitter para criar o Índice de Polarização no Discurso. Este índice permite avaliar a evolução da polarização no discurso, considerando as suas características de estado e processo. Portugal é usado como caso de estudo, mostrando um aumento da polarização política entre 2015 e 2021, para a elite e massa pública, com comportamentos semelhantes. É efetuada uma validação semântica e são dadas recomendações para próximos passos de investigação.

Palavras chave: ciências sociais computacionais; polarização politica; análise de texto; redes sociais; Twitter; parlamento

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Glossary of Terms

ANT – Actor-network theory

API – application interface

Classification – algorithm of machine learning to give a sample a given class

CSS – computational social science methods

DPT- Discourse Polarization Index

Empirical Framework – mathematical model with parameters defined empirically

Git-hub – open-source website for code sharing

LR – Left and Right ideology dualism

NLP- Natural language processing

ML- Machine Learning

Tweets – the posts' name on Twitter social media

Twitter – social media platform

STS – Science and Technology Studies

Chapter 1: Introduction

Recent political events seem to doubt the capacity of liberal democracies to remain globally competitive, the political polarization and the increasing of anti-establishment parties are consequences of complex ideological phenomena not always well understood or measured (Scharfbillig et al., 2021). This ideological phenomenon has been named by scholars political or ideological polarization, which stands for the extent of the divergence of political attitudes and beliefs. Although such a theoretical definition has found some stability in the literature, the different forms of measuring political polarization have not (Gentzkow, 2016a). The measures' type of political polarization is divided into its actors, the elite, composed of the politicians, and the mass polarization, composed of the citizens. These measures use in its majority surveys, measuring ideology, attitudes, and political position. Besides the surveys, other measurements aim to infer voting behaviour based on geography or ideology applying text analysis in parties' manifestos. These types of measurements have the advantage of do not depend on surveys or pooling which are expensive and difficult to scalable for different countries and keep consistency through time. Those are two examples of Computational Social Science (CSS) methods applied in political science, CSS is a growing field that gathers the advantages of computer science and machine learning disciplines to social sciences. Current works in literature aiming for measurement of political polarization use, in its majority, quantitative methods inside the CSS field. The goal is to contribute to a consistent fashion to measure the political polarization phenomenon in its different environments and actors. The distinct evidence in political polarization, which is still very use case dependent, reflects the need for more research in that area. Gathering evidence on if political polarization is increasing is evident in the increasing number of anti-establishment parties in Western Europe, although on voting behaviour and citizens' ideology there is not a clear metric that can show a clear trend for the phenomenon. Scholars' work within CSS has applied five types of measurements, such as statistical and parametric, classification, timeseries analysis, clustering, and scaling. This dissertation uses text-as-data to fetch real-life and digital environments of political polarization and aims to avoid misunderstandings of grouping citizens based on computer science algorithms. For these reasons, and due to the data type, this work uses a statistical and parametric model to measure political polarization and creates a Discourse Polarization Index (DPI) to assess the phenomenon trend through its actors and environments. The DPI has a theoretical basis on political polarization's state and process characteristics, using the Fiorina and Abrams (2008) definition. This dissertation intends to build a metric able to measure political polarization through time and use it to understand how political polarization is evolving in Portugal, considering its actors - both elite and mass society - using real-life environment data from parliament transcripts and online data from the social media platform Twitter. In this sense, it aims to answer the following research questions (RQs):

RQ1: How can political polarization be measured in discourse, in a language and human-task independent fashion, considering the phenomenon state and process?

RQ2: What is the trend of political polarization in the Portuguese parliamentary and online government discourse?

RQ3: What is the trend of political polarization in Portuguese citizens' online discourse?

The work evolves through five chapters, from literature review, methodology, results, and conclusion.

In Literature Review in Chapter 2, the theoretical framework used is presented, the political polarization definitions, as well as the Portuguese use case. The theoretical framework used is the Actor-Network Theory (ANT), and its characteristics are reflected through this work when I am reframing the subject of each discourse, complying with ANT's commitment to localizing knowledge, and assuming technology as an actor in research. Political polarization is defined as a bimodal distribution representing citizens' ideology on a left versus right axis. On this distribution, there are more citizens on the extremes, shown in a graphic with two maximums, one for each xx-axis extreme. This definition is applied to analyse the political polarization of parliamentary discourses and online discourses on Twitter, using the deputies' parliamentary discourse and Tweets to analyse elite polarization, and online citizens' replies to analyse mass polarization. For the Portuguese use case, the multi-party environment is transformed in a bi-party one, grouping the parties BE, PCP, PEV, PAN, and PS, to the left side, and on the right side CDS-PP, PPD/PSD, IL, and CH.

In Methodology in Chapter 3, the focus is on the empirical framework used, on the data collection and pre-processing steps. The empirical framework joins the work of Jensen et al. (2015) with Gentzkow et al. (2019). This data is processed at the word level, concatenating every 3 words in a sentence, called trigrams, and calculating the speech's political polarization as its average of each trigram. The data processed is divided into two datasets, the Twitter dataset which will be used to measure mass and elite polarization, and the parliament dataset which will be used for elite polarization.

In Results in Chapter 4 the data shows a bimodal distribution for the aggregated political polarization by year and by government term, confirming the existence of both elite and mass polarization. The main contribution is the Discourse Polarization Index (DPI), a metric that allows the measurement of political polarization through time considering the state and process of the polarization phenomena in text. The DPI is increasing for both elite and mass polarization online, although the mass polarization increased five times more than the elite, between the 13th and 14th government terms. A qualitative validation is done, showing the consistency between highly polarized speeches and national political events, and similarities were found between literature and the topics found in each polarized extreme. The themes to the right focused on identity slogans and economic issues, and to the left focused on labour and workers.

In Conclusion of Chapter 5, the DPI is proved to be a robust metric to measure political polarization, answering the first research question. The empirical framework applied surpass other CSS methods because it does not need any type of previous categorization by humans (surpassing classification), or any pre built dictionary (like scaling), and avoids categorization based on computer science metrics (such as clustering). The ANT commitments are followed, and technology is taken as a factor in the mass polarization online which influences the human behaviour online, affecting mass and elite polarization.

Chapter 2: Literature Review

2.1 Introduction

In this chapter I will start by defining the theoretical framework chosen for the dissertation, stating fundamental concepts as well as its main critics. The dissertation uses a theoretical framework commonly used when applying Computational Social Science (CSS) methods, named Actor-Network Theory (ANT). A short introduction of the theory is given, followed by main research focus and main critics. Furthermore, it is explained how ANT's theory is related to the topic explored and how it answers the critics. Next, basilar definitions are introduced to aim for consistence of terms throughout the work, about political polarization's definition and history, as well as its actors. Lastly, I will connect the terms defined to the use case used, which overarching the elite and mass political discourse in Portugal.

2.2 Theoretical Framework: Actor-Network Theory

Actor-Network Theory (ANT) is a constructivist approach to social theory that emphasises the work *in* the world and the work *on* the world. ANT was created in 1980 by Science and Technology Studies (STS) scholars, mainly Michel Callon, Madeleine Akrich, Bruno Latour, and the sociologist John Law. This theory takes material-semiotic tools and methods, mapping the relationships between objects (material) and concepts (semiotic), aiming to understand the interactions between elements and not rush to classify them, consequently, everything in the social and natural world is treated as a 'continuously generated effect of webs'(Law, 2009, P.57).

ANT characteristics focus on seven main topics: (1) the sensibility stream, as a set of practices to assess the world being *on* it and *in* it, (2) the slow velocity when acquiring knowledge, (3) the recognition of subjectivity, with a located practice to a point of view, (4) the political role as passionate research work, (5) heterogeneity, (6) relationality, and (7) unfolding and uncertain.

The first characteristic of ANT is the acceptance that theory is not something that pre-exists, and it is waiting to be applied, theory does not separate from the practice, that's why ANT is described as a sensibility. The second characteristic aims for a slow process, prioritizing knowledge instead of conclusions and results. The third characteristic rises from the location's recognition when practicing ANT, assuming that there is no overview or objective point of view, it is always a subject and therefore a location to which knowledge is not neutral. The fourth characteristic stands out ANT's correlation to politics, assuming 'is always there' (Law & Singleton, 2013, P.73). The description as passionate research work rises when the work stays within controversies, doubting about boundaries and common sense, as John Law (2009, P.57) poses it, 'it is passionate because it is disturbing', and as a consequence it is political. The fifth characteristic is heterogeneity, which means considering different actors, and the sixth characteristic is relationality, which is the mapping of relations between the different actors involved. The seventh pillar is the ANT unfolding and uncertain characteristics, which is especially important when looking for results and conclusions, to not look for causality and fixed categorization, stating all the assumptions that come with the use of CSS methods.

The critics of ANT found in the literature are within Information Systems, focusing on the limited analysis of social structures, an amoral stance when ignoring the social consequences of technical choices, and the problems of generalized symmetry and of description (Walsham, 1997). Other more recent critics focus on the gaps of ANT commitments with the CSS methods. I have focus on this type of critics, mainly on the critics done by Dominique Boullier. The reason for this choice is because Boullier (2018) criticizes the ANT used by Médialab, a renowned French research centre fully dedicated to CSS with open-source tools which are widely used by CSS scholars. Boullier (2018) focuses on three main areas: (1) continuity of data; (2) continuity of methods; and (3) network misunderstanding.

The first critique is for the inexistence of continuity of data between qualitative, the real world, and quantitative, the digital world. The former is where the experiences come from, and the latter is where the methodology and analysis are done. The inexistence of continuity of data reflects the difference between nature and digital data, as the digital environment is a discretization of the real world.

The second critique is for the inexistence of continuity of methods, which can be illustrated with a classification, or categorization, exercise. Classification is an important process in computer science, as well it is in categorization in social science. A classification with quantitative methods is as a cluster of individuals and may lead to conclusions in the real world, based on discrete results. Within this scenario, one can look at a cluster of individuals and conclude that they represent a community. This type of interpretation does not take into consideration the discontinuity between the quantitative method of finding nearby sample points based on the features collected, and the qualitative methods within the grouping of specific people becoming a community. Cases of generalization, when classification extrapolates to categorization, are not aligned with ANT principles, because a classification done with computer science methods with good accuracy might not reflect the right categorization within the social sciences' criteria.

The third critique is about network misunderstanding, and it is crucial for this dissertation. The methods are generalized through different use cases, but the findings from this one work do not generalize as they are specific to the use case, timeframe, socioeconomic context and methods used. Due to the high quantity of data analysed, one feels tempted to change the research focus from the agency of the individual to the agency of the research topic process, but again the findings are not possible to generalize, so according to ANT the focus should be on the parts (individual) and the whole (the topic) is studied according to the constrains it is drenched in.

In this work, the ANT is mainly reflected in the actors used, the topic of political discourse, and the experimental methods. Connecting these three main areas is the discourse, as text-as-data. The reflection of ANT in this dissertation is represented schematically in Figure 1, summarizing the seven main ANT characteristics.

Technology is taken as an actor, differentiating measurements made in real life and digital environment. The actors taken into consideration are the humans, the data, and the medium. The humans are divided into mass society and the political elite, the data are the documents with the discourse of what each has to say, such as parliament transcripts or social media posts. The medium is the Twitter social media online and the parliament in real life. The relationship between those 3 actors mirrors the next characteristic. The political role of the work developed is noticeable in its main topic of political polarization, a current phenomenon that scholars are trying to measure and understand. The approach taken is a quantitative experiment, avoiding temptations of applying classification as categorization and with additional semantic validation to avoid network misunderstanding.

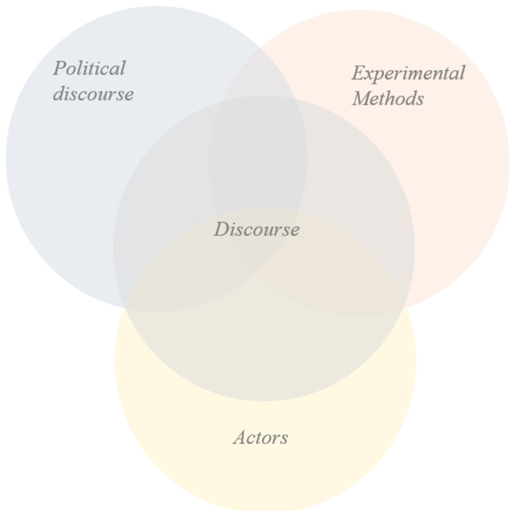


Figure 1: ANT theoretical framework

2.3 Political polarization definition

Here I will make important distinctions and state the theoretical origins of core terms used throughout this dissertation. The definition of political polarization stands for the extent of the divergence of political attitudes and beliefs (Gentzkow, 2016b). The focus of this work will be on political polarization within the context of political parties and democratic systems. I will take into consideration both two-party systems, such as the one from the USA and multi-party systems common within European democracies. I will explore the concepts of ideology, as left versus right, and liberal versus conservative, and connect those with the one of political polarization. Next, I will delve into political polarization actors and the topics within each, always referring to how polarization is being measured in each group. Lastly, the ideology and political polarization for the use case of Portugal are explored.

The first important distinction is between ideology and preferences (Fiorina & Abrams, 2008a). Preferences are choices on reasonable topics with which people disagree. For example, education is not a preference, but whether the government should spend more or less on it is a preference. Ideology is the political strand a citizen follows and can be operational or symbolic. Operational ideology stands for choices that relate to actions, like policies, while symbolic ideology is the way citizens see themselves, related more to perspectives rather than to actions (Ellis & Stimson, 2012a).

In this work, the focus is on the operational ideology, which in the literature is measured through surveys, Likert items, and forced-choice formats (Pew Research Center, 2021). Surveys go from specific to general, observing the specific to infer the latter. Observing specific choices in each question, one can infer the general, which is the ideological position of the citizen who answered. Likert items format poses a statement, and answer options are 'yes' or 'no', or levels of agreement scales. Although still used, this has a response bias, because the statement will always have an ideological leaning perspective, making it difficult to represent citizens' moderate position. Forced choice formats permit the choice of one statement or the other. The problem with this technique is the lack of scientific evidence when creating the opposition statements, there is not a scientific way to be sure that one represents the opposite of the other. Due to the bias characteristic of Likert items, and lack of scientific proving in forced choice format, the surveys are the most used option to measure operational ideology (Akkerman et al., 2014; Gründl, 2022; Hunger & Paxton, 2022). For the USA the most used surveys are ANES (America National Election Studies) or Pew Research (*Home - ANES | American National Election Studies*, n.d.), and for Europe, the most used are the European Social Survey and European Values Study (*POLITICO Poll of Polls — European Polls, Trends and Election News – POLITICO*, n.d.).

Political polarization has its origins in the political ideology of one's country and its citizens. The definitions used in the literature for political polarization derive from finding extremes in political ideology, and scholars use a range of terminology when referring to ideological poles, such as the liberal versus conservative, its reflections into democratic versus republican for the USA or left versus right for Western Europe (Caprara & Vecchione, 2018). I will refer to the binary expression of left versus right as LR, and to the liberal versus conservative as LC. These are terms that reduce ideology to two poles, often connected to economic and moral choices (Caprara & Vecchione, 2018; Jost, 2006), and although widely used today are simplified heuristic definitions. The most common use of these concepts is in interpreting and predicting political attitudes and behaviours (Malka et al., 2019; Piurko et al., 2011). There are critics of the use of such a simplified categorization for human behaviour, although it is much in use between scholars (Belcastro et al., 2020; Esteve Del Valle et al., 2021; Gentzkow & Shapiro, 2010; Jensen et al., 2012; Makrehchi, 2016; Marchal, 2021; Peterson & Spirling, 2018a; Serrano-Contreras et al., 2020).

The left and right terminology, which is used in western European countries, came from 18th century when Louis XVI promoted a voting motion in Versailles to decide whether the credentials of the representatives should be checked all together or within each of the estates they belong. At the time France had three estates: the clergy, the nobility, and the commoners. The voting motions had two fronts, the ones who agreed with the credential checking to be kept inside each estate, prioritizing the existing social order, and the opposition which defended the credential checking to be done all together, aiming for reform on social order (Caprara & Vecchione, 2018). The traditional front was seated to the right of the president in the chamber, and the revolutionary front was on the left. This happened for the first time on that voting but stopped for the next 18 years. The spatial distribution was forced to avoid the left and right division until 1814, when Louis XVIII returns to the constitutional monarchy in France and the conservative groups merged again on the right and the liberals on the left, recovering the distribution from Versailles voting until today. Not only in Europe this dualism persists, but there are also dualism relations in east and central Africa, as well as in Indonesia (Hadden & Wuthnow, 1991).

Liberalism and conservatism in the USA, in comparison with left and right within western Europe, are labels adopted by politicians which developed their meaning over time (Ellis & Stimson, 2012b). Stability, order, and hierarchy are correlated to the right sphere, and reform, poor, and weak to the left one (Caprara & Vecchione, 2018).

Liberalism was a label found by Franklin D. Roosevelt when the 'New Deal' was created with the help of the government as an instrument of cooperation. Franklin Roosevelt inspired himself in the progressivism of Theodore, and the new deal was a strong government's action to solve nations' problems when democrats were in a low popularity wave. 'Liberal' was a word that contrasted with communism, fascism, and socialism, remembering liberty and freedom. He took the term as a label for his ideas, naming his programs liberal, in opposition to conservatism (Rabie, 2013).

The term conservatism appeared before the cold war, stabilizing after 1920, connected to Herbert Hoover and representing a government of minimal size and scope. The preferred term *liberalism* was disputed between Roosevelt and Hoover, but Roosevelt was attached to the term, and Hoover stayed in opposition and connected to the *conservatism* term. Modern conservatism had its origin in 1964 with Barry Goldwater's book, focusing on an attack to welfare strategy of Roosevelt and to government's defence of civil rights. Later, Ronald Reagan capitalized on the social and economic downwards of the 1970's with the cold war and Jimmy Carter's unpopular perceptions, and in 1980 it was established a new brand of ideology for conservatism, adding to the conservation of the social order, the right for individual and market freedom (Rabie, 2013).

Nowadays *liberalism* relates to the Democratic Party in the USA, and *conservatism* to the Republican Party, sharing both the defence of individual and market freedom, although the liberals (or democrats, corresponding to the left), support a bigger government scope than the conservatism. The terms liberalism and conservatism in the USA, are comparative for left and right in western Europe (Caprara & Vecchione, 2018). Within western Europe, the media uses left and right terms vastly for self-reference, but as well for countries in the global south (Bienfait & Beek, 2014).

