

Quantifying polarization across political groups on key policy issues using sentiment analysis

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Abstract

There is growing concern that over the past decade, industrialized democratic nations are becoming increasingly politically polarized. Indeed, elections in the US, UK, France, and Germany have all seen tightly won races, with notable examples including the 2016 Trump vs. Clinton presidential election and the UK's Brexit referendum. However, while there has been much qualitative discussion of polarization on key issues, there are few examples of formal quantitative assessments examining this topic. Therefore, in this paper, we undertake a statistical evaluation of political polarization for representatives elected to the US congress on key policy issues between 2021-2022. The method is based on applying sentiment analysis to Twitter data and developing quantitative analysis for six political groupings defined based on voting records. Two sets of policy groups are explored, including geopolitical policies (e.g., Ukraine-Russia, China, Taiwan, etc.) and domestic policies (e.g., abortion, climate change, LGBTQ, immigration, etc.). We find that out of the twelve policies explored here, gun control was the most politically polarizing, with significant polarization results found for all groups (four of which were $P < 0.001$). The next most polarizing issues include immigration and border control, fossil fuels, and Ukraine-Russia. Interestingly, the least polarized policy topics were Taiwan, LGBTQ, and the Chinese Communist Party, potentially demonstrating the highest degree of bipartisanship on these issues. The results can be used to guide future policy making, by helping to identify areas of common ground across political groups.

1. Introduction

Industrialized democratic countries have experienced a wave of political polarization over the past decade [1]–[3]. For example, a notable case includes the 2016 decision for the United Kingdom to leave the European Union by a relatively narrow margin (52% voting leave, and 48% voting remain) [4]. Moreover, a few months later, the 2016 United States Presidential Election saw a Republican victory in the electoral college with 46.1% of the vote, while the losing Democratic party did so while winning the popular vote with 48.2% [5]. There are similar contexts across a range of other advanced nations, including France, Italy, Spain, and numerous others, suggesting many societies are becoming increasingly ideologically divided [6]–[8].

Sadly, this division has spilled over into the development of new issues between different social groups, which is often popularized and referred to as the ongoing 'Culture War' [9]. This has most notably arisen in the United States between social movements on the extremes of the political spectrum [10]–[12]. These range from the Left to the Right, for example, from the reinvigoration of the century-old Anti-Fascist movement (Antifa) to the emergence of a new Alternative Right (Alt-Right) [10], [13], [14]. This polarization has been affiliated with a hollowing out of the political center ground, which has unfortunately spurred greater division and intolerance. An unfortunate consequence is that the free speech debate has been in retreat in many places. Moreover, intra-party acceptance of working on bipartisan activities has decreased [15]–[18].

Given that strong divisions can lead to more negative societal outcomes, we need to explore a variety of important questions in greater detail. These questions generally pertain to diagnosing polarization on specific current affairs issues. This insight can then be used to identify pluralist strategies which try to encourage bipartisan activities. Consequently, in this paper, we develop methods to answer the following research question:

1. How do the political narratives of different elected representatives compare on key current affairs issues, and to what degree are current political groupings polarized?

One population data source for gaining insight into political narratives is the social network site Twitter [19]. Increasingly, scientists are utilizing Twitter data and natural language processing (NLP) techniques to study public discourse on a wide variety of topics, including the economy, immigration, health, gun controls, clean energy, Covid-19 and vaccines, foreign policy, and climate change. Indeed, fundamental NLP techniques, such as sentiment analysis

and topic modeling, can estimate the meaning of the unstructured text to provide a new systematic understanding of large quantities of data [20]–[26].

In Section 2 of this paper, a literature review is undertaken to evaluate existing political polarization studies, as well as the use of Twitter data and NLP in sentiment analysis. In Section 3, a method is subsequently articulated, enabling the research question to be investigated before the key results are reported in Section 4. Finally, a discussion is undertaken in Section 5, where the results are assessed in relation to the research question before conclusions are provided in Section 6.

2. Literature Review

The literature review is split into three sections. First, we evaluate the relevant literature which uses Twitter data to understand political polarization in Section 2.1. Secondly, the use of Twitter data in NLP studies is then assessed in Section 2.2. Finally, techniques available for conducting sentiment analysis, topic modeling, and other NLP methods for text data are reviewed in Section 2.3.

2.1 Review of literature on political polarization

In a democracy, where political division is a central tenant, the system functions by parties tolerating divergent views and acting a counterbalance to scrutinize an incumbent government as it implements its duties to its citizens [27], [28]. However, in recent years this has led to political extremism and widening ideological differences on fundamental issues. To understand this, researchers have used Twitter extensively to mine public views on various social and foreign policies in many countries. Although, only a small body of literature has focused on the opinion of different political groups, for example, in relation to climate change [29]–[33], solar energy [34], immigration [35], [36], COVID-19 vaccines [37], and Russian election interference [38].

Polarization on these topics can be more prevalent when leading up to a major election, as parties aim to differentiate themselves to voters [39], [40]. This can lead to an increase in political intolerance across competing groups. Indeed, propaganda can become political weapons against opponents [41], and negativity on social media can be amplified and spread faster when compared with positive content. Twitter and other social media sites provide a novel and readily available data source for researchers to study political alignments and the evolution of various qualitative narratives and discussions [42]. For example, in the US, Twitter

data analysis illustrates the hollowing out of the political center between the Left and the Right [43], [44]. This is also observed in other democracies. For instance, using data for Indian politicians, research has investigated how political representatives differ and/or agree on national issues [45]. Moreover, network analysis applied to Twitter data for politicians, i.e., retweets and responses, indicates a similar pattern to existing political grouping, reinforcing existing political divisions. Similar behavior is also notable in European countries such as Sweden [46].

Although the Twitter platform allows users to express themselves on important issues, social media platforms are known to reinforce niche (often very extreme) viewpoints across the political spectrum, on the left and right [14]. This occurs because Twitter users tend to align with their *a priori* political groups [19], with the reinforcement of existing viewpoints due to an 'echo chamber' effect where alternative views are actively or unconsciously excluded (either by human decision, automated algorithmic preference, or both). Indeed, public declaration of political stance can also be leveraged by political rivals and used in future political campaigns.

2.2 Review of applied NLP studies utilizing Twitter data

There are a wide variety of application areas using NLP techniques, particularly by using the Twitter API as a large comprehensive source of linguistic data. Here we summarize a set of relevant papers.

In recent years there has been a substantial assessment of Twitter narratives in relation to the Covid-19 pandemic, making this topic one of the most studied phenomena on Twitter [47]–[52]. For example, there has been a deluge of papers focusing on Covid-19 perceptions and a range of other socio-economic factors related to health disparities, racial disparities [48], [49], [53], and patient-tweeted information regarding drugs or vaccines [37], [49], [54]. There has also been considerable focus on network effects regarding these key topics, such as investigating the influence of leaders in disseminating information and the impact of moral boosting statements during arduous periods of the pandemic [55]. Indeed, appraisal of the emotions which leaders have depicted in Tweets has been examined, focusing on health, news, politics, and other public conversations [56]. Also, scholars have focused on mental health and substance abuse-related incidences using Twitter data due to covid lockdowns and subsequent income losses [57].

There has also been substantial use of Twitter data to explore topics associated with the political sphere, which involve sentiment analysis before or after an election [58], [59]. For example, in

Indonesia and Spain, scholars used pre-election Twitter narratives to predict the outcome of a presidential election [58] and the Catalan independence referendum [60], respectively. However, some have raised concerns about the reliability and trustworthiness of Twitter as an information source due to the ability of these narratives to be negatively affected by misinformation and the spread of 'fake news' (often by adversaries) [42], [61]. Online social media sites have been used as an influence engine to manipulate political outcomes and spread misinformation and misconceptions [62]. In recent years, machine learning approaches have been developed for identifying the spread of hate speech in Twitter spaces, including examining how these narratives evolve based on user retweet patterns [42].

There have also been a range of studies that examine sentiment regarding environmental topics, including biodiversity and climate change [29]–[33], [63]. Climate change is a polarized subject among competing political groups, and the Twitter platform allows researchers to study how leaders from each group differ on climate change policies. For example, n-gram analysis has been used to explore the sentiment of words associated with either 'global warming' or 'climate change' [33]. Indeed, this research attempted to answer if the public is aware of the difference between these two terms, the political association of each terminology, and the point of convergence and divergence between the two discussions. Similar assessments also focused on public awareness of biodiversity [63]. Other contentious social issues studied using Twitter data include abortion, LGBTQ, gender issues, and gender-based violence [64]–[68].

The Twitter micro-blogging feature has been utilized effectively as a distributed sensor system to detect natural disasters, such as earthquakes, and their intensities [69]–[72]. Moreover, the collective market mood can also be captured from Tweets. This approach is an established way for business and finance analysts to explore sentiment regarding investment products and thus be able to conclude how the pricing of these options may respond in the future [73], [74]. Twitter data has also been used to assess customer sentiment towards their fixed and mobile broadband providers [75], [76], with negative sentiment often reflecting the known coverage and capacity issues that exist in broadband infrastructure [77]–[79].

Finally, it is worth acknowledging some of the limitations of this type of data in advance. For example, Twitter has traditionally restricted the length of shared texts [80]. Indeed, the short texts force users to express themselves creatively, albeit at times in less logical ways (for example, using vernacular or slang language). Detecting sarcasm is also a challenging known problem, as it may mean estimated sentiment scores are incorrectly allocated [81].

Furthermore, linguistic diversity, language dynamicity, and rapid switching of public dialogues make it difficult for NLP models to adapt unless retrained with a new set of data [80]. Another challenge is analyzing large quantities of unstructured Tweets, which might be difficult to process without using more sophisticated big data tools [82], [83]. Lastly, Twitter algorithms have been pointed out as biased against some political groups and can amplify or suppress Tweet visibility [84].

Table 1 A review of studies utilizing Twitter data.

Author	Year	Topic	Data Type and Date
Bartelt and Elizabeth [66]	2020	LGBTQ, Abortion	Public Twitter, Date Unknown
Behl et al. [69]	2021	Detection of Natural Disasters	Public Twitter, Nepal, 2015 and Italy, 2016 Earthquake, and Covid datasets
Budiharto et al. [58]	2018	Election Politics	Public Twitter, 2018-2019
Castorena et al. [67]	2021	Gender-Based Violence	Public Twitter, 2019
Chamberlain et al. [44]	2021	Politics	US Legislators Tweets, Date Unknown
Chaudhry et al. [59]	2021	Election Politics	Public Twitter, 2020
Conover et al. [43]	2011	Political Polarization	Public Twitter, 2010
Criss et al. [49]	2021	Covid Vaccines, Ethnicity, Race	Public Twitter, 2020-2021
de Rosa et al. [35]	2021	Immigration	Public Twitter, Date Unknown
Evkoski et al. [42]	2021	Hate speech	Public Twitter, 2018-2020
Falkenberg et al. [31]	2022	Climate Change	Public Twitter, 2014-2021
Fitri et al. [65]	2019	LGBTQ	Public Twitter, 2019
Garcia et al. [47]	2021	Covid	Public Twitter, 2020
Goel et al. [56]	2021	Covid	Public Twitter, 2020
Gunnarsson and David [46]	2014	Political Polarization	Public Twitter, 2012
Hswen et al. [48]	2021	Covid, Ethnic Stigmatization	Public Twitter, 2020
Hswen et al. [53]	2020	Ethnic Disparities, Health	Public Twitter, 2013-2016
Huszár et al. [84]	2022	Political Polarization	Public Twitter, Date Unknown
Jang et al. [30]	2015	Climate Change	Public Twitter, Date Unknown
Jiang et al. [37]	2021	Covid Vaccines	Public Twitter, 2020
Kandasamy et al. [85]	2021	Covid	IEEE Covid Tweets, 2020
Khatua et al. [64]	2019	LGBTQ	Public Twitter, Date Unknown
Kim et al. [34]	2021	Energy, Solar	Public Twitter, 2020
Klein and Adam [14]	2019	Political Polarization	Public Twitter, 2017
Labonte et al. [86]	2021	Energy	Public Twitter, 2017-2018
Luther et al. [38]	2021	Foreign Politics, Political Polarization	Public Twitter, 2016 and 2020
Machuca et al. [51]	2021	Covid	Public Twitter, 2020
Marcecc et al. [54]	2022	Covid Vaccines	Public Twitter, 2020-2021
McGregor et al. [87]	2016	Gender Bias, Elective Politics	US Legislators Tweets, 2014
Naseem et al. [52]	2021	Covid	Public Twitter, 2020
Ohtani and Shimon [63]	2022	Biodiversity	Public Twitter, 2010-2020
Osmundsen et al. [61]	2021	Political Polarization	Public Twitter, 2018-2019
Özerim et al. [36]	2021	Immigration	Public Twitter, 2016
Prabhakar Kaila et al. [50]	2020	Covid	Public Twitter, 2020
Rajendiran et al. [73]	2021	Stock Prediction techniques	Public Twitter, Date Unknown
Rogers et al. [88]	2021	Political Identity	Public Twitter, 2015-2018
Rufai et al. [55]	2020	Political Leadership	Public Twitter, 2020
Ruz et al. [60]	2020	Detection of Natural Disasters	Public Twitter, Chile, 2010 and Catalan, 2017
Sakaki et al. [70]	2010	Natural Disasters Detection	Public Twitter, 2010
Samanta et al. [57]	2023	Mental Health	Public Twitter, 2022
Sanford et al. [29]	2021	Climate Change	Public Twitter, 2019
Schöne et al. [41]	2021	Hate Speech	Public Twitter, 2014-2016
Shi et al. [33]	2020	Climate Change	Public Twitter, 2009-2018
Solovev et al. [68]	2022	Hate Speech, gender, and ethnicity	US 117 Congress Tweets
Swathi et al. [74]	2022	Stock Prediction	Public Twitter, Date Unknown
Yu et al. [32]	2021	Climate Change	115th Congress Tweets

2.3 Review of methodological techniques

Before a researcher may analyze the large amount of unstructured text generated by online social networks, it is necessary to cluster this information into their respective document and topic collections [89]. Topic modeling discovers latent thematic information in large documents [90], [91]. Clustering documents into their respective topics is an essential step in the sentiment computation of unknown pieces of text and is applied in a range of Twitter datasets [41], [47], [50], [63], [92]. Sentiment analysis alone can suffice for known document categories. For Twitter, filtering algorithms are applied to extract specific topic-related Tweets. The latent Dirichlet allocation (LDA) is a popular document clustering algorithm that is frequently used for the analysis of textual content in electronic media, including Twitter data [63], [90]–[92]. LDA effectively analyzes large text corpora, but the performance of this approach degrades when analyzing small text documents, such as Tweets.

