Resistance at the precipice of change: A case study of defensive mechanisms in right-wing online discourse

MSc Social and Cultural Psychology dissertation

Candidate number: 18682
Word count: 9,987

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Acknowledgements: Thanks to my supervisor, Celestin, for invaluable practical wisdom and support. Thanks also goes to Alex Goddard for providing NLP inspiration and technical help with R; and also to Alex Gillespie for keeping me grounded. Finally, thanks goes to my partner, Amy, for putting up with me over the last few months.

Table of contents

1. Abstract

This study explores 25,000 posts taken from the right-wing and conservative social media site, Parler, during the US Capitol Riots of January 6th 2021. Emerging from the theoretical tradition of Dialogism, this research asks what semantic strategies of resistance are used to defend against the disruption of the other? Parler is theorised as a 'monological' communicative context, with an absent critical other. This research uses a triangulation of methods, employing Natural Language Processing (NLP) alongside qualitative research. Firstly, a dictionary analysis using moral words finds a dichotomization where the in-group is characterised as on the side of God and American revolutionary history, whereas the other is represented as evil and cheating. Secondly, an algorithmic form of computerised content analysis, called topic modelling, is constructed to find the main topics of discourse. Finally, a dialogical analysis of 10 topics is used to qualitatively understand the semantic barriers (Gillespie, 2020a, 2020b) used to resist the perspective of others. These were predominantly tactics of avoiding and delegitimising, including (but not limited to) deflecting, distracting, stereotyping and stigmatising. It is argued that combining NLP with qualitative research is fruitful for analysing semantic barriers in large data sets. It is recommended that future research pay attention to the relationship between defensive strategies and the mechanisms of social representations, as well as specific thinking styles.

2. Introduction

On January 6th 2021, at a peak of significant tensions within US politics and culture, a mass of right-wing Republicans stormed the Capitol Hill building in an attempted coup (Bauder, 2021), to resist and reverse the 2020 election result. The rioting lead to numerous injuries and five deaths (Evelyn, 2021). Simultaneously, users on the right-wing dominated, 'free speech' social media site, Parler, were inciting violence and mobilising participation (Nicas & Alba, 2021). Consequently, Parler has been described as a 'preparatory medium' (Munn, 2021), in the way it was used to frame events, identify audiences, set agendas, and enforce the discourse towards a certain goal (Baines et al., 2021).

Because of the evidently problematic nature of isolated, extreme right-wing discourse, it is important to understand the social-psychological factors underneath the proliferation of such views online. Therefore, following Societal Psychology (Himmelweit & Gaskell, 1990), this research aims to play a small part in contributing to the knowledge of social change through the examination of a real world context (Howarth et al., 2013).

To achieve this goal, this paper adopts the tradition of Dialogism, that claims interaction and context are key to human communication and cognition (Linell, 2003), and focuses on the internal conflict between self and other that makes the human mind a fundamentally social entity (Marková, 2003). This conflict is seen to give way to the use of defensive mechanisms to resist the disruptive perspective of the other. These mechanisms appear in individual's use of language, and are therefore known as semantic barriers (Gillespie, 2020a, 2020b). Because social identities depend upon socially shared common knowledge (Marková, 2007), defensive mechanisms themselves are tools shared among members of social groups (Gillespie, 2020a; Gillespie & Zittoun, 2010), and therefore may be studied at the group level.

From this theoretical perspective, it is asked, how are self and other represented in opposition to one another by Parler users? And what defensive tactics are used to dismiss the other? In focusing on a unique case of a right-wing social milieu, and therefore a communicative context lacking a critical other, this research seeks to expand the Dialogism tradition and add to the literature on rhetorical strategies of defence.

3. Literature review

This section elaborates on the tradition of Dialogism in psychology and is explained as the theoretical background to semantic barriers, then it is argued that Parler is 'monological'.

Research questions are stated, and it is further argued that studying defensive strategies in such a context explores a gap in the literature. Finally, a justification is given for the combination of methods used.

3.1 Dialogism – a society of mind

Dialogism is a socio-psychological and epistemological framework that stresses interaction and context to be fundamental to human communication and cognition (Linell, 2003). Mikhail Bakhtin crystallised an existing Hegelian conception of mind that saw the self to be determined by an internal clash of self and other by introducing a semantic focus, and contending that the human experience is "living in a world of other's words" (Bakhtin, 1986, p.143). For Bakhtin, the mind is orientated to this world of words throughout life, and this orientation defines the nature of consciousness itself (Bakhtin, 1986). The role of the self-other relationship in cognition is mirrored in the work of Vygotsky. Here human development is understood as a process of learning the words of others from the earliest stages of cognition, where the words themselves are culturally dependant tools of mediation (L. S. Vygotsky, 1978). Vygotsky succinctly asserts that, "the mechanism of knowing oneself (self-awareness) and the mechanism for knowing others are one and the same" (Vygotsky, 1979, p.29).

A necessary outcome of the fundamentally social nature of the human mind is 'intersubjectivity', that is, the variety of relations between perspectives (Gillespie & Cornish, 2010). Such a conception employs a notion of multiplicity within the mind, as it is perpetually engaged with a variety of interlocuters (Glaveanu, 2019), and therefore 'dialogical' in the way that all symbolic activity is founded on dialogue "between different minds expressing a multitude of multivoiced meanings" (Marková, 2003, p.257). Because dialogism understands there to be a necessary extension of the self outwards towards one's socio-cultural environment, the perspectives of others enter the mind and form positions in disagreement with the ego (Hermans, 2001, 2007). This is conceptualised in Ivana Marková's ego/alter distinction, where the alter – or other self – is co-dependent with the ego and manifested dialogically to give way to the self (Marková, 2006; Marková, 2003).

Importantly, dialogical tensions within the individual can be multifaceted because of the many I-positions a given individual can adopt (Hermans, 2007) and the many others that the self may define itself in opposition to (Aveling et al., 2015). Both identities assigned to the self and voices given to others can take perspectives attributed to social groups, communities and institutions (Aveling et al., 2015). Ego/alter conflict, 'alterity' (Marková, 2003), can therefore reflect social conflict. Fundamentally, it is the communicative intrusion of others into the self-space and the positions the self takes *in opposition* to those others (Marková, 2003) that defines the mind as a social entity, constituted by dialogical tension and conflict.

3.2 A note on social representations

Because of the stated relationship between dialogical tension and perspectives attributed to generalised others, there is a clear link to social knowledge. Firstly, perspectives attributed to others form an aspect of socially shared knowledge (Gillespie, 2008), and secondly, dialogical tension contributes to the social construction of knowledge itself (Gillespie & Cornish, 2010). As Marková states, knowledge is dynamic because of its social co-construction, and individuals within a culture are themselves in a "constant process of becoming" (Marková, 2000, p.435). It is worth acknowledging Social Representation Theory (SRT) (Moscovici, 1988, 2000) to bring all this into a theoretical understanding of social knowledge. According to SRT, social representations are a form of *shared* common knowledge that serve as structures of meaning-making and frameworks for people to guide themselves in the world. They facilitate the understanding of one's social environment (Moscovici, 1981). An important sub type of social representations are 'alternative representations' (Gillespie, 2008). These are representations of the other's ideas, and are 'alter' in the sense of being attributed to other people (Gillespie, 2008). While they allow for communication by giving a perspective to the other, they also maintain distance by reducing the voice of the other to a stereotype. When a social representation exists in ideological opposition to another, the alternative representation exists to mischaracterise and straw-man the other's views (Gillespie, 2008). This itself is a form of defensive strategy designed to block the disruptive other.

3.3 Semantic barriers as strategies of resistance

First outlined by Moscovici (2008), and developed further by Gillespie (Gillespie, 2008, 2020b), semantic barriers are tactics used to prevent dialogical engagement with the other and alternative representations (Gillespie, 2008). They maintain a distance between the self and the other, and "protect the self's universe of meaning from being destabilized" (Gillespie, 2020b).

Semantic barriers occur as an outcome of semantic contact – that is, the "juxtaposition of the views of self with the views of other within a self's stream of thought, talk or text" (Gillespie, 2020, p.22). While the clashing of ideas through semantic contact is necessary for learning it can also be fundamentally threatening and disruptive (Gillespie, 2020a, 2020b). Semantic barriers from a layered defensive system, likened by Gillespie to the biological immune system (Gillespie, 2020a). While there are many kinds of defensive tactics available to the semantic immune system (see Gillespie, 2008, 2020a, 2020b; Sammut et al., 2014), they can be grouped into three *ordered* layers of defence (Gillespie, 2020b).

The first is avoiding (Gillespie, 2020a, 2020b), where the self prevents engagement with the other's disruptive voice. Avoiding tactics are characterised by increasing the distance from the other. A basic form of avoiding is simply *excluding* the other from debate, but avoiding may also take the form of *denying* the other a voice by disagreeing without reason and proper engagement, or *distracting* attention away by overemphasising positive qualities of the self (Cramer, 2014) or raising issues to move the conversation elsewhere. Equally, avoiding may involve *deflecting* responsibility to specified others, especially by placing blame on them (Baumeister et al., 1998).

Next is delegitimizing. Here, the other's voice is invalidated by targeting the source themselves. Fundamentally, delegitimization is about reducing credibility, often by *stereotyping* the other into existing representations of devalued groups (Kadianaki & Andreouli, 2017). This may occur by claiming the out-group is ignorant (Sammut & Sartawi, 2012), or dehumanizing them (Haslam & Loughnan, 2014). Relatedly, *stigmatizing* involves devaluing anyone who voices a disruptive meaning, often via ridicule (Houston & Kramarae, 1991). *Distrusting,* on the other hand, attributes ulterior motives to the other.

The final layer, *limiting*, is where the voice of the other is acknowledged, but the extent of the impact is reduced, often through debate or actual interaction (Gillespie, 2020a). An important limiting tactic is *dichotomizing* (Moscovici, 2008), such as creating an 'us/them, trust/distrust' binary (Avraamidou & Psaltis, 2019). Additionally, limiting can involve *rationalising* away the disruptive meaning, and often takes the form of placing it in a broader context to reduce its impact (Conlon & Murray, 1996).

Importantly, defensive mechanisms themselves are shared tools proliferated among members of social groups (Gillespie, 2020a; Gillespie & Zittoun, 2010). Because the construction of social identities depends on shared common knowledge (Marková, 2007), it can be argued that these defensive mechanisms contribute to the ongoing social co-construction of identity within the self-other-object triangle. Because of this, it is important to note that semantic barriers relate to the social construction of identities.

3.4 Audience – Parler as monological

The other has a second role, beyond providing disruption; that is, as audience (Gillespie, 2020a). As a threat, the presence of an audience who can call out use of defensive tactics

(Gillespie, 2020a; Grenier et al., 2012) encourages the self to use stealth to avoid detection (Gillespie, 2020a). But, in the case of isolated Parler users participating in a right-wing online forum, who is the audience and who is the other? It is argued that the audience in this case is not the 'other' in the sense of outgroups, because this homogenous group are talking among themselves, *within* their group. The outgroup others - Democrats, BLM, Antifa etc. – named here as 'ideological others', are not directly present and therefore not demanding subtlety from those speaking.

A distinction can be made between two kinds of communicative contexts. There are those that are open to dialogical interaction with the other, leading to positive creativity and learning, and those that are more 'monological', in the sense that they aim more towards a one way flow of information (Marková, 2008), which is uncritically challenged and encourages so called 'groupthink' (de Saint Laurent et al., 2020; Janis, 1982). This latter form is strongly reminiscent of Marková's theorising of 'propaganda', that is "part of the ideological […] programmes of institutions or organizations" with the goal "to transform the heterogeneous thoughts of individuals into those of a homogeneous collective mind" (Marková, 2008, p.41).

The institutional nature of propaganda-like communication is worth stressing here, as it is well known that text and talk are situated in and partly determined by their institutional contexts (Gillespie & Cornish, 2010; Markku Haakana et al., 2016; Heritage, 2005). Given that an institution is an organisation or collective entity that that impresses regularities of certain collective experiences upon its inhabitants (Elcheroth et al., 2011), it is sensible to construe specific examples of mass and social media as institutions (Silverblatt, 2004; van Dijck & Poell, 2013), and the talk therein as institutionalised talk.

Two things relate this to Parler. Firstly, users flocked to the site out of a dissatisfaction with content moderation and governance on mainstream sites and Parler's comparatively minute community guidelines (Otala et al., 2021). Secondly, because of the conservative preoccupation with free speech and because several major conservative figures endorsed the platform (Baines et al., 2021), the userbase was populated by an overwhelming proportion of conservative and right-wing users (Hitkul et al., 2021). In light of this and the above theoretical outlay, it is contended that Parler is a 'monological' discursive institution lacking a critical other. Arguably, these dynamics have contributed to the proliferation of unsubstantiated, conspiracy-like discourse on Parler (Baines et al., 2021; Pieroni et al., 2021).

3.5 Literature gap and research questions

A survey of the literature on semantic barriers from the Dialogism perspective finds the majority of research to concern cases where a critical other is much more immediately present than in this case, though Castro & Santos (2020) offer an interesting alternative. Examples of this include literature on crossing cultural borders (Gillespie et al., 2012), employing vulgar language in conversation (Sammut et al., 2014), analysing representations of intercultural conflict in newspapers (Avraamidou & Psaltis, 2019) or intercultural conflict more broadly (Kadianaki & Andreouli, 2017; Nicholson, 2016). Similar research tends to concern comparative analysis of representations of certain concepts commonly held across different groups, such as meat-eating among meat eaters and vegetarians (Panagiotou & Kadianaki, 2019), rather than focusing semantic barriers used by one group in a 'monological' space at a particular time. Furthermore, by considering a drastically non-transformative example of social communication, this research departs from literature concerned with dialogue in the positive sense of social possibility (Glăveanu, 2020) and transformation (Cooper et al., 2013), to examine how it operates in the reverse direction.

Finally, there is little research on social media emanating from the dialogical tradition, with some notable exceptions focusing on the creative potential of the online space (de Saint Laurent et al., 2020; Glăveanu & de Saint Laurent, 2021). However, by looking at this unique context, this research seeks to make a contribution to the literature around online ideological discourse from within this tradition.

With these literature gaps in mind, and emerging from the preceding theoretical outlay, the research questions ask:

In the context of 'monological' Parler discourse on January 6th 2021,

RQ 1: What defensive strategies were used to dismiss the other?

Sub RQ: How were self and other represented in opposition to one another?

3.6 Methodological considerations

Because this research is interested in linguistic, textual expressions that emerge from the online everyday construction of shared reality, this is befitting of a qualitative analysis (Flick et al., 2004). However, this analysis deals with a sample (n=25,000) large enough to go beyond what is possible for manual qualitative methods. As such, quantitative-in-nature, NLP methods are used in combination with traditional qualitative research. NLP refers to a range of computational methods used for analysing naturally occurring unstructured texts to achieve human-like processing (Liddy, 2001), and is used here to find large scale, generalised insights within the corpus to make way for qualitative work that provides 'thick' descriptions (Flick et al., 2004). However, it is important to note that the NLP methods used here, although quantitative based, result in *qualitative* findings, i.e. linguistic expressions of meaning. As such, this research employs a triangulation of methods (Denzin, 2017; Flick, 2018a) as a way of converging upon the same kind of phenomena (Flick, 2018b). The methods used are: an NLP dictionary analysis, leading to a qualitative interpretation of moral expressions; an NLP 'topic model' to probabilistically derive topics of discussion, and a qualitative dialogical analysis to examine defensive mechanisms in more detail.

The majority of research from the dialogism tradition is purely qualitative (Gillespie & Cornish, 2014), because methods seeking to discover definitive findings and not the unfinished nature of meaning are argued as inappropriate for this kind of research (Gillespie & Cornish, 2014; Grossen, 2010; Jackson & Mazzei, 2011). However, because NLP here is designed to lead to qualitative findings about meaning, this research aims to add to the methodological framework of Dialogism, while gently trying to bridge the quantitative/qualitative divide (McKim, 2017; Shah & Corley, 2006). With criticisms of big data research as less reliable and providing more spurious results than qualitative counterparts (Crowston et al., 2012; Shahin, 2016), and criticisms of purely qualitative research as open to researcher bias and lacking reproducibility (Mays & Pope, 1995), this combined methodology hopes to defend against these issues, and increase the validity of the overall study (Hurmerinta-Peltomäki & Nummela, 2006).

NLP and qualitative methods have been used fruitfully together for social media analysis, for example in examining expressions of grief (Patton et al., 2018), the use of memes (Glăveanu & de Saint Laurent, 2021), malevolent creativity (de Saint Laurent et al., 2020), and communication of health issues (Osadchiy et al., 2020). This paper hopes to complement NLP, mixed-methods research.

Finally, returning to Marková, it is argued that the interactions between self and other form a unique relation in each time and context. As such, dialogical research should be conceptualised in terms of single case studies (Marková, 2017b). Although restricted in terms of generalisability, it is argued that dialogical case studies, like this, can lead to 'theoretical' generalisability by looking for “complex and productive data that allow the examination of relevant theories and concepts” (Marková, 2017a, p.42).

4. Data and ethics

4.1 Data collection

A large number of files (n = 1,747,451 million) were downloaded from the Distributed Denial of Secrets[1] website. The files contained posts and comments made on Parler during the Capitol Riots, and which were later scraped by an anonymous member of the organisation. A python script (appendix 11.1) was then used to randomly sample 100,000 files for initial testing. Regular expressions (Friedl, 2006) in conjunction with Text Crawler software were used to extract the relevant data to a CSV. This analysis is only concerned with the text portion of each post/comment, as factors behind post rank and likes are unknown. From the outset this gives equal weight and voice to each text. To preserve anonymity, usernames/handles were not extracted, rather an integer ID column was later created to allow for identification. Again, using regular expressions, html was erased and subsequent empty rows and duplicates removed. After extensive testing of the NLP methods, the final sample size of 25,000 texts was determined because of limitations on computer hardware (this is detailed below). Finally, the data was imported into the statistical programming environment, R, for analysis.

4.2 Ethics

Ethics approval was obtained by the LSE Research and Ethics committee, and a Data Management Plan was created (appendix 11.2). There are three main ethical issues: the data source, consent, and confidentiality. Firstly, although DDOsecrets is a whistle-blower platform like Wikileaks, this dataset was not hacked, but scraped while it was publicly accessible. This is a common practice for academic social science research (see Aliapoulios et al., 2021 for a large example). Relating to the second and third issue together, which are both standard issues with social media research (Moreno et al., 2013), it is not possible to obtain informed consent from the users or 'participants', specifically because this is a large, secondary data

[1] www.ddosecrets.com

set. Because of this, anonymisation is key, and therefore usernames and identifiable information are manually removed from outputs and code sheets. The justification for this research is that it provides a unique opportunity to understand the mechanics of problematic, right-wing discourse. R code is provided for the purposes of replicability.

5. Study 1 – Dictionary analysis

5.1 Methods

All NLP methods used were carried out using the software R and R Studio, and the statistical programming language, also called R (Ihaka & Gentleman, 1996). R is widely used in the social sciences because of its flexibility and ease of use for custom functions (R. Kennedy & Waggoner, 2021), and is well suited to NLP techniques (Silge & Robinson, 2017).

5.1.1 Pre-processing

Firstly, the collection of texts hereafter referred to as the 'corpus' is cleaned. This involves several steps, including removing the most common English words (called stop-words), removing punctuation, and lemmatizing words to reduce them to their root form, for example, 'walked' and 'walking' will become 'walk'. Next, the corpus is transformed into a document-term matrix (DTM), which is a way of mathematically representing the relationship between the frequency of terms and the documents containing them. Consider a (fictional) example:

D1: patriots for trump

D2: trump for president

	for	patriots	president	trump
D1	1	1	0	1
D2	1	0	1	1

Because this approach reduces sentences to their tokenized elements, and word order is not preserved, this is known as the 'bag-of-words' approach (Radovanovic & Ivanovic, 2008). Importantly, the DTM can be used to track words appearing more frequently alongside others, and therefore calculate associations. With a corpus containing a large number of documents and terms, such a matrix can be extremely large. Here the data was limited by the computer's RAM space, thus determining the sample size for this study (n = 25,000).

Finally, the matrix is converted to a 'tidy text' format (Silge & Robinson, 2017), where each token is a row in a table (Wickham, 2014). This is allows for simple data manipulation and for compatibility with several R packages.

5.1.2 Rationale

This method aims to answer the research questions by using a well-researched predefined lexicon of moral words to understand, on a broad level across the corpus, how moral rhetoric is used to represent self and other. Moral words are quantified, placed into context by statistical association with other words, and then trends are qualitatively derived by looking at individual texts.

Psychology has seen widespread use of lexicon based approaches, thanks to the development of the Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2007). For example, lexicons have been used in conjunction with LIWC to measure psychological change over time by analysing diaries (Cohn et al., 2004), the association between personality types and word use (Hirsh & Peterson, 2009), and the relationship between social-media discourse and policy adoption (Zhang & Counts, 2015). Lexicon approaches categorise lists of words and then quantify them within the corpus or individual documents. A popular example is sentiment analysis (Liu, 2012), where lexicons containing positive and negative categories are used to score polarity. Such lexicons are rigorously researched, and often used in a specific context, like the AFINN lexicon for social media (Nielsen, 2011) or the Bing lexicon for opinion in relation to financial markets (Loughran & McDonald, 2020).

The Moral Foundations dictionary developed out of Haidt and Graham's Moral Foundations Theory (MFT) (Graham et al., 2013) that claims there are five moral foundations: Sanctity, loyalty, authority, care and fairness. This research is not concerned with testing the details of Moral Foundations Theory (MFT) *per se*, but it is worth noting two findings from MFT. Firstly, moral rhetoric is used to bolster one's position on a given issue by making noticeable moral concerns (Sagi & Dehghani, 2014), meaning moral rhetoric can be expected in this corpus. Secondly, compared to liberals, conservatives endorse the three binding foundations; sanctity, loyalty and authority (Graham et al., 2009), meaning that we can also expect moral rhetoric from these categories here. An interest in the categories will therefore be retained. Notably, previous research has concerned moral rhetoric in 'culture war' issues (Koleva et al., 2012).

This analysis uses the Moral Foundations Dictionary 2.0 (MFD2) (Frimer et al., 2019) (appendix 11.3), consisting of a larger amount of words (n=2103 vs n=295) and shown to have greater construct validity than the original. Words are categorised by foundation and 'vice' or 'virtue' dimension. This lexicon has been adopted in a range of recent research (see for example, Frimer, 2020; B. Kennedy et al., 2021; Roose et al., 2020).

5.1.3 Process

The dictionary is altered to remove common words which may skew the results, for example 'president' and 'police'. Following tidy text mining principles (Silge & Robinson, 2017), frequencies of moral words are obtained by comparing them against the tidy table of tokenized words from the corpus by using an 'inner_join()' function to keep only the words present in the dictionary and then counting them. To bring these words into context, tm package's 'findAssocs()' function (Feinerer, 2013) is applied to the most frequent and relevant moral words in the DTM. This calculates a Pearson's correlation to find words in the corpus *most* correlated with the given word. Relevant associated words are qualitatively determined and investigated on the document level in terms of their moral category by using LIWC software (Pennebaker et al., 2007) in combination with R.

LIWC simply works by calculating a percentage of words within a text belonging to a category. However, the advice of Will et al (2011), the empirical logit is used for scaling vice/virtue:

$$log\frac{Virtue + 0.5}{Vice + 0.5}$$

This is because considering proportional changes on a symmetrical scale (rather than absolute quantities) better accounts for the way texts are naturally interpreted by readers (Will et al., 2011). This adjustment is made in R to the LIWC output of texts containing the given words, before it is sorted by foundation score and a sample of each (n = 200) is qualitatively examined to understand how the words are used. Sorting by foundation score provides a good way of organising texts where there may be a substantial number containing words under analysis. Using the moral foundation categories aids in the final step of qualitatively drawing together moral themes. This process is partially analogous to Thematic Analysis (Attride-Stirling, 2001) insofar as statistically associated words form something akin to basic codes from which themes are interpreted.

5.2 Results

The total frequency of moral words was 23,350. The results show that the loyalty and sanctity binding foundations are prominent (23.4% and 23.9% of total moral words respectively), however care (21%) is used more than authority (16%) (a binding foundation). This is because words in the care category are describing the most salient issue of ongoing violence at the Capitol. The very popular in-group designator, 'patriot', accounts for the dominance of the loyalty/virtue dimension (see appendices 11.6)

To derive general moral trends, only the most frequent words and correlations are analysed. Moreover, not all moral words and correlated words were relevant. For example 'arrest' was mostly correlated with words found in news articles about Hong Kong. The most relevant terms are included in table 1. Four themes emerge: patriotism/war, treason/fraud, divinity and violence.