This dualism is simplistic and only useful as a first step in the division of citizens' ideology. Its critics (Carson & Rowlands, 2001, 2001; Smith, 2009; Toshkov & Krouwel, 2022) point out the regionality differences, mainly for the eastern soviet bloc countries, where the right appeared as the reform for communism (socialism back then), switching the dualism meaning. Other differences can be found in the spatial location of representatives between France and England, in the British parliament who sits on the right is the party that is in power, even if it's the labour party (left). Nevertheless, for polarization analysis this dualism is useful to describe citizens' ideology through surveys or mathematical methods, creating a simplification that can represent a group's ideology is widely used in literature nowadays (see, for example, Marchal, 2021; Nahon & Hemsley, 2014; Yarchi et al., 2020)

The definition of polarization which is present in standard dictionary definitions appears as either opposing sides, or different perspectives, principles or point of views, which divides the samples of interest into groups (*Polarization | Sociology | Britannica*, 2022). If one describes it as an event that is observed and plotted into a graphic, political polarization is a bimodal distribution of observed events (Fiorina & Abrams, 2008a), such as the one plotted in Figure 2. This means each event observed is a citizen with a LR ideology value attached. The distribution of political polarization will be the number of events, or citizens, within each ideological value. Taking the xx-axis as the polarization value axis and the yy-axis as the number of observations within each value, a polarized distribution would be one with a higher number of observations within the extremes of the xx-axis. Either within the dictionary or within the plot definition, one can easily fetch origins of discordance, such as the definition of 'extreme' in the polarization values, or of 'high values' in the peaks at the yy-axis. How much is enough to define the extreme and high values' limits is not defined within the literature in a consistent fashion. Throughout this thesis a trend analysis is prioritized, aiming for the analysis of an increase and decrease over the years, to avoid being stuck on absolute definitions of high or low classifications of polarization that do not allow comparison between groups of citizens and throughout the time.

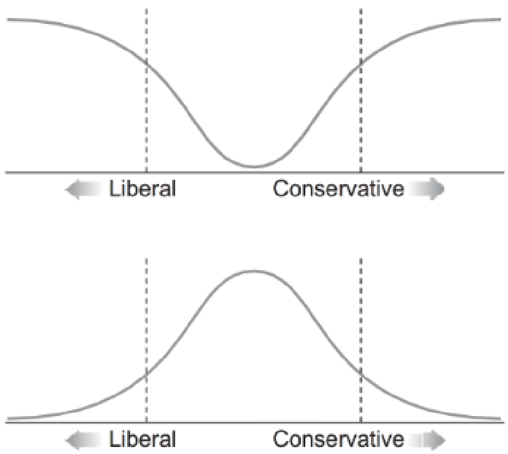


Figure 2: Bimodal (above) ideology distribution and unimodal (bottom) ideology distribution. Source: Fiorina and Abrams (2008).

In this work the political polarization assumed is the one stated by Fiorina and Abrams (2008) which already incorporates an important two-fold concept of state and process for political polarization, taken from DiMaggio (1996). The state of political polarization is the distance between the two polarization peaks and the number of events in the bimodal distribution (the size of each peak). The process of political polarization is the polarization trend of each peak, to grow or diminish, to distance or approximate over time. The blue and red colour map dividing the USA ideology after 2000, came glued to the bimodal distribution, with red on the right axis and blue on the left axis. The choice of this definition of political polarization in quantitative social science works is consistent throughout related literature (Belcastro et al., 2020; Esteve Del Valle et al., 2021; Gentzkow & Shapiro, 2010; Jensen et al., 2012; Makrehchi, 2016; Marchal, 2021; Peterson & Spirling, 2018a; Serrano-Contreras et al., 2020)

2.4 Actors of Political polarization

The agents of the political polarization phenomenon can create, enhance, or diminish political polarization. These agents can be defined into two groups mutually exclusive: mass society and politicians. The political polarization within mass society is defined as mass polarization, and the political polarization within politicians is defined as elite polarization. Although these are separate groups, their interactions and proximities are dynamic.

In the following subsections, both types of polarization are analysed, as well as how they have been measured by scholars and which topics they delve into.

2.4.1 Mass Polarization measurement and its topics

The prediction of voting behaviour techniques was the main trigger to extract metrics such as the citizens' preferences on government policies, political issues, ideology, and consequently mass polarization. The way mass polarization within mass society is measured can be divided into five groups: (1) measurement of social and moral attitudes versus ideology; (2) political position directly asked; (3) political positions on specific issues; (4) elections' exit poll correlating values and voting behaviour; (5) geography and voting behaviour, (6) inferring median voter ideology based on party manifesto ideological score.

For the first group, the correlation between political polarization and social attitudes and moral visions has been studied since 1980, opposing culturally orthodox to culturally progressive citizens (Hadden & Wuthnow, 1991). Examples of scholars' work using that type of measurement are the 1993 General Social Surveys (GSS) used by Evans (1997), the World Values Surveys contrasting traditional versus secular, and survival versus self-expression, used by Baker (2005). The correlation between citizens' values and their ideology is not sufficiently strong to understand which of those social or moral values have an impact on mass ideology (Fiorina & Abrams, 2008b). Due to this, later measurement types were more specifically targeted at citizens' political positions, instead of citizens' values. For the new measurement of political positions, people are asked to identify with political labels, usually done through surveys that fetch a representative sample of a given country. Within the American political environment these surveys range their answer options from extremely liberal, slightly liberal, liberal, moderate, slightly conservative, conservative, extremely conservative, and 'don't know' that is considered moderate in most of the statistical tests. Scholars have found that people can have positions on issues which contradict their ideological frame (Ellis & Stimson, 2012a), meaning they can find themselves liberals or leftists but defending a reduction of government support in healthcare. Therefore, the third type of mass polarization measurement was included in the literature, the specific issues' surveys. On issues' survey type, each specific issue is related to an ideological scale and can range from government spending on health, minorities, military activities, the guarantee of jobs and standards of living. Evidence from these types of surveys show 2 to 5 percentage points of change towards conservative side on some issues and towards liberal side on others, with no apparent polarization over a 20-year period within the USA (Pew Research Center, 2021). The fourth type is the elections' exit pools, which report people's choice of candidates, reflecting their ideology over candidates' positions (De Jonge et al., 2018). Although, the voting behaviour reflects not just citizens' position but also the expectation they have on the politicians' attitudes. Here the citizens' choices can be different from citizens' preferences, and the ideological correlation might be lost (Clinton et al., 2022). The fifth type aims to measure the difference of political positions geographically. This assumes that the segregation of voters within their communities rises from the belief that voters live within homogenous communities and tend to be, act and think alike their neighbours (Hansson, 2022). In the USA the correlation between ideology and geographically homogeneous communities is not larger now than it was before (Glaeser & Ward, 2006), and the majority of the studies use the elections' results to assume geographically distributed political positions, which is not a representative measure. The sixth measurement type aims at inferring the left-right ideology of the median voter through coding the text of party manifestos (Adams & Somer-Topcu, 2009; Kim et al., 2010), this is done by content analysis of parties' electoral manifestos. In Europe, this type of measurement is a common practice, existing several databases with the country's party's manifesto annotated for ideology inference, such as the Comparative Manifesto Project (CMP) in Berlin, Germany (*Manifesto Project Data*, 2022).

In the USA the survey data is more extensive and consistent, meaning the surveys have the same questions, with the same or very similar wording, throughout the years for several states. In European countries, there is a lack of repeated survey questions over several years and European countries (Caughey et al., 2019). The second measurement type, to ask directly about citizens' ideology, is the most commonly used. Examples of those surveys are the European Social Survey (ESS), European Values Survey (EVS), International Social Survey Program (ISSP), and the Pew Global Attitudes Survey (Budge et al., 2001).

The topics within the six measurement types of mass polarization will overlap with the ones found for elite polarization, I will call them 'polarization topics' to embrace both actors. The polarization topics can be divided into three main domains, the economic, social, and immigration domains. The economic domain was the first used because it classically divides citizens into a left-right scale, distinguished by government scope, support, and its role in reducing inequality. As only this variable was not enough to describe one's ideology, two more domains were introduced. The social domain encompasses cultural post-material topics, with issues such as gender equality, environment protection, and libertarianism versus authoritarianism. The immigration domain is the most recent one and comprises topics of immigration as well as relations with the other (Costa Lobo et al., 2019; Pew Research Center, 2021).

2.4.2 Elite Polarization measurement and its topics

Elite polarization is the term for political polarization within and between parties, also named party polarization. There is extensive evidence of the increase of elite polarization over the years, with a bigger increase in the USA, although western Europe is following the same trend (Gentzkow, 2016b). This means parties are adopting more distant political positions, mainly on domestic topics, such as social welfare and cultural issues.

The concepts of cross-pressure and consolidation, and their relationship with issues and party homophily or heterophily are used to explain the relationship between issues, party groups, and polarization (DiMaggio et al., 1996; Fiorina & Abrams, 2008a). This is useful when we talk about political polarization, where the parties' extremes are on the left-center and right-centered, it seems there is no apparent polarization, although when sharing the same issues, the resulting conflict is much bigger. If the issues are highly correlated, there is greater polarization. When parties are internally homogeneous, with high consolidation, and externally distinct, they show a decline in cross-pressure between parties and a higher polarization. When parties are internally heterogeneous, with lower consolidation, they suffer higher constraints, as they have different attitudes within the same party (higher intradistance), and higher cross-pressure because the inter-party distance is lower. This represents a low polarized party environment

For the elite polarization, the measure types of political polarization can be divided into three categories: (1) survey to access citizens' opinions on government (European countries) or presidency (USA), (2) creation of polarization index based on surveys' answers, (3) text analysis of congress or parliament discourses, and (4) the percentage number of anti-political establishment parties.

For the first measure type of citizens' survey, the main databases are the Comparative Study of Electoral System's data (CES), the VDem project for European countries, and the Pew Research Centre database for the USA. Typical questions asked are similar to 'Is society polarized into antagonistic, political camps? ', or specific domain questions on economic, social, or immigration topics. The perceptions of LR by citizens are fetched by the definition that right ideology stands for 'individuals who are less tolerant of immigrants, who have pro-market orientations, who emphasize the value of authority, who are more religious and oppose social liberalism, and who value economic growth more than environmental protection', as for the left side for 'more tolerant of immigrants, have pro-state orientations, they place less emphasis on the value of authority, are more secular, prone to support social liberalism, and value environmental protection more than economic growth'(Freire, 2015, P.6). These definitions encompass both 'socio-economic' values as well as 'non-socio economic' values, although Freire (2015) also found that the impact of party polarization on LR space position was only significant for 'socio-economic' values, in terms of predicting electorate voting patterns. To find political polarization from surveys, an Index of Polarization (IP) can be calculated based on survey results (Sanders et al., 2013).

The second measurement type merges the survey data with voting data, such as the European Government-Opposition Voters (EGOV). A polarization index is created, that calculates the ratio between the supporters of the party in government and the supporters in opposition, adapting the two-party system from the USA to the multi-party European environment (Patkós, 2022). Although it has a strong correlation with other polarization indexes in the literature, a country with a high score on this polarization index is also a country with a stable and supported government.

The third type uses parliamentary discourses, for instance, the work done with UK parliament discourse (Peterson & Spirling, 2018a), or with congress discourse data (Gentzkow et al., 2015; Gentzkow & Shapiro, 2010; Jensen et al., 2012). These works created a measure of partisanship based on word frequency within each faction in the government. These are the only works that measure political polarization in real life environment that does not rely on surveys, voting data, or manual coding.

The fourth metric to compare the political polarization, focused on European countries, is the percentage number of anti-political establishment parties (APEp) which has increased from 17% in 1990-2009, to 24% in 2010-2020 in Western Europe (Casal Bértoa & Rama, 2021). Figure 3 shows an increase in Portugal, reaching an average of 22% in 2020.

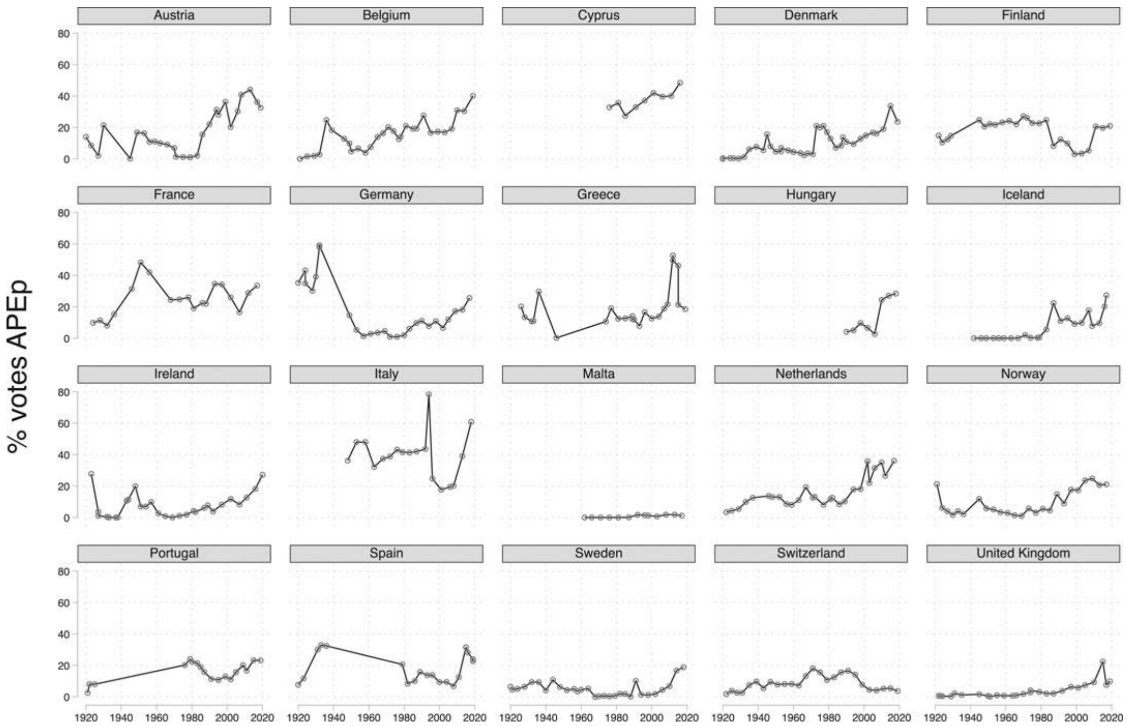


Figure 3: Polarization in Western Europe (1920–2020). Source:Casal Bértoa (2021).

2.4.3 Portugal use case: Ideology and polarization

Portugal was a dictatorship from 1926 until the 25 of Abril of 1974, the day a coup made by junior soldiers started the third wave of democratization worldwide. Free and fair elections, universal suffrage, and a competitive party system were a reality in Portugal one year after the coup. In 1976 the constitutional parliamentary election had four main parties which remained stable. From 1976 until 2005 the electorate tendentially gathered at centrist parties (for more on this see: De Giorgi & Cancela, 2021; Freire, 2005b; Mendes & Dennison, 2021).

Nowadays, the centrist parties are the centre-left Socialist Party (PS), and the centre-right Social Democratic Party (PSD) (which is not social democratic but liberal, as after 1990 has been aligned with the conservative European People's Party). The other two main parties are the Portuguese Communist Party (PCP, belonging to United European Left/Nordic Green Left) and the Social Democratic Centre Popular Party (CDS-PP, before named Christian Social Democratic Centre, and belonging to the European Popular Party). Besides these four parties, it's important to also mention the Left Block (BE) (a coalition of Socialist Revolutionary Party (PSR), Popular Democratic Union (UDP), and political movement: Politics XXI), the Greens (PEV, ecological party from 1982 that has made several coalitions with PCP), and the newly created far-right party Enough (CH) and the liberal right party Liberal Initiative (IL).

The PCP was created in 1921, while the others were created right before or after the 1974 Revolution. The PCP had financial aid from Communist International and the Soviet Union, the PS from Socialist International, the German SPD, and the Scandinavian Democratic parties, the PSD from European Liberal, Democratic and Reformist Group, and the CDS was helped by Christian Democratic Union (Belchior et al., 2022).

The ideological positions of parties taken in this work are from surveys which found how electoral positioned the parties on the left-right scale. The last study done with the Portuguese population was in 2019 within the MAPLE Project (Costa Lobo et al., 2019, p. 3), a project with six European countries such as Belgium, Germany, Greece, Ireland, Portugal, and Spain. As can be seen in Figure *4*, the Portuguese dataset has all the parties with parliamentary representation in 2019, with Left Block (BE) in the left extreme and the Social Democrats (PPD/PSD) in the right extreme. It is important to note that the PCP is ideologically more leftist than BE, and the CDS-PP is more rightist than PSD.

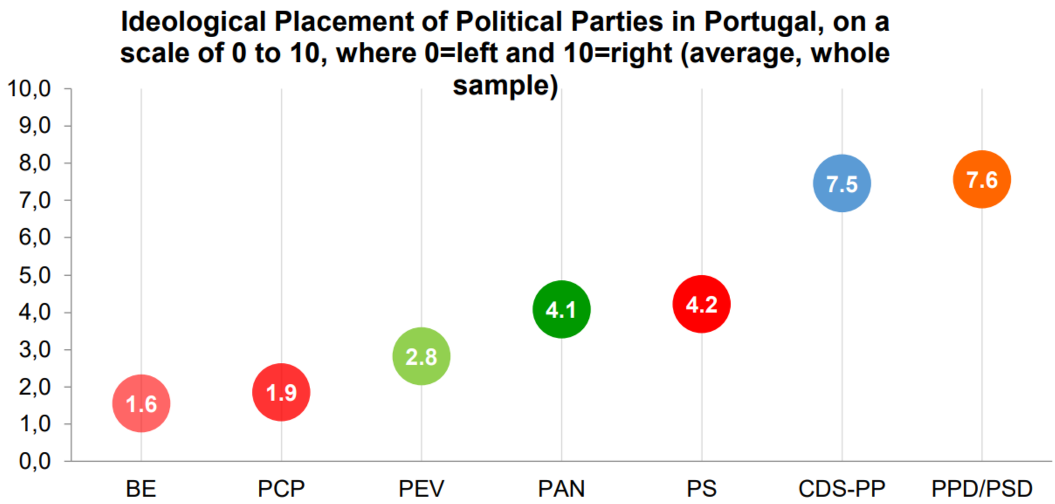


Figure 4: Ideological Placement (Lobo, 2019)

The dual faction of left and right used in this work has on the left side BE, PCP, PEV, PAN, and PS, and on the right side CDS-PP, PPD/PSD, IL, and CH. The last two parties on the right pane gained parliament representation after 2019, the IL obtain one deputy on the 14th government term (2019-2022) and reached 8 deputies in the 15th term (2022-2026), and the CH was formed in 2019 and within less than a year had a deputy in the 14th government term, and 12 in the 15th government term, being the current third political force in Portugal. In 2020, CH officially connected with the European far-right political group named Identity and Democracy (*Chega - Identity and Democracy Party*, 2022).

The voting intention for western democracies tends to depend on three main factors: performance evaluation, policy positions, and nonpolicy factors (such as partisan attachments) (Hellwig, 2008). For Portugal, on bad evaluation, the performance of the incumbent party was the most important factor in the voting force for the 2011 Elections, overcoming welfare policies and the role of the state in the economy (Magalhães, 2014). For the 2005, 2009, and 2011 Elections , the issues' position had a bigger effect on voting for smaller parties than for the incumbent or its main opposition, the 'law and order' versus the 'civil freedoms' had a bigger effect for the right and left centrist parties voting, PSD and PS, respectively (Freire, 2005a; Magalhães, 2014). The ideological polarization in Portugal manifested later in comparison with other European countries, taking the number of anti-establishment parties as the main indicator (Santana-Pereira & Cancela, 2020). The main causes for the voting variation toward far-right parties are economic and cultural. For economic reasons, the most cited is the decline in incomes, the increase in inequality, globalization, and the labour market transformations. The cultural causes are the backlash against cultural changes and conservative decline, as well as actor-centric theories, related to the decrease of both extremist party stigma and the media's negative portrait of the same (Mendes & Dennison, 2021a), which are the recognized ones. A brief reference to the history of the far-right and far-left is given, to have the context of the poles explored in this work.