Also, upon discovering relational semantics within the textual content, sentiment analysis is used to extract constituted emotions. Indeed, sentiment analysis extracts a user's semantic content in verbal or written communications [21], [93]–[95]. In this case, sentiment analysis extracts emotions expressed in textual data such as Tweets and classifies them as neutral, positive, or negative. Further, sentiment analysis entails quantifying expressed opinion, referred to as subjectivity. There are various approaches to text sentiment analysis, including (i) lexicon-based methods, (ii) concept-based methods, (iii) hybrid methods, and (iv) machine learning-based methods [93], [96]–[98]. Lexicon-based sentiment analysis models are commonly used and are built based on relational dictionaries, matching text features and important words with defined sentiment values [54], [58]. In contrast, learning-based models can be more accurate and are increasingly used for the sentiment classification of Tweets. Learning methods are further categorized into supervised and unsupervised methods. Supervised learning employs rule-based, probabilistic, linear, or decision-tree models [97].

These techniques have been widely applied in the literature. For example, using supervised learning techniques, [61] trained linear support vector classification (L-SVC), logistic regression (LR), naive Bayes (NB), and support vector machine (SVM) models on the Kaggle Sentiment140 dataset for Twitter sentiment analysis. Deep learning multi-layered perceptrons such as convolutional neural networks (CNN), long short-term memory (LSTMs), and the gated recurrent unit (GRU), recurrent neural network (RNN) can also be trained to extract emotions in Tweets [99], [100]. The training data is usually pre-annotated. Significantly, the performance of sentiment analysis models and algorithms is tested against benchmark datasets

such as pre-annotated Twitter data, International Movie Database (IMDB) reviews, and Wiki Text [100], [101]. Sentiment analysis of Twitter data is evolving as new models are developed, which are usually more effective, accurate, and easily adaptable. These models can be hybrid, combining different sentiment analysis techniques. For example, using universal language model fine-tuning (ULMFiT) and SVM [101] achieves high accuracy on WikiText-103 and Twitter US airline data. This is true for multilingual language methods, e.g., the cross-lingual language model for Twitter (XLM-T) model [102].

Due to the complexity of Twitter data, extensive research has been conducted into language feature extraction, significantly improving sentiment analysis accuracy. For example, [103] employs a polarity-aware embedding multi-task learning (PEM) model to extract political bias within Twitter political texts. For accurate results and efficient performance of clustering, predictive, or classification machine learning models, it is necessary to preprocess preliminary data. This technique includes the removal of data point redundancies and dimensionality reduction. For example, synonym expansion and negation replacement drastically improve model accuracy [104], [105]. Feature extractions such as n-gram, term frequency-inverse document frequency (TF-IDF), and word embeddings [92] are standard preprocessing algorithms. The n-gram feature processing technique has received much attention, with several studies using it on Twitter data [33], [57], [63], [85], [106].

Table 2 A survey of sentiment analysis and topic modeling techniques of Twitter data

Author	Year	Methods	Data
AlBadani et al. [101]	2022	SVM, ULMFiT	WikiText-103, Twitter US Airline
Barbieri et al. [102]	2022	XLM-T,	Public Twitter, 2020
Bibi et al. [98]	2022	Concept-based sentiment analysis, Deep neural network (DNN), NB	Public Twitter, Date Unknown
Curiskis et al. [92]	2020	LDA, TFIDF,	Twitter and Reddit, Date Unknown
Gandhi et al. [100]	2021	word2vec, LSTM, CNN	IMDB Movie Reviews and Twitter, Date Unknown
Giachanou et al. [95]	2016	Hybrid, ML, Lexicon, Graph techniques	Public Twitter, Date Unknown
Khan et al. [82]	2020	Hadoop, RNN	Public Twitter, Date Unknown
Naseem et al. [105]	2021	Testing text preprocessing techniques against ML and DNN	Davidson et al., Waseem et al., and Golbeck et al. datasets
Nasser et al. [106]	2021	N-Gram, LSVM, TFIDF	Public Twitter Covid dataset
Rodrigues et al. [83]	2022	Flume, Hadoop, Hive, Lexicon, NB classifier	Public Twitter, Date Unknown
Sailunaz et al. [94]	2019	NB	Public Twitter, Date Unknown
Xiao et al. [103]	2022	PEM, Named Entity Recognition (NER)	Twitter ELECTION2020, PARLER, TIMME, and Twitter US Legislators 2019-2020
Yadav et al. [104]	2021	L-SVC, LR, NB, SVM	Kaggle Sentiment140 dataset
Zhang et al. [99]	2018	CNN, GRU	Twitter Benchmark datasets

3. Method

This study uses Twitter to investigate the relationship among US political party members on current affairs topics. By collecting Tweets from the US House of Representatives and Senate (comprised of Democrats, Republicans, and Independents), it is then possible to utilize natural language tools to understand underlying sentiments and emotions.

The United States House of Representatives is the lower chamber of Congress. This legislative branch is responsible for formulating policies, which is the blueprint that steers executive governance - drafting bills, debating them, and passing resolutions. Once the lower house passes a bill, and if the Senate ratifies them, it will be sent to the President for consideration.

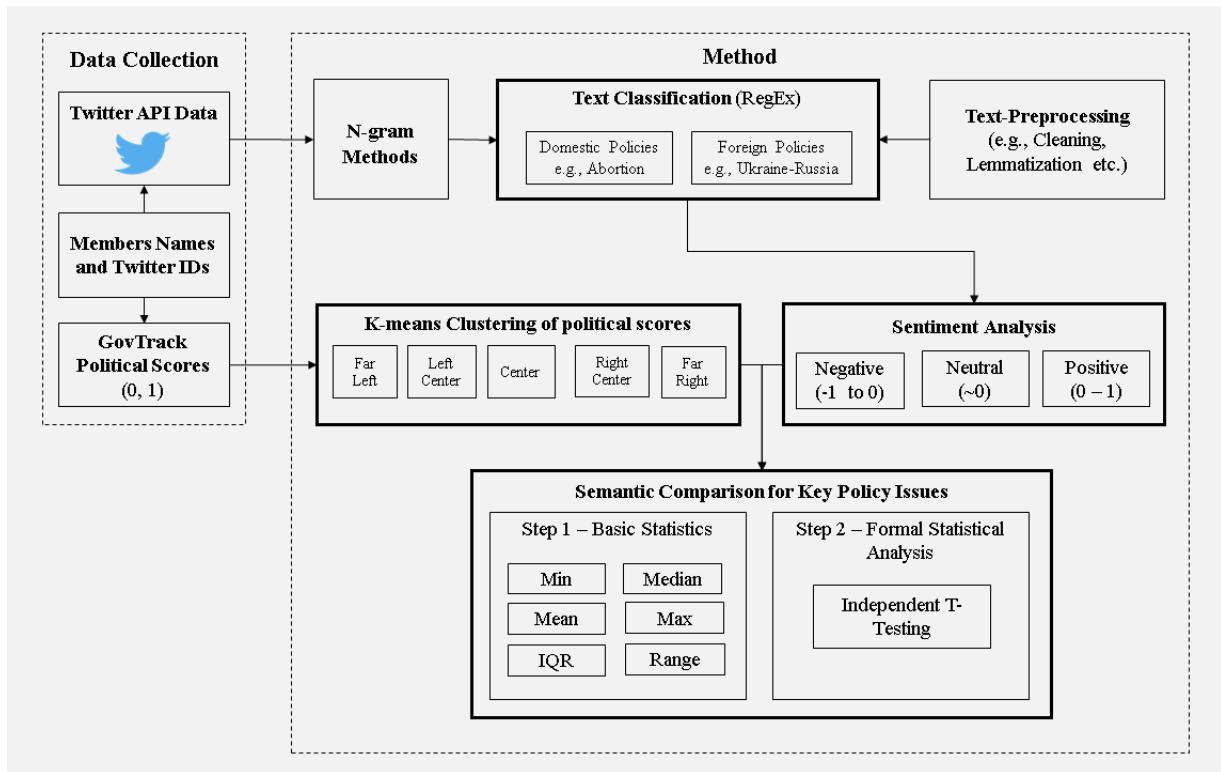
The method to investigate the research question will progress as follows. Firstly, using the Twitter API (Application Programming Interface) Python client to collect data from Congress member accounts, it is possible to develop a dataset that can be mined for new information.

Secondly, based on the voting record of each member, GovTrack data on the political score of each member is used to infer the political stance of each representative [107]. As the political party affiliation is generally known for each member, Tweets from the same party are aggregated and contrasted with the Tweets from other parties. The method is based on the approach that by analyzing the Tweets from this small group, we can more generally infer the sentiment of the general population subscribing to each party's ideologies.

Finally, we can use techniques to estimate the sentiment of the text data, plot the distributions of these scores based on political affiliation, and carry out formal statistical testing of key metrics. Policy themes are based on international geopolitical issues for which there may be greater bipartisanship (and thus, lower polarization) and domestic social and environmental issues where there may be a higher degree of polarization.

Figure 1 illustrates the method, from data collection to analysis.

Figure 1 Overview of the method



3.1 Data

Information about the US congress members was scraped from the web. The data features included the members' names, Twitter handles, party affiliations, and GovTrack scores. Using the Twitter API Python client, *snscreape*, the Tweets from each member were collected between January 2021 and December 2022. From each Tweet, the information extracted was the text (Tweet), date shared, and the Tweet interactivity details (retweets, likes, etc.). The collected Tweets were then saved into a comma-separated values (CSV) file for analysis.

3.2 Text Preprocessing

Before sentiment analysis, the fetched Tweet texts are cleaned. This stage involves lowering the text case, expanding the contracted words, i.e., ‘don’t’ to ‘do not’, removing the hyperlinks embedded in the tweets, removing special characters such as @, #, etc., and removing single characters and white spaces.

3.3 Sentiment Analysis

Valence Aware Dictionary for sEntiment Reasoning (VADER) Python package is leveraged to extract the sentiment values from the Tweets [69]. VADER is a rule-based model, and according to its developers, it is effective when used to compute sentiments from social media

data. The sentiment output of the model is a normalized value of the sum of the text's negative, neutral, and positive scores and ranges from -1 to +1.

3.4 Policy and Political Group Classification

Extracting the underlying topic composition of a large set of textual data is necessary before statistical analysis is undertaken. This section applies an n-gram feature extraction technique to extract the most contiguous terms within the dataset. This is useful as it provides an overview of the currently discussed subjects. The generated sequences of words were one-worded (unigrams), two-worded (bigrams), three-worded (trigrams), and four-worded(fourgrams). The terminologies from n-gram analysis were applied to establish a filtering algorithm that assigned each tweet to a policy category. For example, in the case of extracting tweets related to LGBTQ, the following terms from unigrams and bigrams were used, 'transphobia,' 'homophobia,' 'LGBTQ,' 'trans,' 'biphobia,' and 'sexual identity.'