Patriotism and war

Within loyalty-virtue, we can see the overwhelming use of the term 'patriot'. Plotting the correlations shows the word to be associated with other pro-conservative terms, particularly 'maga' and 'draintheswamp' (a term used by Trump in a speech), but also with a notable outgroup, 'antifa'. Referring to patriotism of course portrays the ingroup as 'true' Americans and so, given this word is reserved for the ingroup, patriot becomes a strong I-position. Consider typical usage:

- *Patriots now occupy the Senate Chamber, have invaded pelosi's office…*
- *WE ARE PATRIOTS WE ARE AWAKE WE ARE COMING*

Meanwhile, 'War' is another popular word within this dimension, and is overwhelmingly used in the context of 'civil war'. This can be used to describe the enormity of the polarisation and situation, but is clearly used as a call to arms and to enhance ingroup cohesion by making a comparison to the historical American Civil War:

- *This is a Civil War of free Americans vs Communist Demtards or is the beginning of the revolution of America…*

While also making threats to ideological outgroups:

- *Civil war is coming and leftists only have themselves to blame…*

- *The left is pure evil We're reaching the point of civil war […]*

When 'antifa' appears alongside 'patriot', it is almost exclusively in terms of shifting blame for the violence and destruction which is evidently disconcerting for many. In terms of representing self and other, there is the implication of self-as-not violent, and an alternative representation of other as violent and wanting to frame 'patriots'. This is perhaps better placed under the violence trend, but is useful here because there is an idea that true patriots would not riot at the Capitol (the home of American history).

<u>Christian divinity</u>

Because words within the sanctity-vice dimension are largely curse words occurring around each other (as reflected in the later topic model), this analysis focuses on sanctity-virtue, which is largely made up of Christian rhetoric. Plotting correlations with the most popular word 'God' is not so helpful, as different aspects of religious language are related to each other, for example 'God', 'Bless' and 'Jesus'. Though 'evil' is a word of interest suggesting the setting up of a self-other opposition.

Examination of the individual texts containing 'God' is more insightful, and shows a clear theme where God is aligned with the in-group. This is frequently seen with the term 'bless', used in conjunction with the group generically, but is present throughout:

- *GOD BLESS THE FREEDOM FIGHTERS IN WASHINGTON DC […]*

- *God bless America so long as the dew shall fall upon the earth so shall America be free*

In conjunction with this, there is a representation of a divine element to the ongoing events and an eventual positive (for them) outcome:

- *Believing that God will show up in a mighty way with a VICTORY Glory to God […]*

As expected, when 'evil' appears alongside 'God' it is in the scope of this ongoing battle for America:

- *God help us defeat evil*

It is somewhat vaguely attributed to others, in the sense that there is a general evil other, which can be assumed from the context are the ideological outgroups taken together and categorised as 'the left':

- *We must not give in to evil demonic satanism that the left promotes[…]*

But occasionally Democrats in particular:

- *Go Figure it's all Democrats such Evil People Their Day Will Come[…]*

Election fraud

Naturally given the context, much moral rhetoric belonging to fairness-vice dimension, particularly 'fraud', 'steal' and 'cheat' which are all related to the belief that the presidential election result was unfairly won by the democrats. A clear other-as-fraudulent emerges here, with an alternative representation of wanting to steal power:

- *[…] Today's focus is on taking back our country and not allowing Democrats to cheat our President out of office […]*

The accusations of 'treason', from authority-vice, also relate to the Democrats having 'stolen' the election, and invokes the sense of other-as-anti American once again:

- *War was declared on us when the election was stolen. That is treason and we fight fire with fire*

Patriot	*Maga*	*0.14*
	Antifa	*0.12*
	draintheswamp	*0.11*
War	*Civil*	*0.44*
	Declare	*0.11*
God	*Bless*	*0.41*
	Jesus	*0.18*
	Evil	*0.18*
	Faith	*0.18*
	pray	*0.18*
Fraud	*Voter*	*0.26*
	Election	*0.25*
	Georgia	*0.25*
Steal	*Stop*	*0.31*
	Election	*0.22*
	Democrat	*0.09*
Cheat	*DeKalb*	*0.12*
	Democrat	*0.11*
	Lie	*0.10*
	Dominion	*0.09*
Treason	*Participant*	*0.25*
	Tribunal	*0.24*
	Commit	*0.22*
Fight	*Freedom*	*0.15*
	War	*0.11*
	Country	*0.11*
	Back	*0.10*
	Battle	*0.08*
Violence	*Condone*	*0.16*
	Advocate	*0.14*
	Incite	*0.14*
	Antifa	*0.14*
Kill	*Unarmed*	*0.28*
	Shoot	*0.22*
	Veteran	*0.16*
	Woman	*0.16*
Murder	*Unarmed*	*0.12*
	Veteran	*0.12*

Table 1 – Selected correlations with moral words

All corrs $p<2.2e-16$

Violence

The most popular word in the care-vice dimension, ‘fight’, is most commonly used to describe the ongoing events as a fight against the Democrats and the left, and as a way of urging action:

- *[…]We have to fight to restore election integrity in our nation*

It is also used in a virtuous sense as being associated with ‘freedom’, and therefore construing the ingroup as ‘freedom-fighters’:

- *Stay strong Patriot we are fighting for our freedom[…]*

Examining the term ‘violence’ shows a conflict which we have seen earlier – rather than accepting the violence of the conservative rioters, antifa are said to be the real perpetrators, having disguised themselves as ‘patriots’, whereas so called true patriots are apparently non-violent:

- *Violence is not the signature of Patriots, check out instructions given to Antifa[…]*

When the violence is accepted as from the ingroup, representations of previous violence from antifa is used as a justification:

- *If you are angry at the people who stormed the Capitol but did not get angry at months of violence from Antifa and others then you are a hypocrite.*

The main issue emerging from terms ‘kill’ and ‘murder’ relate to the death of a rioter, Ashli Babbitt, shot by police. Consistently, her military career is acknowledged to represent her in-group belongingness:

- *“Her name was Ashli Babbit, she was a 14 year veteran […] she was a great Patriot to all who knew her”*

At the same time the police themselves become a violent other from the representation of the incident as a murder:

- *Heard that one unarmed lady was shot and murdered and another old man beaten to death by DC COPS[…]*

In summary, within the broad discourse of rhetoric pertaining to violence, we can see the self as represented as a freedom-fighter, but a hesitation to attribute actual violence and destruction to the self. Rather the other is framed as violent and the police become a violent other.

5.3 Discussion

Using moral rhetoric to draw out trends has been fruitful for understanding the construction of self and other on a broad level across the corpus. Parler users attempt to maximize the distance between themselves and the outgroup. Employing patriotism sets up a dichotomizing rigid binary (Gillespie, 2020a) whereby the self is construed as ‘truly' American and the other is dismissed as an enemy of the nation. This essentialised notion of Americanism (Yzerbyt & Rogier, 2001) is bolstered by invoking the collective memory of the revolutionary historical past to justify the ongoing events (de Saint-Laurent & Obradović, 2019). Christianity is further used to dismiss the ideological other and their perspective as evil in by utilising ‘radical-evil’ rhetoric (Aune, 2003) while elevating the self and their perspective to a level beyond that of mere humanity. Further, the disruption of ‘patriots’ seeing violence at the Capitol is deflected onto Antifa, a radical other, scapegoating them as infiltrators (Baumeister et al., 1998). Parler uses are here avoiding the disruption of the other (Gillespie, 2008, 2020a). However, delegitimizing is seen in the representation of the political other as cheats.

6. Study 2 – Topic Modelling

6.1 Methods

Using a thematic analysis to produce the *general* themes of discussion (outside of necessarily predefined concepts like the previous study) is a standard approach to qualitative data analysis (Braun & Clarke, 2006). However, working with a large corpus makes manually identifying topics challenging and even impossible. In response, this paper uses another NLP technique, Topic Modelling; an unsupervised computational method of deriving latent themes from unstructured textual data (Uys et al., 2008).

The variety of topic modelling used here is Latent Dirichlet Allocation (LDA) (Blei et al., 2003); a probabilistic procedure for assigning k number of topics to every document and generating a probability score for each topic-document relation. Topics themselves are represented by lists of words, ranked by their probability of belonging to a given topic. In essence, an LDA topic model calculates estimates for the probabilities of a word belonging to a topic, and a topic belonging to a document, $P(w|t)$ and $P(t|d)$ respectively (Mimno & McCallum, 2007; Uys et al., 2008). LDA is preferred to the rival method, Latent Semantic Indexing, because it is truly generative in its ability to index unseen documents while also assigning more than a single topic to any given document (Uys et al., 2008). LDA topic modelling is one of the most important methods for analysing large corpora, used widely across fields including the social sciences (Li & Lei, 2021). Nevertheless, semantic coherence is never guaranteed, and careful qualitative attention must be paid to interpreting topic outputs (Brookes & McEnery, 2019).

This study will provide topics from which it is possible to see where self/other conflicts are most salient. While this sheds partial light on both research questions, it is mainly intended as a tool to lead on to Study 3.

6.1.1 Process

The same pre-processing steps take place as those carried out in Study 1, with some extra cleaning. A DTM is created, but this time words are removed that fall below a minimum frequency. As words in natural languages are understood to be distributed according to Zipf's law, where the frequency of a word is inversely proportional to its rank in a frequency table (Zipf, 1949), removing stop-words and infrequently appearing terms eliminates the both tails of the distribution; frequently occurring non-important words on the one side and *in*frequently occurring *non*-important words occurring on the other. This retains only the most important words for analysis. Empty rows resulting from trimming are removed, leaving a sample size of 24,010.

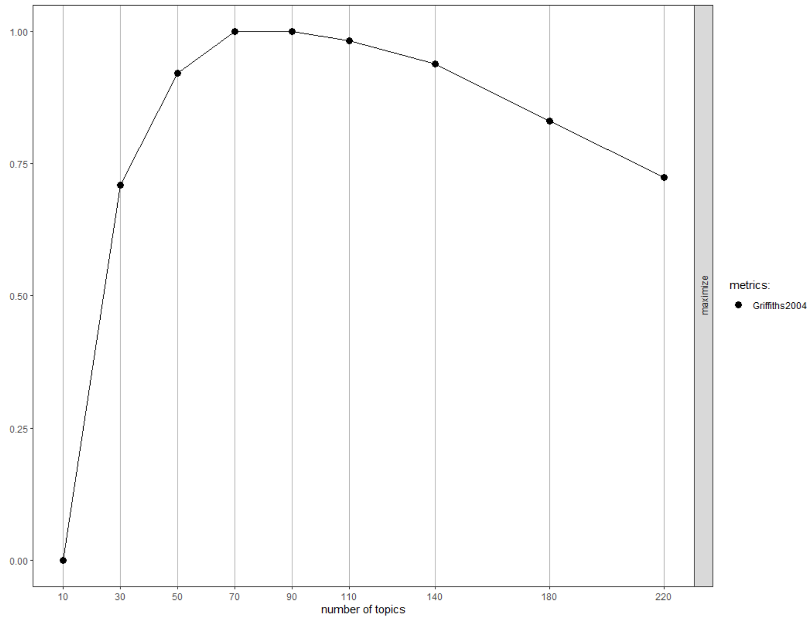


Figure 1 Optimal k

Next, statistical methods are used to find an optimal k number of topics. Firstly, using the ldatuning package, topic models are run in a sequence, k=10:220, yielding a score for each model based on a Markov chain Monte Carlo (MCMC) algorithm for statistical inference (Griffiths & Steyvers, 2004). This algorithm estimates the posterior probability for a model while integrating over all the combinations of assigning words to topics generated through Gibbs sampling. The goal of this process of testing over different k numbers is to find the highest posterior probability. To aid in interpretation, the sequence was carried out a second time, plotting the log-likelihood for each model as a way of measuring the goodness of fit.

After arriving at the optimal k, the final topic model is run using R's topicmodels package, before the model's outputs, matrices for $\mathrm{P(w|t)}$ and $\mathrm{P(t|d)}$, are coerced into tidy data formats (Silge & Robinson, 2017, ch.6). This enables examination of each topic's most probable (and therefore defining) terms, and the extraction of texts belonging to a given topic. Both are used for topic interpretation. Code is provided in appendix 11.4.

6.2 Results

The process of determining the optimal K, derived from Griffiths & Steyvers (2004), yielded a result of between 70 and 90, with both Ks scoring equally high. The subsequent distribution of log-likelihood scores for each model in the sequence yielded 70 as the most likely k number based on the data. Thus K = 70 for this study.

Due to scope, it will not be possible to enumerate all 70 topics and terms here (see appendix 11.8). Nevertheless, the goal is to uncover latent themes relating to language involving the self and other. With this in mind, topics have been selected for further elaboration where the most relevant terms (self/others and terms of conflict) appear among the top most probable terms for each topic, and the topic appears coherent. Many topics are irrelevant to the research, while other less probable topics are difficult to interpret. 10 topics have been selected:

Topic 44	Topic 34	Topic 63	Topic 69	Topic 24	Topic 18	Topic 38	Topic 17	Topic 4	Topic 23
trump	antifa	republican	pence	antifa	biden	law	world	china	know
supporter	blm	democrat	president	guy	president	constitution	child	country	life
antifa	burn	party	mike	flag	joe	criminal	control	america	lose
blame	riot	gop	traitor	little	family	enemy	justice	communist	matter
maga	city	rino	trump	false	trump	protect	expose	corrupt	way
dress	destroy	conservative	vice	bus	harris	order	sick	sell	black
disguise	terrorist	liberal	betray	break	que	rule	evil	politician	much
blend	attack	democratic	coward	photo	kamala	defend	bring	save	even
idiot	police	jones	flynn	grind	hunter	constitutional	pedophile	socialist	doesnt
lose	loot	support	general	stage	bidens	foreign	anti	little	folk

Table 2: Topics

The gamma matrix from the topic model output provides P(w|t) for each document and allows them to be filtered by their probability of belonging to a topic. A brief description of each topic will now follow (in order of topic probability).

Topic 44 - Interpretation of violence in terms of Antifa infiltration. Specific mention of clothing indicating Antifa members within the rioters.

Main other: Antifa

Disruption: Violence at Capitol

Topic 34 - Representation of Antifa and BLM as lawless terrorists. Dissatisfaction at lack of police action.

Main other: Antifa, BLM

Disruption: Violence

Topic 63 – Mention of Republican and Democrat parties, with a strong emphasis on dissatisfaction with the Republican party, and an interest in Vernon Jones.

Main other: Democrats, some Republicans

Disruption: unfavourable election result

Topic 69 - Anger at Mike Pence's 'betrayal' of the Republican Party, having aided the Democrat's 'theft' of the election. References to betrayal of a General Flynn in 2017.

Main other: Mike Pence

Disruption: Election result, failure of Republican officials

Topic 24 - Related to Topic 34, contains accusations of antifa committing a 'false flag' attack to frame conservatives.

Main other: Antifa

Disruption: Violence

Topic 18 – Allegations of plagiarism from Harris and Biden having crime links.

Main other: Biden, Harris

Disruption: Election result

Topic 38 – Dissatisfaction at political elites expressed in demanded action against the 'fraudulent' election, especially by invoking the constitution.

Main other: Senior Republicans

Disruption: Failure to denounce votes

Topic 17 –Highly negative stigmatising terms used to dismiss Democrats and the left. Conspiracy type beliefs.

Main other: The left, Democrats

Disruption: Election result

Topic 4 – Representation of socialism as corrupt. Claims of Chinese intervention, alleging Democrats to be 'owned' by the Chinese.

Main other: Democrats, Chinese

Disruption: Election result

Topic 23 – More difficult to interpret, this topic is included for the mention of Black Lives Matter, who are also treated as scapegoats for the violence. Comparisons are made to previous BLM action.

Main other: BLM

Disruption: Violence

6.3 Discussion

Topic modelling has uncovered several key themes involving the other from which documents can be analysed for semantic barriers. This complements the broader overview of moral representations of self and other offered in Study 1 by offering more detailed and nuanced themes. While some of those earlier moral ideas are (unsurprisingly) reflected in terms like 'corruption' and 'evil', this method has generated nuance by supplying more others, such as the 'Chinese' and Black Lives Matter, as well as specific issues of concern for these Parler users. This study has therefore provided great potential for the use of defensive mechanisms to block the other. This is to be elaborated upon in the final study that completes the triangulation of methods in this paper.

7. Dialogical analysis

7.1 Methods

Dialogical analysis is a qualitative method for analysing the relations of perspectives in talk and text (Aveling et al., 2015; Gillespie & Cornish, 2010), where the key intersubjective aspects for analysis are the voices of self, the voices of inner others, and the relations between them (Aveling et al., 2015). Because the relations between self and other existing in the mind result in semantic contact, a dialogical analysis is the recommended method for researching semantic barriers and defensive mechanisms (Gillespie, 2020b).

The prescribed method involves three steps: Identifying I-positions, identifying perspectives attributed to the other, and identifying the reactions to the other's perspectives, including "framing of words and beliefs" belonging to the other (Gillespie, 2020b, p.22). Semantic contact has been studied mainly with long-form kinds of data, such diaries (Zittoun & Gillespie, 2020), interview transcripts (Aveling & Gillespie, 2008) and biographical texts (Gillespie, 2005). This data is challenging because it is notably short-form. Therefore, in similarity to twitter, Parler may not be suited to ordinary styles of discourse (Elliott-Maksymowicz et al., 2021). Additionally, individual texts under analysis are taken as separate entities related to one another indirectly through context and topic, rather than directly through chains of communication (for example, one text responding to another). In practice, this means that it is difficult to find neatly packaged self and inner-other voices in auto-dialogue.

These limitations can be met in part by remembering this is a group level analysis, and by asking 'Sensitising questions' to guide interpretation; especially 'what is the context?' 'What prompted the utterance?' And, 'what alternative is being argued against?' (Gillespie & Cornish, 2014). While broader discourse within each topic provides context, positions taken, and sources of disruption are often implied. The method of dialogical analysis is somewhat adapted to meet these demands here. For a sample of the 100 most probable texts per topic, the I-position was determined, followed by the inner other and corresponding perspective where possible, and then, guided by the literature (Gillespie, 2020a, 2020b), the defensive mechanism was coded (see appendix 11.10). The data was prepared by inner-joining the corpora of topics to the original (uncleaned) data frame by document ID to retain punctuation. This analysis aims at answering the research question *What defensive strategies were used to dismiss the other?*

7.2 Results

Results are broken down by layer; avoiding, delegitimizing and limiting.

<u>Avoiding Tactics</u>

Avoiding tactics are the most dominant defensive category. Firstly, perhaps in a sense obvious, it is important to consider *excluding* as a primary tactic at work, simply because the echo-chamber of discourse is set up as a home for right-wing voices. This manipulation of the public sphere (Jovchelovitch, 1995) is clear from the social context, but evidenced empirically within the data by the sheer lack of dissenting voices. In moving away from ideological others, Parler users have therefore opted to avoid sources of disrupted meanings (Hart et al., 2009). This sets the scene for some extreme defensive representations of the other to come.

Distracting is strongly present in topics 18, 23, 24 and 34. In these topics the disruptive meaning is avoided in place of emphasising negative aspects of the other. Consider topic 18, concerning allegations of plagiarism from Harris and Biden's apparent links to crime. Given the contextual disruptive meaning from the Democrat election win, this is an effort to shift focus to something that is not necessarily relevant in the grand scheme of things (Harris plagiarising a biographical story) or towards unsubstantiated claims (Biden crime links):

- *Fraud beyond belief Kamala Harris now ripping off Martin Luther King stories[…]*

Moreover, given years of corruption allegations made against the Republican party these allegations amount to ‘whataboutery’, in the way an issue that has previously been brought against the *self* is brought against the other to imply double standards (Headley, 2015).

Whataboutery is evidenced further in the topics pertaining to violence, where it is claimed that neither the media nor the Democrats satisfactorily responded to alleged violence from BLM and Antifa in 2020. Here the disruptive meaning is not the broader political issue, but the challenge of seeing members of one’s own group committing questionable violence, and seeing them called out for it:

- *Fuck these reports on Fox today, why didn't they talk so much shit about black lives matter or antifa*
- *When Antifa and BLM were burning and looting [Biden] couldn’t even ask for peace. See the difference.*

In refusing to acknowledge the disruptive meaning and turning to issues of the other, these allegations serve as distracting ‘red herrings’ (McKee & Diethelm, 2010). In fact, red herrings are present throughout and also serve a stigmatising role; I will return to this.

Relatedly, *Deflecting* is also present in topics concerned with violence, especially where conspiratorial claims are made about infiltration and ‘false-flag’ attacks (topic 44). Again, in refusing to acknowledge the destruction carried out by members of one’s own group, blame is passed on to the other (Joffe, 1999) as a way of denying responsibility (Alicke & Sedikides, 2009).

- *Why, why, why, are people assuming this was Trump supporters and not antifa and BLM dressed as Trump supporters?*

These particular claims are buttressed within the grand narrative of powerful others nefariously out to harm the conservative cause by alleging the police to be helping Antifa:

- *Antifa was escorted in by corrupt police false flag*

An extreme form of deflection is the claims of certain others, figures or groups, being child-abusers or paedophiles. Further discussion of this will follow as other semantic barriers are involved, but consider how a distinctive, horn-wearing rioter who was originally a poster-boy for the rally is then othered as a paedophile after violence erupts:

- *Buffalo horns guy at Capitol Building Break-in is Antifa—NOT a patriot. Note the Boy-lover pedophile symbol tattooed on his chest in the 4th photo.*

<u>Delegitimising Tactics</u>

Staying with the previous example, we can move on to 'Delegitimising tactics', the second defensive layer that focuses on the source of the disruption (Gillespie, 2020a). Two delegitimising mechanisms work closely together in this analysis, *stereotyping* and *stigmatising.* Assigning the horned protestor to the group 'paedophile' is a semantic act carried out in a broader context where paedophiles/child-abusers are a 'known' (albeit vague) group operating in society. Indeed, topic 17 concerns much talk of child-abusers operating at large and within the Democrats:

- *Adam Schiff's secret and pedophile crimes are being exposed. Innocent Anthony Bourdain paid the ultimate price bc Schiff found out he was a witness.*

Because of the obvious stigmatic nature of these claims there is a dual purpose to these utterances. Firstly, stereotyping into the 'known' child-abuser group invites simple dismissal of the other's perspective because that group is as already socially represented as possessing nefarious, untrustworthy ideas. At the same time, stigmatising enforces the rejection of perspective through claims of depravity and evil-mindedness, in a similar way to dehumanisation (Hodson et al., 2014). A disruptive threat of a Democrat challenge to a conservative worldview can be dismissed in this right-wing echo chamber like so:

- *Joe Biden is a sick perverted pedophile and a traitor who should be arrested prosecuted and executed*

Stereotyping occurs even more prominently with regard to the framing of Democrats as socialist and Marxist, while also sometimes as being under control of another supposedly known group, the 'CCP'. This is largely the subject matter of topic 4. The meta-perspective given to this somewhat invented radical leftist enemy is that they want to destroy American (Christian) life:

- *The Marxist socialist Dems say no to celebrating Thanksgiving […] The Marxist socialist Dems will say No to Christmas*

This clearly straw-mans the other (Gillespie, 2008), and means that the Democrat group identity, is stigmatised in the sense of being anti-American, such that a disruptive left-wing other can be quickly stereotyped as belonging to that radical group. Likewise, China and the threat of Communism, is used to further delegitimise the left. This stereotyping works by transferring the meaning (Gillespie, 2020a; Moscovici, 2008) of Democrat liberal politics to that of Communism:

- *The Socialist Democrats will control the House & Senate […] if we don't act upon stopping them they will sell us out to Communist China they will control what we do and what we say*

Anti-American stigmatisation of members of the ingroup who engage with the other are present in topic 63, where resentment is expressed towards 'failing' Republican officials who are frequently labelled as RINOs – "Republicans in Name Only". Engaging with the other in this sense means failing to denounce apparent 'vote-rigging' by the Democrats.

- *…Tomorrow, we will see which Republicans stand for America, and which Republicans stand with Democrats. We will make sure those RINOs never win an election again.*

The same ingroup stigmatizing is true when Republican, Mike Pence, refuses to engage further with selective vote recounting (topic 69):

- *Vice President Pence will NOT support GOP congressional effort to contest electoral votes #MikePence is GUILTY of #TREASON!*

Finally, there is the delegitimising tactic of *Distrust*. With discourse concerning corrupt Chinese influences and radical socialism/Marxism in relation to the Democrats, as well as elite child-abuse rings, nefarious police activities, traitorous 'RINOs', and biased media, there is a prevailing theme of distrust towards those in power, where ulterior motives are attributed to these sources of disruptive meanings (Gillespie, 2020a). This is most evident regarding the apparently fraudulent election, where democracy itself is questioned:

- *[…] The traitorous swamp dwellers and those that support them will never let free elections to take place again. The only way out of socialism is to fight your way out […]*

A specific issue of distrust regards the (debunked) claim that Dominion vote counting machines mis-counted Republican votes:

- C*ounties that used Dominion and Hart InterCivic ballot counting devices and software consistently gave a 5% vote advantage to candidate Joe Biden over President Trump.*

As mentioned, this all falls within a broader context of distrust, where extreme radical leftism, and often outright Chinese communism, is taken to lay behind Democrat party politics, influencing politicians to gain control and threatening the fabric of American life with their ideology.

