Analysis and contextualization of the emotions and the narrative created on Parler through social media posts in the days before the storm on the U.S. Capitol on the 6th of January 2021

Master Thesis for Obtaining the Degree

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Affidavit

I hereby affirm that this Master's Thesis represents my own written work and that I have used no sources and aids other than those indicated. All passages quoted from publications or paraphrased from these sources are properly cited and attributed.

The thesis was not submitted in the same or in a substantially similar version, not even partially, to another examination board and was not published elsewhere.

Abstract

On the 6th of January 2021, many people worldwide asked themselves how an event such as the storm on the U.S. capitol could have happened and how nothing was done to prevent it. The data found in the posts on the social media network Parler can provide ample evidence on how fake news and conspiracy theories could spread freely on a the platform. This study aims to understand and contextualize the talking points communicated through the posts on Parler and to analyze the sentiment and emotions that were experienced around the time of the storm on the Capitol as well as the election in November 2020. This analysis was conducted by filtering and processing a starting dataset of 40.000.000 posts, which were reduced to 974.479 posts to fit the researched timeframe, that were made on Parler and analyzing the data using the R programming language. The studied qualitative data are then set into context using the posts created and supported with evidence from traditional media that also dealt with the topic. The topic of social media listening and sentiment analysis is a prevalent topic in the field of marketing and is used by professionals and schoalrs to analyse the feelings and emotions of customers towards their products and services. This thesis uses the techniques which are common in marketing on a day to day basis, to analyze which sentiments and talking points occurred on Parler and which conspiracy theories were shared around the 6th of January 2021.

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1 Introduction

This thesis tries to give a deeper insight into the social media posts sent out around the events that happened around the 6th of January 2021 in the United States. As the storm on the U.S. Capitol was the central focus of news coverage that day, it is essential to keep the surrounding circumstances in mind and how such an event could happen through mobilization on social media. This is especially interesting from a digital marketing perspective as the method in which narratives and emotions were created beforehand can also be used by marketers worldwide to evoke a particular perception of brands in the future. An increased focus in marketing nowadays is put on social media listening, which has been a tool for companies and marketing agencies alike to understand the emotions, feelings, and perceptions that a brand achieves through its marketing efforts and day-to-day operations.

1.1 Context and relevance of the thesis

When the news and images of the storm on the United States Capitol were shown on TV screens and on social media, many people worldwide were in shock that something like this had occurred in the self-proclaimed "beacon of freedom" in the western hemisphere. Even before the election had happened in November 2020, there had already been rumors and talks about the possibility that the incumbent president, Donald J. Trump, would not accept his loss in the event that he would not have won the election.

Through the sowing of doubts about the elections' integrity and foreign influences in the voting procedure, the groundwork was laid to influence the public's perception regarding the eligibility of the incoming president. Fueling those doubts during the counting of the votes and after the election results came in, the followers of then-President Trump became more and more aware of their disappointment. They were eager to vocalize them on social media. As the discussions and opinions became more and more violent, traditional social media platforms like Facebook, Instagram, and Twitter enforced policies that saw many users blocked or limited in their possibilities to interact. People on the side of Donald J. Trump flocked to new social media sites that offered an unedited and anonymous platform for free speech without the threat of being locked out of their accounts for their views.

The most prevalent platform that was used was Parler. The posts and emotions shared on this social media network are the basis for the analysis in this study. Evaluating the emotions and contextualizing them according to the surrounding circumstances while also looking at the promoted and transported narratives will be examined. An important factor influencing most people's daily lives is the concept of fake news, which has had an increase in frequency due to the nature of social media and the internet, with everyone being able to access it and contribute to the shared pool of information on it. The study will also discuss how these inaccurate representations of reality and why those pieces of information are shared.

As the event only happened one year before the writing of this thesis, the amount of research on this topic has not been extensive. Papers have covered different aspects of the storm on the U.S. Capitol, looking at politics, military, a possible COVID-19 superspreader event, human behavior, and terrorism (Dave et al., 2021; Davidson & Kobayashi, 2022; Kydd, 2021). However, little to no research has been done on the content shared on Parler and the sentiment of this content. This thesis aims to give context to the posts that were made on the aforementioned social network and analyze which conspiracy theories were shared.