Finally, applying the K-means clustering algorithm, the quantitative data of each member from GovTrack is used to classify members into a political group. The two main classes, i.e., Democrats and Republicans, were subdivided into five sub-groups, e.g., the Far left, Left Centrist, Centrist, Right Centrist, and Far Right. The GovTrack data range from 0 to 1, with 0 being more politically left and one more politically right.

3.5 Statistical analysis

An independent t-test is applied to explore whether the mean sentiment scores between the ideological groups are likely to have occurred randomly or otherwise for a 95% confidence level. No difference is assumed in the mean of the sentiments between the political groups as the null hypothesis for each test.

Using the mean sentiment value for each political group, sets of p-values are obtained using the Python library *statsmodels* to estimate the polarization within the groups. We define polarization as the statistically significant difference of the tested group means within a policy category. The mean sentiments of the political groups on twelve key policies are the basis for comparison and indicate the level of polarization between the groups. The statistical data used [108], and the analysis code and results are available for download.

All method code is available online from the GitHub [109]

4. Results

This section reports the descriptive and inferential results examining polarization across political groups on key current issues using sentiment analysis.

4.1 Descriptive statistics

Figure 2 illustrates the distribution of elected representatives based on their historical voting record, with the distribution of Democrats in blue and Republicans in red. Regarding basic statistical metrics, the Democrats have a mean political score of 0.28, a modal score of 0.3, a minimum score of 0.00, a maximum score of 0.64, and a range of 0.64. In contrast, the Republicans have a mean political score of 0.71, a modal score of 0.7, a minimum score of 0.44, a maximum score of 1, and a range of 0.56. As the Democrats have a marginally larger range, it suggests their members vote slightly more widely across the political spectrum compared to Republicans. One caveat is that this plot represents the composition of the two houses in 2021, before the midterm elections of 2022.

Figure 2 Voting record-based political score (lower and upper house elected representatives)

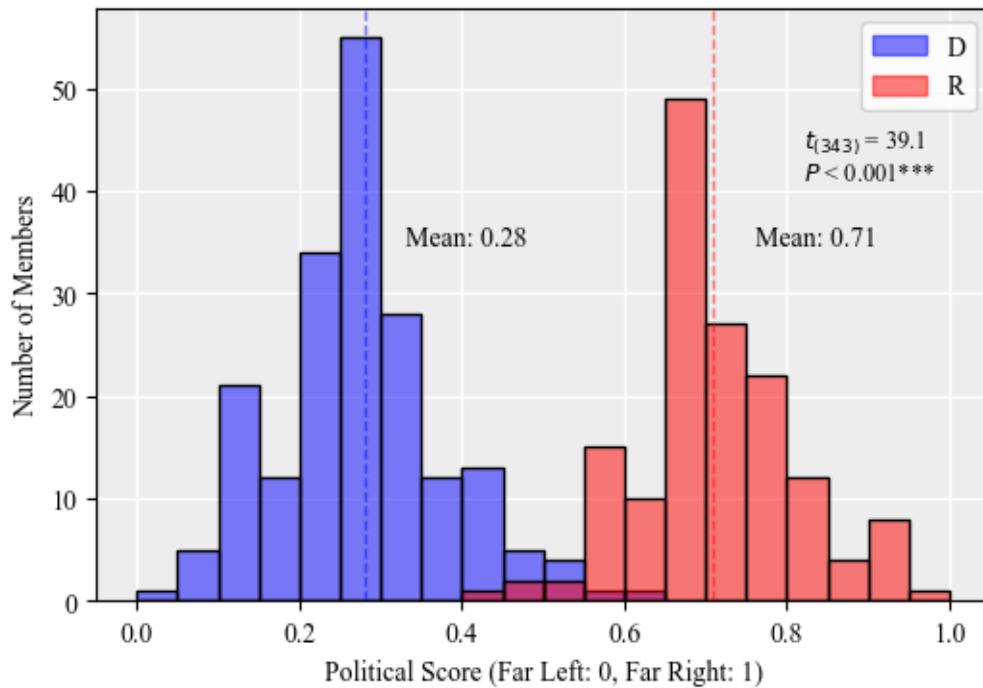


Figure 3 illustrates the frequency of key phrases within the dataset using n-gram methods for single words (unigrams) and phrase sequences consisting of up to a maximum of four (fourgrams). The dataset was collected from Twitter from January 2021 to December 2022.

The most common single word in the dataset is 'biden', which is a similar theme in the two-word phrases, with 'president biden' being the most frequently used. For three-word terms, the most frequent case was 'build back better', which was also top in four-word phrases, based on the phrase 'build back better act'. Compared to the unigram and bigram plots, when allowing for more words per phrase, e.g., with trigrams and fourgrams, we gain much greater insight into the frequency of topics discussed. For example, these include 'bipartisan infrastructure law', 'inflation reduction act', 'woman health protection act', and 'voting rights advancement act', which all provide insight into heavily discussed domestic current affairs topics during the period assessed.

Figure 3 Frequency composition of common phrases in the dataset using n-gram methods

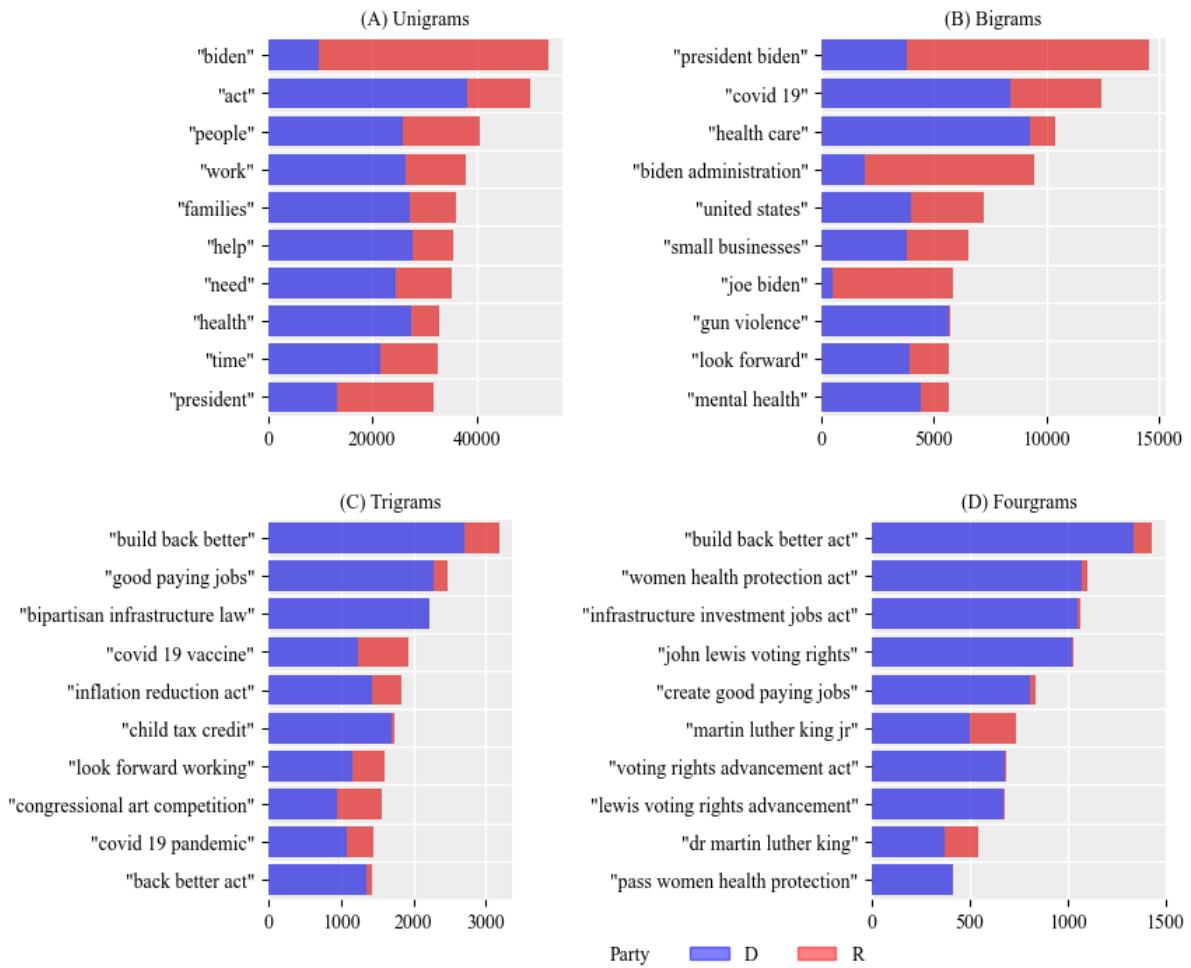


Figure 4 illustrates the estimated sentiment scores for a set of key international geopolitical themes in US politics, including the Chinese Communist Party (CCP), the bipartisan CHIPS and Science Act, Taiwan, and the Ukraine-Russian war. The sentiment is higher for Democrats

across the three key areas except for Ukraine-Russia, where sentiments are almost equal. Sentiment outcomes may be driven by the incumbent President's political alignment (thus, comparing these results to results for the previous administration pre-2021 is an important area of further research).

Figure 4 Key US geopolitical themes and associated sentiment scores

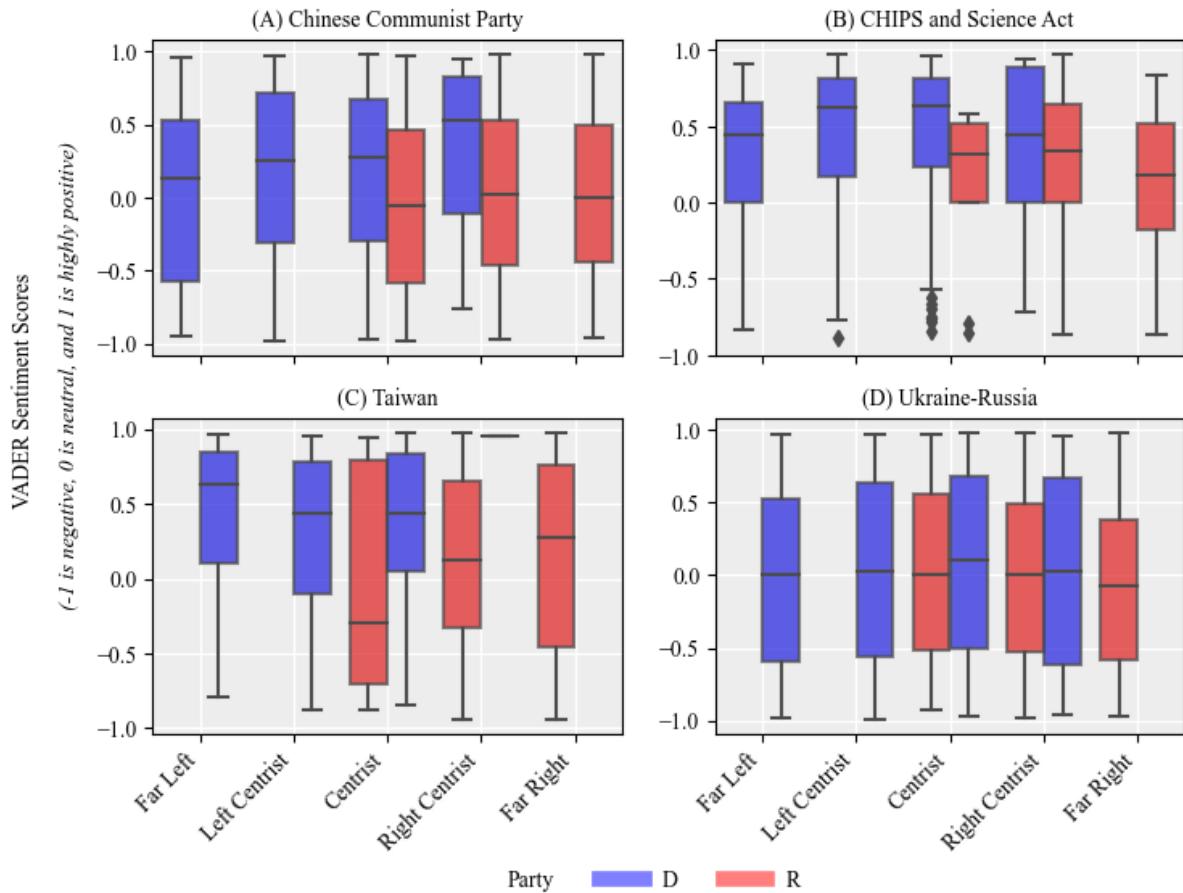
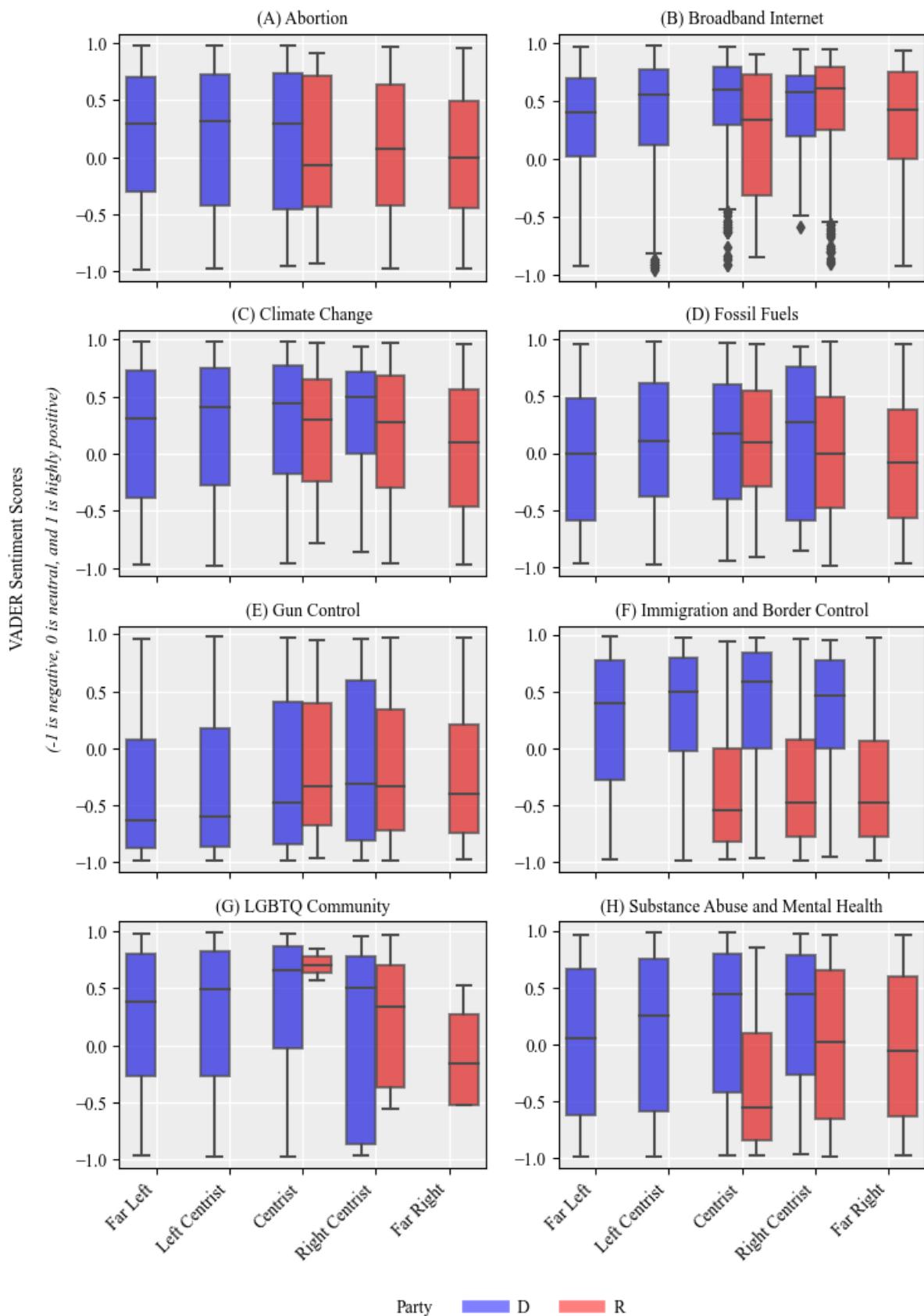