Limiting Tactics

Limiting tactics are less common, though dominant strategy, reinforcing the findings in Study 1, is *dichotomizing*, in order to create rigid binaries to dismiss the other (Gillespie, 2020a). We have seen this with extreme representations of other as anti-American, or deprived and evil. Topic 38, concerning the political elites' failure to stop supposed corruption, contains dichotomising defensive tactics to dismiss the disruption of the Democrat win by making claims about fraud *and* framing the situation as constitutional vs unconstitutional. For example:

- *Everyone...GOP, RINOS, DEMOCRATS […] has been given a chance […] to pick their lane on whether they support the Constitution or whether they are a sellout to the Deep State.*

As we know, this is an aspect of the major dichotomizing theme of we-as-patriots/true-Americans vs other-as-anti-American, and is characterised by extreme black and white thinking (Mathis, 2006).

Finally, *rationalising* dismisses the meaning of the other by playing down its impact (Gillespie, 2020a). As this can be achieve by attempting to 'put something in context' (Conlon & Murray, 1996), it seems clear that the attempt to deflect the meaning of riotous behaviour at the Capitol by contextualising against claims of previous left-wing violence, is a form of rationalising.

7.3 Discussion

Semantic barriers employed by these Parler users are mainly at the levels of avoiding and delegitimising. Avoiding was predominantly characterised by distraction and deflection when the conservative (law-abiding) I-position was disrupted by claims of violence at the Capitol. Delegitimising involved stereotyping, stigmatising and distrust, when the I-position was threatened by the general disruption of a liberal, Democrat challenge to the worldview. These tactics were often applied to the Democrats and political elites more generally, as well as specific individuals. Where limiting was found, *Dichotomizing* was the dominant tactic used to make simple us/them distinctions.

Importantly, these tactics work together and may not necessarily be easily broken down. For example, stereotyping, stigmatizing and distrusting can work together across a representation of a distrusing manipulative other, such as the CCP or child-abusing elites. This in turn creates an extreme dichotomized representation which allows for easy labelling of disruptive others. While the relatively short form of communication in this context, like twitter, may hinder debate, it has also been shown that much can be meant by a single utterance in online discourse (Elliott-Maksymowicz et al., 2021). Therefore, this analysis suggests that an aspect of the institutionalised talk (Gillespie & Cornish, 2010; Heritage, 2005) of Parler involves maximising the dismissal of the other by uttering single statements that block the other in many ways at once.

8. General discussion

This research aimed to understand the tactics employed by conservative and right-wing Parler users for the representation of identities, and the resistance to a disruptive other in right-wing online discourse at a time of political upheaval. Using a dictionary analysis comprising of moral terms uncovered dichotomising representations of self as on the side of God, revolutionary history and America; set against an evil, cheating other. An important inner conflict over violence was found and explored in more detail amongst other themes emerging from Study 2's topic model. This study also found several disruptive others beyond the contextual disruption of the Democrat election win, thus painting a complex picture of the representations at work. A dialogical analysis of 10 topics found that the defensive mechanisms used were predominantly concerned with *avoiding* and *delegitimising* the source of disruptive meaning.

It was notable that semantic barriers are used together in different ways within representations to resist a disruptive other. For this reason, although the three layers of defence and the 'semantic immune system' (Gillespie, 2020a) is a theoretically valuable concept that underpinned this research, there may be other ways in which these defensive tactics may relate to one another, and can be categorised. For example, although *dichotomizing* is a limiting tactic (and therefore part of the final layer), it also clearly underpins representations of identity, which may result in subsequent tactics like *stereotyping*, *stigmatising* and *rationalizing*. Future research in tandem with SRT could elaborate on the relationships between semantic barriers and the mechanisms of shared knowledge.

There is something important to be said about denialism here. Denialism is understood to concern numerous intricate rationalisations (McKee & Diethelm, 2010). Because semantic barriers exist together as part of the institutional milieu of shared representations (Jovchelovitch, 2019), we can see that the tactics used by Parler may well fall within the "web of rationalisations" that constitutes denialism (Gillespie, 2020a). Thinking styles associated with individuals who endorse right-wing beliefs, such as Need for Cognitive Closure (Chirumbolo et al., 2004; Leone & Chirumbolo, 2008) and Need to Evaluate (Bizer et al., 2004; Jost et al., 2009), may play a role in this, and future research ought to explore the relationship between thinking styles and adoption of denialistic rhetorical strategies. Additionally, to what extent denialism and the use of extreme moral rhetoric and defensive mechanisms is owed to the monological, echo-chamber-like structure of Parler's discursive context is hard to answer from a single case study. However, analysis found that engagement with the (inner) others was wholly negative, dismissive and often extreme, and there were few limiting tactics. This supports the theoretical position that subtlety (Gillespie, 2020b), reasonableness and rationality (Carpendale & Müller, 2014; Habermas, 1981) are understood to be demanded by a critical audience. There is evidence to suggest that the lack of critical audience in this case allowed for increasingly unsubstantiated and unreasonable representations to circulate. Because of the significant social consequences to such beliefs, it is worthwhile for research grounded in Dialogism to pay attention to 'monological' discursive scenarios.

9. Conclusion and limitations

This paper has shown that a triangulation of mixed methods, involving NLP and qualitative techniques, can be fruitful for studying dialogical defensive mechanisms as they appear in natural language. One potential issue, however, is that the data generated from algorithmic techniques like topic modelling may still be problematically large and occasionally difficult to interpret. This was seen to some extent with the topic model that generated 70 topics, where some were difficult to interpret - although, this was partly made up for by selecting only the most pertinent to the research question.

The original (secondary) dataset did not possess detailed meta data regarding the time the post was written, and the methods used in this study did not track posts across individual users. It would be worthwhile for similar research to bring these kinds of data together to examine the rhetorical strategies and representations of users for the earlier suggestion of amalgamating semantic barriers and the mechanisms of social representations.

This paper has sought to contribute to the theoretical literature on Dialogism, semantic contact and defensive tactics by examining the representation of identity and semantic barriers in a unique, monological communicative context. At the least, it highlights the importance of serious content guidelines and moderation for online discourse.

10. References

Aliapoulios, M., Bevensee, E., Blackburn, J., Bradlyn, B., De Cristofaro, E., Stringhini, G., & Zannettou, S. (2021). An early look at the parler online social network. *Proceedings of the International AAAI Conference on Web and Social Media*, *15*(1), 943–951. http://arxiv.org/abs/2101.03820

Alicke, M. D., & Sedikides, C. (2009). Self-enhancement and self-protection: What they are and what they do. *European Review of Social Psychology*, *20*(1), 1–48. https://doi.org/10.1080/10463280802613866

Attride-Stirling, J. (2001). Thematic networks: an analytic tool for qualitative research. *Qualitative Research*, *1*(3), 385–405. https://doi.org/10.1177/146879410100100307

Aune, J. A. (2003). The argument from evil in the rhetoric of reaction. *Rhetoric & Public Affairs*, *6*(3), 518–522.

Aveling, E. L., & Gillespie, A. (2008). Negotiating multiplicity: Adaptive asymmetries within second-generation turks' "society of mind"? *Journal of Constructivist Psychology*, *21*(3), 200–222. https://doi.org/10.1080/10720530802070635

Aveling, E. L., Gillespie, A., & Cornish, F. (2015). A qualitative method for analysing multivoicedness. *Qualitative Research*, *15*(6), 670–687. https://doi.org/10.1177/1468794114557991

Avraamidou, M., & Psaltis, C. (2019). Blocking the solution: Social representations of threats and (non)dialogue with alternative representations in Greek-Cypriot newspapers during peace negotiations. *Journal for the Theory of Social Behaviour*, *49*(4), 460–479. https://doi.org/10.1111/jtsb.12222

Baines, A., Ittefaq, M., & Abwao, M. (2021). #Scamdemic, #plandemic, or #scaredemic: What parler social media platform tells us about covid-19 vaccine. *Vaccines*, *9*(5). https://doi.org/10.3390/vaccines9050421

Bakhtin, M. M. (1986). *Speech Genres and Other Late Essays* (C. Emerson & M. Holquist

(Eds.)). University of Texas Slavic Press.

Bauder, D. (2021, January). Riot? Insurrection? Words matter in describing Capitol siege. *AP News*. https://apnews.com/article/donald-trump-capitol-siege-riots-media-8000ce7db2b176c1be386d945be5fd6a

Baumeister, R. F., Dale, K., & Sommer, K. L. (1998). Freudian Defense Mechanisms and Empirical Findings in Modern Social Psychology: Reaction Formation, Projection, Displacement, Undoing, Isolation, Sublimation, and Denial. *Journal of Personality*, *66*(6), 1081–1124. https://doi.org/10.1111/1467-6494.00043

Bizer, G. Y., Krosnick, J. A., Holbrook, A. L., Christian Wheeler, S., Rucker, D. D., & Petty, R. E. (2004). The impact of personality on cognitive, behavioral, and affective political processes: The effects of need to evaluate. *Journal of Personality*, *72*(5), 995–1028.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*, 993–1022.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brookes, G., & McEnery, T. (2019). The utility of topic modelling for discourse studies: A critical evaluation. *Discourse Studies*, *21*(1), 3–21. https://doi.org/10.1177/1461445618814032

Carpendale, J. I. M., & Müller, U. (2014). Social interaction and the development of rationality and morality: An introduction. In *Social interaction and the development of knowledge* (pp. 1–18). Psychology Press.

Castro, P., & Santos, T. R. (2020). Dialogues with the absent Other: Using reported speech and the vocabulary of citizenship for contesting ecological laws and institutions. *Discourse and Society*, *31*(3), 249–267. https://doi.org/10.1177/0957926519889126

Chirumbolo, A., Areni, A., & Sensales, G. (2004). Need for cognitive closure and politics: Voting, political attitudes and attributional style. *International Journal of Psychology*, *39*(4), 245–253. https://doi.org/10.1080/00207590444000005

Cohn, M. A., Mehl, M. R., & Pennebaker, J. W. (2004). Linguistic markers of psychological Change Surrounding September 11, 2001. *Psychological Science*, *15*(10), 687–693. https://doi.org/10.1111/j.0956-7976.2004.00741.x

Conlon, D. E., & Murray, N. M. (1996). Customer perceptions of corporate responses to product complaints: The role of explanations. *Academy of Management Journal*, *39*(4), 1040–1056.

Cooper, M., Chak, A., Cornish, F., & Gillespie, A. (2013). Dialogue: Bridging personal, community, and social transformation. *Journal of Humanistic Psychology*, *53*(1), 70–93. https://doi.org/10.1177/0022167812447298

Cramer, P. (2014). Defense mechanisms: 40 Years of empirical research. *Journal of Personality Assessment*, *97*, 1–9. https://doi.org/10.1080/00223891.2014.947997

Crowston, K., Allen, E. E., & Heckman, R. (2012). Using natural language processing technology for qualitative data analysis. *International Journal of Social Research Methodology*, *15*(6), 523–543. https://doi.org/10.1080/13645579.2011.625764

de Saint-Laurent, C., & Obradović, S. (2019). Uses of the Past: History as a Resource for the Present. *Integrative Psychological and Behavioral Science*, *53*(1). https://doi.org/10.1007/s12124-018-9463-5

de Saint Laurent, C., Glaveanu, V., & Chaudet, C. (2020). Malevolent creativity and social media: Creating anti-immigration communities on Twitter. *Creativity Research Journal*, *32*(1), 66–80. https://doi.org/10.1080/10400419.2020.1712164

Denzin, N. K. (2017). *The research act: A theoretical introduction to sociological methods*. Transaction publishers.

Elcheroth, G., Doise, W., & Reicher, S. (2011). On the knowledge of politics and the politics of knowledge: How a social representations Approach Helps Us Rethink the Subject of Political Psychology. *Political Psychology*, *32*(5), 729–758.

https://doi.org/10.1111/j.1467-9221.2011.00834.x

Elliott-Maksymowicz, K., Nikolaev, A., & Porpora, D. (2021). How much can you say in a tweet? An approach to political argumentation on Twitter. *Humanities and Social Sciences Communications*, *8*(1), 1–9. https://doi.org/10.1057/s41599-021-00794-x

Evelyn, K. (2021, January). *Capitol attack: the five people who died*. The Guardian. https://www.theguardian.com/us-news/2021/jan/08/capitol-attack-police-officer-five-deaths

Feinerer, I. (2013). Introduction to the tm Package Text Mining in R. *Accessible En Ligne: Http://Cran. r-Project. Org/Web/Packages/Tm/Vignettes/Tm. Pdf*.

Flick, U. (2018a). What is triangulation? In *Doing Triangulation and Mixed Methods* (pp. 11–24). SAGE Publications Ltd. https://doi.org/10.4135/9781529716634.n2

Flick, U. (2018b). Why triangulation and mixed methods in qualitative research? In *Doing Triangulation and Mixed Methods* (pp. 1–10). SAGE Publications Ltd. https://doi.org/10.4135/9781529716634.n1

Flick, U., Kardorff, E. Von, & Steinke, I. (2004). What is qualitative research? An introduction to the field A companion to qualitative research. In U. Flick, E. Von Kardorff, & I. Steinke (Eds.), *A Companion to Qualitative Research: Paradigms, Theories, Methods, Practice and Contexts* (1st ed., pp. 3–11). SAGE Publications.

Friedl, J. E. F. (2006). *Mastering regular expressions*. O'Reilly Media, Inc.

Frimer, J. A. (2020). Do liberals and conservatives use different moral languages? Two replications and six extensions of Graham, Haidt, and Nosek's (2009) moral text analysis. *Journal of Research in Personality*, *84*, 103906.

Frimer, J. A., Boghrati, R., Haidt, J., Graham, J., & Dehgani, M. (2019). Moral foundations dictionary for linguistic analyses 2.0. *Unpublished Manuscript*.

Gillespie, A. (2005). Malcolm X and His Autobiography: Identity Development and Self-narration. *Culture & Psychology*, *11*(1), 77–88.

https://doi.org/10.1177/1354067X05050746

Gillespie, A. (2008). Social representations, alternative representations and semantic barriers. *Journal for the Theory of Social Behaviour*, *38*(4), 375–391. https://doi.org/10.1111/j.1468-5914.2008.00376.x

Gillespie, A. (2020a). Disruption, Self-Presentation, and Defensive Tactics at the Threshold of Learning. *Review of General Psychology*, *24*(4), 382–396. https://doi.org/10.1177/1089268020914258

Gillespie, A. (2020b). Semantic contact and semantic barriers: reactionary responses to disruptive ideas. *Current Opinion in Psychology*, *35*, 21–25. https://doi.org/10.1016/j.copsyc.2020.02.010

Gillespie, A., & Cornish, F. (2010). Intersubjectivity: Towards a Dialogical Analysis. *Journal for the Theory of Social Behaviour*, *40*(1), 19–46. https://doi.org/10.1111/j.1468-5914.2009.00419.x

Gillespie, A., & Cornish, F. (2014). Sensitizing questions: A method to facilitate analyzing the meaning of an utterance. *Integrative Psychological and Behavioral Science*, *48*(4), 435–452. https://doi.org/10.1007/s12124-014-9265-3

Gillespie, A., Kadianaki, I., & O'Sullivan-Lago, R. (2012). Encountering alterity: Geographic and semantic movements. In *The Oxford handbook of culture and psychology.* (pp. 695–709). Oxford University Press.

Gillespie, A., & Zittoun, T. (2010). Using resources: Conceptualizing the mediation and reflective use of tools and signs. *Culture and Psychology*, *16*(1), 37–62. https://doi.org/10.1177/1354067X09344888

Glaveanu, V. P. (2019). Being other: Intersubjectivity, allocentrism and the possible. *Journal for the Theory of Social Behaviour*, *49*(4), 443–459. https://doi.org/10.1111/jtsb.12221

Glăveanu, V. P. (2020). *The Possible: A Sociocultural Theory*. Oxford University Press.

Glăveanu, V. P., & de Saint Laurent, C. (2021). Social Media Responses to the Pandemic:

What Makes a Coronavirus Meme Creative. *Frontiers in Psychology*, *12*(March), 1–15. https://doi.org/10.3389/fpsyg.2021.569987

Graham, J., Haidt, J., Koleva, S., Motyl, M., Iyer, R., Wojcik, S. P., & Ditto, P. H. (2013). Moral Foundations Theory: The Pragmatic Validity of Moral Pluralism. In *Advances in Experimental Social Psychology* (1st ed., Vol. 47). Copyright © 2013, Elsevier Inc. All rights reserved. https://doi.org/10.1016/B978-0-12-407236-7.00002-4

Graham, J., Haidt, J., & Nosek, B. A. (2009). Liberals and Conservatives Rely on Different Sets of Moral Foundations. *Journal of Personality and Social Psychology*, *96*(5), 1029–1046. https://doi.org/10.1037/a0015141

Grenier, J., Pomeroy, B., & Reffett, A. (2012). Speak Up or Shut Up? The Moderating Role of Credibility on Auditor Remedial Defense Tactics. *AUDITING: A Journal of Practice & Theory*, *31*(4), 65–83. https://doi.org/10.2308/ajpt-50217

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(SUPPL. 1), 5228–5235. https://doi.org/10.1073/pnas.0307752101

Grossen, M. (2010). Interaction analysis and psychology: A dialogical perspective. In *Integrative Psychological and Behavioral Science* (Vol. 44, Issue 1). https://doi.org/10.1007/s12124-009-9108-9

Haakana, Markku, Laakso, M., & Lindström, J. (2016). Introduction: Comparative dimensions of talk in interaction. In M. Haakana, M. Laakso, & J. Lindström (Eds.), *Talk in interaction: Comparative Dimensions*. Studia Fennica.

Habermas, J. (1981). *The theory of communicative action: Reason and the rationalization of society*. Polity Press.

Hart, W., Albarracín, D., Eagly, A. H., Brechan, I., Lindberg, M. J., & Merrill, L. (2009). Feeling validated versus being correct: A meta-analysis of selective exposure to information. *Psychological Bulletin*, *135*(4), 555–588. https://doi.org/10.1037/a0015701

Haslam, N., & Loughnan, S. (2014). *Dehumanization and Infrahumanization*. https://doi.org/10.1146/annurev-psych-010213-115045

Headley, J. (2015). Challenging the EU's claim to moral authority: Russian talk of 'double standards.' *Asia Europe Journal*, *13*(3), 297–307. https://doi.org/10.1007/s10308-015-0417-y

Heritage, J. (2005). Conversation Analysis and Institutional Talk. In K. L. Fitch & R. E. Sanders (Eds.), *Handbook of Language and Social Interaction* (pp. 103–148). Psychology Press.

Hermans, H. J. M. (2001). The dialogical self: Toward a theory of personal and cultural positioning. *Culture and Psychology*, *7*(3), 243–281. https://doi.org/10.1177/1354067X0173001

Hermans, H. J. M. (2007). *Self , Identity , and Globalization in Times of Uncertainty : A Dialogical Analysis*. *11*(1), 31–61. https://doi.org/10.1037/1089-2680.11.1.31

Himmelweit, H. T., & Gaskell, G. E. (Eds.). (1990). *Societal Psychology*. Sage Publications, Inc.

Hirsh, J. B., & Peterson, J. B. (2009). Personality and language use in self-narratives. *Journal of Research in Personality*, *43*(3), 524–527. https://doi.org/10.1016/j.jrp.2009.01.006

Hitkul, Prabhu, A., Guhathakurta, D., jain, J., Subramanian, M., Reddy, M., Sehgal, S., Karandikar, T., Gulati, A., Arora, U., Shah, R. R., & Kumaraguru, P. (2021). Capitol (Pat)riots: A comparative study of Twitter and Parler. *Proceedings of the ACM on Measurement and Analysis of Computing Systems*, *37*(4), 1–12. http://arxiv.org/abs/2101.06914

Hodson, G., Kteily, N., & Hoffarth, M. (2014). Of filthy pigs and subhuman mongrels: Dehumanization, disgust, and intergroup prejudice. *TPM - Testing, Psychometrics, Methodology in Applied Psychology*, *21*(3), 267–284. https://doi.org/10.4473/TPM21.3.3

Houston, M., & Kramarae, C. (1991). Speaking from silence: Methods of silencing and of resistance. *Discourse & Society*, *2*(4), 387–399.

Howarth, C., Campbell, C., Cornish, F., Franks, B., Garcia-Lorenzo, L., Gillespie, A., Gleibs, I., Goncalves-Portelinha, I., Jovchelovitch, S., Lahlou, S., Mannell, J., Reader, T., & Tennant, C. (2013). Insights from societal psychology: The contextual politics of change. *Journal of Social and Political Psychology*, *1*(1), 364–384. https://doi.org/10.5964/jspp.v1i1.64

Hurmerinta-Peltomäki, L., & Nummela, N. (2006). Mixed methods in international business research: A value-added perspective. *Management International Review*, *46*(4), 439–459.

Ihaka, R., & Gentleman, R. (1996). R: A language for data analysis and graphics. *Journal of Computational and Graphical Statistics*, *5*(3), 299–314.

Jackson, A. Y., & Mazzei, L. (2011). *Thinking with theory in qualitative research: Viewing data across multiple perspectives*. Routledge.

Janis, I. . (1982). *Groupthink: Psychological studies of policy decisions and fiascoes*. Houghton Mifflin.

Joffe, H. (1999). *Risk and 'the other.'* Cambridge University Press. https://doi.org/10.1017/CBO9780511489846

Jost, J. T., Federico, C. M., & Napier, J. L. (2009). Political ideology: Its structure, functions, and elective affinities. *Annual Review of Psychology*, *60*(1), 307–337. https://doi.org/10.1146/annurev.psych.60.110707.163600

Jovchelovitch, S. (1995). Social representations in and of the public sphere: Towards a Theoretical Articulation. *Journal for the Theory of Social Behaviour*, *25*(1), 81–102. https://doi.org/10.1111/j.1468-5914.1995.tb00267.x

Jovchelovitch, S. (2019). *Knowledge in context: Representations, community and culture*. Routledge.

Kadianaki, I., & Andreouli, E. (2017). Essentialism in social representations of citizenship: An Analysis of Greeks' and Migrants' Discourse. *Political Psychology*, *38*(5), 833–848.

https://doi.org/10.1111/pops.12271

Kennedy, B., Atari, M., Davani, A. M., Hoover, J., Omrani, A., Graham, J., & Dehghani, M. (2021). Moral concerns are differentially observable in language. *Cognition*, *212*, 104696.

Kennedy, R., & Waggoner, P. (2021). *Introduction to R for Social Scientists: A Tidy Programming Approach*. Chapman and Hall/CRC.

Koleva, S. P., Graham, J., Iyer, R., Ditto, P. H., & Haidt, J. (2012). Tracing the threads: How five moral concerns (especially Purity) help explain culture war attitudes. *Journal of Research in Personality*, *46*(2), 184–194.

Leone, L., & Chirumbolo, A. (2008). Conservatism as motivated avoidance of affect: Need for affect scales predict conservatism measures. *Journal of Research in Personality*, *42*(3), 755–762. https://doi.org/10.1016/j.jrp.2007.08.001

Li, X., & Lei, L. (2021). A bibliometric analysis of topic modelling studies (2000–2017). *Journal of Information Science*, *47*(2), 161–175. https://doi.org/10.1177/0165551519877049

Liddy, E. D. (2001). Natural language processing. In M. A. Drake (Ed.), *Encyclopedia of Library and Information Science*. Marcel Decker. https://doi.org/10.1016/0004-3702(82)90032-7

Linell, P. (2003). What is Dialogism ? *Communication Studies*, *October*, 1–22.

Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies*, *5*(1), 1–167.

Loughran, T., & McDonald, B. (2020). Textual analysis in finance. *Annual Review of Financial Economics*, *12*, 357–375.

Marková, I. (2006). On “the inner alter” in dialogue. *International Journal for Dialogical Science*, *1*(1), 125–147.

Marková, I. (2000). Amédée or how to get rid of It: Social representations from a dialogical perspective. *Culture and Psychology*, *6*(4), 419–460.

https://doi.org/10.1177/1354067x0064002

Marková, I. (2003). Constitution of the self: Intersubjectivity and dialogicality. *Culture and Psychology*, *9*(3), 249–260. https://doi.org/10.1177/1354067X030093006

Marková, I. (2007). Social identities and social representations. In G. Moloney & I. Walker (Eds.), *Social Representations and Identity* (pp. 215–236). Palgrave Macmillan US. https://doi.org/10.1057/9780230609181_12

Marková, I. (2008). Persuasion and propaganda. *Diogenes*, *55*(1), 37–51. https://doi.org/10.1177/0392192107087916

Marková, I. (2017a). Case Studies and dialogicality. *Journal of Deafblind Studies on Communication*, *3*(1).