The far-right presence in Portugal is divided into four periods (da Silva & Sofia Ferreira, 2020; Mendes & Dennison, 2021b). The first period, between 1960 and 1974, focuses on Salazar's leadership and his successor Marcelo Caetano, until the fall of the New State ('Estado Novo'), a period of dictatorship with 'limited pluralism', but not so severe as fascism in Germany, Italy, or Soviet Union (Freire, 2005b). The second period was one with huge significance, defined right after the Carnation Revolution, from the 25th of April in 1974, until 1982. The coup ended the longest dictatorship in the western world. In 1982 there was a constitutional revision that removed the military control over the political power, resulting in a fourth calmer period (Marchi, 2021). The third period is less impactful and violent, far-right movements in Portugal were subcultural groups, with anti-immigration and racist attitudes, mostly children of returned parents from decolonized African ex-colonies, or proletarians living in the suburbs. The last and most recent period starts after 1999 until 2022, with the creation of the first far-right party named National Renewal Party Renewal National Party (PNR). Recently, the CH party was formed, in 2019, and in 2022 reached the third political force in Portugal, capitalizing on the media portrait of their extremist views, lowering the stigma against extremist ideologies, in a post-crisis environment, and on a gap in the supply of political parties on the right (Mendes & Dennison, 2021a).

The far-left modern history in Portugal can be divided into three periods (da Silva & Sofia Ferreira, 2020). The first period is within the last years of the New State until the Carnation Revolution (1968-1974), and the second period was after the Revolution from the 25th of April 1974 until the early 1980s. The second period was the most violent because the armed groups were unhappy with the established democracy and feared a pushback of the revolution and workers' rights weakening. They performed violent and lethal actions, such as the killing of specific fabric owners who mistreated the employees or managers who did not pay their salaries, with the goal of people's revolt for their rights, aiming for a socialist system. The third period is from 2015 until 2022 when the government was a minority of centre-left socialism (PS) and three far-left parties (BE, the Greens (PEV), and PCP), this was called Contraption ('Gerigonça') (De Giorgi & Cancela, 2021).

Nowadays Portugal is considered a country with a low polarization index (Bértoa & Enyedi, 2022), which had a leadership of PSD, a right ideological party, from 2015 until 2019, a coalition of leftist parties from 2019-2022, and a majority leadership of center-left party PS from 2022-2024. As depicted in Figure 3, Portugal had in 2020 a 20% of vote share for anti-establishment parties, and on Figure 5, where is depicted data from the V-Dem dataset, Portugal appears with lowers levels at 2020 than from 1976 until 1989.

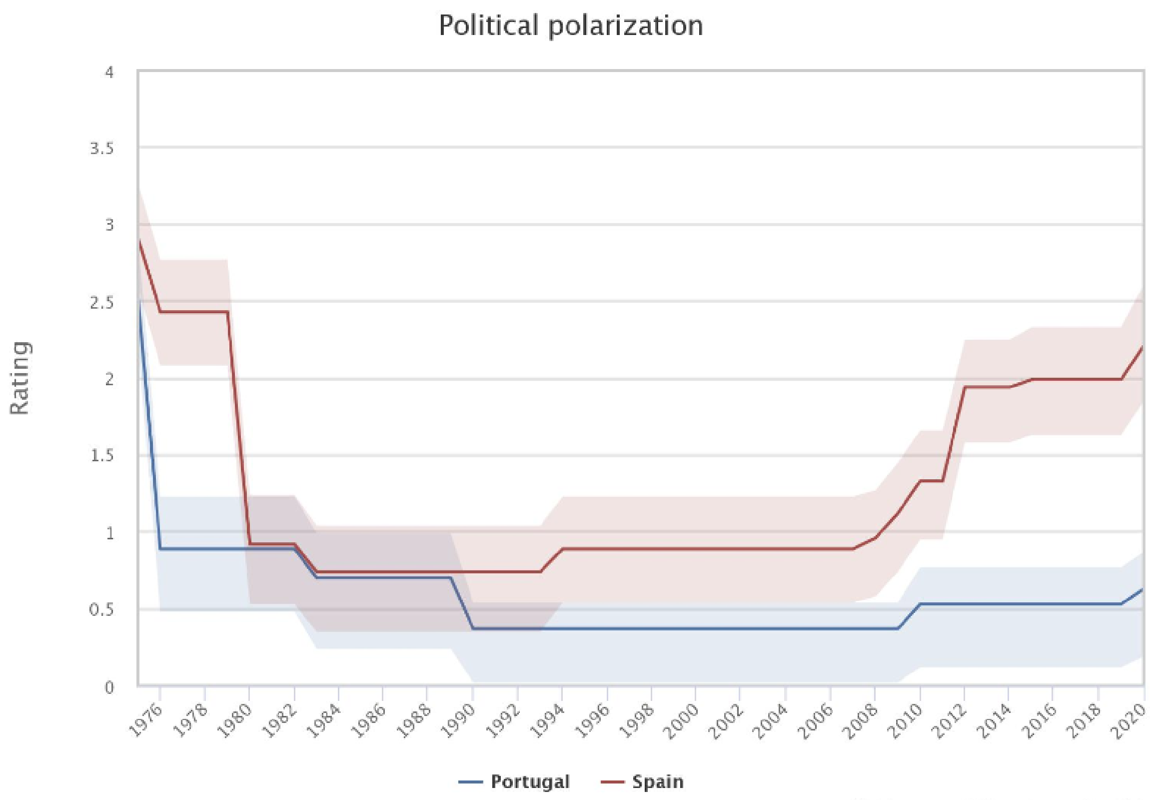


Figure 5: Political Polarization rating from citizens' survey (Schaver, 2021)

2.5 Conclusion

This chapter presented the theoretical framework for the main topic of the thesis, that of political polarization, and a brief historical perspective is given of ideology and polarization to build the conceptual basis of the work.

Following ANT, the dissertation is focused on a political and current issue that is not yet defined consistently by scholars, to approach a possible solution it is followed a robust experimental methodology, which takes technology as an actor in the network of events between data, digital and real-life environments and human actors.

As this dissertation focus on the methodology to measure the political polarization phenomenon, the literature review delves into the measure types of mass and elite polarization. The political polarization definition followed is the bimodal distribution of citizens' ideology because it can apply to the empirical framework chosen as the model to measure political polarization. The model chosen is the text analysis referred to in the elite polarization measurement types. This model is adapted for a multi-party environment and extended further to the elite, adding also mass polarization.

The use case explored is that of Portugal, which is a lowly polarized country with a late entering of the anti-establishment parties' wave in 2019. The measurements presented show the literature gap existing in the field and in the use case, that of missing an automatization in the political polarization measurement. The next chapter will present the methodology used to fill in that gap, and the data collected.

Chapter 3: Methodology

3.1 Introduction

In this Chapter, I will detail the methodology and data collection used to answer the research questions identified, for the Portuguese use case. In the last part of the chapter, the limitations of the research methodology and ethical considerations are stated, following a conclusion.

3.2 Research questions

This dissertation intends to build a metric able to measure political polarization through time, and use it to understand how political polarization is evolving in Portugal, considering its actors - both elite and mass society - using real-life environment data from parliament transcripts and online data from the social media platform Twitter. In this sense, it aims to answer the following research questions (RQs):

RQ1: How can political polarization be measured in discourse, in a language and human-task independent fashion, considering the phenomenon state and process?

RQ2: What is the trend of political polarization in the Portuguese parliamentary and online government discourse?

RQ3: What is the trend of political polarization in Portuguese citizens' online discourse?

3.3 Philosophical commitments

ANT is a result of post-structuralism, offering a range of concepts to understand the relationship between nature and society. Both techno-deterministic and socio-deterministic theories diminish the role of the interaction between technology and the organization, not taking into account that they are mutually changed by each other, one does not deterministically shape the other (Cordella & Shaikh, 2006). ANT defends that reality does not exist per se, but the network of relationships that interplay the different actors gives meaning and characteristics to reality.

ANT is considered an interpretative epistemology, a tool used to collect and interpret data which is then analysed to understand the meaning assigned. ANT can be seen as a powerful methodology, where all actors involved, human and non-human, are at the same level, without hierarchical meaning (Law, 2009; Law & Singleton, 2014).

Ontologically, ANT autonomy to understand the data collected is dependent on the entities which produced that data, and the entities' self-existence is dependent upon the existence of other entities, leading to a non-objective and non-descriptive way of learning the reality. Relating this to the dissertation data collected, the discourses of the deputies are consequences of the online environment there are in, not only the online platform features but the content from other online accounts, the same for the parliament discourse. The environment, the platform, the features, the human, and the machine are equally important actors when in this work I aim to define the political polarization trend. For this reason, ANT is within social constructivism, although its creators aim for a new ontology, named ‘realistic realism’, due to a new way of conceptualizing the understanding of reality and a new way of questioning it. (Argent, 2020)

3.4 The case study design

To be able to study a complex issue like political polarization, which is highly dependent on its context and multi-faceted, I chose to use a single-case research design. The goal is to have a test for the DPI, which can support, or contradict, the theories used. Following Harry Eckstein idea of ‘crucial case’, which tests the theory of most likely or least likely example that would fit the theory to be tested, the use case chosen was on the most likely will follow its neighbouring countries on the political polarization phenomenon (Bennett, 2004).

The choice of Portugal as a use case was based on two main reasons: the exponential emergence of a far-right party as the third political force during the 15^{th} government term, and the inexistence of a quantitative political polarization study with Portugal as a case study. The third political force in Portugal is the party Enough (CH), which was formed in 2019, within the far-right ideology, and had an exponential rise, having 12 deputies in the parliament in 2022. The far-right arrived at Portugal’s government some years after other EU member states, but its force of growth is impressive. This dissertation answers the need to start addressing political polarization from its early stages quantitatively, as there is no measure able to find political polarization trends, independent of surveys and voting data, as well as applicable to the elite and mass population.

3.5 Data collection

The data collection for the dissertation had the goal to cover all actors (elite and mass society) of political polarization and the biggest environments where they interact (real life and online). The type of data used was text due to its high availability in both environments. The real-life environment was captured from parliamentary reunions, available online in transcripts. In the real-life environment, only the elite political polarization was measured, as for the mass political polarization there were no real-life data transcripts available. The online environment was captured through Twitter because this social media platform is the most used by politicians and by social society to discuss political issues (Esteve Del Valle et al., 2021). In the online environment, both elite and mass political polarization was measured. The former was measured using the deputies’ Twitter accounts who spoke on the parliament, during the time they were active in government, and the latter from the replies to those deputies’ tweets, excluding replies from politicians, to fetch the mass society discourse. Two main datasets were collected: the parliament dataset and the Twitter dataset.

The parliament dataset is the transcript of the plenary meetings that occur every two weeks between the deputies elected, being part of the series number 1 (‘série – I’) (Republica, 2022). Every party represented by the deputies has a total time of five minutes to speak, with an extra minute for the party in government (*Regimento Da Assembleia Da República*, 2019). As this speech is controlled while it's happening and time framed, there was no need to sample the speeches.

In each 13th and 14th government term, the number of total deputies is 230, and in every term, all the deputies spoke at least once. In Table 1 the number of speakers mirrors the number of deputies in parliament by party, with fewer speakers in 2021 because not all deputies spoke in that year, and a higher number in 2019 because both terms overlap in that year summing deputies which here in one term but not in the other. The distribution of deputies' speakers follows the number of deputies per party (*Resultados Eleitorais*, 2022), the 13th government term (2015/10/23-2019/10/24) was governed by the right ideology party PSD: PSD with 89 deputies, PS with 86 deputies, BE with 19 deputies, CDS-PP with 18 deputies, PCP with 15 deputies, PEV with 2 deputies, and PAN with 1 deputy. The 14th government term (2019/10/24-2022/03/28) was governed by a colligation between three left parties, the PS, BE, and PCP, with the following distribution of deputies: PS with 108 deputies, PSD with 79 deputies, BE with 19 deputies, PCP with 10 deputies, CDS-PP with 5 deputies, PAN with 4 deputies, PEV with 2 deputies, L, IL and CH with 1 deputy.

Table 1: Portuguese deputies which spoke on 13th and 14th Government Term

Number of Speakers per Party per Year

	PCP	PEV	PAN	BE	L	PS	PSD	CDS-PP	IL	CH
2016	15	2	1	19	0	81	85	19	0	0
2017	15	2	1	20	0	85	89	17	0	0
2018	17	2	1	21	0	87	92	18	0	0
2019	16	3	4	24	1	111	121	18	1	1
2020	10	2	5	19	1	104	80	6	1	1
2021	10	2	4	19	0	97	75	7	1	2

The parliamentary discourse was extracted from the official Portuguese Govern website (Portuguese, 2022), using the *BeatifulSoup* package from Python libraries, creating a parser to extract the text files divided by government term, session, and number. Text transcripts were collected from 2015 until 2021, belonging to the 13th and 14th government terms, making a total of 619 sessions and files. The online discourse was extracted using the Twitter API available in the developer portal (Twitter, 2022), within the academic research subscription to access premium features and more data. To avoid an overwhelming quantity of data and processing time, a cap of 3000 replies was applied. This influenced the number of replies to some active deputies' tweets but did not affect the deputies' tweets collect, because deputies on average tweet once per day. All the code is available on the git-hub public web page of this dissertation: https://github.com/CT-P/portuguese_open_data .

The unit of both datasets was the speech, the tweet, and the reply, having similar theoretical concepts and all processed as a speech in any case.

There were in total 76 754 replies on Twitter, 45 321 tweets, and 1 365 211 speeches in the timeframe from 2015 and 2021. The division of left and right for the politicians was done according to the party of the deputy speaking or tweeting, and within the mass society, the division was according to which deputy he or she was replying to. The parties considered in the left ideology faction were: PCP, PEV, PAN, L, BE, PS, and in the right faction were: PSD, CDS-PP, IL, and CH. To avoid bots or fake accounts, only Twitter accounts with more than 1000 followers were accepted into the dataset, and the deputies' accounts were selected manually. Of the 376 deputies in both government terms, with 230 in each while some repeat on both terms, only 177 have Twitter accounts. Only 20 of them have an official Twitter account, with the party logo in the image and an official position statement in the description, although all 177 were included checking manually if they were followed by official accounts.

3.6 Data processing

After collecting the two main datasets a pre-processing step was needed to create a table format suitable for the model. The pre-processing was done using Natural Language Processing (NLP) techniques, which derive from the Machine Learning (ML) field and are the basis of CSS when using text-as-data. These techniques were performed to uniform the text, delete very frequent words, reduce them to their root, and transform words into n-grams. The uniformization was done with lower casing all text, removing punctuation and special characters. The deletion of frequent words was done with a built-in method within the programming package (Sklearn) which has a list of stop words for many languages, including Portuguese, like 'that' ('aquilo'), 'and' ('e'), 'the' ('a'/'o'). The frequent words, after identified with the help of the built-in method, were removed. This decreased the number of words in the dataset, removing those that would not add meaning to the sentence in terms of political concepts. The reduction to their root transformed words like taxation to tax and was done with a model named Stemmer from Porter Stemmer (Karaa & Gribâa, 2013). This prevents the repetition of words with very similar meanings, almost like the removal of duplicates. The last step was the transformation of words into n-grams, where n can be any integer number from 1. The choice was 3 grams or trigrams, to incorporate sequence. This resulted in distinguishing between 'tax' and 'reduc.tax.labour'. The choice of 1 gram would lead to an enormous dataset and would not incorporate a sequence, that would not distinguish between increase or reduction of taxes within the gram selected. The choice was between 2 grams or 3 grams, in the former I would still miss the subject of the gram, in the latter a good combination of the information needed, and the gram size is reached, avoiding repetitive words in different grams (which could happen for grams of 4 or more words).

3.6 Data Analysis

The research methodology taken was divided into four steps: Categorization Framework of model from a literature review on CSS methodologies to measure political polarization, application of the model to the datasets, and evaluation and validation process. The data analysis uses a method within the CSS methods, as this field is increasing in the literature (Web Of Science, 2022), showing high-performance metrics for several social science topics (Kursuncu et al., 2019; Peterson & Spirling, 2018b; Shaw & Benkler, 2012).

The first step was the choice of the model to use, which was done through the usage of a Categorization Framework built. This categorization framework classifies all quantitative methods used by scholars to measure political polarization in text, from 2000 until 2021. This classification tool was submitted as a scoping paper named 'How CSS Methods Measure Political Polarization In Discourse', and it is part of this thesis work but due to space it is in Appendix A. This Categorization Framework groups model types against nine features. The model types considered are: 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.

Within the scope of this dissertation, the first group type of statistical and parametric models is the one that answers the first research question, avoiding hand coded tasks, surveys or pooling, fitting the dataset type, not being a time-series, and committed to ANT by avoiding mathematical categorization (classification or clustering) to infer social science categorization. The model chosen for the method in data analysis, using this Categorization Framework, was the empirical framework based on the work of Jensen et al. (2012), with the concept of partisanship and polarization, and based also on the work of Gentzkow et al. (2015), which added a parameter to avoid high-dimensional bias. The data analysis model was evolving from 2010 until 2019, showing a high correlation with other polarization metrics, such as vote counting and pooling. The answer to the first research question aims to contribute to that evolution. Jensen et al. (2012) measured partisanship, the identification of the left or right ideological side, and polarization, the distance from the moderate view defined by the ideological centre, of political discourse. This was done by correlating the frequency of words with the speakers' political party. The method was validated against DW-NOMINATE measure, which is widely used since 1997 (Nolan McCarty, Keith Poole, and Howard Rosenthal). This empirical framework has the advantage of independence from pooling or voting, the possibility to be fitted to a large quantity of discourse data, and the integration of new issues spoken by mass society or politicians before they reach political manifestos or policies.

The second step was done through programming, and it is publicly available at https://github.com/CT-P/portuguese_open_data, with the code refactored into classes and notebooks, to be possible to run it independently of the input data.

The last two steps were decided based on lessons learned from the literature research done in the first step. The last step was the validation of the results, which is crucial when applying quantitative methods within social sciences, as algorithms' metrics optimization is different from the optimization of the social problem to solve. It was performed a semantic validation, extracting the top 200 trigrams more polarized to the right and left faction to be qualitatively analysed.

3.7 Empirical Framework

The model used is better described as an empirical framework, as it is a statistical model applied to the experimental results, without having a training part involved.

The first four steps of this empirical framework are based on (Jensen et al., 2012) work, the fifth step is based on (Gentzkow et al., 2015).

The first step is Pearson's Correlation (Equation 1), calculated per trigram χ_t^2 , where f_{tr} is the frequency of trigram used by the right faction of speakers, and the $f_{t\bar{r}}$ is the frequency of all terms except the one being calculated. Trigrams with a correlation smaller than zero were removed to avoid having words only said one time by the right faction representing it.

$$\chi_t^2 \frac{(f_{tr}f_{t\bar{l}} - f_{tl}f_{t\bar{r}}\ )^2}{(\ f_{tr} + f_{tl})(f_{tr} + f_{t\bar{r}})(f_{tl} + f_{t\bar{l}})(f_{t\bar{r}} + f_{t\bar{l}})} \ (1)$$

The second step is the normalization of trigrams, to have a mean of zero and 1 of variance, so all phrases are weighted equally, and interpretation is easier.