Figure 5 illustrates the sentiment scores across political parties for major US domestic policy themes, including abortion, broadband, climate change, fossil fuels, gun rights, immigration, LGBTQ, and substance abuse. On all issues except gun control, Democrats express more positive sentiment than Republicans.

Figure 5 Key US domestic policy themes and associated sentiment scores



4.2 Inferential statistics - Polarization Between Groups

Now the results are reported for the formal testing of polarization on key topics between political groups. Table 3 summarizes the results from the independent t-test of the sentiments across political groupings. The results show that abortion, immigration and border control, gun control, fossil fuels, and Ukraine-Russia discourses have substantive polarization between the political groups tested. The least divisive topics included Taiwan and LGBTQ issues, with no recorded statistically significant difference in sentiment between the political groupings.

When comparing the findings for the sentiment on the topic of abortion, the groups with a significant difference in mean sentiment include Left Centrist and Right Centrist (0.183 vs. 0.095; $p < .001$), the Far Left and the Far Right (0.191 vs. 0.037; $p < .001$), the Far Left and the Right Centrist (0.191 vs. 0.095; $p < .001$), and the Far Right and the Left Centrist (0.037 vs. 0.183; $p < .001$). This demonstrates strong polarization on this issue between opposing groups across the political spectrum. Variance across political groups may be explained by right-leaning elected members generally taking a pro-life stance, compared to left-leaning counterparts generally being more pro-abortion.

Immigration policy and the approach to managing US borders is another highly debated topic among elected representatives. The sentiment comparison of the groups shows a strong significant difference in mean sentiments between the Far Left and the Right Centrist (0.237 vs. -0.288; $p < .001$), and the Far Left and the Far Right (0.237 vs. -0.308; $p < .001$). The difference is also noted with the Left Centrist versus the Right Centrist (0.323 vs. -0.288; $p < .001$) and the Far Right against the Left Centrist (-0.308 vs. 0.323; $p < .001$). Although a difference is realized when the Far Left is contrasted with the Left Centrist, there are very similar positive mean values (0.237 vs. 0.323; $p < .001$). Polarization could be attributed to political ideology whereby left-leaning representatives may be more lenient on how the government should handle illegal immigration. In contrast, right-leaning representatives may take a less tolerant stance, instead advocating for more robust measures to deter future illegal immigration into the US, especially in the US southern border states.

Table 3 Independent T-test Results

Policy	Statistical Metric	Far Left - Far Right	Far Right - Left Centrist	Right Centrist - Left Centrist	Right Centrist - Far Left	Far Right - Right Centrist	Left Centrist - Far Left
Abortion	DF	1670	2427	2603	1846	1164	3109
	T	-5.075	-4.889	3.316	-3.477	-1.739	-0.364
	P	< .001***	< .001***	< .001***	< .001***	0.082	0.716
Broadband Internet	DF	386	1513	1763	636	616	1533
	T	-0.546	-3.649	-0.096	2.569	-3.023	3.052
	P	0.585	< .001***	0.924	0.01*	0.003**	0.002**
Chinese Communist Party	DF	1865	2088	2930	2707	4298	497
	T	0.509	-2.933	2.847	0.581	-0.223	1.951
	P	0.611	0.003**	0.004**	0.561	0.824	0.052
CHIPS and Science Act	DF	83	323	372	132	115	340
	T	-2.237	-4.771	3.284	-0.396	-1.965	2.248
	P	0.028*	< .001***	0.001**	0.693	0.052	0.025*
Climate Change	DF	2727	5973	6490	3244	1247	7970
	T	-2.674	-4.475	0.439	1.826	-3.757	3.572
	P	0.008**	< .001***	0.66	0.068	< .001***	< .001***
Fossil Fuels	DF	1527	2147	3087	2467	2514	2100
	T	-3.269	-7.929	4.42	0.539	-4.511	3.975
	P	0.001**	< .001***	< .001***	0.59	< .001***	< .001***
Gun Control	DF	3144	6979	7554	3719	2359	8339
	T	6.086	4.982	-10.601	11.083	-3.143	2.229
	P	< .001***	< .001***	< .001***	< .001***	0.002**	0.026*
Immigration and Border Control	DF	5781	6782	9601	8600	11539	3843
	T	-32.15	-45.375	46.446	-32.002	-1.904	4.451
	P	< .001***	< .001***	< .001***	< .001***	0.057	< .001***
LGBTQ Community	DF	657	1599	1625	683	32	2250
	T	-0.841	-0.895	1.271	-1.095	-0.338	0.66
	P	0.401	0.371	0.204	0.274	0.737	0.509
Substance Abuse and Mental Health	DF	1228	2537	2965	1656	1236	2957
	T	-2.538	-4.505	2.964	-0.543	-2.077	2.33
	P	0.011*	< .001***	0.003**	0.587	0.038*	0.02*
Taiwan	DF	246	278	261	229	435	72
	T	-1.265	-0.987	1.453	-1.58	0.723	-0.588
	P	0.207	0.324	0.147	0.115	0.47	0.558
Ukraine-Russia	DF	2622	4577	6086	4131	4919	3789
	T	-2.296	-6.627	2.813	1.094	-4.609	2.841
	P	0.022*	< .001***	0.005**	0.274	< .001***	0.005**

Gun control evokes tense political discussions between political groups, as supported by the quantitative metrics derived here. When comparing sentiments across groups, the results find that there is a strong difference in sentiments between the Far Left and Right Centrist (-0.386 vs. -0.164; $p < .001$), the Far Left and the Far Right (-0.386 vs. -0.244; $p < .001$), the Left

Centrist and the Right Centrist (-0.353 vs. -0.164; $p < .001$), and the Far Right and the Left Centrist (-0.244 vs. -0.353; $p < .001$). Moreover, on gun control, the other two groups aligned within the same political segments, the Far Left and Left Centrist (-0.386 vs. -0.353; $p = 0.026$) and the Far Right versus the Right Centrist (-0.244 vs. -0.164; $p = 0.002$) exhibit a considerable difference in sentiment for this dataset. Polarization is associated with ideological differences in the regulation of gun ownership, whereby left-leaning representatives may believe in adopting stringent measures that control the ownership of guns, especially assault rifles. In contrast, right-leaning representatives may believe that such controls infringe fundamental constitutional rights should greater government regulation of gun ownership be introduced.

Russia is an adversary nation of the United States, and the 2022 invasion of Ukraine has furthered geopolitical tensions. For example, there have been many debates on national security and economic globalization processes in the United States and across all industrialized democratic nations. The results obtained by analyzing Ukraine-Russian narratives suggest mixed sentiment across the political groups, as shown by the quantitative metrics in Table 3. For example, a significant difference in sentiment mean is found for the Far Left against the Far Right (-0.024 vs. -0.078; $p = 0.022$), and the Far Left and the Left Centrists (-0.024 vs. 0.043; $p = 0.005$). Moreover, a similar outcome is obtained when comparing the Left Centrist and Right Centrists (0.043 vs. 0.0; $p = 0.005$). The Far Right against the Right Centrist (-0.078 vs. 0.0; $p < .001$), and the Far Right and Left Centrist (-0.078 vs. 0.043; $p < .001$) show a considerable variation in the sample means, representing strong differences in US policy sentiment on this issue, reflecting opinion differences in military aid contributions. For example, right-leaning representatives may be concerned with the escalation of the war. In contrast, groups on the Left may be more supportive of equipping Ukraine with modern weapons (however, attitudes on this topic are highly heterogenous within each party). Although initially funding Ukraine and supplying it with advanced artillery attracted bipartisanship support in 2022, there are questions from right-leaning representatives regarding corruption and the misuse of funds within the Ukrainian government.

Moreover, another area of heightening geopolitics regards China and the Chinese Communist Party (CCP). Indeed, the CCP is perceived as one of the main political, security, and economic risk posed to the United States, now and over the next century [110], [111]. Based on the data analyzed here, the sentiments are fairly equal between the Left and the Right groups, suggesting little polarization between US, political groupings in this policy category. Indeed, the

quantitative data demonstrates that the mean of the Far Left group is lower when compared to those of the Right Centrist (0.029 vs. 0.058; $p = 0.561$), the Left Centrist (0.029 vs. 0.147; $p = 0.052$), and the Far Right (0.029 vs. 0.054; $p = 0.611$). However, there is not a statistically significant difference when explored using independent t-tests of these groups, potentially indicating shared consensus on this issue. This is also true for the Far Right and the Right Centrist (0.054 vs. 0.058; $p = 0.824$), which exhibit similar means. On the other hand, the Far Right and the Left Centrist (0.054 vs. 0.147; $p = 0.003$), and the Left Centrist and Right Centrist (0.147 vs. 0.058; $p = 0.004$) indicate statistically significant differences at the 95% confidence level.