Marková, I. (2017b). La fabrication de la théorie des representations. *Cadernos de Pesquisa*, *47*(163), 358–374. https://doi.org/10.1590/198053143760

Mathis, A. E. (2006). General semantics and Holocaust denial. *ETC: A Review of General Semantics*, *63*(1), 52–61.

Mays, N., & Pope, C. (1995). Qualitative research: Observational methods in health care settings. *Bmj*, *311*(6998), 182. https://doi.org/10.1136/bmj.311.6998.182

McKee, M., & Diethelm, P. (2010). How the growth of denialism undermines public health. *BMJ*, *341*. https://doi.org/10.1136/bmj.c6950

McKim, C. A. (2017). The value of mixed methods research: A mixed methods study. *Journal of Mixed Methods Research*, *11*(2), 202–222. https://doi.org/10.1177/1558689815607096

Mimno, D., & McCallum, A. (2007). Expertise modeling for matching papers with reviewers. *Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 500–509.

Moreno, M. A., Goniu, N., Moreno, P. S., & Diekema, D. (2013). Ethics of social media research: Common concerns and practical considerations. *Cyberpsychology, Behavior,* *and Social Networking*, *16*(9), 708–713. https://doi.org/10.1089/cyber.2012.0334

Moscovici, S. (1981). On Social Representations. In J. P. Forgas (Ed.), *Social cognition: Perspectives on everyday understanding* (pp. 181–209). Academic Press.

Moscovici, S. (1988). Notes towards a description of Social Representations. *European Journal of Social Psychology*, *18*(3), 211–250. https://doi.org/10.1002/ejsp.2420180303

Moscovici, S. (2000). *Social Representations. Explorations in Social Psychology* (G. Duveen (Ed.)). Cambridge: Polity.

Moscovici, S. (2008). Psychoanalysis: Its image and its public. In *Psychoanalysis: Its image and its public.* Polity Press.

Munn, L. (2021). More than a mob: Parler as preparatory media for the U.S. Capitol storming. *First Monday*, *26*(3). https://doi.org/10.5210/fm.v26i3.11574

Nicas, J., & Alba, D. (2021, January). *Amazon, Apple and Google cut off Parler, an app that drew Trump supporters*. The New York Times. https://www.nytimes.com/2021/01/09/technology/apple-google-parler.html

Nicholson, C. (2016). The role of historical representations in israeli-palestinian relations: Narratives from abroad. *Peace and Conflict*, *22*(1), 5–11. https://doi.org/10.1037/pac0000143

Nielsen, F. Å. (2011). A new ANEW: Evaluation of a word list for sentiment analysis in microblogs. *CEUR Workshop Proceedings*, *718*, 93–98.

Osadchiy, V., Mills, J. N., & Eleswarapu, S. V. (2020). Understanding patient anxieties in the social media era: Qualitative analysis and natural language processing of an online male infertility community. *Journal of Medical Internet Research*, *22*(3), 1–8. https://doi.org/10.2196/16728

Otala, J. M., Kurtic, G., Grasso, I., Liu, Y., Matthews, J., & Madraki, G. (2021). Political polarization and platform migration: A study of parler and Twitter usage by United States of America congress members. *The Web Conference 2021 - Companion of the*

World Wide Web Conference, WWW 2021, 224–231. https://doi.org/10.1145/3442442.3452305

Panagiotou, E., & Kadianaki, I. (2019). From cognitive dissonance to cognitive Polyphasia: A sociocultural approach to understanding meat-paradox. *Journal for the Theory of Social Behaviour*, *49*(2), 235–253. https://doi.org/10.1111/jtsb.12201

Patton, D. U., MacBeth, J., Schoenebeck, S., Shear, K., & McKeown, K. (2018). Accommodating grief on Twitter: An analysis of expressions of grief among gang Iivolved Youth on Twitter using Qualitative analysis and natural language processing. *Biomedical Informatics Insights*, *10*, 117822261876315. https://doi.org/10.1177/1178222618763155

Pennebaker, J. W., Chung, C. K., Ireland, M., Gonzales, A., & Booth, R. J. (2007). The Development and Psychometric Properties of LIWC2007 The University of Texas at Austin. *Development*, *1*(2), 1–22. http://www.liwc.net/LIWC2007LanguageManual.pdf

Pieroni, E., Jachim, P., Jachim, N., & Sharevski, F. (2021). Parlermonium: A Data-driven UX design evaluation of the Parler platform. *ArXiv Preprint ArXiv:2106.00163*, *1*(1), 1–8. http://arxiv.org/abs/2106.00163

Radovanovic, M., & Ivanovic, M. (2008). Text Mining: Approaches and applications. *October*, *38*(3), 227–234. http://www.emis.ams.org/journals/NSJOM/Papers/38_3/NSJOM_38_3_227_234.pdf

Roose, J., Flood, M., & Alfano, M. (2020). Challenging the use of masculinity as a recruitment mechanism in extremist narratives. *Department of Justice and Community Safety*.

Sagi, E., & Dehghani, M. (2014). Measuring moral rhetoric in Text. *Social Science Computer Review*, *32*(2), 132–144. https://doi.org/10.1177/0894439313506837

Sammut, G., Clark, M., & Kissaun, G. D. (2014). Dialogue linguistic hinges and semantic barriers: Social psychological uses and functions of a vulgar term. *Journal for the Theory of Social Behaviour*, *44*(3), 326–346. https://doi.org/10.1111/jtsb.12045

Sammut, G., & Sartawi, M. (2012). Perspective-taking and the attribution of ignorance. *Journal for the Theory of Social Behaviour*, *42*(2), 181–200. https://doi.org/10.1111/j.1468-5914.2011.00485.x

Shah, S. K., & Corley, K. G. (2006). Building better theory by bridging the quantitative-qualitative divide. *Journal of Management Studies*, *43*(8), 1821–1835. https://doi.org/10.1111/j.1467-6486.2006.00662.x

Shahin, S. (2016). When scale meets depth: Integrating Natural Language Processing and Textual Analysis for Studying digital corpora. *Communication Methods and Measures*, *10*(1), 28–50. https://doi.org/10.1080/19312458.2015.1118447

Silge, J., & Robinson, D. (2017). *Text Mining with R: A Tidy Approach*. O'Reilly. http://oreilly.com/catalog/errata.csp?isbn=9781491981658

Silverblatt, A. (2004). Media as Social Institution. *American Behavioral Scientist*, *48*(1), 35–41. https://doi.org/10.1177/0002764204267249

Uys, J. W., Du Preez, N. D., & Uys, E. W. (2008). Leveraging unstructured information using topic modelling. *PICMET: Portland International Center for Management of Engineering and Technology, Proceedings*, *c*, 955–961. https://doi.org/10.1109/PICMET.2008.4599703

van Dijck, J., & Poell, T. (2013). Understanding social media logic. *Media and Communication*, *1*(1), 2–14. https://doi.org/10.12924/mac2013.01010002

Vygotsky, L. S. (1978). *Mind in Society* (M. Cole, V. Jolm-Steiner, S. Scribner, & E. Souberman (Eds.)). Harvard University Press. https://doi.org/10.2307/j.ctvjf9vz4

Vygotsky, Lev S. (1979). Consciousness as a problem in the psychology of behavior. *Soviet Psychology*, *17*(4), 3–35.

Wickham, H. (2014). Tidy data. *Journal of Statistical Software*, *59*(10). https://doi.org/10.18637/jss.v059.i10

Will, L., Benoit, K., Slava, M., & Laver, M. (2011). Scaling policy preferences from coded political texts. *Legislative Studies Quarterly*, *36*(1), 123–155. https://doi.org/10.1111/j.1939-9162.2010.00006.x

Yzerbyt, V., & Rogier, A. (2001). Blame it on the group: Entitativity, subjective essentialism, and social attribution. In *The psychology of legitimacy: Emerging perspectives on ideology, justice, and intergroup relations.* (pp. 103–134). Cambridge University Press.

Zhang, A. X., & Counts, S. (2015). Modeling ideology and predicting policy change with social media: Case of same-sex marriage. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 2603–2612.

Zipf, G. . (1949). *Human Behaviour and the Principle of Least Effort*. Addison-Wesley Press.

Zittoun, T., & Gillespie, A. (2020). A sociocultural approach to identity through diary studies. *Cambridge Handbook of Identity*.

11. Appendices

11.1 - Random sampling python script

```
import argparse
import os
import random
import shutil
import time


def parse_args():
   parser = argparse.ArgumentParser(description="Copy a sample of N size number of files from SOURCE_DIR to
DEST_DIR.")
   parser.add_argument("source",
                  type=str,
                  help="The source directory")
   parser.add_argument("dest",
                  type=str,
                  help="The destination directory")
   parser.add_argument("--sample_size",
                  default=1000,
                  type=int,
                  help="The number of files to sample and move (default: 1000)")
   parser.add_argument("--dry_run",
                  action='store_true',
                  help="Print the files to transfer, but don't move them (default: False)")

   return parser.parse_args()


def copy_file(source, dest, dry_run=False):
   print(f"Copying file {source} -> {dest}")

   if dry_run:
      return

   shutil.copy(source, dest)


########################################
# Main
########################################
if __name__ == '__main__':
   # Parse the comamnd line arguments
   args = parse_args()

   # List the source directory
   list_start_time = time.time()
   directory_listing = os.listdir(args.source)
   print(directory_listing)
   list_elapsed_time = time.time() - list_start_time
   print(f"Found {len(directory_listing)} files in {args.source}, (Took {list_elapsed_time}s)")

   # Check the sample size and the actual number of files are compatible
   sample_size = args.sample_size
   if len(directory_listing) < args.sample_size:
      sample_size = len(directory_listing)
```

```
# Create a sample from the file list
sample_start_time = time.time()
sample = random.sample(directory_listing, sample_size)
sample_elapsed_time = time.time() - sample_start_time
print(f"Sampled {sample_size} files, (Took {sample_elapsed_time}s)")

if args.dry_run:
    print("######### DRY RUN MODE #########")

# Loop over the sample files and copy them from soruce to dest directories
copy_start_time = time.time()
for source_file in sample:
    copy_file(f"{os.path.join(args.source, source_file)}", args.dest, args.dry_run)
copy_elapsed_time = time.time() - copy_start_time
print(f"Copied {sample_size} files, (Took {copy_elapsed_time}s)")
```

11.2 - Data management plan

Department:
Department of Psychological and Behavioural Sciences

Supervisor name:
Celestin Okoroji

Project Details

Dissertation/ project title:
Resistance at the precipice of change: A case study of defensive mechanisms in right-wing online discourse

Please summarise your research question in no more than three sentences:
Among members contributing to discourse within the right-wing social media site Parler, how was the perspective of others dismissed?

Data Collection

Will you be using any secondary data for this project? Please outline what kind of secondary data you will be using below:
Yes. Data was scraped from Parler during the the Capitol protests and made publicly available on ddosecrets.com.

Will you require access to any secure datasets i.e. datasets to which LSE Library does not have a subscription, which will need to be requested directly from the supplier:
No

Will you require access to any internal LSE datasets for this project?
No

What research methods will you use for data collection (You can select as many as apply)
Social media content analysis

Please can you describe how you plan on conducting data collection using

these methods:
Data collection involves firstly retrieving the files online from the website. Because this dataset will be an unsorted dump of a large number of files the main effort of data collection will involve making the data usable. This means using a program or set of scripts to convert the files into an appropriate file type before removing unusable files and duplicates. Then, only the relevant information will need to be extracted from the whole batch. It is unlikely that the entire set will be able to be used for the initial quantitative analysis because of the computer processing requirements, therefore another script or program will be used to randomly sort and extract a random sample. For the qualitative analysis a subset of this sample will be extracted for manual coding.

Research Ethics

Please explain how you will collect informed consent:
As this is secondary data from social media, there is no informed consent.

Once you have collected proof of consent, you will need to store it safely.
Please can you explain below how you plan to do this:
There is no informed consent to store in this case, it is secondary social media, scraped data.

Have you submitted a research ethics review for this project?
Yes

If you are collecting primary data from research participants, you are required to anonymise the dataset so that individuals are not identifiable. How do you plan to do this?
This is not primary data but anonymisation will still take place. Usernames will be replaces with a label or number and any identifiable data which could occur within the posts themselves will be scraped.

Are there any circumstances where you will not anonymise research participants?
Yes

Please can you explain below when you will not anonymise research participants:
If I am referring to a post made by an account belonging to a major public figure which is important for the analysis, it may be helpful to name the figure to give context. For example, if it were Ted Cruz.

Data Protection

Do you believe your research will require you to fill in a data protection impact assessment?
No

Data Storage & Security

Are you the lone researcher on this project or do you have collaborators?
I am the lone researcher

Will you require any additional research tools to complete your project?
Yes

Please can you supply details/ links to any additional research tools you'll be using below:
Statistical Analysis and text mining, for tidying data and conducting quantitative analysis:

https://www.r-project.org/
https://www.rstudio.com/products/rstudio/download/
https://www.python.org/
Sorting through many text files to help order and extract relevant parts of the data:
https://www.digitalvolcano.co.uk/textcrawler.html
Possibly (Other text analysis tools for sentiment and dictionary type analyses):
https://www.tlab.it
liwcsoftware.onfastspring.com
Qualitative Coding:
https://www.qsrinternational.com/nvivo-qualitative-data-analysis-software/home

What hardware will you require to complete this project (you can select more than one option):
Personal laptop/ desktop PC

Do all personal devices used on this project meet the LSE's minimum standards for device level security?
Yes

Are all personal devices used on this project secured with passwords that meet the standard of the LSE password policy?
Yes

Where will you store your dissertation/ research project while you are working on it:
LSE OneDrive
Other

You selected 'Other.' Please can you explain below where you will store your dissertation/ research project while you are working on it:
On my pc.

Where will you store any primary data you collect during the research process:
Other

You selected 'Other.' Please explain below where you will store any primary data you collect:
PC and Onedrive

11. 3 – Lexicon extract

word	moral_foundation	word	moral_foundation	word	moral_foundation	word	moral_foundation	word	moral_foundation	word	moral_foundation	word	moral_foundation	word	moral_foundation	word	moral_foundation
compassic	care.virtue	harm	care.vice	equality	fairness.virtue	equalizers	fairness.virtue	player	loyalty.virtue	respect	authority.virtue	lawlessness	authority.vice	purity	sanctity.virtue	degradation	sanctity.vice
empathy	care.virtue	suffer	care.vice	fairness	fairness.virtue	avenged	fairness.virtue	patriot	loyalty.virtue	obey	authority.virtue	subverting	authority.vice	wholesome	sanctity.virtue	depravity	sanctity.vice
kindness	care.virtue	hurt	care.vice	justice	fairness.virtue	avenges	fairness.virtue	loyal	loyalty.virtue	authority	authority.virtue	disrespecting	authority.vice	pureness	sanctity.virtue	desecrate	sanctity.vice
caring	care.virtue	harmed	care.vice	rights	fairness.virtue	cheat	fairness.vice	loyalty	loyalty.virtue	obeyed	authority.virtue	sedition	authority.vice	wholesomeness	sanctity.virtue	desecration	sanctity.vice
generosity	care.virtue	hurting	care.vice	equitable	fairness.virtue	unfair	fairness.vice	patriots	loyalty.virtue	deference	authority.virtue	treason	authority.vice	holiness	sanctity.virtue	repulsiveness	sanctity.vice
benevolen	care.virtue	hurts	care.vice	civil rights	fairness.virtue	cheating	fairness.vice	follower	loyalty.virtue	reverence	authority.virtue	overthrow	authority.vice	dignity	sanctity.virtue	degrading	sanctity.vice
altruism	care.virtue	cruel	care.vice	fairplay	fairness.virtue	unfairness	fairness.vice	fidelity	loyalty.virtue	respecting	authority.virtue	insurrection	authority.vice	godly	sanctity.virtue	decay	sanctity.vice
compassic	care.virtue	endanger	care.vice	impartiality	fairness.virtue	injustice	fairness.vice	allegiance	loyalty.virtue	obeying	authority.virtue	rebellion	authority.vice	piety	sanctity.virtue	filth	sanctity.vice
nurture	care.virtue	harming	care.vice	equal	fairness.virtue	fraud	fairness.vice	ally	loyalty.virtue	tradition	authority.virtue	transgress	authority.vice	sanctify	sanctity.virtue	depravities	sanctity.vice
gentleness	care.virtue	harms	care.vice	fairminded	fairness.virtue	dishonest	fairness.vice	comrade	loyalty.virtue	adhere	authority.virtue	treachery	authority.vice	chastity	sanctity.virtue	defile	sanctity.vice
nurturance	care.virtue	suffering	care.vice	proportionality	fairness.virtue	unjust	fairness.vice	loyalties	loyalty.virtue	obeys	authority.virtue	dissent	authority.vice	undefiled	sanctity.virtue	sin	sanctity.vice
sympathy	care.virtue	threaten	care.vice	equalities	fairness.virtue	cheated	fairness.vice	death do u	loyalty.virtue	revere	authority.virtue	dishonor	authority.vice	holy	sanctity.virtue	fornication	sanctity.vice
nurturing	care.virtue	inflict	care.vice	fair	fairness.virtue	fraudulent	fairness.vice	faction	loyalty.virtue	govern	authority.virtue	dissension	authority.vice	sacrosanct	sanctity.virtue	repulsive	sanctity.vice
motherly	care.virtue	suffered	care.vice	integrity	fairness.virtue	cheats	fairness.vice	comrades	loyalty.virtue	comply	authority.virtue	disrespects	authority.vice	pious	sanctity.virtue	depraved	sanctity.vice
love	care.virtue	harmful	care.vice	impartial	fairness.virtue	frauds	fairness.vice	allegiance:	loyalty.virtue	respectful	authority.virtue	bedlam	authority.vice	righteousness	sanctity.virtue	impiety	sanctity.vice
beneficenc	care.virtue	inflicted	care.vice	reciprocity	fairness.virtue	dishonesty	fairness.vice	sacrifice	loyalty.virtue	honor	authority.virtue	rebelling	authority.vice	dignities	sanctity.virtue	degrade	sanctity.vice
empathize	care.virtue	mistreat	care.vice	honesty	fairness.virtue	cheaters	fairness.vice	allies	loyalty.virtue	adhered	authority.virtue	misrule	authority.vice	sanctified	sanctity.virtue	repugnance	sanctity.vice
helpfulnes	care.virtue	endangers	care.vice	egalitarian	fairness.virtue	deception	fairness.vice	organizatic	loyalty.virtue	allegiance	authority.virtue	transgression	authority.vice	godliness	sanctity.virtue	impure	sanctity.vice
loving	care.virtue	damaging	care.vice	civil right	fairness.virtue	injustices	fairness.vice	followers	loyalty.virtue	dictates	authority.virtue	insurrectional	authority.vice	spirituality	sanctity.virtue	degraded	sanctity.vice
pity	care.virtue	injurious	care.vice	law	fairness.virtue	swindle	fairness.vice	us against	loyalty.virtue	nobility	authority.virtue	pandemonium	authority.vice	chaste	sanctity.virtue	desecrations	sanctity.vice
mercy	care.virtue	victimize	care.vice	justness	fairness.virtue	inequity	fairness.vice	sacrifices	loyalty.virtue	forbid	authority.virtue	mutiny	authority.vice	sanctifies	sanctity.virtue	sinfulness	sanctity.vice
nurturer	care.virtue	inflicts	care.vice	unbias	fairness.virtue	hypocrisy	fairness.vice	all for one	loyalty.virtue	dominion	authority.virtue	mutinies	authority.vice	righteous	sanctity.virtue	impurities	sanctity.vice
compassic	care.virtue	hurtful	care.vice	egalitarians	fairness.virtue	discrimina	fairness.vice	camarader	loyalty.virtue	governed	authority.virtue	misruling	authority.vice	divine	sanctity.virtue	indecencies	sanctity.vice
nurturers	care.virtue	suffers	care.vice	parity	fairness.virtue	unequal	fairness.vice	comradery	loyalty.virtue	obedient	authority.virtue	disobedient	authority.vice	religious	sanctity.virtue	defiled	sanctity.vice
caringly	care.virtue	inflicting	care.vice	objectiveness	fairness.virtue	cheater	fairness.vice	one for all	loyalty.virtue	reveres	authority.virtue	subverted	authority.vice	biblical	sanctity.virtue	defiles	sanctity.vice
empathisir	care.virtue	injures	care.vice	reparations	fairness.virtue	inequities	fairness.vice	fellow	loyalty.virtue	adhering	authority.virtue	transgresses	authority.vice	spiritual	sanctity.virtue	uncleanliness	sanctity.vice
merciful	care.virtue	vulnerable	care.vice	unprejudiced	fairness.virtue	defraud	fairness.vice	family	loyalty.virtue	governs	authority.virtue	transgressed	authority.vice	deity	sanctity.virtue	damnation	sanctity.vice
empathizir	care.virtue	unkind	care.vice	justices	fairness.virtue	racism	fairness.vice	allegiant	loyalty.virtue	governing	authority.virtue	disarray	authority.vice	sanctifying	sanctity.virtue	debauchery	sanctity.vice
nurtures	care.virtue	damage	care.vice	laws	fairness.virtue	scam	fairness.vice	corps	loyalty.virtue	oppress	authority.virtue	misruled	authority.vice	noble	sanctity.virtue	impious	sanctity.vice
warmhear	care.virtue	kill	care.vice	tribunals	fairness.virtue	liar	fairness.vice	unity	loyalty.virtue	respected	authority.virtue	rioting	authority.vice	modesty	sanctity.virtue	sinful	sanctity.vice
empathize	care.virtue	die	care.vice	retribution	fairness.virtue	defrauds	fairness.vice	union jack	loyalty.virtue	respectfull	authority.virtue	lawless	authority.vice	decency	sanctity.virtue	necrophiliacs	sanctity.vice
protective	care.virtue	victimizes	care.vice	reparation	fairness.virtue	betrayal	fairness.vice	uniter	loyalty.virtue	honorable	authority.virtue	transgressing	authority.vice	scriptures	sanctity.virtue	desecrates	sanctity.vice
nurtured	care.virtue	torment	care.vice	lawfully	fairness.virtue	deceit	fairness.vice	old glory	loyalty.virtue	dictate	authority.virtue	illegality	authority.vice	nobility	sanctity.virtue	sleaziness	sanctity.vice
benevolen	care.virtue	destroy	care.vice	lawful	fairness.virtue	defrauded	fairness.vice	companioı	loyalty.virtue	commandı	authority.virtue	overthrowing	authority.vice	religion	sanctity.virtue	desecrating	sanctity.vice
mothering	care.virtue	brutalise	care.vice	honest	fairness.virtue	inequality	fairness.vice	country	loyalty.virtue	commandı	authority.virtue	dishonorable	authority.vice	hallow	sanctity.virtue	desecrated	sanctity.vice
cared	care.virtue	brutalises	care.vice	compensation	fairness.virtue	liars	fairness.vice	companioı	loyalty.virtue	venerate	authority.virtue	dishonoring	authority.vice	soul	sanctity.virtue	grossness	sanctity.vice
healing	care.virtue	distresses	care.vice	lawyers	fairness.virtue	defrauders	fairness.vice	homeland	loyalty.virtue	politeness	authority.virtue	rebelled	authority.vice	hallowed	sanctity.virtue	contaminates	sanctity.vice
empathise	care.virtue	endangerii	care.vice	sportsmanship	fairness.virtue	hypocrite	fairness.vice	sacrificing	loyalty.virtue	respects	authority.virtue	rebellions	authority.vice	deism	sanctity.virtue	sinning	sanctity.vice
humane	care.virtue	mistreats	care.vice	tribunal	fairness.virtue	biased	fairness.vice	indivisible	loyalty.virtue	obedience	authority.virtue	riot	authority.vice	pristine	sanctity.virtue	promiscuity	sanctity.vice
comfort	care.virtue	afflict	care.vice	do unto others	fairness.virtue	ripoffs	fairness.vice	sacrificed	loyalty.virtue	divine righ	authority.virtue	dishonouring	authority.vice	exalted	sanctity.virtue	befouls	sanctity.vice
pitied	care.virtue	distressing	care.vice	golden rule	fairness.virtue	scams	fairness.vice	solidarity	loyalty.virtue	forbids	authority.virtue	disrespected	authority.vice	hallowing	sanctity.virtue	rottenness	sanctity.vice