The third step is the speech partisanship calculation, β_s , where the frequency of the trigrams was multiplied by a dummy variable of 1 to the right faction and -1 to the left faction. The partisanship of speeches was the sum of speeches' trigram partisanship. Partisanship of zero means the speech has the same probability of being said by the right or the left deputies or citizens. Higher positive values mean speeches highly identified by the right (almost only being said by the right), and very low (negative) values mean speeches highly identified by the left (almost only being said by the left).

$$\beta_s = \sum_t dummy_s f_t \ (2)$$

The fourth step is the aggregation of values to create the measures of average partisanship ψ_s, and average polarization $|\beta_s|$.

$$\psi_s = \frac{\sum_t f_t \beta_s}{\sum_t f_t} \ (3)$$

$$\phi_s = \frac{\sum_t f_t |\beta_s|}{\sum_t f_t} \ (4)$$

Adding to these equations, (Gentzkow et al., 2015) used the same measures of partisanship and polarization to create a model to predict a speaker's ideology assuming that the words follow a multinomial distribution. This model has a plug-in estimator using the maximum likelihood estimator, and its experimental equations present a bias toward positive polarization. This bias arises from the fact that the average polarization measure should be zero for a moderate trigram, equally said between the left and the right. Although in a finite sample, this measure will never be zero, Gentzkow et al. solution was to create the frequencies of trigrams from different samples (speakers), so the errors are orthogonal and eliminate the bias in the measure.

Here I will put explicitly the path between the two works. The empirical framework used in this dissertation is the last equation, Equation 8, based on empirical frequency terms.

In the fifth step, it is defined the terms to find the frequencies using other samples, mainly ρ, and the left and right frequencies of trigrams depending on ρ , π^r and π^l.

$$q^r = \frac{\sum_t f_t^r}{\sum_t f_t} \; (5) \; and \; q^l = \frac{\sum_t f_t^l}{\sum_t f_t} \; (6)$$

$$\rho = \frac{q^r}{q^r + q^l} \; (7) \,, \qquad \pi^r = q^r \rho \quad (6) \,, \qquad \pi^l = q^l (1-\rho) \; (8)$$

Picking up Equation 3 of average partisanship, and adding the new frequencies from different samples, leads to the following:

$$\psi_s = \frac{\sum_t f_t \beta_s}{\sum_t f_t} = \frac{1}{2}\frac{\sum_t f_{t\,(\beta=1)}}{\sum_t f_t} + \frac{1}{2}\frac{\sum_t f_{t(\beta=-1)}}{\sum_t f_t} = \frac{1}{2}\frac{q^r}{1-q^r}(\rho - \pi^r) + \frac{1}{2}\frac{q^l}{1-q^l}(1-\rho-\pi^l)$$

$$= \frac{1}{2}\frac{q^r}{1-q^r}(\rho - q^r\rho) + \frac{1}{2}\frac{q^l}{1-q^l}\Big(1-\rho-q^l(1-\rho)\Big) = \frac{1}{2}q^r + \frac{1}{2}q^l(1-\rho) = \pi_s^{MLE} \;\; (8)$$

Equation 8 is then used to calculate the partisanship of each speech, for both left and right speakers. The extremes of partisanship are taken as polarized speeches if the discourse follows a bimodal distribution.

3.8 Limitations of the research methodology

The limitations of the methodology focus on the type of platform, the quantitative modeling evaluation practices, and the parametric nature of the model chosen.

When extracting data from social media, the type of platform affects users' interactions, which can range from hashtags, retweets, reddits, posts, comments, etc., and might affect the polarization of the shared text. The features of the environment in itself can affect the discourse, so it is here noted as one limitation, especially for the Twitter data.

Another limitation within the online environment is online data contamination, where there is the possibility of contamination by fake accounts or bots, and for this reason, a pre-selective choice of the users within the online platform is needed. In this dissertation, the pre-selection of comments to avoid contamination was done when choosing replies to politicians' tweets, as this diminishes the possibility of catching bots, although it does not eliminate this hypothesis of contamination.

Because this work is applying a quantitative method to a social science problem, the metric of the former does not fit the latter. In the model, the goal can be accuracy, which means fitting its parameters to classify more times each sample within its given class. In social science problems, the term 'class' represents the same, but special attention is given to the fact that it was created by a human in an attempt to categorize a situation, and the aim is to find the right class and not the biggest accuracy within the pre-defined class. To avoid misinterpretation of the results, I have performed a qualitative validation.

Lastly, there is a model drawback due to its parametric nature. The need to build an empirical framework is becoming unusual within the Machine Learning field, because it needs to fit the problem and to have the parameters defined explicitly, as the Equation 8. Although, the framework developed by the authors is robust enough and can be applied in multiple environments and it is language-independent.

3.9 Ethical considerations

The parliament discourses are from politicians and are public for research and media. In the data analysis, some sentences are shown as examples, although it does not raise ethical problems as the speaker cannot be identified. The Twitter data, also publicly available, is not shown at an individual level, not even as an example. It is treated as aggregated, and the results from Twitter are the model calculations, protecting any Twitter account from being identified.

3.10 Conclusion

This chapter details the quantitative methodology followed, explaining why I choose Portugal as a use case and defining design research choices. The choices made were taken from conclusions and lessons learned from an extensive literature review on CSS methods for political polarization (Appendix A), following methods that compensate for the limitations identified.

No cross-platform analysis was done on political polarization with text as data, to date, and from my knowledge, this is the first work to apply the same methodology to data from two different sources: the parliament transcripts and the Twitter comments.

The next chapter will show the results and contributions of applying the empirical framework here explained.

Chapter 4: Results

4.1 Introduction

In this chapter, I will present the results of political polarization by its actors and environments, starting with an overview of the datasets by words spoken, engagement, and average tweets. The data input covers two main environments: the parliament and Twitter. The parliament environment data will be referred to as the parliament dataset, and the Twitter environment data as the Twitter dataset. The graphics and tables show the data for the complete years, excluding 2015 and 2022, to avoid misconceptions due to fewer speeches in years where the government term represents less than half of it.

The results shown here are the output of the model, from Equation 8, plotting the density plot for mass polarization in Twitter and elite polarization in Twitter and parliament. As a contribution to the literature and answering to the first research question, this thesis puts forward the metric Discourse Polarization Index, which is explained in chapter 4.3.1.

4.2 Parliament and Twitter environments

The number of words spoken in each year for the government terms was stable, with a peak for 2020, after 2019 which was the year with fewer words spoken. The amount of speech by male deputies is 25% higher than the amount of speech by female deputies, on average through both terms, with fewer male deputies speaking in 2019, which can be seen in Figure 6, where a decrease in the total amount of words was due to a decrease in male spoken words during this year.

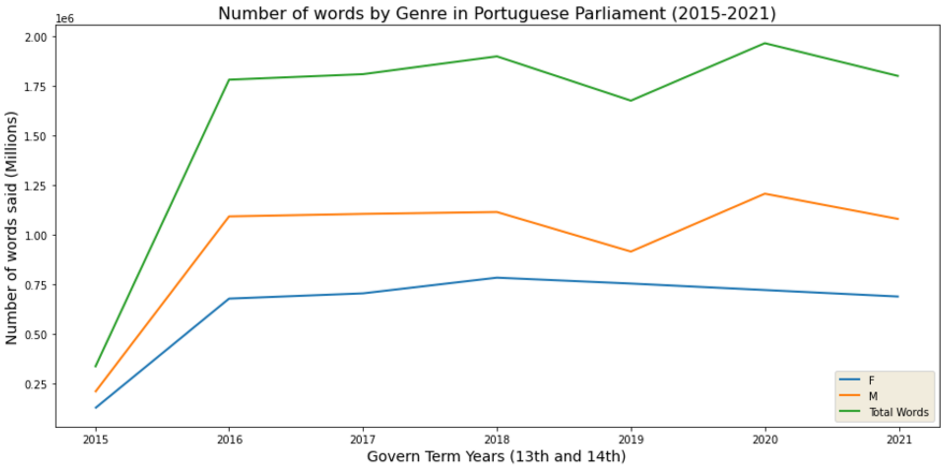


Figure 6: Number of spoken words by genre in Portuguese Parliament

The engagement per party showcases how mass society interacts with deputies online. Surprisingly, the leaders of engagement do not mirror the leaders of tweets' numbers, as shown in Figure 7 and Figure 8. From 2015 until 2018, PCP is the party with higher engagement, which means that it is the one with more replies per post, followed by PSD and PS. In 2019, there is a decrease in engagement on average, with PSD being the leader followed by CDS-PP and BE. In 2020, L party appears with an engagement rate of 1, while for the rest of the years their engagement was near zero. This might be explained by the appearance in the media of Joacine Katar Moreira, a former L deputy (in 2019) with double Portuguese and Guinea Bissau nationality, being the first black deputy, as well as the first Portuguese deputy who shutters. The peak in the engagement was in 2020, the time that Katar Moreira leaves L and continues in parliament as an independent deputy. This engagement of the online community was mainly within Rui Tavares deputy from L, as Katar Moreira made her Twitter account private. The year 2021, has an increase of engagement of 20% shared through all parties, being the BE, CDS-PP, and CH the leaders.

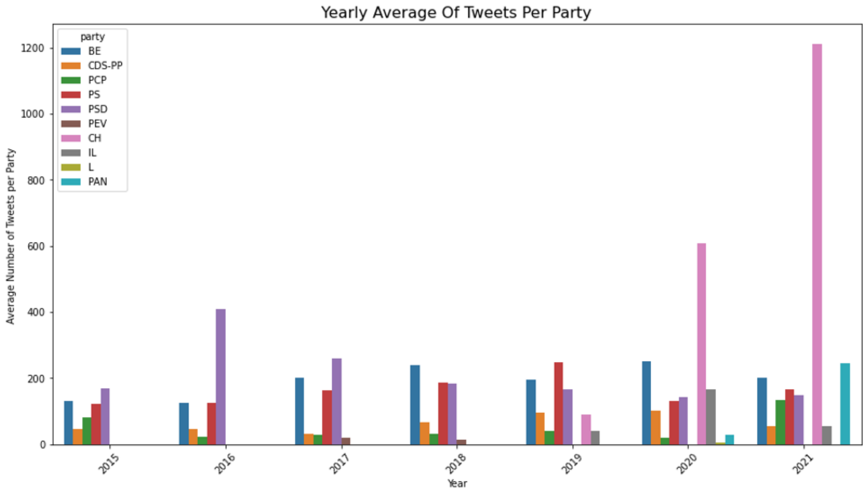


Figure 7: Average number of tweets from active Portuguese deputies on Twitter

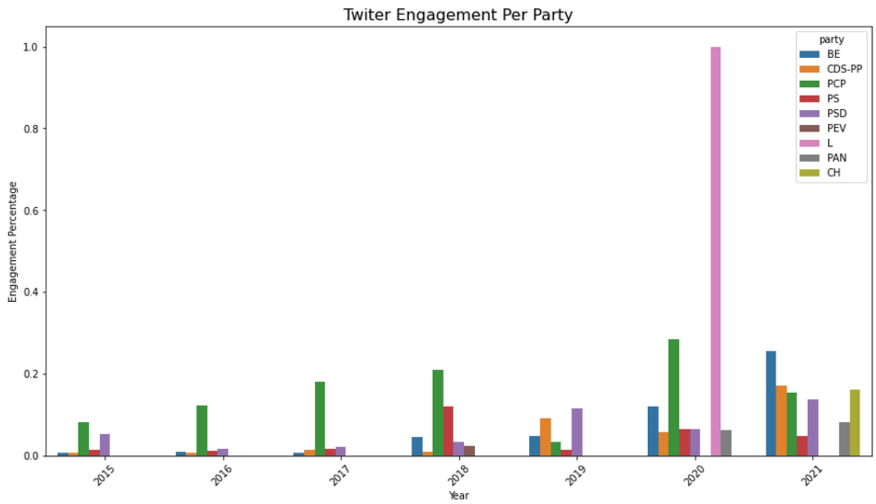


Figure 8: Portuguese deputies' engagement by party

In both Figure 7 and Figure 8, the year 2019 shows a lower number of tweets and engagement. The parliament speech and online speech decreased in the year of changing government term, the same happened in the year 2015. More years would be needed to correlate this pattern with the changing of government. The left parties have a bigger engagement than the ones from the right, although the appearance of CH might change this in the next years due to its exponential growth.

4.3 Results for Political Polarization

The political polarization figures, from Figure 10 to Figure 24, are from a subset of the dataset analyzed in each situation, sampling the lower and higher speeches for political polarization, to get the bimodal distribution characterized by political polarization. For elite polarization from the parliament transcripts, 400 speeches were sampled, and for mass polarization, 500 speeches were sampled. The values in the axis represent the ideology, positive values representing the right faction, and negative values representing the left faction. Because this choice was assigned by design, the positive corresponding to the right and the negative to the left, when looking at the graphics one cannot conclude that the peak at zero means it is moderate discourse for the left faction for example, because if the assignment was positive for the left and negative for the right ideology, the plot would look exactly the same, with the right ideology peaking on zero this time. The yy axis represents the probability of existing speeches with the given xx-axis ideology values. The area under the density plot value in its full sums up to 1.

4.3.1 Discourse Polarization Index

In this thesis, I put forward a new metric to compare political polarization from different speakers through time, named Discourse Polarization Index (DPI). This metric is based on the theoretical definition of polarization from Fiorina & Abrams (2008), which measures the distance between the left and right peaks in a bi-modal distribution of a polarized speech, being zero if such distribution does not exist.

The DPI is calculated recursively and has three steps: (1) identification of a bimodal distribution by a density plot, (2) definition of the two maximum areas to find the argument (the x value of the maximum y value/peak), as explicit in Equation 9, it takes the κ as a threshold, which will select the bottom κ and the top κ speeches of the ordered dataset, which collects the most polarized speeches to the right and the most polarized speeches to the left, (3) difference between the x_{peak_2} and x_{peak_1} to find the DPI.

$$x_{peak\_i} = argmax\{f(x)\colon\ x \in \mathrm{Z}\ \wedge n - \kappa \le x \le n\ \cap\ 0 \le x \le \kappa\}\ (9)$$

The first step automatically performs an exclusion for cases where there is not a bimodal distribution and the polarization assumption is not true, outputting a DPI of zero. This is done with the identification of two local maximums in the density plot and a threshold for the minimum area allowed in each peak. The second step needs to find the x value for the maximum yy value in each peak. Figure 9 shows the pseudo code for the DPI, in the case of the yearly DPI, the same logic applies to the government term DPI. The first line gets the polarization (mass or elite) from Equation 8 by year, being N_i the number of speeches in year i, so each value of y_i is the sum of polarization of all speeches that year divided by the number of speeches. A one-unit value is summed to the each value of x_{peak_i} in line 10, to avoid getting stuck on zero when the peak is at zero.

$line\ 1$: $For\ i\ in$ (2015; 2021): $[y_i] = \frac{1}{N_i}\sum_1^k \pi_s^{MLE}$

$line2$: $if density plot([y_i]) is NOT bimodal$:

$line\ 3$: $DPI_i = 0$

$line\ 4$: $else$:

$line5$: $if area(peak1) > threshold\ and\ area(peak2) > threshold$:

$line6$: $while\ x\ in\ area(peak1)$:

$line\ 7$: x_{peak1}

$$= argmax\left\{f(x):\ x \in Z \bigwedge n - \kappa \leq x \leq n\ \cap\ 0 \leq x \leq \kappa\right\}$$

$line8$: $while\ x\ in\ area(peak2)$:

$line9$: x_{peak2}

$$= argmax\left\{f(x):\ x \in Z \bigwedge n - \kappa \leq x \leq n\ \cap\ 0 \leq x \leq \kappa\right\}$$

$line10$: $DPI_i\ = \mathrm{area}_{\mathrm{peak2}} x_{peak2} - \mathrm{area}_{\mathrm{peak1}} x_{peak1}$

Figure 9: Pseudo-code of Discourse Polarization Index

The DPI stands out from any political polarization metric until now, from my knowledge, due to four main contributions. The first and second reason is the polarization state and process stated by Fiorina and Abrams (2008). The state is fetched in DPI by the peak difference (line 10 in Figure 99), to understand if the distance between poles is increasing or decreasing, the process is fetched by the identification of a bimodal distribution (line 2 in Figure 99), the definition of a threshold to accept the size of the peak (line 5 in Figure 99) and its value incorporation into the DPI formula (line 10 in Figure 99). The third reason is the nonabsolute value collected by DPI, due to the creation of a density plot, and all values come from a density distribution, which allows the application of DPI for different actors and environments, as shown in the next sections. The fourth reason is the application of DPI to the elite, top-down discourses, and to the masses, ground-up discourses, allowing a comparison uncommon in the literature and filling in another research gap by comparing elite and mass polarization. This part of the dissertation, due to space constraints, was further developed in a paper entitled 'Discourse Polarization Index: A Top-Down And Ground-Up Measurement of Text-As-Data', which is currently under review.

4.3.2 Elite Polarization

4.3.2.1 Elite Polarization in parliament

For elite polarization, years with a clear polarization are followed by a year with low polarization, Figure 10 shows the years 2016,2018, and 2021 with low polarization, in contrast with 2017, 2019, and 2020. The years of the 13th govern term have an ideology range from 0.4 until 3, and for the 14th between 0.25 and 2.5, overlapping a lot. The left peaks on the density plots are more common than the right peaks, as can be seen in Figure 11 (right part), where the probability of left speeches ranges between

0.8 and 1, and of right speeches ranges between 0 and 0.17. The right peaks appear at xx-ideology values around 1, from 0.75 (2017), increasing to 1.47 (2019), and 1.8 (2020). This shows a discourse polarized to the right ideology, with a low probability to happen (lower yy values on the right peaks), but an increasing trend to further polarization. The same conclusion can be described as an increasing right polarized discourse that is not discussed by the left. Although it has a low probability it presents a trend to further distance from the left discourse.