This study can be of interest to many different research fields, but the main link to the authors' study program is that social media listening and sentiment analysis are already a large part of digital marketing. The tools used are focused on the tracking of mentions of a brand on social media and how consumers perceive the brand throughout a set amount of time. Additionally, in politics, just like on social media, narrative transportation, and electronic word-of-mouth are used to convey messages and evoke emotions. Both of these factors are to be analyzed in this study, which also overlaps with digital marketing.

1.2 Research Purpose

The general purpose of the study will be to understand the usage of narrative creation by opinion leaders in the right-wing conspiracy theorist field. It will discuss the results that they were able to achieve in the sense of emotions created and the emotionality of responses on the social media network Parler, which was the central platform used to share their theories, which created a bubble in which those theories were able to grow.

The main theories that will be drawn from in this study will include the five-factor model of personality, electronic word of mouth, and narrative transportation. However, cognitive dissonance will play a significant role in better understanding fake news spread and how people cope with it. The three theories mentioned previously will be used to understand how people who used the social media network Parler were receptive to the information spread on the website. Additionally, an understanding of how right-wing media and conspiracy theorists use certain narratives to control their talking points and attract people towards their agendas will be derived from narrative transportation theory. The concept of electronic word-of-mouth will be used to identify the spread of possibly fake news and how the social impact of reading other peoples' "true" experiences might change the readers' perception of reality. Furthermore, the five-factor model will also be used to understand how personality traits might also shift people's proneness to be sucked into the area of misinformation and how emotional or scholarly education might be able to change these effects, as has been discussed in other papers.

As this thesis is intended to be of exploratory nature to understand the events that occurred on the 6th of January through the perspective of Parler, text mining and text analytics will be used to better understand the drivers and opinions behind the actions that happened.

As the paper will focus on the social media posts created on Parler around the 6th of January 2021 and the election night on November 3^{rd,} 2020, an analysis of sentiment will be carried out as well as a correlation and word association analysis.

Previous literature has focused on the social media site Parler in general and the concept of fake news, conspiracy theories, and narrative transportation separately. However, no paper has combined the different research approaches to look at the events that happened on the 6th of January 2021 from a holistic point of view. This thesis wants to take this step and contextualize the impact that Parler and conspiracy theories had on public opinion and its sentiment.

1.3 Thesis Structure

The thesis, being designed as an exploratory case study, following this introduction, will consist of a literature review, in which the main theories drawn from, will be discussed. These will include a general discussion about emotions, the five-factor model of personality, traditional and electronic word of mouth, narrative transportation, cognitive dissonance, right-wing terrorism, social media in general, fake news on social and traditional media, and conspiracy theories. Following that will be a further exploration of the research intent and the methodology of the undertaken analysis. The results that were found will be described after that and will be followed by a discussion of the findings. Lastly, a conclusion of the study will be drawn. Additionally, the further implications of the results and their impact on different research fields will be proposed while also acknowledging the limitations of the study. The appendix will hold all additional information and data sources used to create the thesis.

2 Literature Review

2.1 Emotions

The concept of emotions and humans' understanding of them dates back to the ancient Greek philosophers. However, a definitive definition has been hard to come by. Emotions have been analyzed mainly through philosophy and psychology, which resulted in different approaches and results. One of the first publications that dealt with a philosophical view of human emotions was "A Treaties of Human Nature," authored by David Hume in 1739 (Collier, 2011). The central notions discussed by philosophers were the origin of emotions and their classification, while psychologists were focused on the effects and the mental activities behind emotions (Fehr & Russell, 1984). Fehr and Russel argue that many psychologists believe that a singular definition of emotions will not be possible when looking at each of the mental, behavioral, or physiological aspects separately. The same argument is taken by Plutchik (2001), who states that the concept of emotions, on the one hand, has been explored thoroughly, with there being nearly one hundred theories of how emotions can be classified, while on the other hand, the field still being open as no consensus on one single definition has been found (Förster, 2014). Therefore, several theories pertaining to emotions will be discussed, and the best fitting approach will be used in this research. One main point of contention between different theorists is the way in which emotions are processed.