11.4 - R code

```
# Dictionary Analysis

## Set wd

setwd("D:/Postgrad/R and data analysis work/Dissertation_working_dir")

## Packages

library(tm)
library(quanteda)
library(textstem) # for lemmatising
library(qdap)
library(textclean)
library(dplyr)
library(ggplot2)
library(tidytext)
library(forcats)
library(magrittr)
library(radarchart)

## Data

library(readr)

text_data <- read_csv("Clean_50863UTF.csv")

View(text_data)

str(text_data)


##text_data_small <- read_csv("Clean_10000.csv")

text_data_small <- text_data[1:25000, ]

#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####

## Text preprocessing


text_data_small <- as.data.frame(text_data_small)

colnames(text_data_small) <- c("doc_id", "text")

text_data_small <- text_data_small[complete.cases(text_data_small), ]



# load stopwords
english_stopwords <- quanteda::stopwords()

# create corpus object
corpus <- Corpus(DataframeSource(text_data_small))
```

```
# Before example
content(corpus[[9]])


# Preprocessing chain

clean_corpus <- tm_map(corpus, content_transformer(tolower)) # makes all lowercase

clean_corpus <- tm_map(clean_corpus, removeWords, c(english_stopwords, "echo")) # removes a list of stopwords

## clean_corpus <- tm_map(clean_corpus, content_transformer(replace_contraction))

clean_corpus <- tm_map(clean_corpus, removePunctuation, preserve_intra_word_dashes = TRUE) # removes punctuation

clean_corpus <- tm_map(clean_corpus, removeNumbers) # remove numbers

clean_corpus <- tm_map(clean_corpus, lemmatize_strings, language = "en") # we're


count(moral_foundation) %>%
arrange(desc(n)) %>%
mutate(moral_foundation2 = fct_reorder(moral_foundation, n))


# ggplot(clean_corpus_dtm_tidy_mfd_plot2, aes(x = moral_foundation2, y = n, fill = moral_foundation)) +
# geom_col()


ggplot(clean_corpus_dtm_tidy_mfd_plot2, aes(x = reorder(moral_foundation, -n), y = n , fill = moral_foundation)) +
geom_col() +
labs(
title = "Moral Foundation Word Counts",
x = "Moral foundation", y = "n") +
theme(legend.position = "none")
clean_corpus_dtm_tidy_mfd_radar <- clean_corpus_dtm_tidy_mfd %>%
count(moral_foundation)
# Review scores
clean_corpus_dtm_tidy_mfd_radar
# JavaScript radar chart
chartJSRadar(clean_corpus_dtm_tidy_mfd_radar)


# Now do it grouped
mfd_2_grouped <- read_csv("mfd_2.0_grouped.csv")
mfd_2_grouped_adjusted <- mfd_2_grouped[-c(1207, 1150, 1198, 1174),]
clean_corpus_dtm_tidy_mfd_grouped <- inner_join(clean_corpus_dtm_tidy, mfd_2_grouped_adjusted, by = c("term" = "word"))

# Get counts by foundation
clean_corpus_dtm_tidy_mfd_grouped %>%
count(moral_foundation) %>%
arrange(desc(n))
# Plot
clean_corpus_dtm_tidy_mfd_grouped_plot <- clean_corpus_dtm_tidy_mfd_grouped %>%
```

```
count(term, moral_foundation) %>% # change to term
group_by(moral_foundation) %>%
top_n(10, n) %>%
ungroup() %>%
mutate(word2 = fct_reorder(term, n))


ggplot(clean_corpus_dtm_tidy_mfd_grouped_plot, aes(x = word2, y = n, fill =
moral_foundation)) +
geom_col(show.legend = FALSE) +
facet_wrap(~ moral_foundation, scales =             "free") +
coord_flip() +
labs(
title = "Moral foundation word counts   (grouped) ",
x = "Words"
)


# Rather than breaking down by individual           words, let's get an overall picture
clean_corpus_dtm_tidy_mfd_grouped_plot2 <- clean_corpus_dtm_tidy_mfd_grouped %>%
count(moral_foundation) %>%
arrange(desc(n)) %>%
mutate(moral_foundation2 = fct_reorder(moral_foundation, n))




# ggplot(clean_corpus_dtm_tidy_mfd_plot2, aes(x = moral_foundation2, y = n, fill moral_foundation))
+
# geom_col()           =



ggplot(clean_corpus_dtm_tidy_mfd_grouped_plot2, aes(x = reorder(moral_foundation, -n)
, y = n, fill = moral_foundation)) +
geom_col() +
labs(
title = "Moral foundation word Counts (grouped)",
x = "Moral foundation", y = "n") +
theme(legend.position = "none")
clean_corpus_dtm_tidy_mfd_grouped_radar <- clean_corpus_dtm_tidy_mfd_grouped %>%
count(moral_foundation)
# Review scores
clean_corpus_dtm_tidy_mfd_grouped_radar
# JavaScript radar chart
chartJSRadar(clean_corpus_dtm_tidy_mfd_grouped_radar)

## Creating totals from LIWC output
LIWC <- read_csv("LIWC_results.csv")
LIWC <- LIWC %>% mutate(care.TOTAL = care.virtue + care.vice)
LIWC <- LIWC %>% mutate(fairness.TOTAL = fairness.virtue + fairness.vice)
LIWC <- LIWC %>% mutate(loyalty.TOTAL = loyalty.virtue + loyalty.vice)
LIWC <- LIWC %>% mutate(authority.TOTAL = authority.virtue + authority.vice)
LIWC <- LIWC %>% mutate(sanctity.TOTAL = sanctity.virtue + sanctity.vice)
str(LIWC)
LIWC <- LIWC[, c(1, 2, 3, 4, 5, 14, 6, 7, 15, 8, 9, 16, 10, 11, 17, 12, 13, 18)]
LIWC <- LIWC %>% mutate(overall.TOTAL = care.TOTAL + fairness.TOTAL +loyalty.TOTAL +
authority.TOTAL + sanctity.TOTAL)
```

```
LIWC <- LIWC[, c(1, 2, 3, 5, 4, 6, 8, 7, 9, 11, 10, 12, 14, 13, 15, 17, 16, 18, 19)]

# Using a log ratio
LIWC_log_test <- LIWC
LIWC_log_test <- LIWC %>% mutate(care.log = log(care.virtue + 0.5) - log(care.vice + 0.5))
LIWC_log_test <- LIWC_log_test %>% mutate(fairness.log = log(fairness.virtue + 0.5) - log(fairness.vice + 0.5))
LIWC_log_test <- LIWC_log_test %>% mutate(loyalty.log = log(loyalty.virtue + 0.5) - log(loyalty.vice + 0.5))
LIWC_log_test <- LIWC_log_test %>% mutate(authority.log = log(authority.virtue + 0.5) - log(authority.vice + 0.5))
LIWC_log_test <- LIWC_log_test %>% mutate(sanctity.log = log(sanctity.virtue + 0.5) - log(sanctity.vice + 0.5))

LIWC_log_test <- LIWC_log_test[, c(1, 2, 3, 4, 5, 6, 20, 7, 8, 9, 21, 10, 11, 12, 22
, 13, 14, 15, 23, 16, 17, 18, 24, 19)]

# log(1.69) + 0.5
# log(0) + 0.5
# 3.16/2.50

LIWC_output <- LIWC_log_test
write.csv(LIWC_output, "LIWC_output_with_log.csv")

# Finding associations ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####


fraud_assoc <- findAssocs(DTM, "fraud", 0.08)
fraud_assoc_df <- list_vect2df(fraud_assoc, col2 = "word", col3 = "score")
fraud_plot <- ggplot(fraud_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "fraud word association correlations") +
theme_light()


steal_assoc <- findAssocs(DTM, "steal", 0.07)
steal_assoc_df <- list_vect2df(steal_assoc, col2 = "word", col3 = "score")
steal_plot <- ggplot(steal_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "steal word correlations") +
theme_light()


shoot_assoc <- findAssocs(DTM, "shoot", 0.07)
shoot_assoc_df <- list_vect2df(shoot_assoc, col2 = "word", col3 = "score")
shoot_plot <- top_n(shoot_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "shoot word correlations") +
theme_light()



fight_assoc <- findAssocs(DTM, "fight", 0.07)
fight_assoc_df <- list_vect2df(fight_assoc, col2 = "word", col3 = "score")
fight_assoc_df <- fight_assoc_df[-c(9),]
fight_plot <- top_n(fight_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
```

```
geom_point(size = 3) +
labs(title = "Fight word correlations") +
theme_light()


arrest_assoc <- findAssocs(DTM, "arrest", 0.07)
arrest_assoc_df <- list_vect2df(arrest_assoc, col2 = "word", col3 = "score")
arrest_assoc_df <- arrest_assoc_df[-c(4),]
arrest_plot <- top_n(arrest_assoc_df, n=20, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Arrest word correlations") +
theme_light()


war_assoc <- findAssocs(DTM, "war", 0.07)
war_assoc_df <- list_vect2df(war_assoc, col2 = "word", col3 = "score")
war_plot <- top_n(war_assoc_df, n=20, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "War word correlations") +
theme_light()


violence_assoc <- findAssocs(DTM, "violence", 0.07)
violence_assoc_df <- list_vect2df(violence_assoc, col2 = "word", col3 = "score")
violence_plot <- top_n(violence_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Violence word correlations") +
theme_light()


cheat_assoc <- findAssocs(DTM, "cheat", 0.07)
cheat_assoc_df <- list_vect2df(cheat_assoc, col2 = "word", col3 = "score")
cheat_plot <- top_n(cheat_assoc_df, n=14, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Cheat word correlations") +
theme_light()


protest_assoc <- findAssocs(DTM, "protest", 0.07)
protest_assoc_df <- list_vect2df(protest_assoc, col2 = "word", col3 = "score")
protest_plot <- top_n(protest_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Protest word correlations") +
theme_light()



kill_assoc <- findAssocs(DTM, "kill", 0.09)
kill_assoc_df <- list_vect2df(kill_assoc, col2 = "word", col3 = "score")
kill_plot <- top_n(kill_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Kill word correlations") +
```

```
theme_light()

destroy_assoc <- findAssocs(DTM, "destroy", 0.07)
destroy_assoc_df <- list_vect2df(destroy_assoc, col2 = "word", col3 = "score")
destroy_plot <- top_n(destroy_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Destroy word correlations") +
theme_light()

treason_assoc <- findAssocs(DTM, "treason", 0.07)
treason_assoc_df <- list_vect2df(treason_assoc, col2 = "word", col3 = "score")
treason_plot <- top_n(treason_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Treason word correlations") +
theme_light()



good_assoc <- findAssocs(DTM, "good", 0.07)
good_assoc_df <- list_vect2df(good_assoc, col2 = "word", col3 = "score")
good_plot <- top_n(good_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Good word correlations") +
theme_light()

supporter_assoc <- findAssocs(DTM, "supporter", 0.07)
supporter_assoc_df <- list_vect2df(supporter_assoc, col2 = "word", col3 = "score")
supporter_plot <- top_n(supporter_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Supporter word correlations") +
theme_light()

god_assoc <- findAssocs(DTM, "god", 0.07)
god_assoc_df <- list_vect2df(god_assoc, col2 = "word", col3 = "score")
god_plot <- top_n(god_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "God word correlations") +
theme_light()

win_assoc <- findAssocs(DTM, "win", 0.02)
win_assoc_df <- list_vect2df(win_assoc, col2 = "word", col3 = "score")
win_assoc_df <- win_assoc_df[-c(36),]
win_plot <- top_n(win_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Win word correlations") +
theme_light()

love_assoc <- findAssocs(DTM, "love", 0.06)
love_assoc_df <- list_vect2df(love_assoc, col2 = "word", col3 = "score")
love_plot <- top_n(love_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
```

```
labs(title = "Love word correlations") +
theme_light()

freedom_assoc <- findAssocs(DTM, "freedom", 0.14)
freedom_assoc_df <- list_vect2df(freedom_assoc, col2 = "word", col3 = "score")
freedom_plot <- top_n(freedom_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Freedom word correlations") +
theme_light()

great_assoc <- findAssocs(DTM, "great", 0.06)
great_assoc_df <- list_vect2df(great_assoc, col2 = "word", col3 = "score")
great_plot <- top_n(great_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Great word correlations") +
theme_light()

pray_assoc <- findAssocs(DTM, "pray", 0.10)
pray_assoc_df <- list_vect2df(pray_assoc, col2 = "word", col3 = "score")
pray_plot <- top_n(pray_assoc_df, n=10, score) %>%
ggplot(., aes(score, word)) +
geom_point(size = 3) +
labs(title = "Pray word correlations") +
theme_light()

traitor_assoc <- findAssocs(DTM, "traitor", 0.08)
traitor_assoc_df <- list_vect2df(traitor_assoc, col2 = "word", col3 = "score")
traitor_plot <- ggplot(traitor_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "traitor word association correlations") +
theme_light()
traitor_plot

corrupt_assoc <- findAssocs(DTM, "corrupt", 0.06)
corrupt_assoc_df <- list_vect2df(corrupt_assoc, col2 = "word", col3 = "score")
corrupt_plot <- ggplot(corrupt_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "corrupt word association correlations") +
theme_light()
corrupt_plot

patriot_assoc <- findAssocs(DTM, "patriot", 0.10)
patriot_assoc_df <- list_vect2df(patriot_assoc, col2 = "word", col3 = "score")
patriot_plot <- ggplot(patriot_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "patriot word association correlations") +
theme_light()
patriot_plot

right_assoc <- findAssocs(DTM, "right", 0.08)
right_assoc_df <- list_vect2df(right_assoc, col2 = "word", col3 = "score")
right_plot <- ggplot(right_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "right word association correlations") +
theme_light()
```

```
right_plot

peaceful_assoc <- findAssocs(DTM, "peaceful", 0.08)
peaceful_assoc_df <- list_vect2df(peaceful_assoc, col2 = "word", col3 = "score")
peaceful_plot <- ggplot(peaceful_assoc_df, aes(score, word)) +
geom_point(size = 3) +

labs(title = "peaceful word association correlations") +
theme_light()
peaceful_plot

protect_assoc <- findAssocs(DTM, "protect", 0.08)
protect_assoc_df <- list_vect2df(protect_assoc, col2 = "word", col3 = "score")
protect_plot <- ggplot(protect_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "protect word association correlations") +
theme_light()
protect_plot


peace_assoc <- findAssocs(DTM, "peace", 0.07)
peace_assoc_df <- list_vect2df(peace_assoc, col2 = "word", col3 = "score")
peace_plot <- ggplot(peace_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "peace word association correlations") +
theme_light()
peace_plot


trust_assoc <- findAssocs(DTM, "trust", 0.09)
trust_assoc_df <- list_vect2df(trust_assoc, col2 = "word", col3 = "score")
trust_plot <- ggplot(trust_assoc_df, aes(score, word)) +
geom_point(size = 3) +
labs(title = "trust word association correlations") +
theme_light()
trust_plot

# LIWC sub setting of analysis for prototypical word usage ~~~~~~~~~~~~~~~~~~~~####
## Import data
LIWC_log_for_analysis <- read_csv("LIWC_output_with_log.csv")
View(LIWC_log_for_analysis)

# First subset for 'patriot'.
# First specify the string for detection and the location (i.e. the data frame and column), define it
contains_patriot <- str_detect(LIWC_log_for_analysis$text, fixed("patriot", ignore_case=TRUE))

# Now use the defined object to subset from the data frame
patriot_sub <- LIWC_log_for_analysis[contains_patriot, ]

# Sort by log loyalty virtue
patriot_sub <- patriot_sub[order(patriot_sub$loyalty.log, decreasing = TRUE),]

# write.csv(patriot_sub, "patriot_loyalty.csv")



# Subset for 'war'
# First specify the string for detection and the location (i.e. the data frame and column), define it
```

```
contains_war <- str_detect(LIWC_log_for_analysis$text, fixed("war", ignore_case=TRUE))
# Now use the defined object to subset from the data frame
war_sub <- LIWC_log_for_analysis[contains_war, ]

# Sort by log loyalty virtue
war_sub <- war_sub[order(war_sub$loyalty.log, decreasing = TRUE),]

# write.csv(war_sub, "war_loyalty.csv")



# Subset for 'God'
# First specify the string for detection and the location (i.e. the data frame and column), define it
contains_god <- str_detect(LIWC_log_for_analysis$text, fixed("god", ignore_case=TRUE))
# Now use the defined object to subset from the data frame
god_sub <- LIWC_log_for_analysis[contains_god, ]

# Sort by log sanctity virtue
god_sub <- god_sub[order(god_sub$sanctity.log, decreasing = TRUE),]

write.csv(god_sub, "god_sanctity.csv")


# Subset for 'cheat'
# First specify the string for detection and the location (i.e. the data frame and column), define it
contains_cheat <- str_detect(LIWC_log_for_analysis$text, fixed("cheat", ignore_case= TRUE))

# Now use the defined object to subset from the data frame
cheat_sub <- LIWC_log_for_analysis[contains_cheat, ]

# Sort by log sanctity virtue
cheat_sub <- cheat_sub[order(cheat_sub$fairness.log, decreasing = TRUE),]

write.csv(cheat_sub, "cheat_fairness.csv")

# Subset for 'treason'
# First specify the string for detection and the location (i.e. the data frame and column), define it
contains_treason <- str_detect(LIWC_log_for_analysis$text, fixed("treason", ignore_case=TRUE))

# Now use the defined object to subset from the data frame
treason_sub <- LIWC_log_for_analysis[contains_treason, ]
# Sort by log
treason_sub <- treason_sub[order(treason_sub$authority.log, decreasing = TRUE),]

write.csv(treason_sub, "treasont_authority.csv")


# Subset for 'fight'
# First specify the string for detection and the location (i.e. the data frame and column), define it
contains_fight <- str_detect(LIWC_log_for_analysis$text, fixed("fight", ignore_case= TRUE))

# Now use the defined object to subset from the data frame
fight_sub <- LIWC_log_for_analysis[contains_fight, ]

# Sort by log
fight_sub <- fight_sub[order(fight_sub$care.log, decreasing = TRUE),]

```

```
write.csv(fight_sub, "fight_care.csv")



# Subset for 'violence'
# First specify the string for detection and the location (i.e. the data frame and column), define it
contains_violence <- str_detect(LIWC_log_for_analysis$text, fixed("violence", ignore_case=TRUE))

# Now use the defined object to subset from the data frame
violence_sub <- LIWC_log_for_analysis[contains_violence, ]

# Sort by log
violence_sub <- fviolence_sub[order(violence_sub$care.log, decreasing = TRUE),]

write.csv(violence_sub, "violence_care.csv")



# Subset for 'kill'
# First specify the string for detection and the location (i.e. the data frame and column), define it
contains_kill <- str_detect(LIWC_log_for_analysis$text, fixed("kill", ignore_case= TRUE))

# Now use the defined object to subset from the data frame
kill_sub <- LIWC_log_for_analysis[contains_kill, ]

# Sort by log
kill_sub <- kill_sub[order(kill_sub$care.log, decreasing = TRUE),]

write.csv(kill_sub, "kill_care.csv")


# Subset for 'murder'
# First specify the string for detection and the location (i.e. the data frame and column), define it
contains_murder <- str_detect(LIWC_log_for_analysis$text, fixed("murder", ignore_case =TRUE))

# Now use the defined object to subset from the data frame
murder_sub <- LIWC_log_for_analysis[contains_murder, ]

# Sort by log
murder_sub <- murder_sub[order(murder_sub$care.log, decreasing = TRUE),]

write.csv(murder_sub, "murder_care.csv")


# Topic model script

library(tm)
library(topicmodels)
library(ldatuning)
library(Rmpfr)
library(reshape2)
library(ggplot2)
library(pals)
library(quanteda)
library(textstem)
library(qdap)
library(readr)
```

```
library(ggpubr)
library(broom)
library(tidytext)
library(dplyr)


## Set wd

setwd("D:/Postgrad/R and data analysis work/Dissertation_working_dir")

## Data

text_data <- read_csv("Clean_50863UTF.csv")

# View(text_data)

# str(text_data)



text_data_small <- text_data[1:25000, ]

text_data_small <- as.data.frame(text_data_small)

colnames(text_data_small) <-  c("doc_id", "text")

text_data_small <- text_data_small[complete.cases(text_data_small), ]


# Apply cleaning to the dataframe (as some of these functions do not work on the corpus)

text_data_small$text <- gsub("[][!#$%()*,.:;<=>@^”_|?'“~.{}],@" , text_data_small$text)

# text_data_small <- text_data_small[!(text_data_small$text==""), ]

text_data_small$text <- replace_contraction(text_data_small$text)


# load stopwords
english_stopwords <- quanteda::stopwords()

# create corpus object
corpus <- Corpus(DataframeSource(text_data_small))

content(corpus[[9]])

#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####


# Pre-processing

clean_corpus <- tm_map(corpus, content_transformer(tolower))

clean_corpus <- tm_map(clean_corpus, removeWords, c(english_stopwords, "echo"))

clean_corpus <- tm_map(clean_corpus, removePunctuation, preserve_intra_word_dashes = TRUE)

clean_corpus <- tm_map(clean_corpus, removeNumbers)
```

```
clean_corpus <- tm_map(clean_corpus, lemmatize_strings, language = "en")

clean_corpus <- tm_map(clean_corpus, stripWhitespace)

clean_corpus <- tm_map(clean_corpus, content_transformer(gsub), pattern = "penny", replacement = "pence",
fixed=TRUE) # Fixes Pence/penny issue



# Test
content(clean_corpus[[9]])
content(clean_corpus[[16]])


#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####

# Create DTM

# Set a minimum frequency
minimumFrequency <- 10

DTM <- DocumentTermMatrix(clean_corpus, control = list(bounds = list(global = c(minimumFrequency, Inf))))


# Select a smaller DTM deleting documents with no contributing terms (some rows are empty after cleaning)

sel_idx <- slam::row_sums(DTM) > 0
DTM <- DTM[sel_idx, ]
text_data_small <- text_data_small[sel_idx, ]


#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####


## Identify optimum number of topics (k)


# Using the ldatuning package

# Create a sequence
topic_search <- c(10, 30, 50, 70, 90, 110, 140, 180, 220)

# Run models across sequence
system.time(find_topics3 <- FindTopicsNumber(DTM, topics = topic_search, method = "Gibbs", control =
list(seed=1234, keep=50)))
FindTopicsNumber_plot(find_topics3)


# Plot log-likelihood as a back-up

List_LDA <- lapply(
  X = 2:100,
  FUN = function(x) topicmodels::LDA(DTM, k = x)
)

v_loglik2 <- sapply(
  X = List_LDA2,
```

```
  FUN = topicmodels::logLik
)

plot(topic_search, v_loglik2, type = "o", main = "Log likelhood of LDA models")



#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####

##  Running the model


#  State k
k <- 70

# compute the LDA model, inference via 1000 iterations of Gibbs sampling
topicModel <- LDA(DTM, k, method="Gibbs", control = list(seed=1234, keep=50, verbose = 25))


#~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####

## Examining topics

# Get topics by term
topics_beta <- tidy(topicModel, matrix = "beta")

# write.csv(topics_beta, "topics_beta_terms.csv")

top_topics <- topics_beta %>% # We're looking at the top 20 terms per topic
  group_by(topic) %>%
  slice_max(beta, n = 20) %>%
  ungroup() %>%
  arrange(topic, -beta)

# Visualisation

# Plotting probability one at a time
top_topics %>%
  filter(topic == 24) %>%
  mutate(term = reorder_within(term, beta, topic)) %>%
  ggplot(aes(beta, term, fill = factor(topic))) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free") +
  scale_y_reordered()

# Creating individual plots that can be merged into one layout using ggbupr

topic_1_plot <- top_topics %>%
  filter(topic == 1) %>%
  mutate(term = reorder_within(term, beta, topic)) %>%
  ggplot(aes(beta, term, fill = factor(topic))) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free") +
  scale_y_reordered()

topic_3_plot <- top_topics %>%
  filter(topic == 3) %>%
  mutate(term = reorder_within(term, beta, topic)) %>%
```

```
  ggplot(aes(beta, term, fill = factor(topic))) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free") +
  scale_y_reordered()

topic_5_plot <- top_topics %>%
  filter(topic == 5) %>%
  mutate(term = reorder_within(term, beta, topic)) %>%
  ggplot(aes(beta, term, fill = factor(topic))) +
  geom_col(show.legend = FALSE) +
  facet_wrap(~ topic, scales = "free") +
  scale_y_reordered()

# Put them all together

ggarrange(topic_1_plot, topic_3_plot, topic_5_plot + rremove("x.text"),
          labels = c("A", "B", "C"),
          ncol = 2, nrow = 2)

# Inspect results)

tmResult <- posterior(topicModel)

attributes(tmResult)

beta <- tmResult$terms   # get beta from results

dim(beta)                # K distributions over nTerms(DTM) terms

top_10_terms <- terms(topicModel, 10)

top_20_terms <- terms(topicModel, 20)

top_30_terms <- terms(topicModel, 30)

theta <- tmResult$topics



top5termsPerTopic <- terms(topicModel, 5)

topicNames <- apply(top5termsPerTopic, 2, paste, collapse=" ")


# visualise topic distribution for stated docs

# getting the example IDs

exampleIds <- c(9, 1137, 14152)
N <- length(exampleIds)

# get topic proportions form example documents

topicProportionExamples <- theta[exampleIds,]
colnames(topicProportionExamples) <- topicNames
vizDataFrame <- melt(cbind(data.frame(topicProportionExamples), document = factor(1:N)), variable.name =
"topic", id.vars = "document")
```

```
# visualise the three documents' distribution across topics
ggplot(data = vizDataFrame, aes(topic, value, fill = document), ylab = "proportion") +
  geom_bar(stat="identity") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  coord_flip() +
  facet_wrap(~ document, ncol = N)


# Show likelihood of which topic is most likely based on the data

# re-rank top topic terms for topic names

topicNames <- apply(lda::top.topic.words(beta, 5, by.score = T), 2, paste, collapse = " ")

# What are the most probable topics in the entire collection?

topicProportions <- colSums(theta) / nDocs(DTM)  # mean probablities over all paragraphs

names(topicProportions) <- topicNames # assign the topic names we created before

sort(topicProportions, decreasing = TRUE) # show summed proportions in decreased order

soP <- sort(topicProportions, decreasing = TRUE)

paste(round(soP, 5), ":", names(soP))


topic_probabilities <- paste(round(soP, 5), ":", names(soP))

View(topic_probabilities)
topic_probabilities_df <- as.data.frame(topic_probabilities)


# ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####

# Filter documents into topics

# Tidy the gamma matrix and transform into a df
document_topic2 <- as.data.frame(tidy(topicModel, matrix = "gamma"))

# Make the document column an integer
document_topic2$document <- as.integer(document_topic2$document)

View(document_topic2)

# Join the df to the original df
df_join2 <- inner_join(text_data_small, document_topic2, by = c("doc_id" = "document"))

# Filter out a specific topic
df_join_topic7_v2 <- filter(df_join2, topic == 7)

View(df_join_topic7_v2) # Every document in the corpus is here, with its probability of belonging to topic 7

# Filter out the top 300
sorted300 <- df_join2 %>%
  group_by(topic) %>%
  slice_max(gamma, n = 300) %>%
  ungroup() %>%
```

```
  arrange(topic, -gamma)

# Testing that the filtering has worked.
Topic37 <- df_join2 %>% filter(topic == 37)
test_37 <- sorted300 %>% group_by(topic) %>% arrange(topic, -gamma)

# Repeat above for each topic to be extracted
```