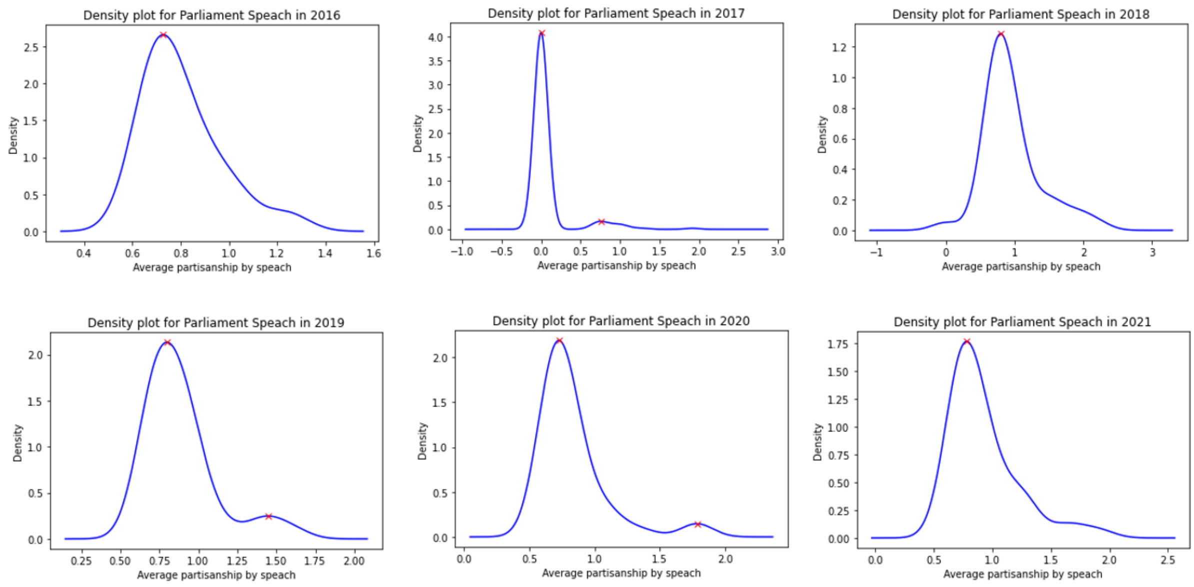


Figure 10: Density plots for elite polarization in Parliament by year

The year 2019 was the one with a higher polarization, with the highest probability and highest polarization value to the right. This was the last year of the 13th right government term, followed by decreasing years of polarization in 2020 and 2021. The results show consistency with the ideology of the government in leadership, showing a clear decrease in right polarization probability, and an increase in left polarization probability (Figure 11, left part).

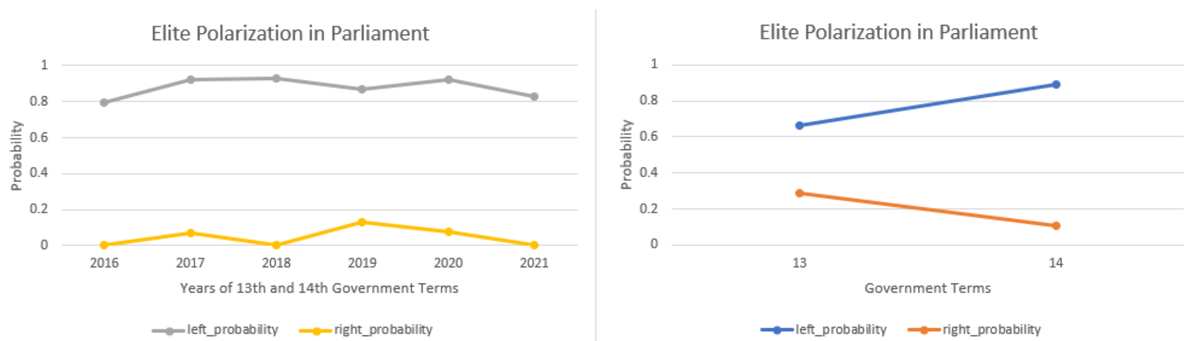


Figure 11: Elite polarization on parliament: density plot probability by year and government term

In Figure 12, the density plots from government terms show a clear bimodal distribution for the 13th term (higher polarization), and a lesser polarization for the 14th term. Both peaks are within positive values, the 13th government was led by a right party and presents a higher probability of speeches polarized to the right, while on the 14th the probability is lower, but the polarization value is higher.

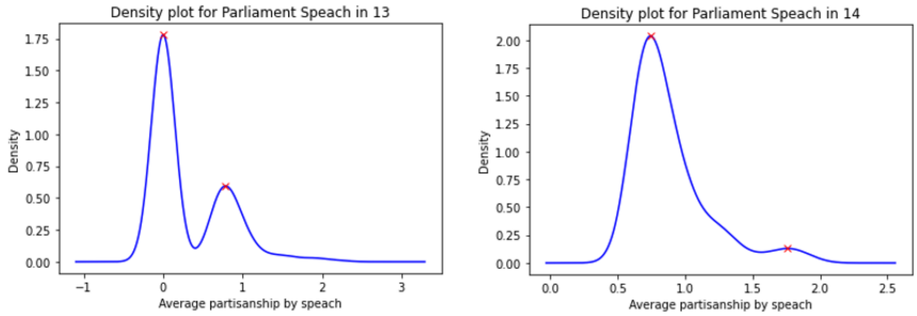


Figure 12: Density plots for elite polarization in Parliament by government term

4.3.2.2 Elite Polarization in Twitter

The elite discourse presents a higher polarization online on Twitter than in the parliament. Although the online data has 77% of the deputies in the parliament, some of them do not have a Twitter account. All the years show a bimodal distribution, with the lack of data for 2017 as the number of tweets was not sufficient to plot a density graphic. The range of ideology values of the years belonging to the 13th government term is from 0.7 to 1, and for the 14th between -0.5 and 1.5 (Figure 14). The 14th government had a higher polarization than the 13th, being the year 2020 the most right polarized. The left polarization shows the same moderation values around zero in the online environment as in the real environment.

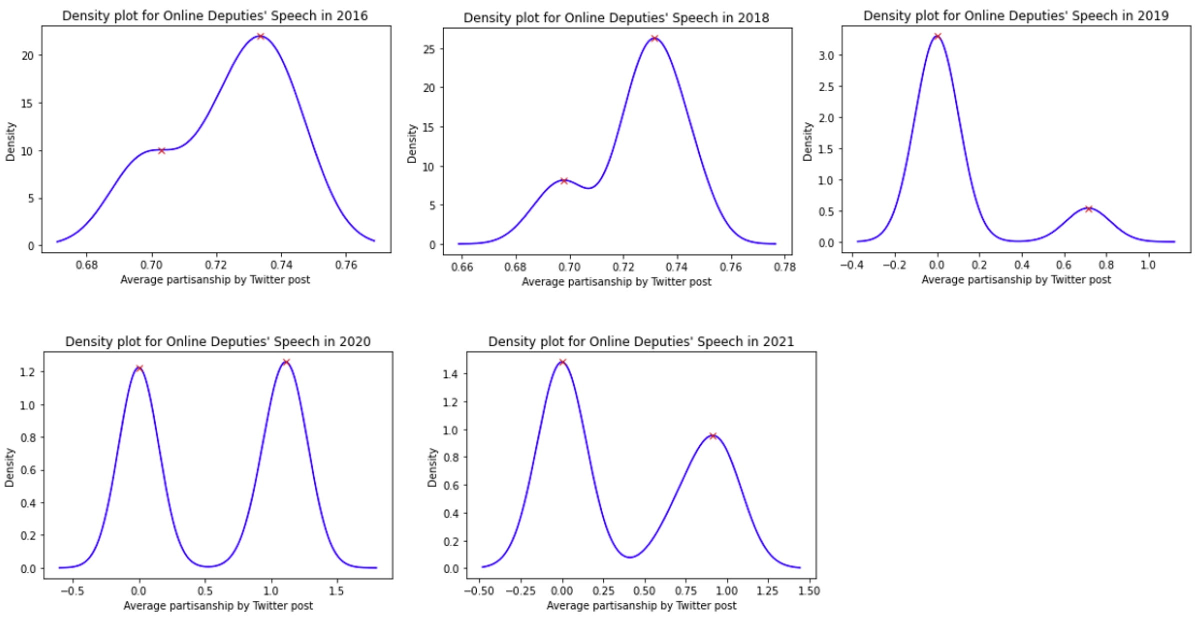


Figure 13: Density plots for elite's polarization on Twitter by year

Figure 144 shows a clear polarization to the right between the 13th and 14th governments, supported also by Figure 15, where the right polarized discourses probability increases while the left decreases.

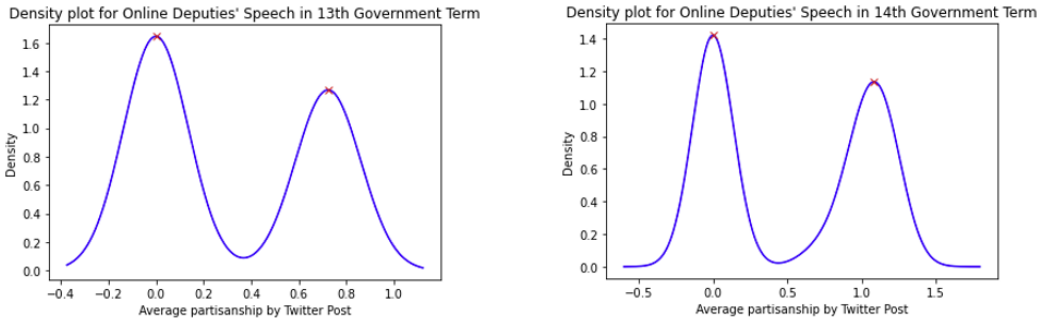


Figure 14: Density plots for elite polarization on Twitter by government term

Figure 15: Elite polarization on Twitter: density plot probability by year and government term

4.3.2.3 Elite DPI in parliament

The DPI metric represents how is behaving the distance between right and leaf peaks. With DPI, we can analyse if the discourses are getting more polarized over time. When zero value is presented, such as the years 2016, 2018 and 2021 in Figure 16 (left part), due to the inexistence of bimodal distribution. The metric is only calculated if there is polarization, even if small, in the discourse. In Figure 16 (right part), the 14th government shows a higher polarization than the 13th. This is the first measure of Portuguese political polarization in discourse, and the first evidence of an increasing elite political polarization. The results are aligned with the addition of the far-right party CH to the parliament in 2020, and its creation at 2019.

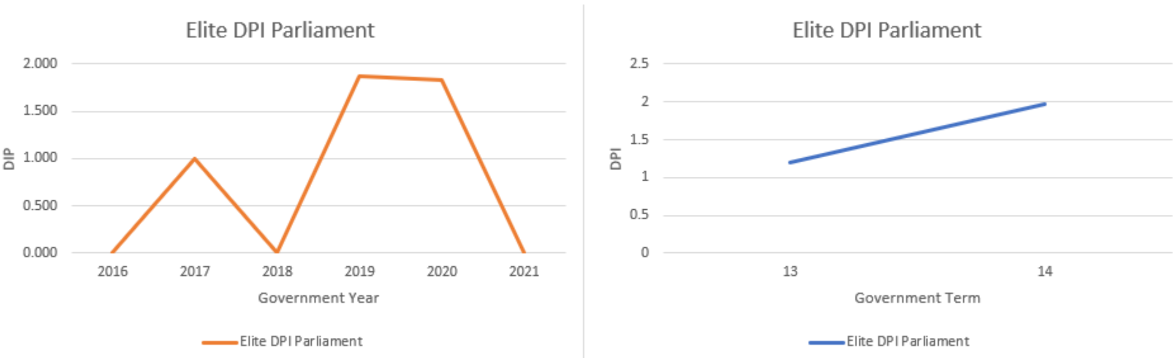


Figure 16: Elite polarization Discourse Polarization Trend on parliament, by year and government term

4.3.2.4 Elite DPI on Twitter

The DPI metric online for elite polarization follows the same trend on Twitter as in the parliament, with an increased polarization trend through time, as Figure 17 shows.

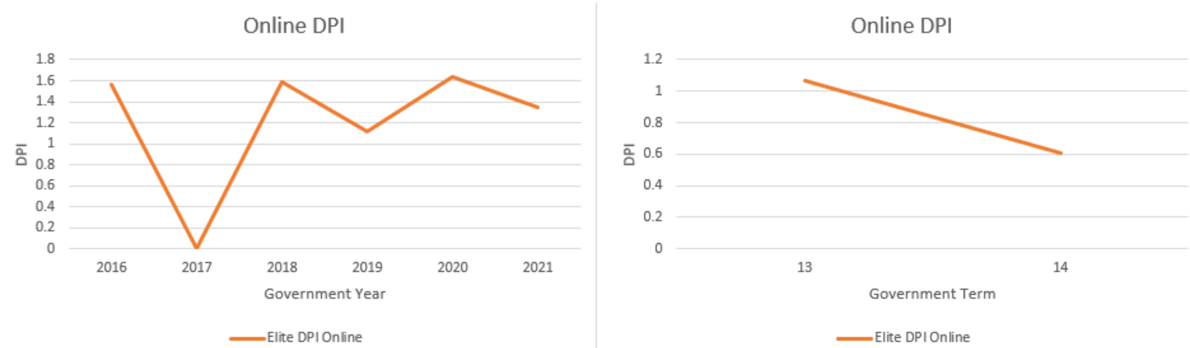


Figure 17: Elite DPT on Twitter, by year and government term

4.3.3 Mass Polarization

4.3.3.1 Mass Polarization in Twitter

The mass polarization for online Twitter data does not present a bimodal distribution in the years 2016 and 2017. For the years between 2018, 2019, and 2021 the mass society discourse follows a polarization like the polarization in elite discourse, with left ideology around zero values, and right ideology in a range of intervals between 0.1 and 0.5. The year 2020 is different from all the others due to the right peak polarization density, which is higher than the left, as Figure 18 shows.

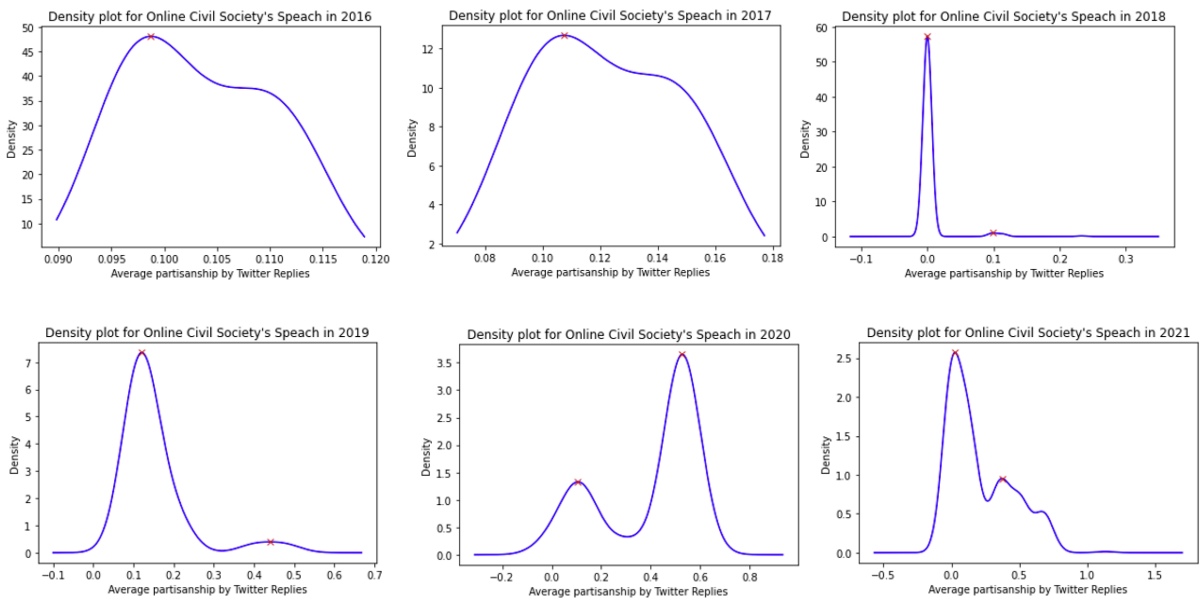


Figure 18: Density plots for mass polarization in Twitter by year

The polarization between government terms increased, Figure 19 shows a more defined bimodal distribution for the latter, with an increased right probability (Figure 20).

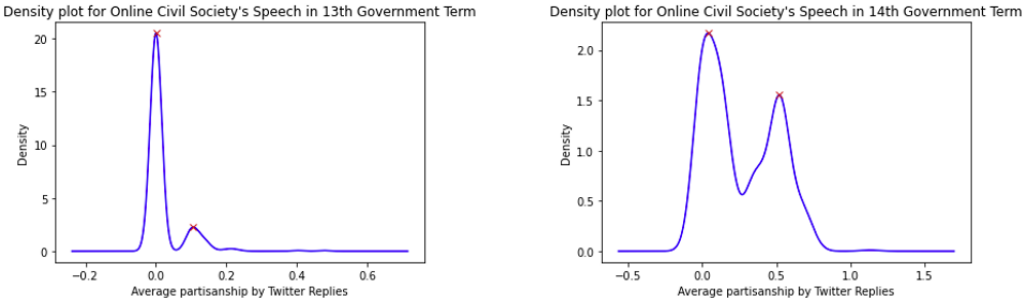


Figure 19: Density plots for mass polarization in Twitter by term

Figure 20: Mass polarization probabilities of density plot, by year and government term

4.3.3.2 Mass DPI

The DPI between the 14th and 13th government increased between both terms, being clear in Figure 21 (left part) that the first years the discourse had a DPI of zero, meaning it has not a bipolar distribution. , show a non-polar latter (Figure 21 and Figure 17).

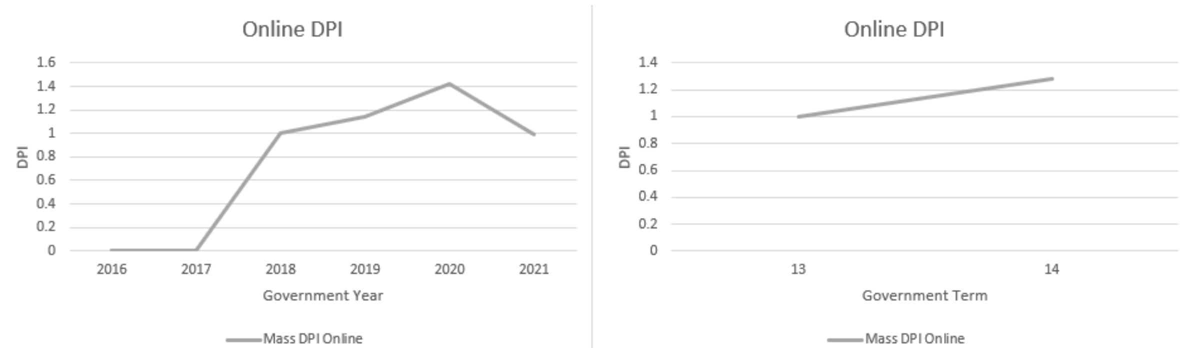


Figure 21: Mass Polarization DPT, by year and government term

4.3.4 DPI comparison

Comparing the DPI in elite and mass for online environment, the mass society has a higher polarization online than the elite one, shown on Figure 22. This results support scholars' work that defends that social media has higher political polarization values than the real life environment (Esteve Del Valle et al., 2021; Nahon & Hemsley, 2014; Yarchi et al., 2020), although the literature does not compare the same population through different environments. In the Figure 22, it is visible that for the same population, the elite one, this does not stand.

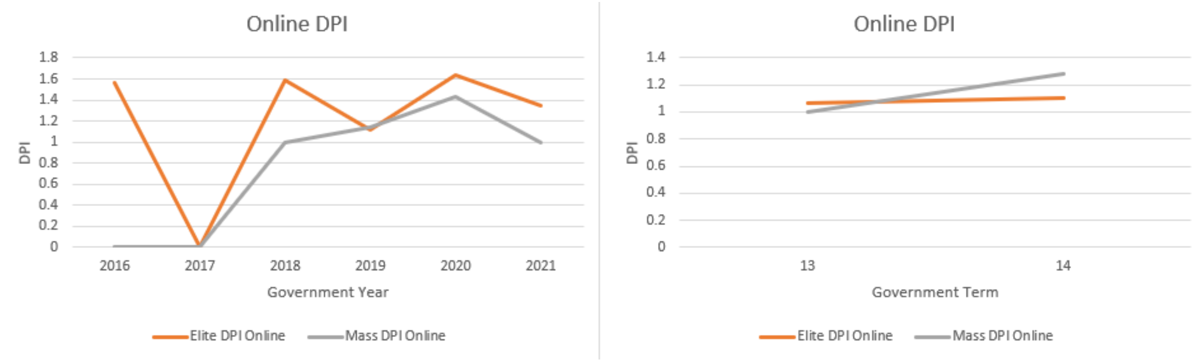


Figure 22: Online DPI for mass and elite

Comparing the elite DPI, for both online and real-life environments, the Figure 23 shows a bigger polarization for elite in the parliament that in the online setting.