In Bagozzi et al. (1999), it is argued that an emotion is a mental response to the reception of a cue that is given by an external or internal input. It is also discussed that it elicits a response that traditionally is physical. There is also an argument made for the differentiation between having a specific mood and experiencing an emotion. In the paper, a mood is described as a state of mind which is extended over a more extended period of time while being less extreme (Bagozzi et al., 1999). Contrasting that, Schachter and Singer (1962) propose to follow a concept in which emotions are classified purely as a physical response to an external input eliminating the mental aspect completely. It is argued that humans will try to find an explanation for their physiological response to an input if there is no immediate explanation had by them. This factor is labeled the only input that cognition has on the emotional response (Schachter & Singer, 1962). A holistic approach regarding emotions has to be taken to account for physiological and mental reactions to stimuli. Morrison and Crane (2007) argued that the differentiation in approaches to emotions mentioned earlier was not of significance. Therefore the definition *"...emotion will be defined as a state of physical and mental readiness that involves valence (directional force), evaluative appraisal, a target (or object or stimulus) and behavioral tendencies.*" will be used in this thesis (Morrison & Crane, 2007).

The Merriam-Webster dictionary defines the meaning of emotions as *"a conscious mental reaction (such as anger or fear) subjectively experienced as strong feeling usually directed toward a specific object and typically accompanied by physiological and behavioral changes in the body."* Which is also in line with the definition given by Morrison and Crane and also comprises the two aforementioned theories in which it is a conscious as well as a physical response towards an external input. Additionally, there is a consensus that emotions are an inherent human trait, as well as that they change the way humans see and interact with their surroundings (Morrison & Crane, 2007). Bagozzi et al. (1999) argue that even if emotions are inherently human, the response to stimuli is dependent on the individual and how they deal with the external influence. Ekman (1999) writes that there are ten basic emotions that differ in how they are dealt with and shown, five of them positive and five negative. Those emotions are contempt, anger, disgust, sadness, fear, amusement, pride, satisfaction, relief, and contentment. However, it is also argued that there are several emotions that are not fundamental but rather are a combination of two or more of the previously mentioned ones (Ekman, 1999). He acknowledges that there is a consensus that emotions are generally experienced when having interactions with other entities. However, he also mentions that emotions can be experienced without the need for interactions with another human being or the outside world. This view is in contrast to how Burkitt (2014) argues that emotions are relational and that emotions arise in the context through interactions with an external influence. It is argued that through the interactions that people have and the emotions that are experienced, patterns in human behavior emerge. Those then, in turn, become involuntary mechanisms with which emotions and situations are dealt with (Burkitt, 2014). When talking about how emotions are measured, which is essential in the context of this thesis, researchers usually focus on a combination of internal and external evaluations of the behavior and feelings of the subject. This is rooted in a variety of the different approaches to emotions which, as mentioned before, are either purely mental or physical (Bagozzi et al., 1999). The measurement of emotions has developed over the years, and different scholars have come up with differing results. Several approaches ended up with three types of emotions underlying all other feelings experienced by a subject. However, the terminology and findings between the approaches differ (Edell & Burke, 1987; Holbrook & Batra, 1987). A more simplified model resulted in a two-factor approach that classified the emotions experienced as either positive or negative (Oliver, 1994; Westbrook, 1987). The approach of having two factors was taken on by researchers; however, the way in which the two-factor structure is used has changed, which can be seen in Figure 1. The underlying theory for this model is still a two-factor analysis that frames each different emotion along a strong-weak axis which always relates a positive with a negative emotion.