11.5 – Dictionary analysis extracts

Short texts (Top log rating)

	doc_id	text	loyalty.TO	loyalty.log	I dentity position
3	6771	Patriots	100	5.303305	
4	18746	Patriots	100	5.303305	
5	1089	Love patriots	50	4.615121	
6	2643	Attack Patriots	50	4.615121	
7	3089	Go Patriots	50	4.615121	
8	6577	A PATRIOT	50	4.615121	
9	7056	BREATHE PATRIOTS	50	4.615121	
10	7896	Not Patriots	50	4.615121	
11	8163	Patriot Party	50	4.615121	
12	9094	Rcfjr Patriot	50	4.615121	
13	9737	A patriot	50	4.615121	
14	10492	RIP Patriot	50	4.615121	
15	10800	Pray patriots	50	4.615121	
16	11053	True Patriot	50	4.615121	
17	13316	And Patriots	50	4.615121	
18	13666	Echo Patriots	50	4.615121	
19	14932	RIP patriot	50	4.615121	
20	15562	Patriots Praying	50	4.615121	
21	17193	Go Patriots	50	4.615121	
22	17282	Patriot party	50	4.615121	
23	18150	Repost patriots	50	4.615121	We as patriot
24	18354	A PATRIOT	50	4.615121	
25	18972	Patriots BS	50	4.615121	
26	19070	True Patriot	50	4.615121	
27	19318	HOLDTHELINE PATRIOTS	50	4.615121	
28	20073	Patriots Rise	50	4.615121	
29	22102	Godspeed Patriots	50	4.615121	
30	24657	Great Patriot	50	4.615121	
31	24983	Patriots Rule	50	4.615121	
32	3736	This is Civil War patriots	40	4.394449	
33	273	Stay alert patriots	33.33	4.214495	
34	672	Patriots in control	33.33	4.214495	
35	2249	Antifa NOT Patriots	33.33	4.214495	

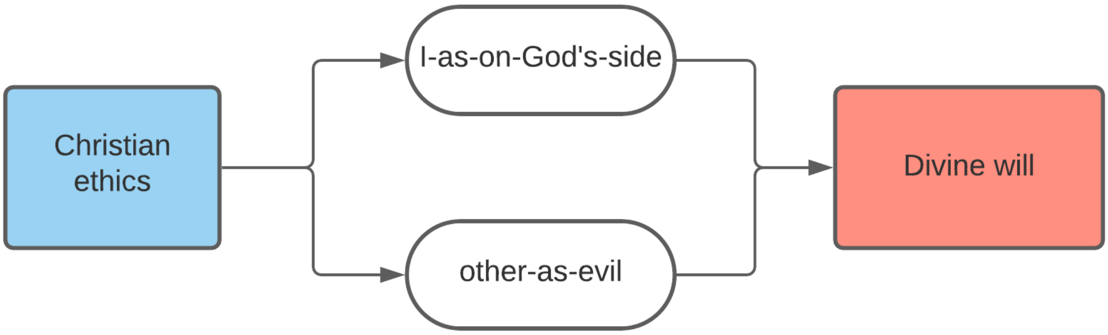
Longer texts

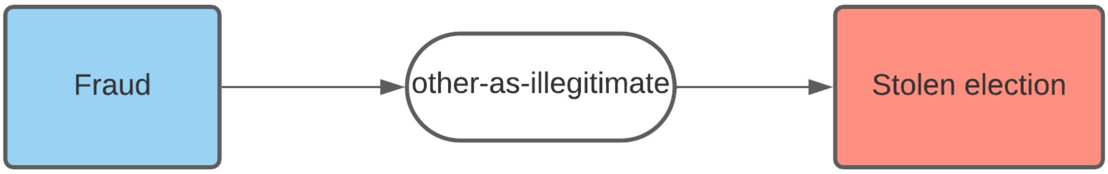
doc_id	text	loyalty.TO	loyalty.log	I dentity position
19650	And to think the Democrats put their money on Antifa & BLM You GO	7.14	2.726545	
20366	We need to start a fund for our Patriots who get arrested in DC	7.14	2.726545	
20499	The DemiRATS sicked the Guard on the Patriots but NOT BLM AND AN	7.14	2.726545	
20511	Wow So many cowards popping up and tucking tail tonight Sorry cant	7.14	2.726545	
21439	PATRIOTS HERE IS PROOF GEORGIA CHEATED AGAIN LAST NIGHTHER	7.14	2.726545	
23439	A leader with that power cannot be a president of a democratic coun	7.14	2.726545	
23895	Tonight we sit on the precipice america patriots constitutionalrepubli	7.14	2.726545	
24212	Super Patriot hit with CS and a rubber bullet for you God Bless Americ	7.14	2.726545	
12786	No more peaceful protest The proud boys and the patriot citizens in t	6.98	2.70538	
7204	Maybe patriots should show at the mayors house to give her the trea	6.9	2.694627	
13552	Nothing changed No accountability Why would the results be differen	6.9	2.694627	
20702	WASHINGTON DC MARCH FOR TRUMP Great pictures from Patriots g	6.9	2.694627	
1038	BREAKING Patriots Have Made Their Way INSIDE THE CAPITOL Pence	6.67	2.663053	
1531	BREAKING Patriots Have Stormed the Capitol Building Masses Breach	6.67	2.663053	
2486	KekNo need to stress Patriots are in Control Nothing Can Stop What I	6.67	2.663053	
2591	Patriotism - Its An Ideology American Patriots have had enough They	6.67	2.663053	
3203	MORE PATRIOTS ENTERING THE CAPITAL BUILDINGFollow me for up	6.67	2.663053	
3238	PATRIOTS HAVE FORCED THEIR WAY IN PHOTOGRAPHS COMING IN	6.67	2.663053	
3727	Theres NO WAY thats a patriot That guy has antifa thug written all ov	6.67	2.663053	
4341	Hundreds of Thousands of Patriots Cheer Fight For Trump - Americans	6.67	2.663053	
5126	I agree And knowing what is coming makes this all the sweeterPop yo	6.67	2.663053	We as patriot
5238	MreeeNews New Pence Unfollows Trump penceKnew mikepence 19	6.67	2.663053	
7219	Mitt Romney is welcomed by the patriots Follow me to keep updated	6.67	2.663053	
7744	Good morning again Please pray for our Patriot friends in DC today th	6.67	2.663053	
8548	Well done patriots Follow me if you love all these photos and to see	6.67	2.663053	
8688	Its been reported that antifa was dressed up like patriots that attacke	6.67	2.663053	
8901	Echo Echo Echo NO WHERE ELSE WILL THIS BE SEEN OR HEARD ROLL	6.67	2.663053	
8913	Mitt Romney on a flight full of patriots on their way to DC chanting Tr	6.67	2.663053	
9163	If Anybody calls this Satanic Pedo Disgusting communist c a Patriot Ag	6.67	2.663053	
10513	ABSOLUTELYThe actions of a few RADICALS do Not Speak for the Th	6.67	2.663053	
13706	Are you ready patriots Be praying for safety of our republic and its pe	6.67	2.663053	
14458	Utah Patriots Also Confronted Mitt Romney at the Airport Before Cha	6.67	2.663053	
15176	For the idiots saying its antifa no its not patriots are pissed Its 1776 ag	6.67	2.663053	

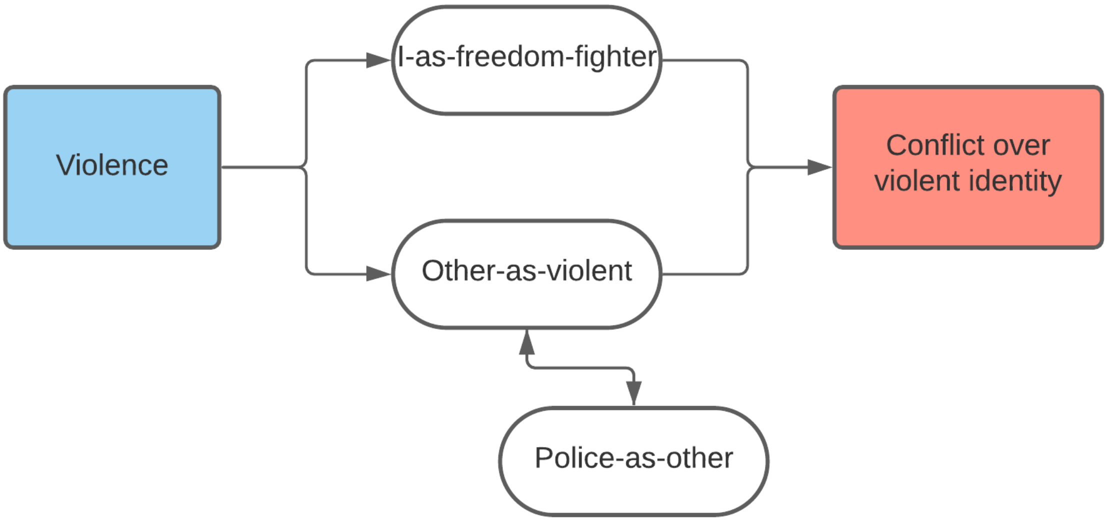
1		Short texts (Top log rating)								Longer texts			
2	X1	doc_id	text	loyalty.TO	loyalty.log				doc_id	text	loyalty.TOTAL	loyalty.log	
3	14303	14891	War	100	5.303304908				22956	23895	Tonight we sit on the precipice america patriots constitutio	7.14	2.726545
4	16840	17545	WAR	100	5.303304908				6298	6518	Yes sir Youre rightGrow a pair and give it back to themIts an	6.98	2.70538
5	8835	9181	WAR trumpwon	50	4.615120517				2558	2656	Its not a Civil War its a revolution disguised as a Civil War B	6.9	2.694627
6	16671	17371	1776 WAR	50	4.615120517				10553	10977	Flag of United StatesCol Rob Maness retRobManessDonald	6.67	2.663053
7	21487	22374	Revolutionary War	50	4.615120517				10784	11214	And were supposed to back the blue fuck the blue now its w	6.67	2.663053
8	3611	3736	This is Civil War patriots	40	4.394449155				11938	12432	Conservative Pundit Jesse Kelly Provides His Proof Dems Are	6.67	2.663053
9	2525	2622	Be aware Patriots	33.33	4.214495163				12416	12929	The war for America is still gonna be fought in the schools a	6.67	2.663053
10	8248	8564	Looks like war	33.33	4.214495163				16002	16678	You cant say Biden didnt warn usWe have put together I thi	6.67	2.663053
11	8759	9101	Civil War time	33.33	4.214495163				18176	18932	Communist Chinese Dictator XI Jinping Orders Peoples Liber	6.67	2.663053
12	16263	16948	Dem Civil War	33.33	4.214495163				18822	19602	My hope is that 98 of the people here on Parler are Russian	6.67	2.663053
13	19813	20628	This is WAR	33.33	4.214495163				23579	24545	Zwin But not a vet yourself right I have three combat tours	6.67	2.663053
14	173	179	The fog of war Patriots in control	28.57	4.062853895				23686	24658	Lin WoodLLinWood1mListen to our leader Name Hidden Pr	6.67	2.663053
15	13707	14265	War Room Pandemic LIVE War Room Pandemic	28.57	4.062853895				16942	17651	Lets get one thing clearTHIS IS NOT OUR WAY Dont get me	6.56	2.647592
16	6594	6827	Chinas Unrestricted War On The United States ZeroHedge	25	3.931825633				4318	4468	24 MIN IN PATRIOT WAR HOUNDS FIND FOX NEWS SUX HII	6.45	2.631889
17	11435	11891	War cry and victory	25	3.931825633				1007	1048	Despite military might & strong will of American spirit USA r	6.38	2.621766
18	14213	14795	Yup War has started	25	3.931825633				975	1016	Chinese Dictator Xi Jinping Orders the Peoples Liberation Ar	6.25	2.60269
19	14352	14943	Civil war get ready	25	3.931825633				3543	3668	Fear Not Stay Strong and Stay United America God Bless Pre	6.25	2.60269
20	15095	15725	PATRIOTS beware of IMPLANTS	25	3.931825633				7121	7380	Sorry Pelosi Eliminating official use of mother isnt inclusive	6.25	2.60269
21	15458	16106	We are at war	25	3.931825633				9333	9701	So you can have a civil war over trumpStop the reatarded sl	6.25	2.60269
22	17202	17915	You got your war	25	3.931825633		Referencing Civil War, implied violence		9575	9952	TO EVERY AMERICAN PATRIOTS ANY INFORMATION IS VAL	6.25	2.60269
23	18519	19290	Hes blmThats war	25	3.931825633				10675	11101	Sad most of your freinds in Republicparty are Cowards and	6.25	2.60269
24	20122	20955	Civil war is coming	25	3.931825633				12349	12860	This should make people very angry This never happened in	6.25	2.60269
25	22581	23510	Civil war is coming	25	3.931825633				12495	13014	PatriotFighterFlight203 7mdk7 ASSANGE IS FREEFollow Patr	6.25	2.60269
26	22741	23676	So its war then	25	3.931825633				16348	17034	Police escorting Antifa in Then hours later pepper spray rub	6.25	2.60269
27	23576	24542	Whens the war beginning Not wordage war	25	3.931825633				17826	18568	Raffensperger wont let a Republican win Kemp sold out to	6.25	2.60269
28	20256	21095	HawgRiderBC Yes my fellow patriot but not a civil war THIS IS 1776	23.08	3.853546076				18508	19277	Here we go Big tech doesnt care about peace This is WAR d	6.25	2.60269
29	14387	14980	PATRIOTS WILL NOT STAND FOR ANOTHER STEALTHIS MEANS WAR	22.22	3.816392774				19263	20060	The American people need to go to war on the Democrats	6.25	2.60269
30	4303	4452	It is time for war	20	3.713572067				19512	20312	PatriotFighterFlight197 7mdk7YOU DID NOTHINGFollow Pa	6.25	2.60269
31	5464	5653	The government murdered an unarmed female patriot This is war	20	3.713572067				21781	22687	Protesters storming the capitol wearing all black Looks like	6.25	2.60269
32	11243	11691	THIS MEANS FUCKIN WAR FOLKS	20	3.713572067				23694	24666	Unfortunately civil war is underway The left thinks it can do	6.25	2.60269
33	17329	18047	The war games have started	20	3.713572067				1850	1922	Democrats stealing KLoeffler s seat for Warnock Theres no	6.06	2.574138
34	19339	20136	Declare War KILL THEM ALL	20	3.713572067				20460	21303	They stole the Georgia run-off electionsCivil war is imminer	6.06	2.574138
35	19531	20331	The Patriots warned you cocksuckers	20	3.713572067				23912	24894	A sick demonrat sociopath has just shot and killed a Trump	6.06	2.574138
36	21142	22011	United in hate of government is better than civil war	20	3.713572067				1140	1186	PatriotFighterFlight204 7mdk7 SETHPENCEFollow Patriots ir	5.88	2.546315
37	21969	22881	War is the only remedy	20	3.713572067				1840	1912	2 PATRIOT EXPRESS JOIN INFOLLOW &ECHO ECHO NO RID	5.88	2.546315
38	3583	3708	EdTrueReality War Only fix after today	16.67	3.536310855				6774	7019	WOMAN MURDERED BY DC POLICE IDENTIFIED ASHLI BAB	5.88	2.546315
39	7130	7389	The Civil War is starting now	16.67	3.536310855				9290	9654	Anyone raiding the capitol needs jailedTrump needs arreste	5.88	2.546315
40	10490	10911	Pretty sure civil War starts tomorrow	16.67	3.536310855				17233	17950	UNITE AND DO ITKick Ass Rebel and ARISEOPEN ALL BUSIN	5.88	2.546315
41	11351	11806	God Bless the Salt of the Earth Patriot-Saints + Freedom Patriots TruthW	16.67	3.536310855				17460	18184	Civil War is coming and leftists only have themselves to blar	5.88	2.546315
42	13858	14423	GLOWIE WAR/CONFIRMATION CALLITALIAN NEWS COVERAGE	16.67	3.536310855				17606	18340	PatriotFighterFlight194 7mdk7FIGHT LIKE HELLFollow Patric	5.88	2.546315

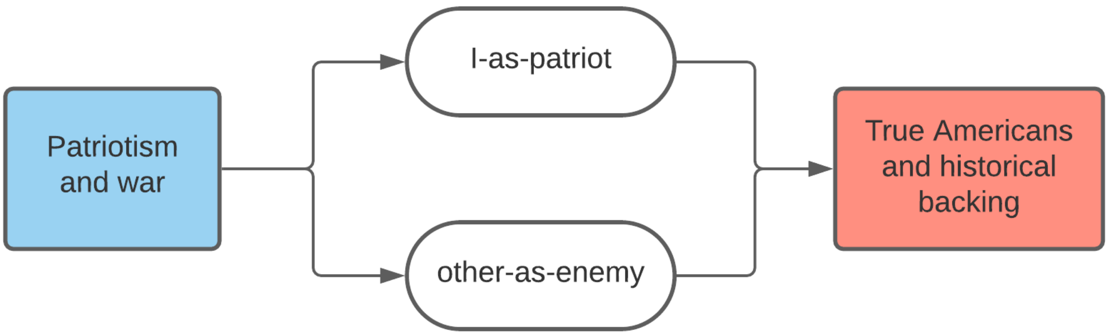
	X1	doc_id	text	sanctity.TOTAL	sanctity.lo	overall.TOTAL		doc_id	text	sanctity.T(	sanctity.lo	overall.TOTAL
1	15913	16583	God bless	100	5.303305	100		11033	Weaponized with GODs Word & Prayer Through Yeshua Messiah Name	20	3.713572	20
2	16949	17658	God Bless	100	5.303305	100		11557	Believing that God will show up in a mighty way with a VICTORY Glory to God Ir	20	3.713572	20
3	9255	9618	God bless her soul	75	5.01728	75		11690	THANK YOU FOR ALL YOUR SUPPORT GOD BLESS YOU ALL	20	3.713572	20
4	5104	5281	God Bless America	66.67	4.900374	66.67		11840	Keep your Faith They will get theirs In Gods time not ours Just keep praying	20	3.713572	20
5	8503	8830	God Bless America	66.67	4.900374	66.67		12852	This is certainly a David and Goliath situation Stay calm patriots God will prevai	20	3.713572	25
6	14086	14663	Fantastic god bless	66.67	4.900374	66.67		13386	God please lead the way	20	3.713572	20
7	15268	15908	God bless America	66.67	4.900374	66.67		14945	Dear God please help us	20	3.713572	40
8	22070	22985	God Bless Patriots	66.67	4.900374	100		17573	PrepareFor God & CountryFor HumanityWe FIGHTQ	20	3.713572	20
9	22436	23363	God bless America	66.67	4.900374	66.67		17662	Well god told him to do it Praying and all	20	3.713572	20
10	12839	13367	Blood for the blood god	60	4.795791	60		17943	Southbay14 Where is God now	20	3.713572	20
11	91	92	PLEASE GOD	50	4.615121	50		20424	Look at all the MAGA hats God Bless America	20	3.713572	20
12	360	376	Thank God	50	4.615121	50		20747	God will not forsake us	20	3.713572	20
13	1435	1494	God bless General Flynn	50	4.615121	50		23534	whoever wishes to be a friend of the world makes himself an enemy of God Jai	20	3.713572	25
14	2533	2630	GOD bless these PATRIOTS	50	4.615121	75		1100	I never lack Faith in God God never lets me downSadly mankind sometimes let	18.75	3.650658	18.75
15	3014	3124	Papabear2106 God bless you	50	4.615121	50		13694	Click ServantsoftheShieldofFaith for more Lord Jesus sayingsgrace inGodwetru:	18.75	3.650658	25
16	3397	3518	God knows	50	4.615121	50		22984	God bless and protect our great Patriots Victory is ours In the name of Jesus An	18.75	3.650658	31.25
17	7339	7608	God bless Vernon Jones	50	4.615121	50		33	God bless you lady stay safe President Trump has this handled	18.18	3.620601	27.27
18	7747	8039	GOD BLESS YOU LINlinwood	50	4.615121	50		5063	Your re a true Patriot and woman of God Bless you	18.18	3.620601	27.27
19	8145	8457	May God Bless him	50	4.615121	50		13846	PRAYERS FOR PRESIDENT TRUMP I wish to dedicate this very song to one of Gc	18.18	3.620601	18.18
20	11421	11877	God bless all Patriots	50	4.615121	75		15474	Yes he deserves this position a righteous patriot God-fearing man	18.18	3.620601	27.27
21	11630	12097	God Bless them all	50	4.615121	50	Aligning God to ingroup	23075	Its all happening now man spread this and God Bless you	18.18	3.620601	18.18
22	12846	13374	Thank God God Speed	50	4.615121	50		24651	What happens to onehappens to all Patriots god bless my countrymen	18.18	3.620601	27.27
23	13712	14270	God wins	50	4.615121	50		16573	An absolute must watch tonight Please watch and share Patriots We are going	17.39	3.577389	26.09
24	14603	15208	GOD BLESS PRESIDENT TRUMPTRUMP2020TheDilleyShow	50	4.615121	50		262	The Holy Spirit is present and unraveling/revealing TRUTHGODs YHWY Truth Pr	17.24	3.568969	17.24
25	14645	15250	GOD BLESS OUR AMERICA	50	4.615121	50		794	The games continue Keep Praying hard that God brings out the truth	16.67	3.536311	16.67
26	15678	16338	My God	50	4.615121	50		1529	Thank you to everyone whos sent their support God bless you all	16.67	3.536311	16.67
27	16773	17475	God & Country	50	4.615121	100		2917	From your lips to Gods ears	16.67	3.536311	16.67
28	18803	19582	God Bless Americans Patriots	50	4.615121	75		3390	A TRUE PATRIOT WITH GUTS AND LOYALTY TO GOD COUNTRY AND CONSTITU	16.67	3.536311	38.9
29	19177	19973	God bless you all	50	4.615121	50		3506	God will do the right thing	16.67	3.536311	16.67
30	19690	20501	Thank you God Bless	50	4.615121	50		4462	GOD HELP US HELP USA TRUMP	16.67	3.536311	50
31	20943	21806	God bless our President	50	4.615121	50		5004	Amen Our God will never forsake us He is righteous and just	16.67	3.536311	16.67
32	21309	22185	God bless you sir	50	4.615121	50		6397	And God will smite them all	16.67	3.536311	33.34
33	21323	22199	God bless these patriots	50	4.615121	75		7414	AMEN GOD IS ON OUR SIDE	16.67	3.536311	16.67
34	21740	22643	Beverly God Bless you	50	4.615121	50		7757	GOD IS KIKG NOT THE GOVERNMENT	16.67	3.536311	16.67
35	22061	22976	Thank God	50	4.615121	50		11123	Sad God be with her family	16.67	3.536311	33.34
36	23560	24526	God Bless our President	50	4.615121	50		13568	Thank you God be with you	16.67	3.536311	16.67
37	23847	24825	God bless Ted Cruz God bless him mightily	50	4.615121	50		14922	Get em Colonel Gods speed Sir	16.67	3.536311	16.67
38	10456	10874	God bless President TrumpGod bless you linwood God bless the US	41.67	4.434856	41.67		15067	CNN Hosts Mock Republican Lawmakers For Their Faith In God - Redline Headli	16.67	3.536311	16.67
39	7789	8087	God Bless you Mr President	40	4.394449	40		17363	Please pray for Gods mercy and protection upon our country today	16.67	3.536311	41.66
40	10263	10674	God bless President Trump todayStopTheStealFightBack	40	4.394449	40		18023	Please god let this be true	16.67	3.536311	16.67
41	1855	1928	Just a reminder Praying for you all God Bless	33.33	4.214495	33.33		19476	Thank God for President TrumpFollow Conservativarmy	16.67	3.536311	16.67