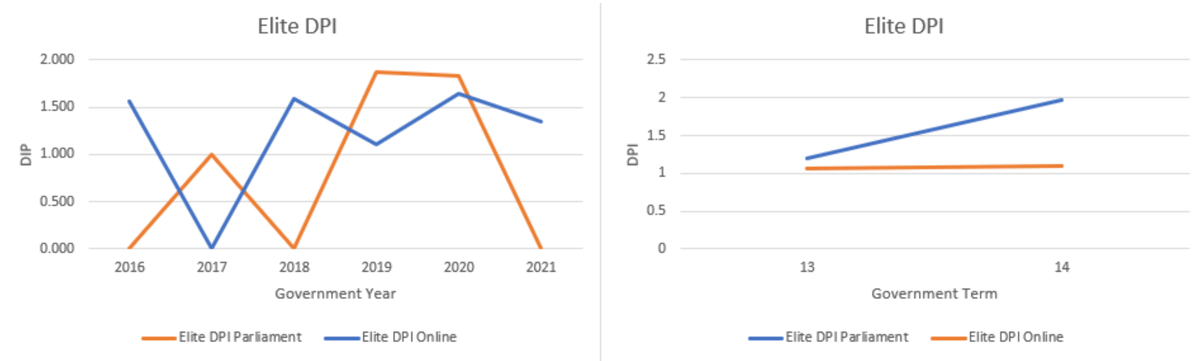


Figure 23: Elite DPI, for online and real-life environments

At last, comparing the DPI for all actors and environments, in the government terms, it is easier to gather a common political polarization trend. Figure 24 shows a common increase trend in political polarization, with the discourse at the parliament by the elite being the most polarized and the one with a higher increasing trend.

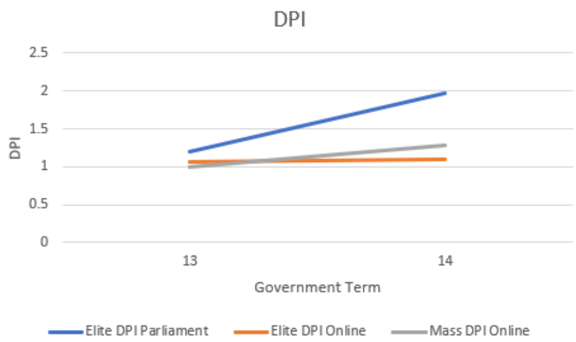


Figure 24: DPI for elite and mass

4.4 Semantic validation

As part of the data analysis methodology followed, I have performed a qualitative validation of the quantitative results. This allows to see a sample of the results and avoids the misunderstanding of having a good mathematical model that does not make sense in the use case context. For the semantic validation, I extract the top 200 trigrams more polarized to the right and left faction to be qualitatively analysed.

The trigrams of elite polarization in parliament have higher values of polarization for the years 2018 and 2019 for the right parties, and 2018 and 2020 for the left parties. In the year 2020, it is clear the focus is on the national health service, here the left stands out the words such as nurses and doctors, and the right has more trigrams with hospitals and equipment references. The parties with higher polarization speeches are the PCP on the left and the PSD on the right.

For elite polarization online, the year with the highest values of right-wing polarization is 2020, fully led by PSD, and for left-wing polarization is BE for the years 2020 and 2021. The right parties stand out from the left on Twitter due to their use of the social media platform to promote campaign slogans, being quite repetitive in its discourse and with little ideological content (see Table 2). While the right uses Twitter as a marketing tool, the left parties use it to discuss some international themes such as Trumpism or attacks in Israel, sharing some controversial topics such as the approximation of PSD to the far-right CH party, or the financial scandals of big Portuguese companies, such as *Amorim*.

For mass polarization, the years with more polarized speeches (replies in this case) are 2020 and 2021. Both the right and left citizens use the platform to express their emotions towards deputies, while the left citizens make references to energy companies as *Endesa* or old state naval companies as *Lisnave*.

	Parliament		Twitter	
	Left	Right	Left	Right
Elite	national.health.inaquacy ('nacional saud inadequ')	profix.tax(iva).growing ('receit iva cresc')	open.door.extreme-right ('abre port extremadireit')	we .are.together.portugal ('estam junt portugal')
	desiguality.salaries.excessive ('dispar salari excess')	economic.growth.predicted ('cresciment econom previst')	delivery.dividens.amorim ('entregu dividend amorim')	vaccine.tested.heathcare ('vacinaca testag cuid')
	medium.salary.before ('salari medi antes')	contract.service ('contrat contrat servic')	closing.PSD.CH ('aproximaco ppdpsd cheg')	
Mass			guy.wins.endesa ('ganh gaj endes')	rio.stop.wining ('rio deix lamur')
			coelho.destroied ('coelh consegu destru')	shoot.in.the.foot ('dar tir pezinh')
			old.shipyard.lisnave ('antig estaleir lisnav')	been.spleeping ('tens andad dorm')

Table 2: Trigrams terms found in the most polarized speeches with English translation

The step of qualitative validation was very important to evaluate what the empirical framework was outputting because it connected the results to the Portuguese environment. This avoids merging the empirical framework algorithm goal with the research question goal, making a distinction between mathematical optimization and social science understanding, while following ANT commitments.

The elite polarization topics overlap with the ones found by Gentzkow et al. (2019) and Peterson & Spirling (2018), with a focus on finance themes for the right and inequality and health care for the left (Table 2). The labor focus on the type of contract, the term 'contract.service' in Table 1, is

Portuguese specific and was not found in works that analyzed congress or parliament discourses in other contexts.

The mass polarization discourse found is consistent with the latest research work, where concepts of echo chambers, homophily, and judgment are explored due to the affective discourse online by citizens (Belcastro et al., 2020; Makrehchi, 2016).

This semantic validation step helped to understand what kind of information can be extracted based on actors and environment. It is consistent with the literature and with the data, reflecting the difficulty in measuring mass polarization online as the discourse is a manifestation of support or despise towards the deputies as individuals and not a deliberation about political topics.

4.5 Conclusion

The theoretical assumption of using a bimodal distribution as a polarization definition gathers evidence in this work's results. This mathematical assumption allows the comparison of political polarization in terms of left-right discourse probability, defined by the process characteristic, and its distance from one another, defined by its state characteristic, committing with ANT considering the dynamic process here analysed. The results here shown are the first measure of Portuguese political discourse, and the first evidence of an increasingly elite and mass political polarization.

The discourse both in parliament and on Twitter, independent of its actor, is has had an increasing political polarization trend between 13th and 14th government terms. The density plots show a higher probability in the left peak, meaning that a majority of the speakers 'discourse is found in the left ideology. The absolute value of zero found in the figures for the left peak has no absolute reading value, due to the formula and dummy variable assigned to the left and right poles. Through the results' graphics, it's evident that the left peak does not change a lot, while the right peak increases and diminishes its probability.

In the elite polarization discourse in parliament, there is an increasing trend for the right discourse further distance itself from the left discourse, due to the existence of new polarized right-wing discourse.

In mass polarization, the bimodal distribution is not clear for all the years, although the mass DPI trend is similar to the elite DPI trend, with increasing polarization through the years.

Comparing the DPI in elite and mass for online environment, the mass society has a higher polarization online than the elite one. This results support scholars' work that defends that social media has higher political polarization values than the real life environment, although the literature does not compare the same population through different environments. This is a result that shows the importance of being in Twitter or outside it, complying to ANT sensibility and no hierarchy commitments .

In both environments and actors, political polarization is increasing. This is supported by the new radical right party in Portugal, but also follows a trend in EU member states as well in the USA, captured through surveys and CSS methods (Marchal, 2021; Yarchi et al., 2020).

The semantic validation shows two important points: the Portuguese right-wing parties use Twitter as a campaign tool, with a discourse full of campaign slogans, and mass polarization online is very difficult to measure due to the affective discourse type the citizens take online. The qualitative validation is aligned with previous works, validating the empirical framework chosen and the DPT metric built.

The empirical framework adopted, and the DPI metric built are valid choices to measure political polarization, with the advantage of language, survey, pooling, and environment independence, enabling a relative fashion of measuring political polarization.

Chapter 5: Conclusion

This dissertation aims to contribute to the political polarization measurements, with a CSS method, applied to a Portuguese use case. It follows an Actor-Network theoretical framework, going along with its characteristics and adapting to its critics to avoid being its target. The model applied is an empirical framework, which was built and tested upon the discourse data, fitted to it, avoiding imposing a theoretical framework on the data observed. The results taken were the analysis of 8 years of data, which shows how slow it is to gather knowledge from the real world, and its subjectivity was incorporated on both elite and mass society data, which were processed at the individual level, being the speech the unit of the methodology. A range of environments and actors are used, and its relationality is taken into consideration when mass society discourses selected are the replies to the elite. Lastly, no causality efforts are made, and no fixed conclusions were drawn, the conclusions are trends identified considering the assumptions taken.

Attending to the ANT critics, I was careful when comparing what politicians said in real life environment, the parliament, and what citizens respond to it online, on Twitter. To avoid falling into the misperception of continuity of methods, I perform a semantic validation. Lastly, the findings from this work do not generalize as they are specific to the use case, timeframe, socioeconomic context, and methods used. The use case of Portugal serves the robustness of the DPI metric built.

This work answers the need to start addressing political polarization from its early stages, and quantitatively, as there is no measure able to find a political polarization trend, independent of surveys and voting data, as well as applicable to the elite and mass population. The main questions are stated, with their answers summarized here: How can political polarization be measured in discourse, in a language and human-task independent fashion, considering the phenomenon state and process? (RQ1); What is the trend of political polarization in the Portuguese parliamentary and online government discourse? (RQ2); and What is the trend of political polarization in Portuguese citizens' online discourse? (RQ3). Answering the first research question covered an important research gap in political science methodology literature. The empirical framework adopted, based on Jensen et al., (2012) and Gentzkow et al. (2015) work arises from the theoretical assumption from Fiorina & Abrams (2008), which states that political polarization can be described by a bimodal distribution, with a state and a process. This was also the starting point to build the new metric DPI, which prove to be scalable and independent of language, environment, and actors. The empirical framework applied to build the DPI surpass other CSS methods because it does not need any type of previous categorization by humans (surpassing classification), or any pre built dictionary (like scaling), and avoids categorization based on computer science metrics (such as clustering). The DPI results for the Portuguese use case are aligned to the literature, which gives consistency to the metric.

For the second and third research questions, the main conclusion is the increasing political polarization among both mass and elite, and similar behaviour between real and online environments. Elite polarization shows higher polarization online than in the parliament, supporting scholars' work defending that social media increases polarization (Esteve Del Valle et al., 2021; Nahon & Hemsley, 2014; Yarchi et al., 2020). Mass polarization follows the same trend as elite polarization, supporting scholars' work that finds a correlation between what politicians say and what citizens say (Ho & Quinn, 2008; Sloman et al., 2021).

The increase of political polarization in Portugal is aligned with the entrance of a new radical right party in Portugal but also follows a trend in EU member states as well in the USA, captured through surveys and CSS methods. The main causes for the voting variation towards far-right parties are economic and cultural. For economic reasons, the most cited is the decline of incomes, the increase in inequality, globalization, and the labour market transformations. The cultural causes, the backlash against cultural changes and conservative decline, as well as actor-centric theories, related to the decrease of extremist party stigma and the media's negative portrait of the same (Mendes & Dennison, 2021a), are the recognized ones.

Most of the discourse, both in parliament and Twitter, independent of its actor, is increasing its political polarization, where the right parties' discourse has been distancing itself from the left parties' discourse, with periods of increasing and diminishing probability.

The semantic validation showed two important points: the right Portuguese parties use Twitter as a campaign tool, with a discourse full of campaign slogans, and mass polarization online is very difficult to measure due to the affective discourse type citizens take online. The qualitative validation is aligned with previous works, validating the empirical framework chosen and the DPI metric built.

Limitations of the dissertation can be found in the quantity of data analysed which could be increased, as well the validation metric used could be further extended to a convergent validation. The convergent validation is the adding of a classification algorithm based on speeches, to see if its accuracy was good enough in distinguishing left from right speeches. For online mass polarization, Twitter does not show good quantitative results, due to the affective share in the polarized replies. Online research on political polarization, extending to more than one social media platform might be a good next research step to overcome this issue.

Lastly, an important reminder of the conclusions of this work is 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).

Appendix A

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

Abstract

Political polarization is rising within western societies, latest events such as the United States presidential 2016 elections, or the United Kingdom exit from the European Union are a reflect of that. Computational social science (CSS) methods offer a scalable and language independent fashion to measure political polarization, enabling the processing of big data.

This work offers the first scoping review of works which apply CSS methods to the analysis of political polarization through text as data. A Categorization Framework is proposed, advantages and disadvantages of the different models used in the literature are provided. Additionally, we found the need of adding the temporal characteristic of political polarization, the mathematical approach to the use cases, and of widen the location and platform used for the use cases. Recommendations for future research are provided.

Keywords: political polarization; computational social science (CSS) methods; text analysis; discourse; Twitter

Introduction

Recent political events, such as the Capitol riot in the USA when the 2020 presidential elections, Hungary's prime minister Viktor Orbán publicity doubting that liberal democracies could 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 ideological phenomena not very well understood or measured (Scharfbillig et al., 2021). This ideological phenomenon is named by scholars as political or ideological polarization, which stands for the extent of the difference on political opinion, attitudes, and beliefs. Although the theoretical definition is stable through last years of literature, the different forms of measuring it are not (Matthew Gentzkow, 2016). If left and right ideology are plotted in the xx-axis, a distribution of a political polarized population would show two peaks, one for extreme values of left and another for right, respectively. While for the opposite population, with the majority of the people having moderate political positions, the plot shows only one peak for the middle values in left-right ideology (Fiorina & Abrams, 2008).

It is known that the reference to the term political polarization is increasing over the last years in the literature (Gentzkow et al., 2019; Jensen et al., 2012), and the political differences in existing parties, and the establishment of new ones with radical ideological positions are given as the main causes for that (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 behaviour, which denies and excludes different ideological stands (Yarchi et al., 2020). The events described in the beginning are attacks on democratic norms and serve as examples of the negative side of political polarization. Although, it is not clear if these ideological divisions are being overstated, due to its difficulty in measuring it. The three main methods to measure ideological polarization are (1) value surveys, such as World Values Survey or the European Social Survey, (2) voting analysis, to understand if the citizen's vote is being polarized, and (3) policy views, to investigate whether the distribution of voter preferences on moral or economic issues is polarized. The value surveys show no evident political polarization since 1975 until 2019, the voting analysis is highly dependent on candidates' characteristics and still the magnitude of the upward polarization trend that is observed is far away from previous peaks. Lastly, the policy views on specific issues are highly studied from 1993, maintaining a normal distribution instead of a bimodal polarized one (Ellis & Stimson, 2012; Matthew 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 measurable the increasing distance between the consistently liberal and the consistently conservative populations. The evidence goes in hand with DiMaggio group's theory on inter and intra constrains between electorate ideological groups. While the cross-pressure between different ideological groups diminish, they became more internally homogeneous and externally distinct. This is what evident shows that is consistently happening in last years due to increasing cross party antipathy. This explanation is parallel to good clustering criteria, where well defined groups are those more polarized, which correspond to groups more cohesive (less constrains internally) and distant (higher cross-pressure intra clusters). This is the motivation for this work, an interception with known statistical models, such as clustering, with political science, to contribute for the consistency in measuring the latest ideological phenomena named political polarization. To be able to do a scoping review, we focused on text as data, because enabled us to encompass both real and online environments, as well as both political polarization actors, known as the political elite, composed by political parties' members; and the mass society, composed by civilians belonging to a specific country or political system (Lee, 2013).

The interception of statistical models, computer science and political science is represented by Computational Social Science (CSS) methods, a research field which fills 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 in a workshop entitled *Proceedings of the 1st 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).

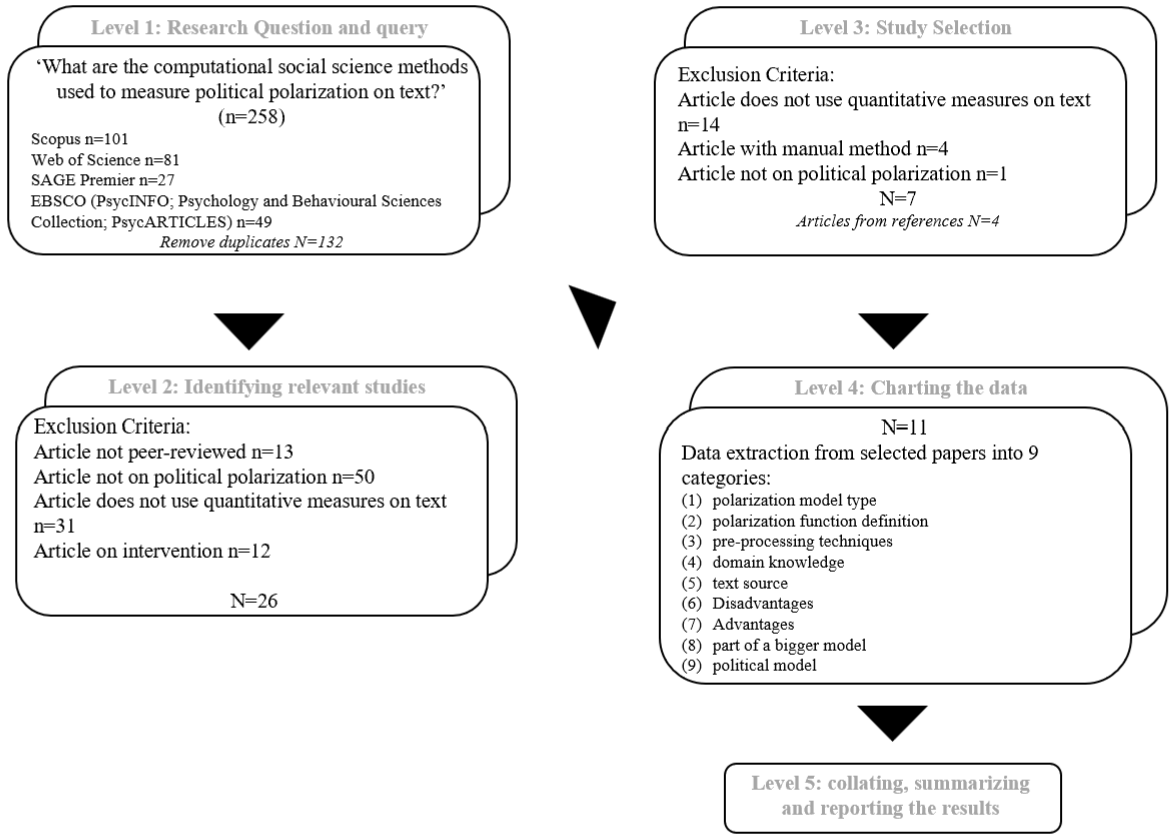
The use of CSS methods for the analysis of real-life and online political polarization, both by the political elite and the mass society, is increasing in the literature (Web Of Science, 2022), showing high-performance metrics within the field (Kursuncu et al., 2019; Peterson & Spirling, 2018; Shaw & Benkler, 2012) . Nevertheless, the methods' categorization is 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 work aims to fill that gap, collecting all the work done so far and structuring the methodologies used, sharing lessons learned and recommendations to contribute to 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). Having 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 such as political science, computational social science, economics, and social sciences, 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. Besides this main query, we performed a second one 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 from the main query. We used this 'text analysis' query to perform a comparison between our specific main query with a broader one within text analysis for social sciences and political sciences. Using these queries, we divide the results into trend over time and space (Figure 2 and Figure 3).