Linked to China is the issue of Taiwanese independence and the current US dependence on microchip production in Taiwan by the Taiwanese Semiconductor Manufacturing Company (TSMC). Only two global foundries have mastered sub-10 nanometer chip production (TSMC and Samsung) [112], [113], introducing a strategic vulnerability for countries that rely on state-of-the-art microchips for economic activities and national security. In recent years, US legislators have pushed toward investment in developing semiconductor foundries and advanced scientific research within the continental United States. For example, the Creating Helpful Incentives to Produce Semiconductors (CHIPS) and Science Act are viewed to attract bipartisan support. The statistical models employed show a significant difference between the Far Right and Left Centrist (0.115 vs. 0.491; $p < .001$), and the Left Centrist and Right Centrist (0.491 vs. 0.309; $p = 0.001$). Indeed, a considerable significant difference in the mean is noted between the Far Left and the Far Right (0.343 vs. 0.115; $p = 0.028$), and between the Far Left and the Left Centrist (0.343 vs. 0.491; $p = 0.025$). No difference in the mean is observed between the Far Right and Right Centrists (0.115 vs. 0.309; $p = 0.052$) or the Far Left and the Right Centrists (0.343 vs. 0.309; $p = 0.693$). Regardless of the inter-political group variation, the average mean of the sentiments is positive overall, suggesting this sentiment supports the bipartisanship that took place in the production of the legislation. Separately, issues pertaining to Taiwanese independence were tested, and results show little political polarization on this key issue. For example, when considering the Far Left group against the Right Centrist (0.41 vs. 0.2; $p = 0.115$), the Far Left and the Left Centrist (0.41 vs. 0.327; $p = 0.558$), and the Far Left and the Far Right (0.41 vs. 0.24; $p = 0.207$) no significant differences were found. This was also true for all other groups, suggesting a strong degree of bipartisanship in Taiwanese independence.

In the literature, right-leaning representatives have had reservations in support of climate change combat efforts compared to the stance of left-leaning political groups. By comparing the mean sentiments of these groups, we find that there is a significant difference between the Far Right and the Left Centrist (0.093 vs. 0.234; $p < .001$), and the Far Right and the Right Centrist (0.093 vs. 0.224; $p < .001$). This is also notable between the Far Left against the Left Centrist (0.182 vs. 0.234; $p < .001$), and the Far Left and the Far Right (0.182 vs. 0.093; $p = 0.008$). Contrary to expectations, there is no statistical significance between the two groups, the Far Left and Right Centrist (0.182 vs. 0.224; $p = 0.068$), and the Left Centrist and the Right Centrist (0.234 vs. 0.224; $p = 0.66$). Disagreements on climate change issues still exist across political groups because there is still a lack of consensus regarding the policy instruments required to combat climate change effects (including on fiscal matters, such as taxation and spending). Furthermore, climate change issues are also strongly related to the use of fossil fuels and the potential shift to cleaner, more sustainable forms of energy. T-test results indicate strong differences in mean values between the left-leaning and right-leaning groups, with the left being more positive than the Right. Indeed, when formally tested, significant differences were found between almost all groups derived here. For example, the Far Left against the Far Right (0.01 vs. -0.083; $p = 0.001$), the Far Left and the Left Centrist groups (0.01 vs. 0.111; $p < .001$), the Left Centrist and the Right Centrist (0.111 vs. 0.023; $p < .001$), as well as the Far right against the Left Centrist groups (-0.083 vs. 0.111; $p < .001$) show a significant difference.

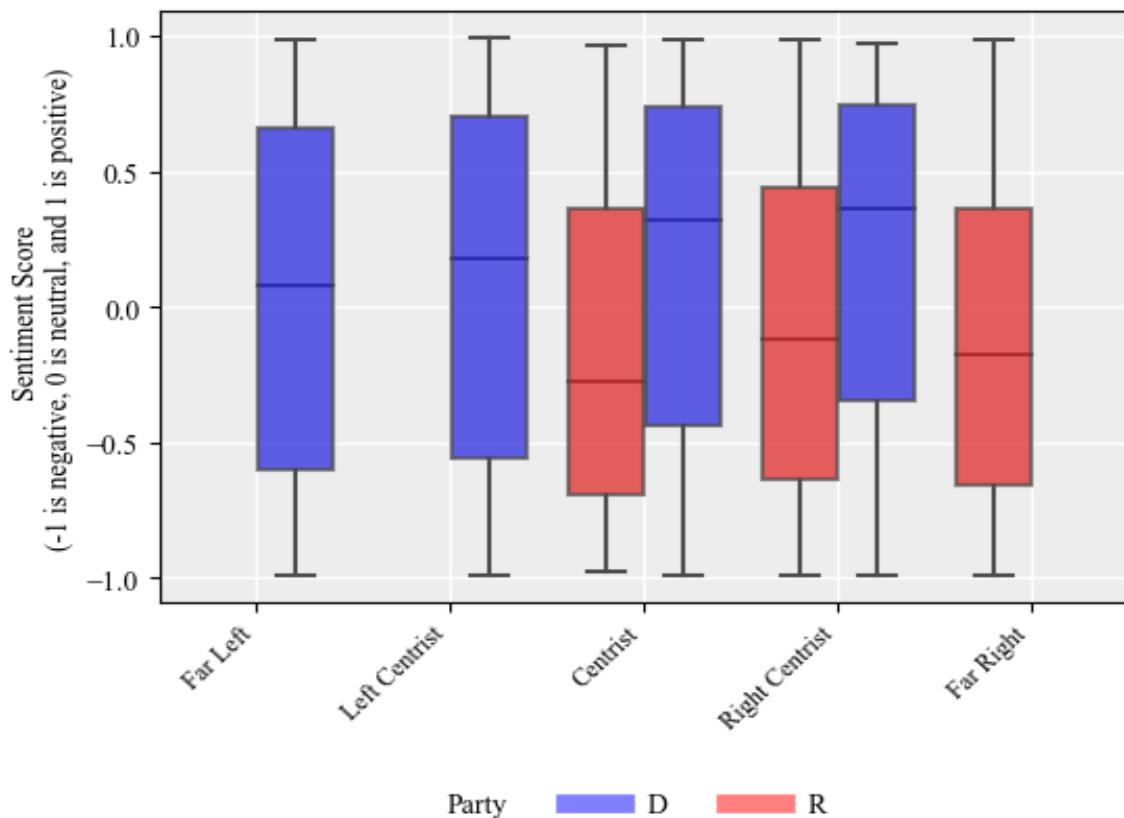
Amidst COVID-19 and rising inflation, there has been growing concern regarding mental health issues, mainly as they may be related to substance abuse. We note a significant difference in mean between the Far Right and the Left Centrist (-0.033 vs. 0.128; $p < .001$) groups on these issues, suggesting strong polarization. Moreover, a substantial difference in means was also found between the Far Right and the Right Centrist (-0.033 vs. 0.048; $p = 0.038$), and the Left Centrist and the Right Centrist (0.128 vs. 0.048; $p = 0.003$). This is also true between the Far Left and the Left Centrist (0.065 vs. 0.128; $p = 0.02$), and the Far Left and the Far Right (0.065 vs. -0.033; $p = 0.011$). There is no difference in mean between the Far Left and the Right Centrist (0.065 vs. 0.048; $p = 0.587$).

Broadband availability in the United States is challenging for many households and businesses, especially those in rural and remote areas. However, there is no consensus on this topic, particularly with regard to how to overcome disparities in broadband infrastructure access. The results on this topic suggest that while there may be a positive sentiment overall across political

grouping, there is still a strong degree of polarization. For example, there are statistically significant differences between the Far Left and Left Centrists (0.35 vs. 0.443; $p = 0.002$), Far Left and Right Centrists (0.35 vs. 0.445; $p = 0.01$), Far Right and the Left Centrist (0.324 vs. 0.443; $p < .001$), and the Right Centrists and Far Right (0.445 vs. 0.324; $p = 0.003$). There is no statistically significant difference between the Far Left and Far Right (0.35 vs. 0.324; $p = 0.585$), and between the Left Centrist and Right Centrist (0.443 vs. 0.445; $p = 0.924$).

Finally, the results for LGBTQ issues are examined with no statistically significant differences between the Far Left and the Left Centrist (0.284 vs. 0.303; $p = 0.509$), the Far Left and the Far Right (0.284 vs. 0.029; $p = 0.401$), and the Far Left and Right Centrist (0.284 vs. 0.159; $p = 0.274$). This is also true for the Far Right against the Left Centrist (0.029 vs. 0.303; $p = 0.371$), and the Far Right and the Right Centrist (0.029 vs. 0.159; $p = 0.737$). The center groups, the Left Centrist and the Right Centrist (0.303 vs. 0.159; $p = 0.204$), show no statistical difference in their means.

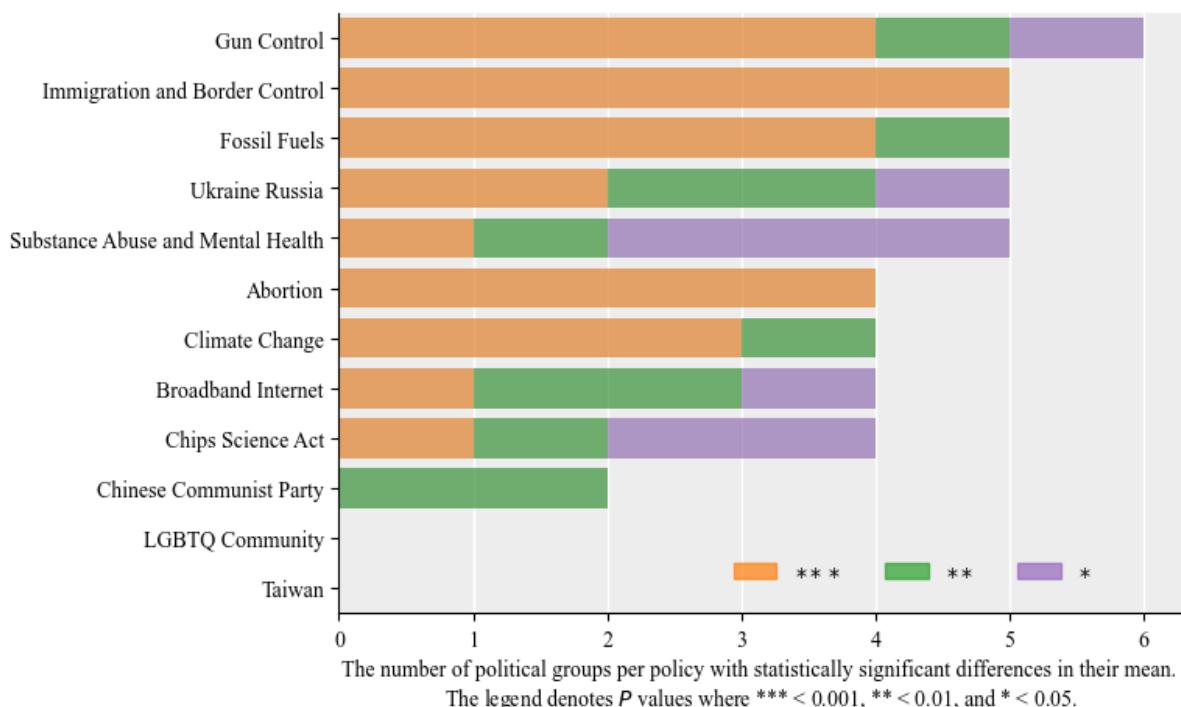
Figure 6 Aggregated sentiments of the political groups across the tested policies



In Figure 7, summary metrics are presented for the degree of polarization found across political groups. The y-axis represents the qualitative policy topic, whereas the x-axis represents the number of statistically significant t-test results for all political groupings where the means were found to differ formally at the 95% confidence level. The shade of each bar component indicates the strength of the significant p-value results found.

The ranking indicates that gun control is the most polarizing policy topic among legislators for the period assessed, with a significant difference across the six political groups, four of which achieved p-values below 0.001. In the second position was immigration which had the largest number of highly significant results by political group, followed by fossil fuels, Ukraine-Russia, and then substance abuse and mental health. In contrast, no significant differences were found in the mean samples of political groups on topics relating to LGBTQ issues and Taiwan, suggesting that these policies are the least polarizing and potentially have the highest degree of bipartisanship.

Figure 7 Ranking levels of political polarization on key policy issues.



5. Discussion

In this discussion, the results will be reviewed with reference to the research question.

How do the political narratives of different elected representatives compare on key current affairs issues, and to what degree are current political groupings polarized?

The initial analysis of voting records demonstrated two clear political groups. The bi-modal distribution consisted of Democrat-affiliated representatives with a mean political score of 0.28 and Republican-affiliated representatives having a mean score of 0.71 (where 0 is the most extreme Far Left, and 1 is the most extreme Far Right) ($p < 0.001$). Little difference was present in terms of the distributional statistics of these groups, other than Democrats having a marginally larger range, suggesting members vote slightly more widely across the political spectrum compared to Republicans. This voting record distributional information provided important background prior to analyzing the policy topics results.

Subsequently, on the issues assessed sentiment was found to be more positive for Democrats across many of the policy areas examined, as shown in Figure 6, except on topics relating to Ukraine-Russia, where sentiments were practically equal across political groups. Indeed, as on most issues, Democrats expressed a more positive sentiment than Republicans. This suggests there may be a correlation between the incumbent President's political alignment and the sentiment of each group. This is logical as Twitter is used as a public platform to promote or critique policy on key issues, thus making the sentiment outcomes frequently partisan.