		X1	doc_id	text	fairness.log			doc_id	text	fairness.log	
1		X1	doc_id	text	fairness.log			doc_id	text	fairness.log	
2	389	16365	17051	Cheating	-5.303304908			8471	8797	Cheaters at it again in Georgia	-3.53631
3	388	9693	10073	CROOKS cheated again	-4.9003739			8978	9332	Dont concede They cheated again	-3.53631
4	378	1918	1991	Cheating again	-4.615120517			17384	18105	Cheated again Its over for democracy	-3.53631
5	379	3728	3858	Cheating again	-4.615120517			20715	21566	Thats all BS All of the communist outlets enjoy	-3.53631
6	380	4511	4665	Cheating Again	-4.615120517			22239	23161	More voter fraud Same story new day They lies	-3.4837
7	381	4632	4792	Cheating bastards	-4.615120517			7388	7660	America is no longer America its dead The Dem	-3.43399
8	382	9824	10215	BS Liars and cheaters	-4.615120517			19289	20086	Liars Cheaters Frauds need to be jailed now Vo	-3.42165
9	383	12620	13142	Cheating again	-4.615120517			7628	7913	DEMONRATS KNOW THAT THEY CHEATED AND	-3.3871
10	384	13386	13935	Such cheaters	-4.615120517			9451	9823	Cheating happened and PA legislators found it	-3.3871
11	385	17948	18695	Despicable cheats	-4.615120517			10350	10762	Dont concede Cheaters shouldnt prosper	-3.3871
12	386	19298	20095	To cheat	-4.615120517			12269	12773	Easy to cheat when controlling the election	-3.3871
13	387	19493	20293	Cheating again	-4.615120517			17165	17878	JUST CHANGE THE VOTES cheater barrackisach	-3.3871
14	369	1876	1949	They cheated again	-4.214495163			19067	19859	INSURRECTIONAct or Revolution We will not s	-3.3871
15	370	3148	3262	Dems cheated again	-4.214495163			22181	23101	Dems can win if they dont cheat	-3.3871
16	371	5512	5704	He cheated tho	-4.214495163			13490	14045	March to GA and tear the cheaters from limb t	-3.31999
17	372	8018	8321	Stop the Cheating stop the Cheat	-4.214495163			16589	17289	The only people responsible for this PROTEST a	-3.31999
18	373	14510	15108	Cheating MoFos	-4.214495163			22396	23322	The poor Dems wouldnt win an election ever a	-3.31999
19	374	16280	16965	Democrats cheating again	-4.214495163			657	684	This fucker is cheating you again Stealing yet ar	-3.2581
20	375	16882	17589	DEFINITELY CHEATING AGAIN	-4.214495163			1693	1761	Look at them cheating live on air AGAIN	-3.2581
21	376	20234	21071	Absolutely cheated again	-4.214495163			2821	2927	Dave how does it feel to be cheated	-3.2581
22	377	22647	23580	They cheated America	-4.214495163			3261	3377	Democrats Busted Cheating in Georgia AGAIN I	-3.2581
23	368	11968	12464	I believe it cheaters and liars sicking	-4.062853895			3493	3618	Georgia Fuckery more cheating Time to spill bl	-3.2581
24	357	275	288	Cheating in plain sight	-3.931825633		Democrats as cheaters	4580	4739	They fixed it again How does a racist communi	-3.2581
25	358	1931	2004	Mother daughter cheater team here for a second turn at stealing votes cheating and defraudin	-3.931825633			4691	4854	THEY CHEATED AGAIN DRAIN THE FRIGGIN SW	-3.2581
26	359	2963	3070	Democrats CHEAT AGAINStopTheSteal Georgia	-3.931825633			6924	7177	Looks like the democrats have perfected the c	-3.2581
27	360	3677	3804	Happening again Those cheaters	-3.931825633			9195	9557	Disgusted once again Will their cheating ever st	-3.2581
28	361	5613	5810	Cheating is not winning	-3.931825633			13017	13550	PLEASE WATCH SHARE WITH EVERYONE HOW	-3.2581
29	362	6196	6415	The cheat is in	-3.931825633			21271	22143	Evidence of more Dem cheating in GA runoffst	-3.2581
30	363	8732	9072	Let the cheating begin	-3.931825633			21363	22243	I truly hate those cheating sons of bitches	-3.2581
31	364	16572	17271	Cheating again So predictable	-3.931825633			11002	11440	Steele13 Now we probably have to defraud the	-3.19949
32	365	21163	22033	MyPresidentTrump Its all theyre good for lying cheating and stealing	-3.931825633			1398	1456	Yup cheating started at that pointThere is your	-3.14501
33	366	22005	22918	They are pulling the same fraud cheating crap	-3.931825633			3062	3173	Democrats have Perfected the Cheat Just look	-3.14501
34	367	22768	23703	Look at The Cheaters	-3.931825633			4922	5092	This is what cheating with no consequences ge	-3.14501
35	355	13109	13645	They cheated again I am done with crooked elections	-3.816392774			8858	9204	Fight Patriots this is our land Fuck those cheate	-3.14501
36	356	22219	23141	Just a bunch of cheaters and liars So disgusting	-3.816392774			11029	11469	Obama and his acorn pals are pro at cheating	-3.14501
37	346	3070	3182	You shouldnt have cheated Democrats	-3.713572067			12724	13248	This is the result of cheating No one wins	-3.14501
38	347	3374	3494	Thats how they cheat	-3.713572067			14445	15041	Cheating the exact same way they did last time	-3.14501
39	348	5988	6199	Cheater just like creepy Joe	-3.713572067			22600	23530	Cheating again they dont know when to stop	-3.14501
40	349	9676	10054	The Democrats are cheating again	-3.713572067			4043	4183	No were like you President Trump we know the	-3.09377
41	350	11771	12244	He is going to CHEAT	-3.713572067			20382	21223	If they cheated the 1st time and didnt get in tr	-3.09377
42	351	15774	16438	America says NO JOE CHEATER	-3.713572067			7212	7479	If you have to cheat to win Youre a loser	-3.04452


Christian ethics
I-as-on-God's-side
other-as-evil
Divine will

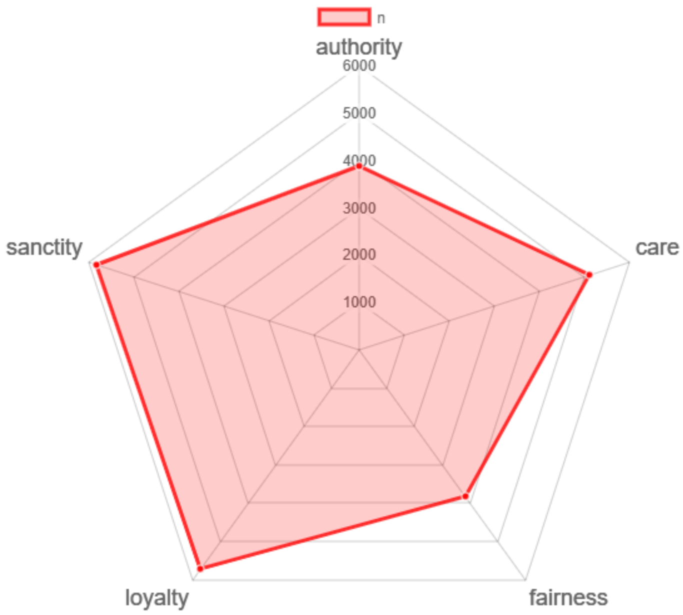

Fraud
other-as-illegitimate
Stolen election

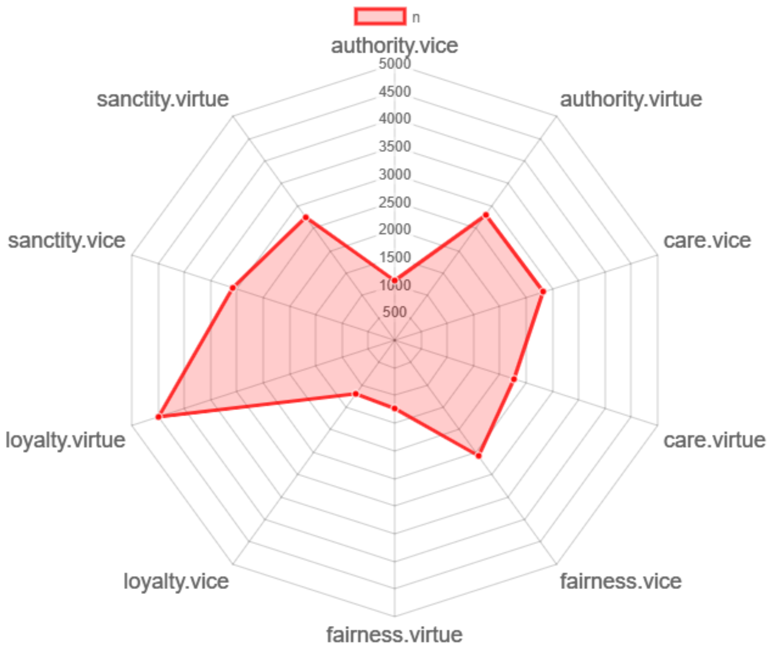

Violence
I-as-freedom-fighter
Other-as-violent
Police-as-other
Conflict over violent identity

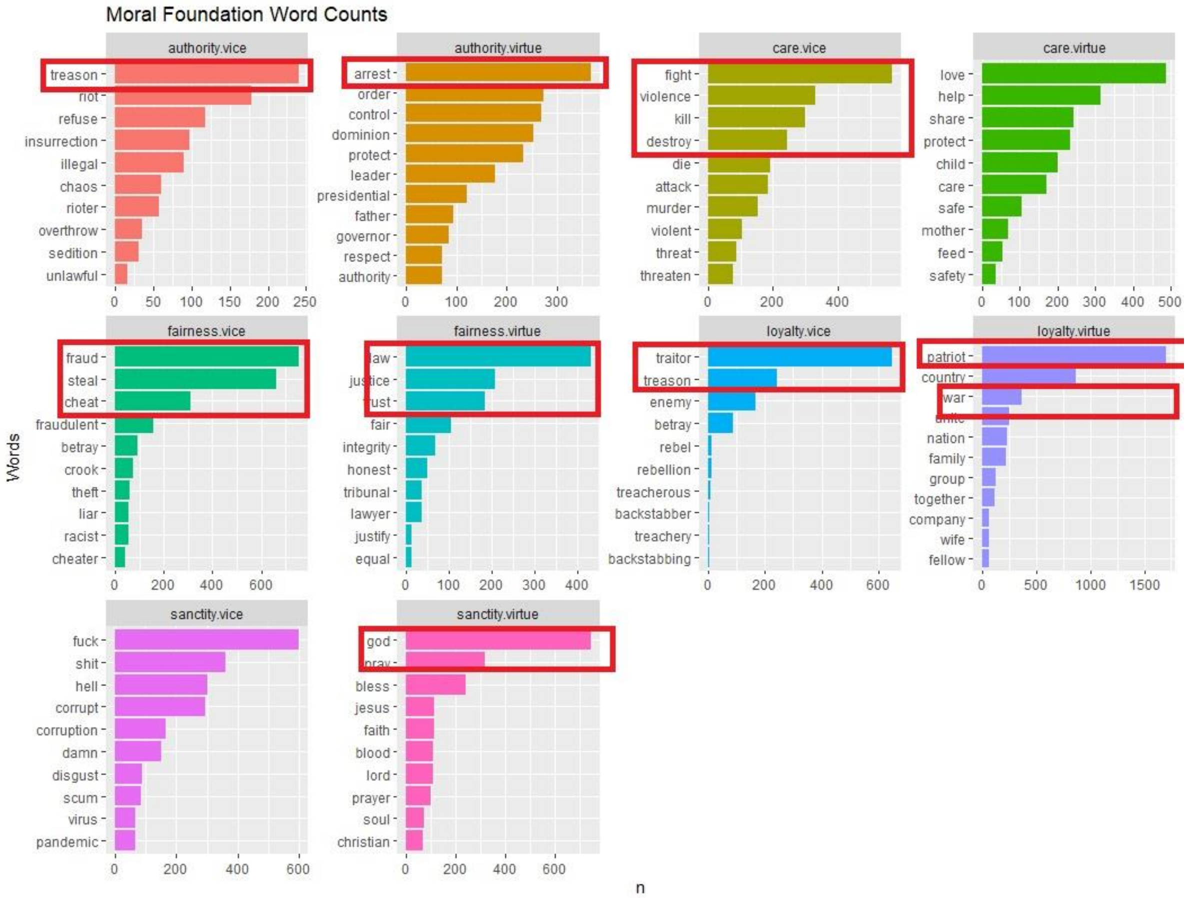

Patriotism and war
I-as-patriot
other-as-enemy
True Americans and historical backing

11.6 - Moral foundation plots

Overall MF use







Red box indicates chosen for futher analysis. Not all words relevant.

11. 7 - Correlations Table (extract)

Key word associations		
Patriot	Maga	0.14
	Antifa	0.12
	draintheswamp	0.11
War	Civil	0.44
	Declare	0.11
God	Bless	0.41
	Jesus	0.18
	Evil	0.18
	Faith	0.18
	pray	0.18
Fraud	Voter	0.26
	Election	0.25
	Georgia	0.25
Steal	Stop	0.31
	Election	0.22
	Democrat	0.09
Cheat	DeKalb	0.12
	Democrat	0.11
	Lie	0.10
	Dominion	0.09
Treason	Participant	0.25
	Tribunal	0.24
	Commit	0.22
Fight	War	0.11
	Country	0.11
	Back	0.10
	Battle	0.08
Violence	Condone	0.16
	Advocate	0.14
	Incite	0.14
	Antifa	0.14
Kill	Unarmed	0.28
	Shoot	0.22
	Veteran	0.16
	Woman	0.16
Murder	Unarmed	0.12
	Veteran	0.12
Arrest	Enrique	0.16
	Tarrio	0.14
Traitor	Romney	0.18
	Grill	0.18
Law	Enforcement	0.32
	martial	0.22
Riot	Loot	0.21
	Protest	0.11

11.8 – Topic list

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10	Topic 11	Topic 12	Topic 13	Topic 14	Topic 15	Topic 16	Topic 17	Topic 18	Topic 19	Topic 20
fuck	say	please	china	think	act	can	need	maga	call	get	trump	state	ballot	now	people	world	biden	one	try
shit	want	share	country	know	treason	many	yes	stopthesteal	say	ass	president	unite	vote	right	american	child	president	every	tell
bullshit	just	keep	america	really	military	still	mitch	electionfrauc	leave	away	win	court	georgia	•	million	control	joe	way	thing
bitch	come	everyone	communist	want	arrest	see	mcconnell	wwgwga	question	hand	donald	deep	machine	damn	politician	justice	family	thing	anyone
piece	let	help	corrupt	play	hang	people	swamp	kag	far	lot	support	ask	county	thing	elect	expose	trump	always	someone
little	dems	thank	sell	get	crime	word	run	fightback	now	just	already	send	dominion	come	work	sick	harris	single	expect
give	okay	listen	politician	anyone	insurrection	even	give	qanon	remember	hes	death	legislature	poll	huge	official	evil	que	another	even
bastard	set	ask	save	let	yes	believe	come	trump	answer	ready	speech	supreme	count	warn	real	bring	kamala	hand	else
pos	everything	message	socialist	anything	charge	continue	start	usa	eye	communis	racist	legislator	mail	good	step	pedophile	hunter	run	fool
lol	total	can	little	already	treasonous	leave	people	parler	phone	kick	top	refuse	block	refuse	angry	anti	bidens	scum	course
commie	take	important	communism	head	commit	take	everything	trumptrain	talk	gonna	anymore	secretary	republican	care	care	miss	para	tell	system
idiot	friend	send	destroy	game	still	TRUE	agree	freedom	isnt	deserve	takeover	certify	hour	okay	class	can	campaign	person	change
stupid	people	everywher	ccp	crazy	justice	mind	understan	voterfraud	run	reason	usa	elector	fulton	hear	funny	elite	investigati	time	different
mother	whatever	word	job	actually	coup	back	without	wethepeople	liar	beat	hear	governor	signature	lawyer	take	let	exclusive	yet	fix
rat	next	explain	take	hurt	legal	result	now	americafirst	racist	see	other	constitutic	process	blow	middle	wake	interview	proof	show
pussy	nobody	spread	socialism	you	jail	start	office	donaldtrump	refuse	rid	first	rule	worker	protect	represent	kid	truth	problem	whole
get	think	informatic	become	sorry	traitor	amen	leader	draintheswar	sit	thats	outside	contest	view	believe	scare	baby	não	reason	shame
suck	opinion	proof	buy	guess	know	eye	face	fakenews	whole	like	hunter	pennsylvar	abrams	crap	hold	traffic	corruption	lie	theyre
eat	experience	everybody	own	ever	potus	witness	drain	election	laugh	back	gitmo	fraudulent	fill	sit	many	everything	break	need	everyone
hang	night	thing	shut	even	invoke	never	want	thegreatawal	omg	head	establishm	allow	receive	fact	claim	conspiracy	com	accept	way

Topic 21	Topic 22	Topic 23	Topic 24	Topic 25	Topic 26	Topic 27	Topic 28	Topic 29	Topic 30	Topic 31	Topic 32	Topic 33	Topic 34	Topic 35	Topic 36	Topic 37	Topic 38	Topic 39	Topic 40
work	shoot	know	antifa	name	see	patriot	capitol	come	love	take	national	turn	antifa	let	trump	’	law	steal	like
enough	woman	life	guy	hide	hear	follow	build	arrest	man	free	order	part	blm	plan	washingto	have	constitutic	stop	look
cant	police	lose	flag	comment	believe	stay	storm	now	great	…	guard	high	burn	bad	rally	‘	criminal	election	just
say	kill	matter	little	linwood	evidence	update	capital	first	country	citizen	break	around	riot	trust	america	will	enemy	democrat	feel
just	unarmed	way	FALSE	stopthest	tomorrow	drop	police	boy	thank	nation	sign	two	city	good	speak	didn	protect	cheat	sound
wont	die	black	bus	follow	wait	handle	inside	proud	hate	–	chinese	help	destroy	way	save	wasn	order	lie	agree
can	force	much	break	sidneypow	today	serremmy	break	take	family	action	mayor	now	terrorist	now	thousand	yet	rule	win	figure
even	capitol	even	photo	addvibes	tonight	support	breach	say	rest	place	california	attempt	attack	maybe	march	footage	defend	allow	past
hard	veteran	doesnt	grind	genflynn	voice	ride	protester	american	protect	press	threat	point	police	may	jan	seem	constitutic	america	listen
believe	murder	folk	stage	mstigress	talk	leave	hill	release	hero	speech	security	level	loot	along	freedom	interest	foreign	low	familiar
didnt	air	mean	thug	add	tire	safe	rush	leader	honor	first	behind	fact	business	elect	event	doubt	enforceme	nothing	happen
start	ashli	need	confirm	list	feel	search	enter	yes	beautiful	hold	deny	coup	murder	know	ahead	tuesday	federal	look	head
anything	young	anything	escort	train	thing	win	chamber	wake	peace	america	company	rich	month	actor	crowd	much	domestic	welcome	yep
tell	officer	come	load	mdk	make	emmyexpr	protestor	face	sacrifice	agree	executive	numb	mob	understan	january	result	declare	honest	wow
know	dead	hope	infiltrate	oann	present	serremmy	outside	soon	stand	even	use	–	nothing	step	washingto	put	oath	today	team
check	serve	easy	wow	loose	promise	everyone	lockdown	yet	america	fly	include	entire	rioter	forward	hundred	corruption	terrorist	nice	piss
job	neck	truly	picture	without	let	fellow	security	charge	sir	pass	send	political	capital	soon	arrive	wolf	remember	thief	wouldnt
friend	female	pretty	fbi	tedcruz	doubt	please	tear	speak	give	see	deploy	together	property	official	plaza	georgia	swear	mind	theyve
learn	year	get	proof	sezz	concern	express	evacuate	enrique	something	january	request	come	damage	since	tomorrow	join	official	art	life
win	identify	dear	wear	rudyg	witness	plan	federal	target	reason	ultimate	word	seth	summer	clear	wednesda	bet	corrupt	stay	great

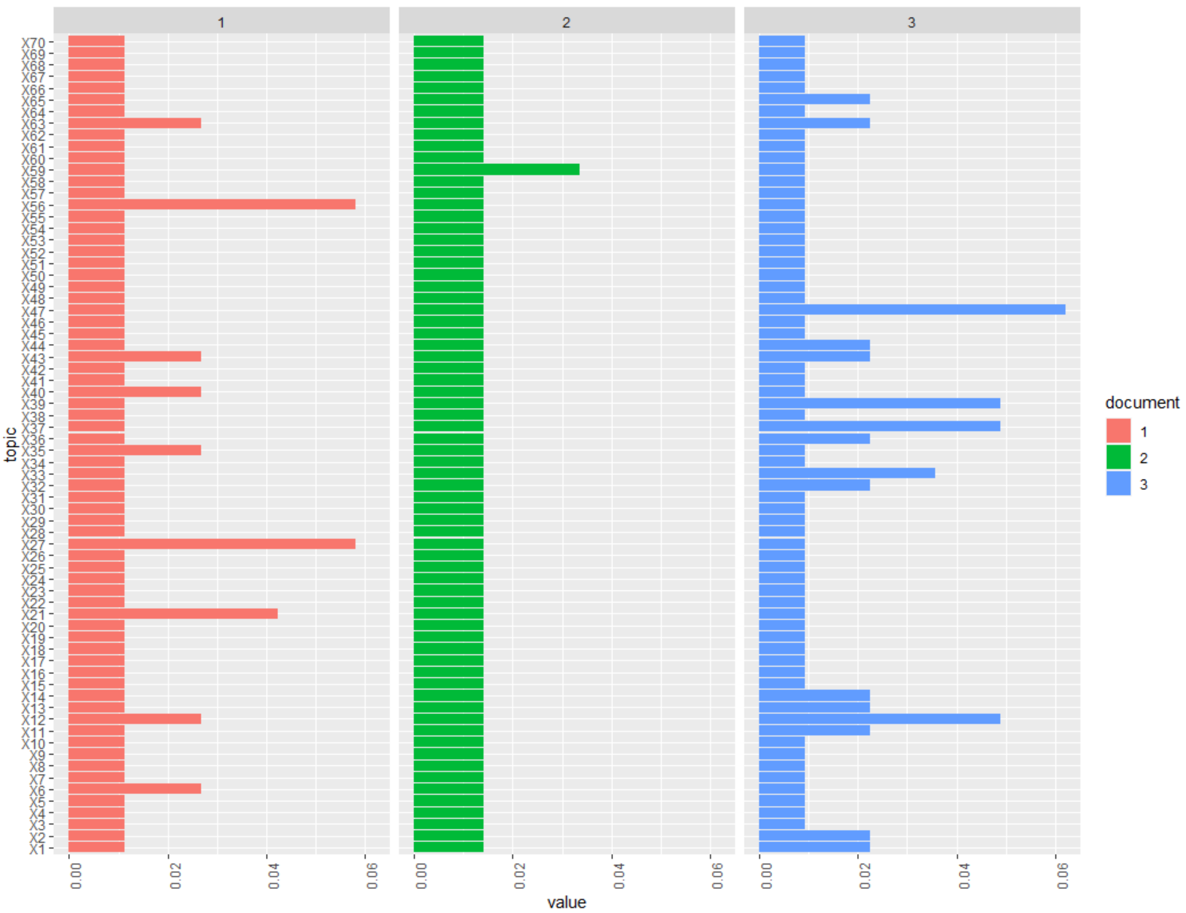
Topic 41	Topic 42	Topic 43	Topic 44	Topic 45	Topic 46	Topic 47	Topic 48	Topic 49	Topic 50	Topic 51	Topic 52	Topic 53	Topic 54	Topic 55	Topic 56	Topic 57	Topic 58	Topic 59	Topic 60
good	fight	god	trump	news	’	stand	back	obama	twitter	day	patriot	never	people	police	make	big	vote	medium	house
hope	war	pray	supporter	report	don	must	take	italy	post	today	traitor	ever	governmei	cop	sure	read	georgia	today	white
may	freedom	bless	antifa	just	doesn	patriot	country	election	parler	america	full	one	right	fire	truth	post	count	violence	pelosi
TRUE	civil	evil	blame	find	didn	support	get	italian	trump	end	romney	give	power	side	lin	just	senate	protest	congress
find	start	lord	maga	fake	isn	line	blue	cia	peace	history	watch	hell	use	open	wood	link	perdue	peaceful	member
youre	republic	jesus	dress	break	anymore	hold	stop	defense	tweet	sad	mitt	forget	allow	gun	big	tech	lead	cause	senate
morning	patriot	faith	disguise	fox	aren	keep	gijoevets	datum	account	long	flight	another	now	door	base	pass	warnock	social	office
show	begin	prayer	blend	watch	wouldn	put	stopthestε	involve	home	january	chant	concede	long	street	fact	app	race	violent	remove
chance	usa	give	idiot	cnn	haven	nation	codjt	military	president	remember	board	allow	throw	walk	viral	meet	loeffler	problem	nancy
nothing	revolution	heart	lose	newsmax	care	strong	way	via	video	choose	tie	people	find	attack	sidney	story	runoff	show	break
become	country	father	violent	bomb	around	now	pro	former	call	fall	plane	happen	always	tear	sense	late	night	conservati	amendmei
crook	lose	truth	record	medium	couldn	together	push	system	hour	begin	able	probably	seem	claim	echo	article	ossoff	remain	floor
time	liberty	shall	hammer	source	know	side	ain	use	facebook	last	catch	support	future	group	release	click	dump	leftist	control
also	end	may	mind	dnc	either	can	marine	audio	lock	forever	hang	political	become	weapon	statement	clinton	david	ignore	majority
awesome	democracy	amen	personal	tonight	set	demand	corrupt	leonardo	remove	world	fill	surrender	nothing	gas	say	create	kelly	call	congressio
agree	face	name	capital	network	shouldn	good	cocass	contractor	block	much	airport	let	duty	start	powell	email	presidential	mostly	face
luck	arm	christ	crowd	rnc	weak	beautiful	ive	orchestrat	potus	come	utah	mention	new	front	info	file	raffensperger	condemn	seat
type	america	soul	attempt	’	always	TRUE	turn	iran	delete	minute	confront	time	form	brick	mistake	other	switch	responsibl	immediate
believe	either	son	washingto	discuss	color	face	run	theft	ban	rise	care	today	change	public	talk	site	candidate	completel	leader
use	prepare	earth	whole	wrong	fault	rinos	without	satellite	suspend	prove	grill	unless	human	protester	time	join	catch	peacefully	statement