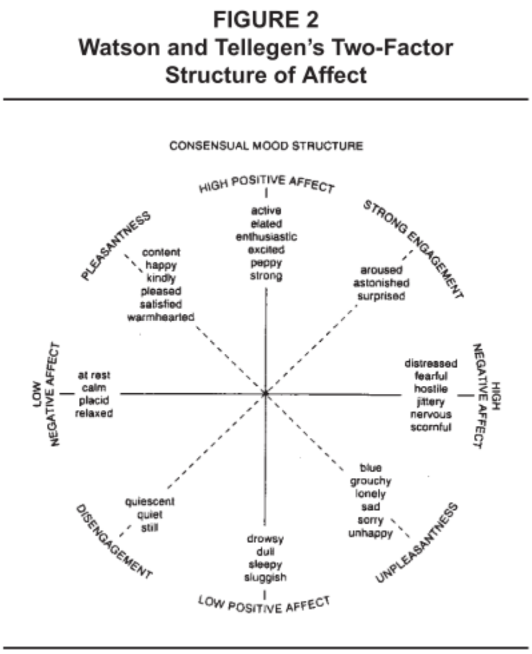

Figure 1 Watson & Tellegen (1985:225)

This also results in the assumption that the more proximate emotions are on the scale the more alike they are and harder to differentiate when experienced (Watson & Tellegen, 1985). Even as this model seems intuitive to use, it has been criticised by scholars that it leaves nuanced differences between emotions without recognition while also not taking the influences that resulted in the experienced emotions into account (Bagozzi et al., 1999). Additionally, it also does not include emotions which are felt on a regular basis.

One aspect that has not been taken into account with the approaches presented in this thesis until now is the fact that emotions are hardly ever singular, and there are often multiple emotions experienced together (Bagozzi et al., 1999). Even though most researchers acknowledge that the different types of emotions are usually had in conjuncture with similar either positive or negative ones (Bagozzi et al., 1998; Oliver, 1994). Bagozzi et al. (1999) conclude that the best way of measuring emotions is still a binary measuring scale with seven to nine steps where it can be indicated how a subject feels under certain conditions.

2.2 Five-Factor Model

The way in which a person's personality is classified and through which traits this influence is happening has been a contested field of research. Categorizing personalities into the commonly known five-factor model, which is accepted today, had its emergence through the usage of commonly used vocabularies to describe the behavior and appearance of humans through studies in the early 20th century (Digman, 1990; Thurstone, 1934).

McCrae and John (1992) argue that the way in which human beings understand themselves and their own personality is through the usage of descriptive words. Therefore, psychologists and scholars, to better understand the way in which those terms are used, have to use a scale on which the impact of the vocabulary used can be measured. This is supported by research in which it is argued that as there is such a large stem of words describing traits in the English language, to understand human personality, it is vital to decipher the actual meaning behind those words and summarize them (Allport & Odbert, 1936).

The research conducted by Thurstone then elicited other researchers to build upon this approach and the most prevalent one, Cattell, kept developing his approach by reducing the apparent traits in human personality from 60 down to 12 through clustering similar words with the same meaning and creating scales to measure the strength of those traits (Cattell, 1943a, 1943b, 1945, 1947; McCrae & John, 1992). In the approach that Cattell chose, traits were built upon through education and upbringing as well as rooted in the social influence a person was found in. The different versions of Cattell's approach to personality, however, were not supported by other researchers as none of them were able to find as many factors as were described by Cattell (Digman & Takemoto-Chogk, 1981; Goldberg, 1981). In the 1960s, various researchers built upon this theory and drew from the multiple traits that Cattell developed and showcased that there are only five different elements that can be found in all instances and are seen as the basis for human personalities (Tupes & Christal, 1962; cited in McCrae & John, 1992; Norman, 1963). This approach was only taken on by the majority of scholars in the 1980s. This was corroborated through research in different languages as well as throughout all ages (John, 1990). Norman (1963) coined the terms "*Surgency, Agreeableness, Conscientiousness, Emotional Stability and Culture.*" An understanding of these terms since then has developed further, and the names for Surgency and Emotional Stability were changed respectively to "*Extraversion and Neuroticism*" (Eysenck, 1963). Additionally, "*Experience*" replaced the term Culture (Costa & McCrae, 1980). This terminology was accepted and has been widely used by researchers since then (Borkenau & Ostendorf, 1990; Funder & Colvin, 1988; Wiggins & Pincus, 1989). To summarize the developments of the previous research, the current nomenclature of the five factors is "*Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness.*" This has been supported by research across different languages and even through different approaches; as in one study, the frequency of how a humans personality was described across other activities resulted in the researchers strongly supporting the argument for the five-factor model of personality (Botwin & Buss, 1989; Buss & Craik, 1983).