The results suggest the most polarizing policy topics across the political groupings explored include gun control, fossil fuels, immigration and border control, Ukraine-Russia, climate change, and abortion. Such findings are commensurate with *a priori* evidence in both the literature and other media outlets. Moreover, the lack of statistically significant differences on key issues such as Taiwanese independence and LGBTQ suggests a high degree of bipartisan support on these topics. Moreover, with only two significant t-test results on the CCP, this suggests a high degree of commonality in the linguistic narratives used by elected representatives for the data analyzed.

6. Conclusions

There has been growing concern that industrialized democratic countries have been experiencing a growing wave of political polarization in recent years. For example, this polarization has been affiliated with greater division and intolerance accelerated by shifts by many parties from the political center ground. It is concerning that strong political divisions could have ramifications for formulating effective policy, potentially leading to more negative societal outcomes.

Therefore, this paper set out to explore the degree of polarization in current political narratives on key policy issues. Using Twitter data between 2021-2022, a sentiment analysis was carried out for elected members of the US House of Representatives and Senate (comprised of Democrats, Republicans, and Independents). After categorizing elected members into political groupings based on past voting records, sentiment values were estimated using Valence Aware Dictionary and sEntiment Reasoner (VADER) for Tweets that contain key policy-related terms. Finally, the dataset developed was explored by formally testing to examine statistical differences in group mean values.

Out of the twelve policy topics explored here, only one topic had statistically significant polarization across all political groups (gun control). However, eight other topics were polarized across either five political groups (immigration and border control, fossil fuels, Ukraine-Russia, and substance abuse and mental health), or four political groups (abortion, climate change, broadband infrastructure, and the CHIPS and Science Act), suggesting these were also highly partisan issues. The least polarized policy topics included Taiwan, LGBTQ, and the CCP.

There are limitations to the work which are important to discuss. For example, the study period between 2021 and 2022 takes place when Democrat-affiliated elected representatives held control of the House of Representatives and Senate and the Presidency. Moreover, prior to the 2020 election, there was a splintering in the usage of social media platforms along party lines, such as Twitter. In the most high-profile case, the incumbent President was banned from the platform, which caused other politically affiliated followers to be less active. Therefore, this could have affected participation across the political spectrum. To overcome these limitations, future research needs to be undertaken which examines the temporal aspects of political

sentiment, by analyzing data from previous periods (e.g., 2014-2016, 2016-2018, 2018-2020, 2020-2022). This would help (i) clarify the relationship between sentiment and control of the Presidency or the House of Representatives and Senate and (ii) provide insight into whether political polarization is increasing or decreasing over time.

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References

- [1] A. E. Wilson, V. A. Parker, and M. Feinberg, “Polarization in the contemporary political and media landscape,” *Curr. Opin. Behav. Sci.*, vol. 34, pp. 223–228, Aug. 2020, doi: 10.1016/j.cobeha.2020.07.005.
- [2] E. A. West and S. Iyengar, “Partisanship as a Social Identity: Implications for Polarization,” *Polit. Behav.*, vol. 44, no. 2, pp. 807–838, Jun. 2022, doi: 10.1007/s11109-020-09637-y.
- [3] R. Rekker, “Political Polarization Over Factual Beliefs,” in *Knowledge Resistance in High-Choice Information Environments*, Routledge, 2022.
- [4] S. B. Hobolt, T. J. Leeper, and J. Tilley, “Divided by the Vote: Affective Polarization in the Wake of the Brexit Referendum,” *Br. J. Polit. Sci.*, vol. 51, no. 4, pp. 1476–1493, Oct. 2021, doi: 10.1017/S0007123420000125.
- [5] J. Sides, M. Tesler, and L. Vavreck, “The 2016 U.S. Election: How Trump Lost and Won,” *J. Democr.*, vol. 28, no. 2, pp. 34–44, 2017, doi: 10.1353/jod.2017.0022.
- [6] S. Iyengar, G. Sood, and Y. Lelkes, “Affect, Not Ideology: A Social Identity Perspective on Polarization,” *Public Opin. Q.*, vol. 76, no. 3, pp. 405–431, Jan. 2012, doi: 10.1093/poq/nfs038.
- [7] A. M. Oberhauser, D. Krier, and A. M. Kusow, “Political Moderation and Polarization in the Heartland: Economics, Rurality, and Social Identity in the 2016 U.S. Presidential Election,” *Sociol. Q.*, vol. 60, no. 2, pp. 224–244, Apr. 2019, doi: 10.1080/00380253.2019.1580543.
- [8] J. N. Druckman, S. Klar, Y. Krupnikov, M. Levendusky, and J. B. Ryan, “Affective polarization, local contexts and public opinion in America,” *Nat. Hum. Behav.*, vol. 5, no. 1, Art. no. 1, Jan. 2021, doi: 10.1038/s41562-020-01012-5.
- [9] D. Baldassarri and B. Park, “Was There a Culture War? Partisan Polarization and Secular Trends in US Public Opinion,” *J. Polit.*, vol. 82, no. 3, pp. 809–827, Jul. 2020, doi: 10.1086/707306.
- [10] D. C. Atkinson, “Charlottesville and the alt-right: a turning point?,” *Polit. Groups Identities*, vol. 6, no. 2, pp. 309–315, Apr. 2018, doi: 10.1080/21565503.2018.1454330.
- [11] P. Love and A. Karabinus, “Creation of an Alt-Left Boogeyman: Information Circulation and the Emergence of ‘Antifa,’” in *Platforms, Protests, and the Challenge of Networked Democracy*, J. Jones and M. Trice, Eds. Cham: Springer International Publishing, 2020, pp. 173–198. doi: 10.1007/978-3-030-36525-7_10.
- [12] G. LaFree, “Is Antifa a Terrorist Group?,” *Society*, vol. 55, no. 3, pp. 248–252, Jun. 2018, doi: 10.1007/s12115-018-0246-x.
- [13] M. Alizadeh, I. Weber, C. Cioffi-Revilla, S. Fortunato, and M. Macy, “Psychology and morality of political extremists: evidence from Twitter language analysis of alt-right and Antifa,” *EPJ Data Sci.*, vol. 8, no. 1, Art. no. 1, Dec. 2019, doi: 10.1140/epjds/s13688-019-0193-9.
- [14] A. Klein, “From Twitter to Charlottesville: Analyzing the Fighting Words Between the Alt-Right and Antifa,” *Int. J. Commun.*, vol. 13, no. 0, Art. no. 0, Jan. 2019.
- [15] A. Mayer, “Partisanship, politics, and the energy transition in the United States: A critical review and conceptual framework,” *Energy Res. Soc. Sci.*, vol. 53, pp. 85–88, Jul. 2019, doi: 10.1016/j.erss.2019.02.022.
- [16] G. Grossman, S. Kim, J. M. Rexer, and H. Thirumurthy, “Political partisanship influences behavioral responses to governors’ recommendations for COVID-19 prevention in the United States,” *Proc. Natl. Acad. Sci.*, vol. 117, no. 39, pp. 24144–24153, Sep. 2020, doi: 10.1073/pnas.2007835117.
- [17] D. Hsiehchen, M. Espinoza, and P. Slovic, “Political partisanship and mobility

- restriction during the COVID-19 pandemic,” *Public Health*, vol. 187, pp. 111–114, Oct. 2020, doi: 10.1016/j.puhe.2020.08.009.
- [18] M. Wagner, “Affective polarization in multiparty systems,” *Elect. Stud.*, vol. 69, p. 102199, Feb. 2021, doi: 10.1016/j.electstud.2020.102199.
- [19] M. Z. Ansari, M. B. Aziz, M. O. Siddiqui, H. Mehra, and K. P. Singh, “Analysis of Political Sentiment Orientations on Twitter,” *Procedia Comput. Sci.*, vol. 167, pp. 1821–1828, Jan. 2020, doi: 10.1016/j.procs.2020.03.201.
- [20] A. Kumar and A. Jaiswal, “Systematic literature review of sentiment analysis on Twitter using soft computing techniques,” *Concurr. Comput. Pract. Exp.*, vol. 32, no. 1, p. e5107, 2020, doi: 10.1002/cpe.5107.
- [21] M. Birjali, M. Kasri, and A. Beni-Hssane, “A comprehensive survey on sentiment analysis: Approaches, challenges and trends,” *Knowl.-Based Syst.*, vol. 226, p. 107134, Aug. 2021, doi: 10.1016/j.knosys.2021.107134.
- [22] P. Nandwani and R. Verma, “A review on sentiment analysis and emotion detection from text,” *Soc. Netw. Anal. Min.*, vol. 11, no. 1, p. 81, Dec. 2021, doi: 10.1007/s13278-021-00776-6.
- [23] M. Wankhade, A. C. S. Rao, and C. Kulkarni, “A survey on sentiment analysis methods, applications, and challenges,” *Artif. Intell. Rev.*, vol. 55, no. 7, pp. 5731–5780, Oct. 2022, doi: 10.1007/s10462-022-10144-1.
- [24] K. Mishev, A. Gjorgjevikj, I. Vodenska, L. T. Chitkushev, and D. Trajanov, “Evaluation of Sentiment Analysis in Finance: From Lexicons to Transformers,” *IEEE Access*, vol. 8, pp. 131662–131682, 2020, doi: 10.1109/ACCESS.2020.3009626.
- [25] A. H. Alamoodi *et al.*, “Sentiment analysis and its applications in fighting COVID-19 and infectious diseases: A systematic review,” *Expert Syst. Appl.*, vol. 167, p. 114155, Apr. 2021, doi: 10.1016/j.eswa.2020.114155.
- [26] L. Yang, Y. Li, J. Wang, and R. S. Sherratt, “Sentiment Analysis for E-Commerce Product Reviews in Chinese Based on Sentiment Lexicon and Deep Learning,” *IEEE Access*, vol. 8, pp. 23522–23530, 2020, doi: 10.1109/ACCESS.2020.2969854.
- [27] O. Oshri, O. Yair, and L. Huddy, “The importance of attachment to an ideological group in multi-party systems: Evidence from Israel,” *Party Polit.*, vol. 28, no. 6, pp. 1164–1175, Nov. 2022, doi: 10.1177/13540688211044475.
- [28] B. M. J. Kzy and F. T. Khaldibekova, “The establishment of a multiparty system in Turkey and its role in the country’s socio-political life.,” *Eurasian Sci. Her.*, vol. 5, pp. 31–35, Feb. 2022.
- [29] M. Sanford, J. Painter, T. Yasseri, and J. Lorimer, “Controversy around climate change reports: a case study of Twitter responses to the 2019 IPCC report on land,” *Clim. Change*, vol. 167, no. 3, p. 59, Aug. 2021, doi: 10.1007/s10584-021-03182-1.
- [30] S. M. Jang and P. S. Hart, “Polarized frames on ‘climate change’ and ‘global warming’ across countries and states: Evidence from Twitter big data,” *Glob. Environ. Change*, vol. 32, pp. 11–17, May 2015, doi: 10.1016/j.gloenvcha.2015.02.010.
- [31] M. Falkenberg *et al.*, “Growing polarization around climate change on social media,” *Nat. Clim. Change*, vol. 12, no. 12, Art. no. 12, Dec. 2022, doi: 10.1038/s41558-022-01527-x.
- [32] C. Yu, D. B. Margolin, J. R. Fownes, D. L. Eiseman, A. M. Chatrchyan, and S. B. Allred, “Tweeting About Climate: Which Politicians Speak Up and What Do They Speak Up About?,” *Soc. Media Soc.*, vol. 7, no. 3, p. 20563051211033816, Jul. 2021, doi: 10.1177/20563051211033815.
- [33] W. Shi, H. Fu, P. Wang, C. Chen, and J. Xiong, “#Climatechange vs. #Globalwarming: Characterizing Two Competing Climate Discourses on Twitter with Semantic Network and Temporal Analyses,” *Int. J. Environ. Res. Public. Health*, vol. 17, no. 3, p. 1062,