Topic 61	Topic 62	Topic 63	Topic 64	Topic 65	Topic 66	Topic 67	Topic 68	Topic 69	Topic 70
covid	happen	republican	new	year	time	live	election	pence	vote
vaccine	know	democrat	pay	last	—	video	fraud	president	electoral
mask	just	party	money	old	real	see	voter	mike	senator
death	nothing	gop	million	next	many	watch	rig	traitor	congress
bill	something	rino	move	tell	political	show	fraudulent	trump	object
wear	wrong	conservati	use	ago	long	follow	evidence	vice	college
virus	mean	liberal	governmei	night	change	catch	massive	betray	certification
gate	people	democrati	fund	give	career	also	fair	coward	cruz
pandemic	thats	jones	plan	week	exactly	fee	result	flynn	arizona
test	hell	support	tax	since	yet	youtube	november	general	transparenc
world	surprise	join	also	two	suppose	moment	illegal	authority	challenge
cover	whats	rep	dollar	yet	TRUE	smash	integrity	mikepence	ted
die	exactly	senate	buy	maybe	bear	pull	process	courage	session
agendum	already	rinos	business	late	come	broadcast	msm	presidency	objection
great	wtf	leadership	shock	long	already	crowd	audit	stab	debate
everyone	gonna	vernon	now	deserve	forward	camera	accept	must	rep
positive	hard	weak	soros	today	patriotpar	disappear	overturn	act	sen
case	dems	seat	continue	matt	history	coverage	landslide	decide	elector
lockdowns	hope	establishm	much	wow	ago	yall	investigate	possible	john
make	cheat	corruption	include	month	strong	bring	apparently	claim	joint

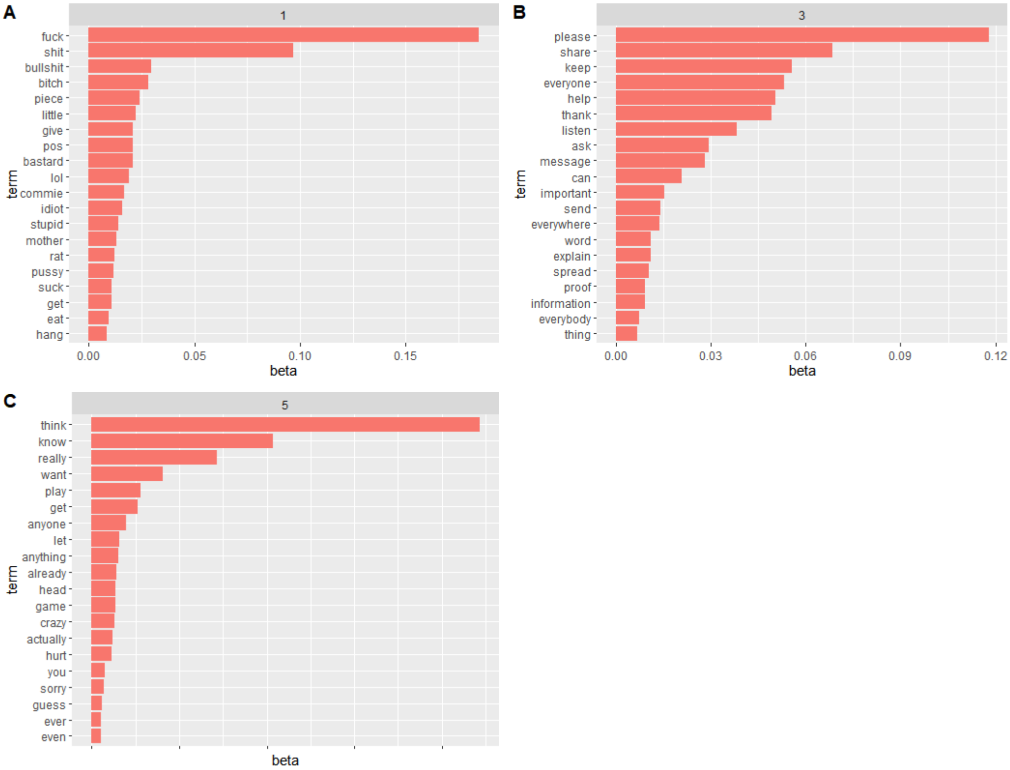
Topic 44	Topic 34	Topic 63	Topic 69	Topic 24	Topic 18	Topic 38	Topic 17	Topic 4	Topic 23		
trump	antifa	republican	pence	antifa	biden	law	world	china	know		
supporter	blm	democrat	president	guy	president	constitutic	child	country	life		
antifa	burn	party	mike	flag	joe	criminal	control	america	lose		
blame	riot	gop	traitor	little	family	enemy	justice	communis	matter		
maga	city	rino	trump	FALSE	trump	protect	expose	corrupt	way		Notable other
dress	destroy	conservati	vice	bus	harris	order	sick	sell	black		Implies conflict
disguise	terrorist	liberal	betray	break	que	rule	evil	politician	much		Notable self
blend	attack	democrati	coward	photo	kamala	defend	bring	save	even		
idiot	police	jones	flynn	grind	hunter	constitutic	pedophile	socialist	doesnt		

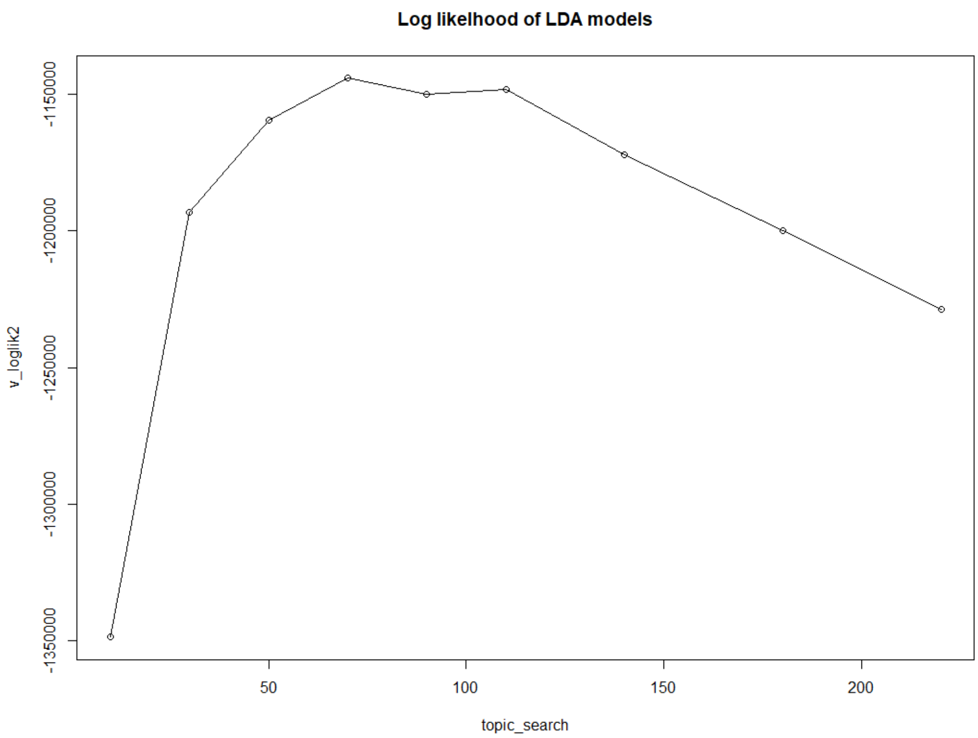
11.9 – Supplementary topic plots

Example of probability of topic distribution across three documents



Example of top terms probabilities within topics





11.10 – Dialogical analysis examples codes excerpt

5x from each topic

doc_id	posts_comments	topic	gamma	Tactic	i-position	others/other's perspectives
14527	"When I hear Christine Lagarde (former Finance Minister of France, former IMF Direct	4	0.316	Distrust, Stereotyping	Contextual - Conservative, Mentioned - Us little people	Dems and RINOS, China, Bezos
17577	Rallies Rallies Rallies President Trump!!!!The Marxist socialist Dems say no to celebrat	4	0.187	Stereotyping	Patriot	Marxist socialist Dems - "say no to Christmas/private sector"
13660	WE ARE in DC.. WAITING FOR THE CALL. ONLY WE CAN SAVE AMERICA NOW.WE ARE	4	0.108	Dichotomizing, stereotyping	Contextual - Conservative	Other as China centric, implied - reomove American life, introduce socialism
21120	No, Dumb-a-crats won because they cheated. And in so many ways its hard to count t	4	0.102	Stereotyping, dichotomizing, deflecting	Contextual - Conservative	Democrat - Implied, want to win nefariously. China - implied pulling strings
22665	We have to take our country back from these corrupt politicians, there is no doubt our	4	0.097	Dichotomizing, stereotyping, distrusting	Our country - true American	Corrupt satanic democrats, implied - nefarious control
11679	All the tweets in one place, plain text:Lin Wood drops major bombshells: Entire world	17	0.204	Deflecting, stereotyping, dichotomizing	Contextual - Conservative	Mysterious, powerful and evil 'other'
2186	And they also hate President Trump because they knew he would uncover their child a	17	0.121	Deflecting, stereotyping , dichotomising	Contextual - Conservative	Evil depraved Democrats
24062	Human trafficking and Pedophilia ...it's what makes them available for blackmail. Ask	17	0.116	Distrusting, deflecting	Contextual - Conservative	Depraved other in control, do not want to be discovered
15676	??????????????????????IT'S PEDOPHILE JUSTICE JOHN ROBERTS FAULT FIRST!! HE DI	17	0.113	Deflecting, stereotyping, dichotomizing	Contextual - Conservative	John Roberts thinks riots are bad - perpective dismissed as 'peadophile'
5403	1/6/2021- "Joe Biden is full of shit. He says nothing about human trafficking, pedophili	17	0.112	Stereotyping, distrusing	Contextual - Conservative	Biden on the side of evil but wants to challenge Republicans
13714	Harris caught immediate flak for the too-perfect correlation between the stories. "Pla	18	0.226	dichotomizing, distrusting	Contextual - Conservative	Harris, Biden, implied want to obtain position by embellishing/lying
1365	Fraud beyond belief Kamala Harris now ripping off Martin Luther King stories when he	18	0.143	Distracting	Contextual - Conservative	Harris, implied wish to obtain place by dishonesty
21018	"The left didn't quite think through their plan to take over the United States of Americ	18	0.142	Distracting, stigamtising	Implied/contextual - the right	The left' Intention to steal election
6403	This analysis revealed that counties that used Dominion and Hart InterCivic ballot cou	18	0.125	Distrusting, relativizing	Contextual - Conservative	Democrats, wish to cheat to a win
14080	Hunter Biden's Laptop Exposes Joe Biden Big Time! ??China Was Colluding With Joe Bi	18	0.121	Distracting	Contextual - Conservative	Biden intention to cheat with China's help
8684	I'm sitting here in Canada watching these surreal developments. Canada is currently cr	23	0.123	Distrusting	Contextual - Conservative	Democrat leadership grand plan to involve China - ulterior motive
19960	Voting doesn't matter anymore. They fucking mock you with voting. The law no longer	23	0.082	Distrusting	Contextual - Conservative	Democrat nefarious methods of controlling vote
14977	Fuk these reports on Fox today,why didn't they talk so much shit about black lives mat	23	0.095	Distracting	Contextual - Conservative	Media/Fox - not interested in representing republican issues/bias against Trump supporters
9670	The way there wasnt much resistance when they entered the building makes me believ	23	0.090	Distraction, distrust, denialism	Contextual - Conservative	Left wing 'bad actors' want to stage Trump supporters as violent
12113	It doesn't matter if the GOP is dead, because we will never again be "allowed" to parti	23	0.083	Distrust, dichotomising	Contextual - Conservative, implied true American	Left wing as untrustworthy manipulators and on the side of evil
1348	BREAKING: Former FBI agent on the ground at U.S. Capitol confirmed that at least 1 "	24	0.224	Distracting and deflecting, distrusting	Contextual - Conservative, implied non-violent	Antifa as wanting to frame Trump supporters
7261	??BEWARE FALSE FLAG OPS??...ARE IN PROGRESS. ANTIFA AT THE HEAD OF IT.Paul Sp	24	0.220	Distracting and deflecting	Contextual - Conservative, implied non-violent	Antifa trying to initiate 'false flag' operation
6626	BREAKING: Former FBI agent on the ground at U.S. Capitol just (texted)me and confir	24	0.207	Distracting and deflecting	Contextual - Conservative, implied non-violent	Antifa trying to initiate 'false flag' operation
8975	From my cousin on the ground in DC: Zia ShieldsHERE'S The Scoop:Cody NelsonThis is	24	0.197	Distracting, distrusting, denial	Patriot, implied non-violent	Antifa and police working together to stage violence
19591	Buffalo horns guy at Capitol Building Break-in is Antifa—NOT a patriot. Note the Boy-	24	0.147	Deflecting, distracting	Contextual - Conservative	Poster boy with horns now othered as peadophile and left supporter
13342	So we watched for 9 months Antifa and BLM burn down cities, destroy businesses, att	34	0.208	Distracting	Patriot	Left as portraying Trump supporters as terrorists while wanting to be violent themselves
16659	Hollywood actresses now run country. Except she had 0 to say about massive violent	34	0.199	distracting	Contextual - Conservative	Elite bias in favour of Antifa etc, Antifa as violent
19674	Unforgivable that burn. Loot murder has terrorized our country for 10 months shut do	34	0.190	distracting, rationalising	Contextual - Conservative	Left as advicating violence, unnamed other as overemphasising right-wing violence
24474	They planned this. They sent in Antifa to infiltrate the protest! They did it so the Patrio	34	0.173	distracting, rationalising, deflecting	Contextual - Conservative	Left as violence loving, wanting to frame Trump supporters
13066	The heights of the Propaganda Machine on mainstream media cannot be compared to	34	0.150	distracting, rationalising	Contextual - Conservative	Media bias against conservatives, Antifa as infiltrators
11506	Antifa activists have brutally attacked our law-abiding friends, neighbors, and business	38	0.266	Dichotomizing	Lawful respectful American	Antifa as lawless, wanting to committ acts of terror and destruction of American heritage
2320	They broke the law and it's an invalid election. everyone is expected to follow the law	38	0.139	Distrusting, dichotomizing	Contextual - Conservative, implied lawful	Vague left other, likely democrats willing to go beyond the law to win
15679	The fact is, when we have no law or semblance of law, we, as patriots have an obligati	38	0.180	Dichotomizing	Patriots, abiding by the constitution	Left happy to take part in lawless anti American destruction
12398	??WHERE WE GO FROM HERE??1. Everyone...GOP, RINOS, DEMOCRATS, PUBLIC OFFI	38	0.154	Dichotomizing	Contextual - Conservative, constitutional	Deep state' nefarious other wanting to control the political order
4266	As a geniuine constitutional crisis looms today, Congressional cowards show their met	38	0.148	Dichotomizing, stigmatizing	Contextual - Conservative, constitutional	Political other who is afraid to object to the alleged vote-rigging
24466	I totally believe the people who broke into the White House are antifa disguised as Tru	44	0.126	Deflecting	Contextual - Conservative, knower of truth	Antifa as wanting to frame Trump supporters
12045	This was most likely Antifa dressed like Trump supporters! Who else would want Trum	44	0.124	Deflecting	Contextual - Conservative	Antifa as wanting to frame Trump supporters
11105	Whose says it's all Trump supporters? Antifa and BLM put out info for their supporters	44	0.115	Deflecting, denialism/denial	Contextual - Conservative	Antifa as wanting to frame Trump supporters
10224	Cracks me up; Trump supporters A.K.A antifa and BLM in Trump supporter camo! If po	44	0.113	Deflecting	Contextual - Conservative	Antifa as wanting to frame Trump supporters
13774	Tens of thousands of freedom-loving Amer. patriots peacefully protested at Capitol to	44	0.113	Deflecting Denialism/denial/dichotomizing	Patriotic, peaceful conservative	Potential ambition to cause distruption, Attributed to Antifa
22766	Remember Millard Fillmore? He was our last Whig President. His Whig Party collapsed	63	0.147	Dichotomising, distrusting	Republican/conservative	Other as Republican officials afraid to challenge, other as evil Democrat wishing to bring down the state
15062	Well, here's some good news out of Georgia. State Rep Vernon Jones just quit the Der	63	0.137	Distraction by idealising?	Republican/conservative	Unclear
8622	I call on all honest politicians to leave the Democrat party and join the Republican part	63	0.117	Idealising vernon Jones set up distraction	Contextual - Conservative	Unclear
7327	Time to leave these parties of Judas or the new socialist communist parties! Time for	63	0.108	Dichotmomising	Republican as good 'Disciples of Christ'	Vague intentions of evil communist other
20992	May 22, 1856. Sa southern Democrat caned a northern Congressman to near death Su	63	0.092	Distracting, relativizing	Contextual - Conservative/Republican	Lawless anti-American BLM
24826	Pence Betrayed General Flynn in 2017 and Today He Betrayed President Trump and Ar	69	0.145	Stigmatizing	Contextual - Conservative, implied true Republican	Pence as evil, traitor, implied willingness to bring down Conservative cause
1738	MIKE PENCE KILLED HER!! ECHO! Vice President Pence And His Family Are Nothing But	69	0.130	Stigmatizing, dichotomizing	Contextual - Conservative, implied true Republican	Pence as wanting to undermine Republicanism
746	Pence Betrayed General Flynn in 2017 and Today He Betrayed President Trump and Ar	69	0.129	Stigmatizing	Contextual - Conservative, implied true Republican	Pence as wanting to undermine Republicanism
8476	NOBODY SHOULD BE SURPRISED. EVERYBODY SHOULD BE UPSET. Vice President Pen	69	0.112	Stigmatizing	Contextual - Conservative, implied true Republican	Pence as wanting to undermine Republicanism
21612	Vice President Pence will NOT support GOP congressional effort to contest electoral v	69	0.109	Stigmatizing, dichotmizing	Contextual - Conservative, implied true Republican	Pence as wanting to undermine Republicanism

Example from Topic 4:

Text:

Is this a Civil War of free Americans vs Communist Demtards, or is the beginning of the Revolution of America throwing off the bonds of our Chinese Communist Party oppressors?

I-position: 'Free American', implied conservative

Other/perspective: Democrats, want to bring socialism

Disruption: Contextual election result

Tactic: Stereotype, distrust (Communist, Chinese control)

Example from Topic 17:

Text:

Dirty Impeachable Joe, Has Got To Go!!! Let the "TRUTH" and "HISTORY" of a crime family flow!!!The majority of Americans are saying NO, NO, NO!!!Even around the world, the people are letting out their thoughts about Joe Biden as U.S. President be known. Children and women worldwide are cringing at the thought of touchy, feely Joe in a position of power and trust. A man who can't keep his hands out of the personal space of women and children should "NOT" be the POTUS!!!The cake depicts the "TRUTH" about Joe Biden.The Villa Villa Cafe and Bar in Hong Kong published a photo of a custom cake it baked for a customer this week depicting American presidential candidate Joe Biden sniffing the hair of a distressed cartoon...#BreitbartNews #HongKong #JoeBiden #pedophiles #incest #NXIVM #ChildAbuse #CrimesAgainstChildren #CrimesAgainstHumanity #China #Ukraine #PuertoRico?

I-position: Implied conservative, knower of truth

Other/perspective: Joe Biden, implied Democrats

Disruption: Contextual election result

Tactic: Stereotype, stigmatise (Child abuse, crime links)

Example from Topic 18:

Text:

Kamala Harris plagiarized Martin Luther King Jr. in her recent interview The mainstream media won't hold her accountable Could you imagine if a Republican did this?

I-position: Implied conservative

Other/perspective: Democrats, Kamala Harris, wants to cheat to win

Disruption: Contextual election result

Tactic: Distract (Plagiarism issue)

Example from Topic 23:

Text:

Black lives matter and Antifa were bused into DC. They broke windows and one is sitting inside . A message says mingle with the protesters and get inside the WH.

I-position: Implied conservative

Other/perspective: BLM, want to frame 'patriots'

Disruption: Violence

Tactic: Distract, deflect/blame

Example from Topic 24:

Text:

Proof. These police working to stage "false flag" with Antifa acting like they are Trump supporters breaking in White House.

I-position: Implied conservative

Other/perspective: Police, working with Antifa

Disruption: Violence, police response to protests

Tactic: Deflect

Example from Topic 34:

Text:

When Democrats Revolt; they burn down Small Businesses & shoot people in cold blood for MONTHS at a time. When Republicans Revolt; We just Storm the Capitol. Barely any damage & No Destruction.

I-position: Implied conservative

Other/perspective: Democrats (also BLM, Antifa), violent disruptive

Disruption: Violence

Tactic: Distract, whatabouting (contextualising self's actions)

Example from Topic 38:

Text:

It's sad but understandable to see the violence in DC today. We have lost confidence in our election and elected officials. To me there is a very simple fix. VOTER ID!!!With out confidence that the voters and votes are legitimate this will not end. We need national election laws for national elections. I understand that the states have their own laws regarding the election process but they MUST uphold their own laws and not ignore their own constitution. I pray that the rational leaders will come together and try to solve the problem. God Bless ????

I-position: Implied conservative, religious

Other/perspective: Democrats, elected officials – Dems want to manipulate to win

Disruption: Election result

Tactic: Distract, Distrusting, denying

Example from Topic 44:

Text:

Police Pepper Spray Trump Supporters After They Refuse To Arrest BLM Supporter Who Assaulted WomanThe DC PD is now the uniformed BLM /ANTIFA Uniformed Auxiliary.

I-position: Implied conservative

Other/perspective: Police, BLM/Antifa – Looking to frame Trump supporters

Disruption: Violence, police response

Tactic: Stereotyping police into known group, deflecting

<u>Example from Topic 63</u>:

Text:

I am behind the President 100%.I will support Eric Trump in his effort to purge the Republican Party of RINOs, weak Republicans and those who have betrayed us.

I-position: Implied conservative

Other/perspective: RINO (Republican in name only), afraid to call out vote fraud

Disruption: Election, lack of Republican action

Tactic: Stigmatizing, stereotyping, dichotomizing (us/them)

<u>Example from Topic 68</u>:

Text:

MOTHER FUCKER TRAITOR Mike Pence you “don’t believe” you have the authority to reject votes? Tell that to Thomas Jefferson when he did it while he was V.P. You are a traitor.

I-position: Implied conservative

Other/perspective: Mike Pence, afraid to challenge votes

Disruption: Election result

Tactic: Stigmatizing, dichotomizing (us/them – true American patriots)