The first query retrieved 258 papers, at the date of 11/11/2021. From those, on the second level 26 were selected, after reading only the abstract and removing the duplicates (Figure 1). This followed a five inclusion 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 selected papers were fully read by the three authors and further analysed, resulting in a final selection of 7 papers and in the addition of 4 papers through references. At level 4, 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. 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/.

Figure 25 Flowchart of the scoping framework



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 literature named *Categorization Framework*.

Analysing quantitatively the results after level 4, there is 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 sub field 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 USA 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, we defined it here by 'English-online', as a digital region defined by language, instead of country, which is quite useful when exploring online platforms, but hinders the possibility of correlating digital findings with offline parameters, as location.

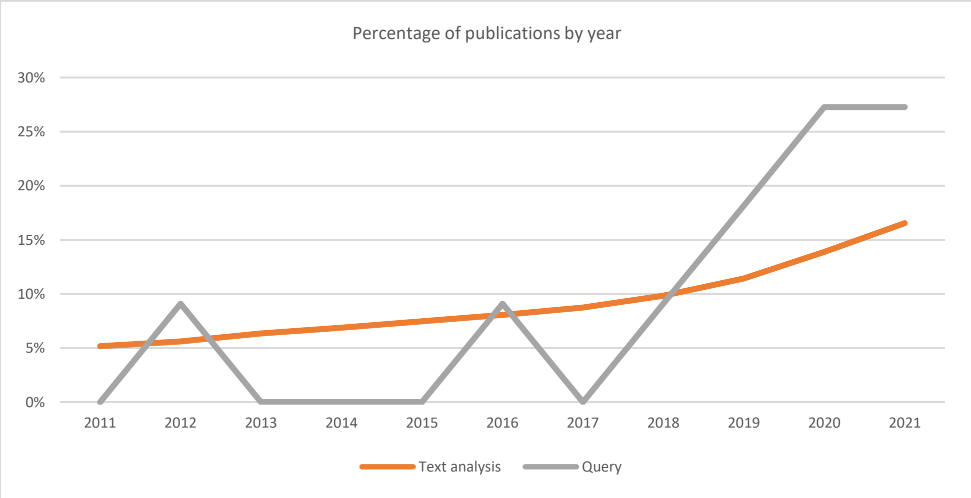


Figure 26: Line graph with percentage of publications selected from query (after coding) and its comparison with percentage of publications within the topic of 'text analysis and computational social science methods' query.

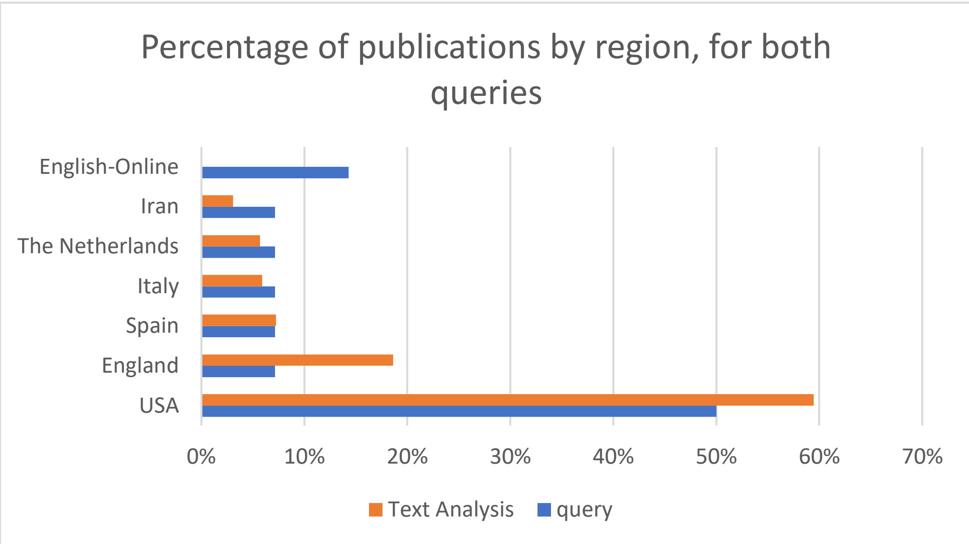


Figure 3: Percentage of publications by region, for the query (after coding) of the study and for the 'text analysis and computational social science methods' query.

Analysing qualitatively the results at level 5, we examined 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 works selected for this study can be split equally 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 works use congress speech on USA, being the congress transcripts the majority of IRL data text, and 3 works use Twitter data, as this platform is the most used for online discourse analysis. The work of Peterson and Spirling (2018) analyse the British parliament discourse, being the only work on IRL speech outside the USA.

The online data contamination is a crucial topic for online environments, such as YouTube, Reddit and blogs, which are text medium sources in the works' use cases. In this 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 2 of the works perform the bots 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 text shared. No cross-platform analysis was done in political polarization with text as data, to date and from our knowledge, as none of the works 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 the scholars are dealing with and their aims. One common feature to collect text data, is picking a specific time period before and after the event of interest. Only one work deals with the time dependence on possible polarized terms (Jiang et al., 2020).

As text analysis models, they are dependent on the language, although can be replicated to other languages as well, as the procedures remain. When dealing with dictionaries, this dependence can be overpassed if the scholars build their own dictionary. The work with higher dependence is Serrano-Contreras et al. (2020) study, because it uses sentiment analysis, which has a better performance for English than any other language.

Categorization Framework

The Categorization Framework here detailed was build based on patterns found in the literature with the aim to easily identify the best model type for each problem use case within political polarization, using text as data. The models of interest are the ones which measure the extent of political polarization, although not all the works focus solely on that. From the studies selected, 5 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. It was added one more category which is related to techniques which precede machine learning ones, 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 analysed 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 works from Belcastro et al. (2020), Gentzkow and Shapiro (2010), Gentzkow et al. (2019) and Jensen et al. (2012) fit into the 1) Statistical and Parametric Model category. The less sophisticated work of this category is Belcastro et al. (2020) study, 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. The work chosen to be representative of this category is the one from Gentzkow et al. (2019). This work 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 are 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 words such as 'tax.increas' (notice it is a bigram having 2 terms concatenated, the 'increase' work 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 a parametric one, dependent on the bigrams counts for each speaker per session in congress and assumes that these follow a multinomial distribution (the probability each bigram being said by a particular speaker is independent and identically distributed), it does not need domain knowledge to be applied once the empirical framework is defined. 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 study. 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 scholars circle, because it needs to be fitted for the problem and to have the parameters defined explicitly.

The 2) Classification models identified in this study 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 this work, the ideological leaning of a Reddit user has a neutral *a priori* distribution, updated by the number of comments done to liberal subreddits and number of comments done for conservative subreddits. No political system is assumed, as the accounts are selected based on English language criteria, and not on a region or country location criteria. Although, the work uses the same ideological axis with left/right poles as the biparty system. The main advantage of Marchal (2021) work is the approach taken to build the ideology labels. The coding of the ideology of replies is done manually in the first part of 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 with the first part and enables to scale it with 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 usage of the Bayesian Estimation Framework classification model with less manual work. One of the disadvantages of this work comes from the usage 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).

For the category 3) Timeseries we choose the work of Jiang et al. (2020), which analyses the polarization of online discourse within the covid-19 topic, looking for correlations between pandemic events and political polarization on online discourse on Twitter, having in mind geolocation and social network parameters. For the classification of political ideology, the American liberal and democratic classification is used, as all comments are within USA locations. It takes hand coded initial keywords as input, to distinguish liberal comments from democratic ones. 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 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.

The work of Sloman et al. (2021) was selected for the 4) Clustering model and for the 5) Scaling categories. 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; then it is calculated the partial Kullback-Leibler divergence (PKL), 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 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 studies 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 organizes the works developed. The categorization done here is not mutually exclusive, meaning we can find multiple model types ensembled into one model. The work of Sloman et al. (2021) and of Jiang et al. (2020) show how the scaling and clustering model types fit into classification and empirical model type, improving the results with the combination. Besides intending for a consistent definition of 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 the 3) location and platform bias found in the literature. Throughout the works selected for this scoping review, two types of model improvement were identified.

The Jiang et al. (2020) contribution for the political polarization analysis 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 1) dynamic characteristic of discourse and polarization. As only one work explicitly addresses the time analysis within polarization, while others relate polarization with conflict events (Makrehchi, 2016), or polarization through the years (Jensen et al., 2012), this is a topic in need of further exploration,

Following a 2) mathematical approach familiar to CSS methods, the work of Sloman et al. (2021) defines the political polarization into independent, dependent and cofactors variables. This practice was not followed by the authors of the other works selected, although it is aligned with CSS practices.

None of the works analyse one topic through 3) different online platforms, this would contribute for the mass polarization research field, as the work of Jensen et al. (2012) contributes for the elite polarization research by analysing congress speeches' transcripts and Google Books corpus. 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.

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 for 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 works on text classification which can also be extended to polarization measurement. A common first step in the works analysed by this scoping review is the partisanship classification of text. Within this field the work of Ho and Quinn (2008) uses machine learning techniques as logistic regression and support vector machines to classify text according to ideology. Additionally, the work of Iyyer et al. (2014) uses deep learning techniques such as semi-supervised recursive autoencoders. The

Iyyer'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, having in mind, however, 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).

References

Belcastro, L., Cantini, R., Marozzo, F., Talia, D., & Trunfio, P. (2020). Learning political polarization on social media using neural networks. *IEEE Access*, *8*, 47177–47187. https://doi.org/10.1109/ACCESS.2020.2978950

Boullier, D. (2018). Médialab stories: How to align actor network theory and digital methods. *Big Data and Society*, *5*(2), 1–13. https://doi.org/10.1177/2053951718816722

Cantini, R., Marozzo, F., & Trunfio, P. (2020). Learning Political Polarization on Social Media Using Neural Networks. *IEEE Access*, *8*, 47177–47187. https://doi.org/10.1109/ACCESS.2020.2978950

Dimock, M., Kiley, J., Keeter, S., & Doherty, C. (2014). *Political Polarization in the American Public: How Increasing Ideological Uniformity and Partisan Antipathy Affect Politics, Compromise and Everyday Life*.

Ellis, C., & Stimson, J. A. (2012). Ideology in America. In *Cambridge University Press*. https://doi.org/10.1017/CBO9781139094009

Esteve Del Valle, M., Broersma, M., & Ponsioen, A. (2021). Political Interaction Beyond Party Lines: Communication Ties and Party Polarization in Parliamentary Twitter Networks. *Social Science Computer Review*, 1–20. https://doi.org/10.1177/0894439320987569

Fiorina, M. P., & Abrams, S. J. (2008). Political polarization in the American public. *Annual Review of Political Science*, *11*, 563–588. https://doi.org/10.1146/annurev.polisci.11.053106.153836

Gentzkow, Mathew, & Shapiro, J. (2010). What Drives Media Slant? Evidence From U.S. Daily Newspapers. *Econometrica*, *78*(1), 35–71. https://doi.org/10.3982/ecta7195

Gentzkow, Matthew. (2016). Polarization in 2016. *Toulouse Network for Information* , 1–23.

Gentzkow, Matthew, Shapiro, J. M., & Taddy, M. (2015). Measuring Polarization in High-dimensional Data: Method and Application to Congressional Speech. *Working Paper*, *16*, 1–46.

Gentzkow, Matthew, Shapiro, J. M., & Taddy, M. (2019). Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech. *Econometrica*, *87*(4), 1307–1340. https://doi.org/10.3982/ecta16566

Grimmer, J., & Stewart, B. M. (2013). *Text as Data : The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts*. 1–31. https://doi.org/10.1093/pan/mps028

Ho, D. E., & Quinn, K. M. (2008). *Measuring Explicit Political Positions of Media*. *October*, 353–377. https://doi.org/10.1561/100.00008048

Iyyer, M., Enns, P., Boyd-graber, J., & Resnik, P. (2014). *Political Ideology Detection Using Recursive Neural Networks*. 1113–1122.

Jensen, J., Kaplan, E., Naidu, S., & Wilse-Samson, L. (2012). Political polarization and the dynamics of political language: Evidence from 130 years of partisan speech. *Brookings Papers on Economic Activity*, *FALL*, 1–81. https://doi.org/10.1353/eca.2012.0017

Jiang, J., Chen, E., Yan, S., Lerman, K., & Ferrara, E. (2020). Political polarization drives online conversations about COVID-19 in the United States. *Human Behavior and Emerging Technologies*, *2*(3), 200–211. https://doi.org/10.1002/hbe2.202

Jost, J. T. (2006). The end of the end of ideology. *American Psychologist*, *61*(7), 651–670. https://doi.org/10.1037/0003-066X.61.7.651

Kursuncu, U., Gaur, M., Castillo, C., Alambo, A., Thirunarayan, K., Shalin, V., Achilov, D., Arpinar, I. B., & Sheth, A. (2019). Modeling islamist extremist communications on social media using contextual dimensions: Religion, ideology, and hate. *Proceedings of the ACM on Human-Computer Interaction*, *3*(CSCW). https://doi.org/10.1145/3359253

Lee, J. M. (2013). Elite Polarization and Mass Political Engagement : Information , Alienation , and Mobilization. *Journal of International and Area Studies*, *20*(1), 89–109.

Makrehchi, M. (2016). Predicting political conflicts from polarized social media. *Web Intelligence*, *14*(2), 85–97. https://doi.org/10.3233/WEB-160333

Marchal, N. (2021). “Be Nice or Leave Me Alone”: An Intergroup Perspective on Affective Polarization in Online Political Discussions. *Communication Research*, 1–23. https://doi.org/10.1177/00936502211042516

Nahon, K., & Hemsley, J. (2014). Homophily in the Guise of Cross-Linking: Political Blogs and Content. *American Behavioral Scientist*, *58*(10), 1294–1313. https://doi.org/10.1177/0002764214527090

Ozer, M., Sapienza, A., & Ferrara, E. (2020). Discovering patterns of online popularity from time series. *Expert Systems with Applications*. https://doi.org/10.1016/j.eswa.2020.113337

Peterson, A., & Spirling, A. (2018). Classification Accuracy as a Substantive Quantity of Interest : Measuring Polarization in Westminster Systems. *Political Analysis*, 120–128. https://doi.org/10.1017/pan.2017.39

Pew Research Center. (2021). *The partisan divide on political values grows even wider*. Pew Research Center. https://www.people-press.org/2017/10/05/the-partisan-divide-on-political-values-grows-even-wider/

Scharfbillig, M., Smillie, L., Mair, D., Sienkiewicz, Keimer, M., Pinho Dos Santos, R. ., Vinagreiro Alves, H., Vecchione, E., & Scheunemann, L. (2021). *Values and Identities - a policymaker's guide*. https://doi.org/10.2760/349527

Serrano-Contreras, I. J., García-Marín, J., & Luengo, Ó. G. (2020). Measuring online political dialogue: Does polarization trigger more deliberation? *Media and Communication*, *8*(4), 63–72. https://doi.org/10.17645/mac.v8i4.3149

Shaw, A., & Benkler, Y. (2012). A Tale of Two Blogospheres: Discursive Practices on the Left and Right. *American Behavioral Scientist*, *56*(4), 459–487. https://doi.org/10.1177/0002764211433793

Sloman, S. J., Oppenheimer, D. M., & DeDeo, S. (2021). Can we detect conditioned variation in political speech? Two kinds of discussion and types of conversation. *PLoS ONE*, *16*(2 Febuary), 1–28. https://doi.org/10.1371/journal.pone.0246689

Stahlschmidt, S., Stephen, D., & Forschungspoolprojekt, K. B. (2020). *Comparison of Web of Science , Scopus and Dimensions databases KB Forschungspoolprojekt 2020*. *October*, 37.

Wallach, H. (2018). Viewpoint Computational Social Science ≠ Computer Science + Social Data.