- 2020, doi: 10.3390/ijerph17031062.
- [34] S. Y. Kim, K. Ganesan, P. Dickens, and S. Panda, “Public Sentiment toward Solar Energy—Opinion Mining of Twitter Using a Transformer-Based Language Model,” *Sustainability*, vol. 13, no. 5, Art. no. 5, Jan. 2021, doi: 10.3390/su13052673.
- [35] A. S. de Rosa, E. Bocci, M. Bonito, and M. Salvati, “Twitter as social media arena for polarised social representations about the (im)migration: The controversial discourse in the Italian and international political frame,” *Migr. Stud.*, vol. 9, no. 3, pp. 1167–1194, Sep. 2021, doi: 10.1093/migration/mnab001.
- [36] M. G. Özerim and J. Tolay, “Discussing the Populist Features of Anti-refugee Discourses on Social Media: An Anti-Syrian Hashtag in Turkish Twitter,” *J. Refug. Stud.*, vol. 34, no. 1, pp. 204–218, Mar. 2021, doi: 10.1093/jrs/feaa022.
- [37] X. Jiang *et al.*, “Polarization Over Vaccination: Ideological Differences in Twitter Expression About COVID-19 Vaccine Favorability and Specific Hesitancy Concerns,” *Soc. Media Soc.*, vol. 7, no. 3, p. 20563051211048412, Jul. 2021, doi: 10.1177/20563051211048413.
- [38] C. Luther, B. Horne, and X. Zhang, “Partisanship over security: Public narratives via Twitter on foreign interferences in the 2016 and 2020 U.S. presidential elections,” *First Monday*, Jul. 2021, doi: 10.5210/fm.v26i8.11682.
- [39] E. Hernández, E. Anduiza, and G. Rico, “Affective polarization and the salience of elections,” *Elect. Stud.*, vol. 69, p. 102203, Feb. 2021, doi: 10.1016/j.electstud.2020.102203.
- [40] R. J. Dalton, “Modeling ideological polarization in democratic party systems,” *Elect. Stud.*, vol. 72, p. 102346, Aug. 2021, doi: 10.1016/j.electstud.2021.102346.
- [41] J. P. Schöne, B. Parkinson, and A. Goldenberg, “Negativity Spreads More than Positivity on Twitter After Both Positive and Negative Political Situations,” *Affect. Sci.*, vol. 2, no. 4, pp. 379–390, Dec. 2021, doi: 10.1007/s42761-021-00057-7.
- [42] B. Evkoski, N. Ljubešić, A. Pelicon, I. Mozetič, and P. Kralj Novak, “Evolution of topics and hate speech in retweet network communities,” *Appl. Netw. Sci.*, vol. 6, no. 1, p. 96, 2021, doi: 10.1007/s41109-021-00439-7.
- [43] M. Conover, J. Ratkiewicz, M. Francisco, B. Goncalves, F. Menczer, and A. Flammini, “Political Polarization on Twitter,” *Proc. Int. AAAI Conf. Web Soc. Media*, vol. 5, no. 1, Art. no. 1, 2011, doi: 10.1609/icwsm.v5i1.14126.
- [44] J. M. Chamberlain, F. Spezzano, J. J. Kettler, and B. Dit, “A Network Analysis of Twitter Interactions by Members of the U.S. Congress,” *ACM Trans. Soc. Comput.*, vol. 4, no. 1, p. 1:1-1:22, Feb. 2021, doi: 10.1145/3439827.
- [45] A. Borah and S. R. Singh, “Investigating political polarization in India through the lens of Twitter,” *Soc. Netw. Anal. Min.*, vol. 12, no. 1, p. 97, Jul. 2022, doi: 10.1007/s13278-022-00939-z.
- [46] D. Gunnarsson Lorentzen, “Polarisation in political Twitter conversations,” *Aslib J. Inf. Manag.*, vol. 66, no. 3, pp. 329–341, Jan. 2014, doi: 10.1108/AJIM-09-2013-0086.
- [47] K. Garcia and L. Berton, “Topic detection and sentiment analysis in Twitter content related to COVID-19 from Brazil and the USA,” *Appl. Soft Comput.*, vol. 101, p. 107057, Mar. 2021, doi: 10.1016/j.asoc.2020.107057.
- [48] Y. Hswen, X. Xu, A. Hing, J. B. Hawkins, J. S. Brownstein, and G. C. Gee, “Association of ‘#covid19’ Versus ‘#chinesevirus’ With Anti-Asian Sentiments on Twitter: March 9–23, 2020,” *Am. J. Public Health*, vol. 111, no. 5, pp. e1–e9, 2021, doi: 10.2105/ajph.2021.306154.
- [49] S. Criss *et al.*, “Advocacy, Hesitancy, and Equity: Exploring U.S. Race-Related Discussions of the COVID-19 Vaccine on Twitter,” *Int. J. Environ. Res. Public. Health*, vol. 18, no. 11, p. 5693, 2021, doi: 10.3390/ijerph18115693.

- [50] D. R. Prabhakar Kaila and D. A. V. K. Prasad, “Informational Flow on Twitter – Corona Virus Outbreak – Topic Modelling Approach.” Rochester, NY, Mar. 31, 2020. Accessed: Sep. 11, 2022. [Online]. Available: <https://papers.ssrn.com/abstract=3565169>
- [51] C. R. Machuca, C. Gallardo, and R. M. Toasa, “Twitter Sentiment Analysis on Coronavirus: Machine Learning Approach,” *J. Phys. Conf. Ser.*, vol. 1828, no. 1, p. 012104, Feb. 2021, doi: 10.1088/1742-6596/1828/1/012104.
- [52] U. Naseem, I. Razzak, M. Khushi, P. W. Eklund, and J. Kim, “COVIDSenti: A Large-Scale Benchmark Twitter Data Set for COVID-19 Sentiment Analysis,” *IEEE Trans. Comput. Soc. Syst.*, vol. 8, no. 4, pp. 1003–1015, Aug. 2021, doi: 10.1109/TCSS.2021.3051189.
- [53] Y. Hswen *et al.*, “Racial and Ethnic Disparities in Patient Experiences in the United States: 4-Year Content Analysis of Twitter,” *J. Med. Internet Res.*, vol. 22, no. 8, p. e17048, 2020, doi: 10.2196/17048.
- [54] R. Marcec and R. Likic, “Using Twitter for sentiment analysis towards AstraZeneca/Oxford, Pfizer/BioNTech and Moderna COVID-19 vaccines,” *Postgrad. Med. J.*, vol. 98, no. 1161, pp. 544–550, Jul. 2022, doi: 10.1136/postgradmedj-2021-140685.
- [55] S. R. Rufai and C. Bunce, “World leaders’ usage of Twitter in response to the COVID-19 pandemic: a content analysis,” *J. Public Health*, vol. 42, no. 3, p. fdaa049, 2020, doi: 10.1093/pubmed/fdaa049.
- [56] R. Goel and R. Sharma, “Studying leaders & their concerns using online social media during the times of crisis - A COVID case study,” *Soc. Netw. Anal. Min.*, vol. 11, no. 1, p. 46, doi: 10.1007/s13278-021-00756-w.
- [57] P. Samanta, P. Kumar, S. Dutta, M. Chatterjee, and D. Sarkar, “Depression Detection from Twitter Data Using Two Level Multi-modal Feature Extraction,” in *Data Management, Analytics and Innovation*, Singapore, 2023, pp. 451–465. doi: 10.1007/978-981-19-2600-6_32.
- [58] W. Budiharto and M. Meiliana, “Prediction and analysis of Indonesia Presidential election from Twitter using sentiment analysis,” *J. Big Data*, vol. 5, no. 1, p. 51, Dec. 2018, doi: 10.1186/s40537-018-0164-1.
- [59] H. N. Chaudhry *et al.*, “Sentiment Analysis of before and after Elections: Twitter Data of U.S. Election 2020,” *Electronics*, vol. 10, no. 17, Art. no. 17, Jan. 2021, doi: 10.3390/electronics10172082.
- [60] G. A. Ruz, P. A. Henríquez, and A. Mascareño, “Sentiment analysis of Twitter data during critical events through Bayesian networks classifiers,” *Future Gener. Comput. Syst.*, vol. 106, pp. 92–104, May 2020, doi: 10.1016/j.future.2020.01.005.
- [61] M. Osmundsen, A. Bor, P. B. Vahlstrup, A. Bechmann, and M. B. Petersen, “Partisan Polarization Is the Primary Psychological Motivation behind Political Fake News Sharing on Twitter,” *Am. Polit. Sci. Rev.*, vol. 115, no. 3, pp. 999–1015, Aug. 2021, doi: 10.1017/S0003055421000290.
- [62] Y. Wang, M. McKee, A. Torbica, and D. Stuckler, “Systematic literature review on the spread of health-related misinformation on social media,” *Soc. Sci. Med.*, vol. 240, p. 112552, 2019, doi: 10.1016/j.socscimed.2019.112552.
- [63] S. Ohtani, “How is People’s Awareness of ‘Biodiversity’ Measured? Using Sentiment Analysis and LDA Topic Modeling in the Twitter Discourse Space from 2010 to 2020,” *SN Comput. Sci.*, vol. 3, no. 5, p. 371, 2022, doi: 10.1007/s42979-022-01276-w.
- [64] A. Khatua, E. Cambria, K. Ghosh, N. Chaki, and A. Khatua, “Tweeting in Support of LGBT? A Deep Learning Approach,” in *Proceedings of the ACM India Joint International Conference on Data Science and Management of Data*, New York, NY, USA, Jan. 2019, pp. 342–345. doi: 10.1145/3297001.3297057.

- [65] V. A. Fitri, R. Andreswari, and M. A. Hasibuan, “Sentiment Analysis of Social Media Twitter with Case of Anti-LGBT Campaign in Indonesia using Naïve Bayes, Decision Tree, and Random Forest Algorithm,” *Procedia Comput. Sci.*, vol. 161, pp. 765–772, Jan. 2019, doi: 10.1016/j.procs.2019.11.181.
- [66] E. Bartelt, “LGBTQ+ Abortion Discourse Analysis of Twitter Users,” May 2020, Accessed: Dec. 12, 2022. [Online]. Available: <https://scholarworks.iu.edu/dspace/handle/2022/25486>
- [67] C. M. Castorena, I. M. Abundez, R. Alejo, E. E. Granda-Gutiérrez, E. Rendón, and O. Villegas, “Deep Neural Network for Gender-Based Violence Detection on Twitter Messages,” *Mathematics*, vol. 9, no. 8, Art. no. 8, Jan. 2021, doi: 10.3390/math9080807.
- [68] K. Solovev and N. Pröllochs, “Hate Speech in the Political Discourse on Social Media: Disparities Across Parties, Gender, and Ethnicity,” in *Proceedings of the ACM Web Conference 2022*, New York, NY, USA, Apr. 2022, pp. 3656–3661. doi: 10.1145/3485447.3512261.
- [69] S. Behl, A. Rao, S. Aggarwal, S. Chadha, and H. S. Pannu, “Twitter for disaster relief through sentiment analysis for COVID-19 and natural hazard crises,” *Int. J. Disaster Risk Reduct.*, vol. 55, p. 102101, Mar. 2021, doi: 10.1016/j.ijdrr.2021.102101.
- [70] T. Sakaki, M. Okazaki, and Y. Matsuo, “Earthquake shakes Twitter users: real-time event detection by social sensors,” in *Proceedings of the 19th international conference on World wide web - WWW '10*, 2010, pp. 851–860. doi: 10.1145/1772690.1772777.
- [71] Q. Hou and M. Han, “Incorporating Content Beyond Text: A High Reliable Twitter-Based Disaster Information System,” in *Computational Data and Social Networks*, Cham, 2019, pp. 282–292. doi: 10.1007/978-3-030-34980-6_31.
- [72] M. Mendoza, B. Poblete, and I. Valderrama, “Nowcasting earthquake damages with Twitter,” *EPJ Data Sci.*, vol. 8, no. 1, p. 3, Jan. 2019, doi: 10.1140/epjds/s13688-019-0181-0.
- [73] P. Rajendiran and P. L. K. Priyadarsini, “Survival study on stock market prediction techniques using sentimental analysis,” *Mater. Today Proc.*, Jul. 2021, doi: 10.1016/j.matpr.2021.07.217.
- [74] T. Swathi, N. Kasiviswanath, and A. A. Rao, “An optimal deep learning-based LSTM for stock price prediction using twitter sentiment analysis,” *Appl. Intell.*, vol. 52, no. 12, pp. 13675–13688, Sep. 2022, doi: 10.1007/s10489-022-03175-2.
- [75] F. Napitu, Moch. A. Bijaksana, A. Trisetyarso, and Y. Heryadi, “Twitter opinion mining predicts broadband internet’s customer churn rate,” in *2017 IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom)*, Nov. 2017, pp. 141–146. doi: 10.1109/CYBERNETICSCOM.2017.8311699.
- [76] I. K. A. Aryadinata, D. Pangesti, G. B. Anugerah, I. E. Aditya, and Y. Ruldeviyani, “Sentiment Analysis of 5G Network Implementation in Indonesia Using Twitter Data,” in *2021 6th International Workshop on Big Data and Information Security (IWBIS)*, Depok, Indonesia, Oct. 2021, pp. 23–28. doi: 10.1109/IWBIS53353.2021.9631863.
- [77] E. J. Oughton and W. Lehr, “Surveying 5G Techno-Economic Research to Inform the Evaluation of 6G Wireless Technologies,” *IEEE Access*, vol. 10, pp. 25237–25257, 2022, doi: 10.1109/ACCESS.2022.3153046.
- [78] E. J. Oughton, “Policy options for broadband infrastructure strategies: A simulation model for affordable universal broadband in Africa,” *Telemat. Inform.*, vol. 76, p. 101908, Jan. 2023, doi: 10.1016/j.tele.2022.101908.
- [79] E. J. Oughton, D. Amaglobeli, and M. Moszoro, “Estimating Digital Infrastructure Investment Needs to Achieve Universal Broadband,” *IMF Work. Pap.*, vol. Working Paper No. 2023/027, 2023, Accessed: Feb. 15, 2023. [Online]. Available: https://scholar.google.co.uk/citations?view_op=view_citation&hl=en&user=ZsyYn4cA

- AAAJ&sortby=pubdate&citation_for_view=ZsyYn4cAAAAJ:dfsIfKJdRG4C
- [80] P. Martí, L. Serrano-Estrada, and A. Nolasco-Cirugeda, “Social Media data: Challenges, opportunities and limitations in urban studies,” *Comput. Environ. Urban Syst.*, vol. 74, pp. 161–174, Mar. 2019, doi: 10.1016/j.compenvurbsys.2018.11.001.
 - [81] D. Sharma, M. Sabharwal, V. Goyal, and M. Vij, “Sentiment Analysis Techniques for Social Media Data: A Review,” in *First International Conference on Sustainable Technologies for Computational Intelligence*, Singapore, 2020, pp. 75–90. doi: 10.1007/978-981-15-0029-9_7.
 - [82] M. Khan and A. Malviya, “Big data approach for sentiment analysis of twitter data using Hadoop framework and deep learning,” in *2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE)*, Feb. 2020, pp. 1–5. doi: 10.1109/ic-ETITE47903.2020.901.
 - [83] A. P. Rodrigues and N. N. Chiplunkar, “A new big data approach for topic classification and sentiment analysis of Twitter data,” *Evol. Intell.*, vol. 15, no. 2, pp. 877–887, Jun. 2022, doi: 10.1007/s12065-019-00236-3.
 - [84] F. Huszár, S. I. Ktena, C. O’Brien, L. Belli, A. Schlaikjer, and M. Hardt, “Algorithmic amplification of politics on Twitter,” *Proc. Natl. Acad. Sci.*, vol. 119, no. 1, p. e2025334119, Jan. 2022, doi: 10.1073/pnas.2025334119.
 - [85] V. Kandasamy *et al.*, “Sentimental Analysis of COVID-19 Related Messages in Social Networks by Involving an N-Gram Stacked Autoencoder Integrated in an Ensemble Learning Scheme,” *Sensors*, vol. 21, no. 22, p. 7582, 2021, doi: 10.3390/s21227582.
 - [86] D. Labonte and I. H. Rowlands, “Tweets and transitions: Exploring Twitter-based political discourse regarding energy and electricity in Ontario, Canada,” *Energy Res. Soc. Sci.*, vol. 72, p. 101870, Feb. 2021, doi: 10.1016/j.erss.2020.101870.
 - [87] S. C. McGregor and R. R. Mourão, “Talking Politics on Twitter: Gender, Elections, and Social Networks,” *Soc. Media Soc.*, vol. 2, no. 3, p. 2056305116664218, Jul. 2016, doi: 10.1177/2056305116664218.
 - [88] N. Rogers and J. J. Jones, “Using Twitter Bios to Measure Changes in Self-Identity: Are Americans Defining Themselves More Politically Over Time?,” *J. Soc. Comput.*, vol. 2, no. 1, pp. 1–13, Mar. 2021, doi: 10.23919/JSC.2021.0002.
 - [89] A. A. Jalal and B. H. Ali, “Text documents clustering using data mining techniques,” *Int. J. Electr. Comput. Eng. IJECE*, vol. 11, no. 1, p. 664, Feb. 2021, doi: 10.11591/ijece.v11i1.pp664-670.
 - [90] K. Isoaho, D. Gritsenko, and E. Mäkelä, “Topic Modeling and Text Analysis for Qualitative Policy Research,” *Policy Stud. J.*, vol. 49, no. 1, pp. 300–324, 2021, doi: 10.1111/psj.12343.
 - [91] E. S. Negara, D. Triadi, and R. Andryani, “Topic Modelling Twitter Data with Latent Dirichlet Allocation Method,” in *2019 International Conference on Electrical Engineering and Computer Science (ICECOS)*, Oct. 2019, pp. 386–390. doi: 10.1109/ICECOS47637.2019.8984523.
 - [92] S. A. Curiskis, B. Drake, T. R. Osborn, and P. J. Kennedy, “An evaluation of document clustering and topic modelling in two online social networks: Twitter and Reddit,” *Inf. Process. Manag.*, vol. 57, no. 2, p. 102034, Mar. 2020, doi: 10.1016/j.ipm.2019.04.002.
 - [93] M. Elsaid Moussa, E. Hussein Mohamed, and M. Hassan Haggag, “Opinion mining: a hybrid framework based on lexicon and machine learning approaches,” *Int. J. Comput. Appl.*, vol. 43, no. 8, pp. 786–794, Sep. 2021, doi: 10.1080/1206212X.2019.1615250.
 - [94] K. Sailunaz and R. Alhajj, “Emotion and sentiment analysis from Twitter text,” *J. Comput. Sci.*, vol. 36, p. 101003, Sep. 2019, doi: 10.1016/j.jocs.2019.05.009.
 - [95] A. Giachanou and F. Crestani, “Like It or Not: A Survey of Twitter Sentiment Analysis Methods,” *ACM Comput. Surv.*, vol. 49, no. 2, p. 28:1-28:41, Jun. 2016, doi:

10.1145/2938640.

- [96] C. Diamantini, A. Mircoli, D. Potena, and E. Storti, “Social information discovery enhanced by sentiment analysis techniques,” *Future Gener. Comput. Syst.*, vol. 95, pp. 816–828, Jun. 2019, doi: 10.1016/j.future.2018.01.051.
- [97] S. Zad, M. Heidari, J. H. Jones, and O. Uzuner, “A Survey on Concept-Level Sentiment Analysis Techniques of Textual Data,” in *2021 IEEE World AI IoT Congress (AIIoT)*, May 2021, pp. 0285–0291. doi: 10.1109/AIIoT52608.2021.9454169.
- [98] M. Bibi *et al.*, “A novel unsupervised ensemble framework using concept-based linguistic methods and machine learning for twitter sentiment analysis,” *Pattern Recognit. Lett.*, vol. 158, pp. 80–86, Jun. 2022, doi: 10.1016/j.patrec.2022.04.004.
- [99] Z. Zhang, D. Robinson, and J. Tepper, “Detecting Hate Speech on Twitter Using a Convolution-GRU Based Deep Neural Network,” in *The Semantic Web*, Cham, 2018, pp. 745–760. doi: 10.1007/978-3-319-93417-4_48.
- [100] U. D. Gandhi, P. Malarvizhi Kumar, G. Chandra Babu, and G. Karthick, “Sentiment Analysis on Twitter Data by Using Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM),” *Wirel. Pers. Commun.*, May 2021, doi: 10.1007/s11277-021-08580-3.
- [101] B. AlBadani, R. Shi, and J. Dong, “A Novel Machine Learning Approach for Sentiment Analysis on Twitter Incorporating the Universal Language Model Fine-Tuning and SVM,” *Appl. Syst. Innov.*, vol. 5, no. 1, Art. no. 1, Feb. 2022, doi: 10.3390/asi5010013.
- [102] F. Barbieri, L. Espinosa Anke, and J. Camacho-Collados, “XLM-T: Multilingual Language Models in Twitter for Sentiment Analysis and Beyond,” in *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, Marseille, France, Jun. 2022, pp. 258–266. Accessed: Dec. 15, 2022. [Online]. Available: <https://aclanthology.org/2022.lrec-1.27>
- [103] Z. Xiao *et al.*, “Detecting Political Biases of Named Entities and Hashtags on Twitter,” Sep. 2022. Accessed: Dec. 16, 2022. [Online]. Available: <https://ui.adsabs.harvard.edu/abs/2022arXiv220908110X>
- [104] N. Yadav, O. Kudale, A. Rao, S. Gupta, and A. Shitole, “Twitter Sentiment Analysis Using Supervised Machine Learning,” in *Intelligent Data Communication Technologies and Internet of Things*, Singapore, 2021, pp. 631–642. doi: 10.1007/978-981-15-9509-7_51.
- [105] U. Naseem, I. Razzak, and P. W. Eklund, “A survey of pre-processing techniques to improve short-text quality: a case study on hate speech detection on twitter,” *Multimed. Tools Appl.*, vol. 80, no. 28, pp. 35239–35266, Nov. 2021, doi: 10.1007/s11042-020-10082-6.
- [106] N. Nasser, L. Karim, A. El Ouadhriri, A. Ali, and N. Khan, “n-Gram based language processing using Twitter dataset to identify COVID-19 patients,” *Sustain. Cities Soc.*, vol. 72, p. 103048, Sep. 2021, doi: 10.1016/j.scs.2021.103048.
- [107] “Members of the United States Congress,” *GovTrack.us*. <https://www.govtrack.us/congress/members> (accessed Feb. 24, 2023).
- [108] D. Bor and O. Edward, “Quantifying polarization across political groups Twitter Dataset.” Zenodo, Feb. 10, 2023. doi: 10.5281/zenodo.7628481.
- [109] D. Bor, “Quantifying polarization across political groups on key policy issues using sentiment analysis.” Feb. 10, 2023. Accessed: Feb. 15, 2023. [Online]. Available: https://github.com/denniesbor/twitter_political_polarization
- [110] A. Goldstein, “US–China Rivalry in the twenty-first century: Déjà vu and Cold War II,” *China Int. Strategy Rev.*, vol. 2, no. 1, pp. 48–62, Jun. 2020, doi: 10.1007/s42533-020-00036-w.

- [111] N. Yuan, “Reflections on China–US relations after the COVID-19 pandemic,” *China Int. Strategy Rev.*, vol. 2, no. 1, pp. 14–23, Jun. 2020, doi: 10.1007/s42533-020-00049-5.
- [112] S. K. Moore, “Another step toward the end of Moore’s law: Samsung and TSMC move to 5-nanometer manufacturing - [News],” *IEEE Spectr.*, vol. 56, no. 6, pp. 9–10, Jun. 2019, doi: 10.1109/MSPEC.2019.8727133.
- [113] M. A. Peters, “Semiconductors, geopolitics and technological rivalry: the US CHIPS & Science Act, 2022,” *Educ. Philos. Theory*, vol. 0, no. 0, pp. 1–5, Sep. 2022, doi: 10.1080/00131857.2022.2124914.

Appendix

Table A1. Descriptive Statistics

Policy	Metric	Far Left	Far Right	Left Centrist	Right Centrist
Abortion	Count	1177	495	1934	671
	Mean	0.191	0.037	0.183	0.095
	Median	0.318	0	0.361	0.094
	STD	0.577	0.541	0.606	0.569
Broadband Internet	Count	204	184	1331	434
	Mean	0.35	0.324	0.443	0.445
	Median	0.402	0.44	0.557	0.599
	STD	0.431	0.484	0.403	0.442
Chinese Communist Party	Count	138	1729	361	2571
	Mean	0.029	0.054	0.147	0.058
	Median	0.115	0.024	0.25	0.052
	STD	0.601	0.536	0.601	0.551
CHIPS and Science Act	Count	51	34	291	83
	Mean	0.343	0.115	0.491	0.309
	Median	0.45	0.115	0.637	0.382
	STD	0.453	0.467	0.43	0.491
Climate Change	Count	2363	366	5609	883
	Mean	0.182	0.093	0.234	0.224
	Median	0.318	0.166	0.402	0.351
	STD	0.595	0.577	0.582	0.555
Fossil Fuels	Count	741	788	1361	1728
	Mean	0.01	-0.083	0.111	0.023
	Median	0.026	-0.077	0.128	0
	STD	0.569	0.536	0.55	0.548
Gun Control	Count	2253	893	6088	1468
	Mean	-0.386	-0.244	-0.353	-0.164
	Median	-0.649	-0.402	-0.623	-0.311
	STD	0.594	0.587	0.614	0.602
Immigration and Border Control	Count	1422	4361	2423	7180
	Mean	0.237	-0.308	0.323	-0.288
	Median	0.402	-0.48	0.511	-0.477
	STD	0.597	0.541	0.562	0.558
LGBTQ Community	Count	655	4	1597	30
	Mean	0.284	0.029	0.303	0.159
	Median	0.468	0.058	0.542	0.384
	STD	0.607	0.466	0.613	0.745
Substance Abuse and Mental Health	Count	825	405	2134	833
	Mean	0.065	-0.033	0.128	0.048
	Median	0.103	-0.048	0.291	0.103
	STD	0.636	0.643	0.661	0.646
Taiwan	Count	21	227	53	210
	Mean	0.41	0.24	0.327	0.2
	Median	0.681	0.382	0.44	0.307
	STD	0.587	0.588	0.528	0.58
Ukraine-Russia	Count	918	1706	2873	3215
	Mean	-0.024	-0.078	0.043	0
	Median	0	-0.052	0.026	0
	STD	0.612	0.553	0.617	0.567