Communications of the ACM, *3*. https://doi.org/10.1145/3132698

Web Of Science. (2022). *Web Of Science Results*. https://www.webofscience.com/wos/woscc/analyze-results/7c3e90ce-b713-425e-9995-410de39d4781-1d787a26

Yarchi, M., Baden, C., & Kligler-Vilenchik, N. (2020). Political Polarization on the Digital Sphere: A Cross-platform, Over-time Analysis of Interactional, Positional, and Affective Polarization on Social Media. *Political Communication*, *38*(1–2), 1–42. https://doi.org/10.1080/10584609.2020.1785067

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	10.1177/0894439320 987569

Appendix B

term	party	genre	Deputies active on Twitter	Female Deputies	Male Deputies	Ideology
13	BE	female	2	16%	37%	left
	BE	male	7			
	L	female	0			
	PCP	female	1			
	PCP	male	2			
	PEV	female	1			
	PS	female	6			
	PS	male	14			
	PSD	female	8	15%	32%	right
	PSD	male	17			
	CDS-PP	female	1			
	CDS-PP	male	3			
14	BE	female	3	19%	37%	left
	BE	male	7			
	PAN	female	2			
	L	female	1			
	PCP	female	2			
	PCP	male	2			
	PS	female	5			
	PS	male	17			
	PSD	female	8	12%	32%	right
	PSD	male	18			
	CDS-PP	male	2			
	IL	male	1			
	CH	male	1			

Table 3: Number of active accounts of Portuguese deputies on Twitter, by genre and ideology

Term	Party	Genre	Number of Tweets	Female Tweets	Male Tweets	Ideology
13	BE	female	1287	23%	33%	left
	BE	male	5383			
	PCP	female	77			
	PCP	male	299			
	PEV	female	35			
	PS	female	5041			
	PS	male	3298			
	PSD	female	2107	9%	35%	right
	PSD	male	9287			
	CDS-PP	female	276			
	CDS-PP	male	361			
	IL	male	41			
	CH	male	90			
14	BE	female	1762	18%	34%	left
	BE	male	2051			
	PAN	female	301			
	L	female	6			
	PCP	female	184			
	PCP	male	291			
	PS	female	1087			
	PS	male	3979			
	PSD	female	1206	7%	41%	right
	PSD	male	5159			
	CDS-PP	female	7			
	CDS-PP	male	404			
	IL	male	221			
	CH	male	1821			

Table 4: Number of tweets of Portuguese deputies on Twitter, by genre and ideology

Term	Party	Genre	Engagement Norm.	Female Engagement	Male Engagement	Ideology
13	BE	female	0.0165	11%	48%	left
	BE	male	0.128142857			
	L	female	0			
	PCP	female	0.011333333			
	PCP	male	0.092166667			
	PEV	female	0.002666667			
	PS	female	0.036833333			
	PS	male	0.099714286			
	PSD	female	0.090166667	14%	29%	right
	PSD	male	0.142862745			
	CDS-PP	female	0.002333333			
	CDS-PP	male	0.049333333			
14	BE	female	0.416111111	16%	15%	left
	BE	male	0.335857143			
	PAN	female	0.059833333			
	L	female	0.030666667			
	PCP	female	0.0495			
	PCP	male	0.162333333			
	PS	female	0.002066667			
	PS	male	0.029588235			
	PSD	female	0.147833333	4%	65%	right
	PSD	male	0.114703704			
	CDS-PP	male	0.090666667			
	IL	male	1			
	CH	male	1			

Table 5: Twitter engagement norm of Portuguese deputies on Twitter, by genre and ideology

References

Adams, J., & Somer-Topcu, Z. (2009). Policy Adjustment by Parties in Response to Rival Parties' Policy Shifts: Spatial Theory and the Dynamics of Party Competition in Twenty-Five Post-War Democracies. *British Journal of Political Science*, *39*(4), 825–846. https://doi.org/10.1017/S0007123409000635

Akkerman, A., Mudde, C., & Zaslove, A. (2014). How Populist Are the People? Measuring Populist Attitudes in Voters. *Comparative Political Studies*, *47*(9), 1324–1353. Scopus. https://doi.org/10.1177/0010414013512600

Argent, N. (2020). Nature. In A. Kobayashi (Ed.), *International Encyclopedia of Human Geography (Second Edition)* (pp. 273–283). Elsevier. https://doi.org/10.1016/B978-0-08-102295-5.10794-2

Baker, W. (2005). America's crisis of values: Reality and perception. In *Princeton University Press* (Vol. 9781400849). https://doi.org/10.1177/009430610603500137

Belcastro, L., Cantini, R., Marozzo, F., Talia, D., & Trunfio, P. (2020). Learning political polarization on social media using neural networks. *IEEE Access*, *8*, 47177–47187. https://doi.org/10.1109/ACCESS.2020.2978950

Belchior, A. M., Moury, C., Hanenberg, L., & Nunes, P. (2022). Compliance with electoral programmes in Portugal: Trends, policy reforms, and the role of veto players (1995-2019). *Analise Social*, *57*(242), 160–184. Scopus. https://doi.org/10.31447/as00032573.2022242.07

Bennett, A. (2004). Case Study Methods: Design, Use, and Comparative Advantages. In *Models, numbers, and cases: Methods for studying international relations* (pp. 19–55).

Bértoa, F., & Enyedi, Z. (2022). Who governs Europe? A new historical dataset on governments and party systems since 1848. *European Political Science*, *21*, 150–164. https://doi.org/10.1057/s41304-021-00342-w

Bienfait, F., & Beek, W. E. A. Van. (2014). Commentaries Political Left and Right: Our Hands-On Logic. *Journal of Social and Political Psychology*. https://doi.org/10.5964/jspp.v2i1.323

Boullier, D. (2018). Médialab stories: How to align actor network theory and digital methods. *Big Data and Society*, *5*(2), 1–13. https://doi.org/10.1177/2053951718816722

Budge, I., Hans-Dieter, K., Volkens, A., Bara, J., & Tanenbaum, E. (2001). *Mapping Policy Preferences: Estimates for Parties, Electors and Governments 1945–1998*. Oxford University Press.

Caprara, G. V., & Vecchione, M. (2018). On the Left and Right Ideological Divide: Historical Accounts and Contemporary Perspectives. *Political Psychology*, *39*, 49–83. https://doi.org/10.1111/pops.12476

Carson, R. N., & Rowlands, S. (2001). A Critical Assessment of Dewey's Attack On Dualism. *The Journal of Educational Thought (JET) / Revue de La Pensée Éducative*, *35*(1), 27–60.

Casal Bértoa, F., & Rama, J. (2021). Polarization: What Do We Know and What Can We Do About It? *Frontiers in Political Science*, *3*. https://www.frontiersin.org/articles/10.3389/fpos.2021.687695

Caughey, D., O'Grady, T., & Warshaw, C. (2019). Policy Ideology in European Mass Publics, 1981–2016. *American Political Science Review*, *113*(3), 674–693. https://doi.org/10.1017/S0003055419000157

Chega—Identity and Democracy Party. (2022). https://www.id-party.eu/chega

Clinton, J. D., Lapinski, J. S., & Trussler, M. J. (2022). Reluctant Republicans, Eager Democrats? *Public Opinion Quarterly*, *86*(2), 247–269. Scopus. https://doi.org/10.1093/poq/nfac011

Cordella, A., & Shaikh, M. (2006). *From Epistemology to Ontology: Challenging the Constructed Truth of ANT*. https://www.researchgate.net/publication/301295219_From_Epistemology_to_Ontology_Challenging_the_Constructed_Truth_of_ANT

Costa Lobo, M., Santos, N., Silva, T., Rogeiro Nina, S., & Lean Heyne, P. (2019). *Wave 3 Portugal: Pre-election Study October 2019*.

da Silva, R., & Sofia Ferreira, A. (2020). From the Armed Struggle against the Dictatorship to the Socialist Revolution: The Narrative Restraints to Lethal Violence among Radical Left Organisations in Portugal. *PERSPECTIVES ON TERRORISM*, *14*(6).

De Giorgi, E., & Cancela, J. (2021). The Portuguese Radical Left Parties Supporting Government: From Policy-Takers to Policymakers? *Government and Opposition*, *56*(2), 281–300. https://doi.org/10.1017/gov.2019.25

De Jonge, C. P. K., Langer, G., & Sinozich, S. (2018). Predicting state presidential election results using national tracking polls and multilevel regression with poststratification (MRP). *Public Opinion Quarterly*, *82*(3), 419–446. Scopus. https://doi.org/10.1093/poq/nfy023

DiMaggio, P., Evans, J., & Bryson, B. (1996). Have American's Social Attitudes Become More Polarized ? *University of Chicago Press*, *102*(3), 690–755.

Ellis, C., & Stimson, J. A. (2012a). Ideology in America. In *Cambridge University Press*. https://doi.org/10.1017/CBO9781139094009

Ellis, C., & Stimson, J. A. (2012b). *Ideology in America*. Cambridge University Press. https://doi.org/10.1017/CBO9781139094009

Esteve Del Valle, M., Broersma, M., & Ponsioen, A. (2021). Political Interaction Beyond Party Lines: Communication Ties and Party Polarization in Parliamentary Twitter Networks. *Social Science Computer Review*, 1–20. https://doi.org/10.1177/0894439320987569

Evans, J. H. (1997). Worldviews or social groups as the source of moral value attitudes: Implications for the culture wars thesis. *Sociological Forum, 12*(3), 371–404. https://doi.org/10.1023/A:1024625210910

Fiorina, M. P., & Abrams, S. J. (2008a). Political polarization in the American public. *Annual Review of Political Science*, *11*, 563–588. https://doi.org/10.1146/annurev.polisci.11.053106.153836

Fiorina, M. P., & Abrams, S. J. (2008b). Political polarization in the American public. *Annual Review of Political Science*, *11*, 563–588. https://doi.org/10.1146/annurev.polisci.11.053106.153836

Freire, A. (2005a). Party system change in Portugal, 1974–2005: The role of social, political and ideological factors. *Portuguese Journal of Social Science*, *4*(2), 81–100. https://doi.org/10.1386/pjss.4.2.81/1

Freire, A. (2005b). Party system change in Portugal, 1974–2005: The role of social, political and ideological factors. *Portuguese Journal of Social Science*, *4*(2), 81–100. https://doi.org/10.1386/pjss.4.2.81/1

Freire, A. (2015). Left–right ideology as a dimension of identification and of competition. *Journal of Political Ideologies*, *20*(1), 43–68. https://doi.org/10.1080/13569317.2015.991493

Gentzkow, M. (2016a). Polarization in 2016. *Toulouse Network for Information* , 1–23.

Gentzkow, M. (2016b). Polarization in 2016. *Toulouse Network for Information*, 1–23.

Gentzkow, M., & Shapiro, J. (2010). What Drives Media Slant? Evidence From U.S. Daily Newspapers. *Econometrica*, *78*(1), 35–71. https://doi.org/10.3982/ecta7195

Gentzkow, M., Shapiro, J. M., & Taddy, M. (2015). Measuring Polarization in High-dimensional Data: Method and Application to Congressional Speech. *Working Paper, 16*, 1–46.

Gentzkow, M., Shapiro, J. M., & Taddy, M. (2019). Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech. *Econometrica*, *87*(4), 1307–1340. https://doi.org/10.3982/ecta16566

Glaeser, E. L., & Ward, B. A. (2006). Myths and realities of american political geography. *Journal of Economic Perspectives*, *20*(2), 119–144. https://doi.org/10.1257/jep.20.2.119

Gründl, J. (2022). Populist ideas on social media: A dictionary-based measurement of populist communication. *New Media and Society*, *24*(6), 1481–1499. Scopus. https://doi.org/10.1177/1461444820976970

Hadden, J. K., & Wuthnow, R. (1991). The Struggle for America's Soul: Evangelicals, Liberals, and Secularism. *Contemporary Sociology, 20*(4), 614. https://doi.org/10.2307/2071861

Hansson, E. (2022). Subjects supposed to know, believe, and enjoy: The geopolitics of ideological transference in the Swedish begging question. *Political Geography, 98*. Scopus. https://doi.org/10.1016/j.polgeo.2022.102706

Hellwig, T. (2008). Globalization, policy constraints, and vote choice. *The Journal of Politics, 70*(4), 1128–1141.

Ho, D. E., & Quinn, K. M. (2008). *Measuring Explicit Political Positions of Media*. *October*, 353–377. https://doi.org/10.1561/100.00008048

Home—ANES | American National Election Studies. (n.d.). Retrieved 20 July 2022, from https://electionstudies.org/

Hunger, S., & Paxton, F. (2022). What's in a buzzword? A systematic review of the state of populism research in political science. *Political Science Research and Methods*, *10*(3), 617–633. https://doi.org/10.1017/psrm.2021.44

Jensen, J., Kaplan, E., Naidu, S., & Wilse-Samson, L. (2012). Political polarization and the dynamics of political language: Evidence from 130 years of partisan speech. *Brookings Papers on Economic Activity*, *FALL*, 1–81. https://doi.org/10.1353/eca.2012.0017

Jost, J. T. (2006). The end of the end of ideology. *American Psychologist*, *61*(7), 651–670. https://doi.org/10.1037/0003-066X.61.7.651

Karaa, W. B. A., & Gribâa, N. (2013). Information Retrieval with Porter Stemmer: A New Version for English. In D. Nagamalai, A. Kumar, & A. Annamalai (Eds.), *Advances in Computational Science, Engineering and Information Technology* (Vol. 225, pp. 243–254). Springer International Publishing. https://doi.org/10.1007/978-3-319-00951-3_24

Kim, H., Jr., & Fording, R. C. (2010). Electoral Systems, Party Systems, and Ideological Representation An Analysis of Distortion in Western Democracies. *Comparative Politics*, *42*(2), 167–185. JSTOR.

Kubin, E., & von Sikorski, C. (2021). The role of (social) media in political polarization: A systematic review. *Annals of the International Communication Association*, *45*(3), 188–206. https://doi.org/10.1080/23808985.2021.1976070

Kursuncu, U., Gaur, M., Castillo, C., Alambo, A., Thirunarayan, K., Shalin, V., Achilov, D., Arpinar, I. B., & Sheth, A. (2019). Modeling islamist extremist communications on social media using contextual dimensions: Religion, ideology, and hate. *Proceedings of the ACM on Human-Computer Interaction*, *3*(CSCW). https://doi.org/10.1145/3359253

Law, J. (2009). *Actor Network Theory and Material Semiotics.* (T. new B. companion to social Theory, Ed.).

Law, J., & Singleton, V. (2013). ANT and Politics: Working in and on the World. *Qualitative Sociology*, *36*(4), 485–502. https://doi.org/10.1007/s11133-013-9263-7

Law, J., & Singleton, V. (2014). ANT, multiplicity and policy. *Critical Policy Studies*, *8*(4), 379–396. https://doi.org/10.1080/19460171.2014.957056

Magalhães, P. C. (2014). The Elections of the Great Recession in Portugal: Performance Voting under a Blurred Responsibility for the Economy. *Journal of Elections, Public Opinion and Parties*, *24*(2), 180–202. https://doi.org/10.1080/17457289.2013.874352

Makrehchi, M. (2016). Predicting political conflicts from polarized social media. *Web Intelligence*, *14*(2), 85–97. https://doi.org/10.3233/WEB-160333

Malka, A., Lelkes, Y., & Soto, C. J. (2019). Are Cultural and Economic Conservatism Positively Correlated? A Large-Scale Cross-National Test. *British Journal of Political Science*, *49*(3), 1045–1069. https://doi.org/10.1017/S0007123417000072

Manifesto Project Data. (2022). https://visuals.manifesto-project.wzb.eu/mpdb-shiny/cmp_dashboard_dataset/

Marchal, N. (2021). “Be Nice or Leave Me Alone”: An Intergroup Perspective on Affective Polarization in Online Political Discussions. *Communication Research*, 1–23. https://doi.org/10.1177/00936502211042516

Marchi, R. (2021). *Political Violence from the Extreme Right in Contemporary Portugal*. *13*(6), 17.

Mendes, M. S., & Dennison, J. (2021a). Explaining the emergence of the radical right in Spain and Portugal: Salience , stigma and supply. *West European Politics*, *44*(4), 752–775. https://doi.org/10.1080/01402382.2020.1777504

Mendes, M. S., & Dennison, J. (2021b). Explaining the emergence of the radical right in Spain and Portugal: Salience , stigma and supply. *West European Politics*, *44*(4), 752–775. https://doi.org/10.1080/01402382.2020.1777504

Nahon, K., & Hemsley, J. (2014). Homophily in the Guise of Cross-Linking: Political Blogs and Content. *American Behavioral Scientist*, *58*(10), 1294–1313. https://doi.org/10.1177/0002764214527090

Patkós, V. (2022). Measuring partisan polarization with partisan differences in satisfaction with the government: The introduction of a new comparative approach. *Quality & Quantity*. https://doi.org/10.1007/s11135-022-01350-8

Peterson, A., & Spirling, A. (2018a). Classification Accuracy as a Substantive Quantity of Interest: Measuring Polarization in Westminster Systems. *Political Analysis*, 120–128. https://doi.org/10.1017/pan.2017.39

Peterson, A., & Spirling, A. (2018b). Classification Accuracy as a Substantive Quantity of Interest: Measuring Polarization in Westminster Systems. *Political Analysis*, 120–128. https://doi.org/10.1017/pan.2017.39

Pew Research Center. (2021). The partisan divide on political values grows even wider. In *Pew Research Center*. https://www.people-press.org/2017/10/05/the-partisan-divide-on-political-values-grows-even-wider/

Piurko, Y., Schwartz, S. H., & Davidov, E. (2011). Basic Personal Values and the Meaning of Left-Right Political Orientations in 20 Countries. *Political Psychology*, *32*(4), 537–561. https://doi.org/10.1111/j.1467-9221.2011.00828.x

Polarization | sociology | Britannica. (2022). https://www.britannica.com/topic/polarization-sociology

POLITICO Poll of Polls—European polls, trends and election news – POLITICO. (n.d.). Retrieved 20 July 2022, from https://www.politico.eu/europe-poll-of-polls/

Portuguese, P. (2022). *Dados Abertos*. https://www.parlamento.pt/Cidadania/Paginas/DAIntervencoes.aspx

Rabie, M. (2013). Ideology and History. In M. Rabie (Ed.), *Global Economic and Cultural Transformation: The Making of History* (pp. 127–153). Palgrave Macmillan US. https://doi.org/10.1057/9781137365330_8

Regimento da Assembleia da República, (2019) (testimony of Assembleia da Republica).

Republica, A. da. (2022, August 15). *Debates Parlamentares—Série II-B DAR/R3*. https://debates.parlamento.pt/catalogo/r3/dar/s2b

Resultados Eleitorais. (2022). https://www.parlamento.pt:443/Parlamento/Paginas/ResultadosEleitoraisAnteriores.aspx

Sanders, D., Magalhaes, P., & Toka, G. (2013). Citizens and the European Polity: Mass Attitudes Towards the European and National Polities. In *Oxford: Oxford University Press* (Vol. 15, Issue 1). https://doi.org/10.1093/acprof

Santana-Pereira, J., & Cancela, J. (2020). Demand without Supply? Populist Attitudes and Voting Behaviour in Post-Bailout Portugal. *South European Society and Politics*, *25*(2), 205–228. Scopus. https://doi.org/10.1080/13608746.2020.1864910

Scharfbillig, M., Smillie, L., Mair, D., Sienkiewicz, Keimer, M., Pinho Dos Santos, R. J., Vinagreiro Alves, H., Vecchione, E., & Scheunemann, L. (2021). *Values and Identities—A policymaker's guide*. https://doi.org/10.2760/349527

Serrano-Contreras, I. J., García-Marín, J., & Luengo, Ó. G. (2020). Measuring online political dialogue: Does polarization trigger more deliberation? *Media and Communication*, *8*(4), 63–72. https://doi.org/10.17645/mac.v8i4.3149

Shaw, A., & Benkler, Y. (2012). A Tale of Two Blogospheres: Discursive Practices on the Left and Right. *American Behavioral Scientist*, *56*(4), 459–487. https://doi.org/10.1177/0002764211433793

Sloman, S. J., Oppenheimer, D. M., & DeDeo, S. (2021). Can we detect conditioned variation in political speech? Two kinds of discussion and types of conversation. *PLoS ONE*, *16*(2 Febuary), 1–28. https://doi.org/10.1371/journal.pone.0246689

Smith, M. E. G. (2009). Against Dualism: Marxism and the Necessity of Dialectical Monism. *Science & Society*, *73*(3), 356–385. JSTOR.

Toshkov, D., & Krouwel, A. (2022). Beyond the U-curve: Citizen preferences on European integration in multidimensional political space. *European Union Politics*, *23*(3), 462–488. Scopus. https://doi.org/10.1177/14651165221080316

Twitter, I. (2022). *Developer portal* [Python]. https://developer.twitter.com/en/docs/developer-portal/overview

Walsham, G. (1997). Actor-Network Theory and IS Research: Current Status and Future Prospects. *Information Systems and Qualitative Research*, 466–480. https://doi.org/10.1007/978-0-387-35309-8_23

Web Of Science. (2022). *Web Of Science Results*. https://www.webofscience.com/wos/woscc/analyze-results/7c3e90ce-b713-425e-9995-410de39d4781-1d787a26

Yarchi, M., Baden, C., & Kligler-Vilenchik, N. (2020). Political Polarization on the Digital Sphere: A Cross-platform, Over-time Analysis of Interactional, Positional, and Affective Polarization on Social Media. *Political Communication*, *38*(1–2), 1–42. https://doi.org/10.1080/10584609.2020.1785067