When applying the framework of the five-factor model to the topic of this research, the influence of the theory on human behavior on the internet has been widely researched and concluded that for users who use social media, extraversion is rated higher and conscientiousness lower than for users who do not (Brailovskaia & Margraf, 2016; Montag et al., 2016; Ryan & Xenos, 2011; Sindermann et al., 2020). As the way in which subjects are classified using the five-factor model of personality enables researchers to make predictions about their behavior in regards to the sharing of fake news and their actions in general, research has also been conducted to find a deeper understanding of the role of conscientiousness as a moderator (Lawson & Kakkar, 2021).

The impact that a high score of conscientiousness has on the subjects' personality range from being less impulsive, as well as in control of themselves, to be more likely to feel guilty about wrongdoings while not being as likely to behave in that manner (Courneya et al., 1999; Fayard et al., 2012; Saklofske et al., 2007). In line with those findings, research has shown that subjects with high conscientiousness are less likely to share fake news (Petrocelli et al., 2020). In their research, Sindermann et al. (2020) show that there is a correlation between the personality trait of openness and fake news as well as conspiracy theories, as a lack of openness results in less diverse means of sourcing information while also not being open to discussing different points-of-views, which is also in line with previous research being done (Boulianne & Koc-Michalska, 2022; Gerber et al., 2011). Lawson and Kakkar (2021) argue that the sharing of and believing in fake news is more prone to occur in conservative circles rather than in liberal thinking groups. This is supported by a lot of research in the field (Bago et al., 2020; Guess et al., 2020; Pennycook et al., 2018; Vosoughi et al., 2018). In conjuncture with this trend in politically conservative groups, studies have shown that the behavior of people who belong to these ideologies are also more likely to be adverse to societal change and to be aggressive when defending their belief system as well as putting other ideologies down (Jost et al., 2003; Kugler et al., 2014). What can be seen in combination with the previously mentioned facts is that research has shown that people are likely to believe fake news and conspiracy theories when it aids them in creating a positive look for their own ideology while also diminishing another group's beliefs, therefore increasing the positive image of their own (Douglas et al., 2019; Lawson & Kakkar, 2021). Of course, the process of sharing fake news can also happen intentionally, as people with a low score of conscientiousness and, therefore, a desire to promote their own ideology at all costs while also trying to defame other beliefs (Arceneaux et al., 2021; Douglas et al., 2017). In their studies, Lawson and Kakkar (2021) showcased that the current climate of heightened political polarization is enhancing the frequency in which fake news and conspiracy theories are shared while not being influenced by one singular topic as the political affiliation or a lack of perceived reliability of tradional media channels. Additionally, people with a higher score in neuroticism were more prevalent using the internet to consume news and are therefore more at risk of entering a filter bubble, a topic which will be discussed later on in this thesis (Rammstedt & Danner, 2016).

2.3 Narrative Transportation

The first evidence of humans using narrative transportation in the most basic sense was them visualizing their experiences through murals on cave walls. This showcases that even then, they were inclined to share their stories (Visconti et al., 2010). The task of telling a story of past experiences as well as fictional stories is inherently human in nature and gives us the possibility to deal with the past as well as to make sense of our surroundings and ourselves (Bruner, 1991). One important aspect of narrative transportation is the fact that it can be used to transport emotions and also generate an emotional response in the listener (Oatley, 2002). Nowadays, humans are confronted with carefully crafted texts and visuals that are meant to influence their opinion on different topics and products (M. Green & Brock, 2000). Green and Brock (2000) defined narrative transportation as a "*distinct mental process, an integrative melding of attention, imagery, and feelings.*" Green and Clark (2013) built upon this definition and added the components of "*emotional investment*" into the process of narrative transportation.

Research has shown that the process of narrative transportation is decoupled from traditional decision making as the receiver will be fully immersed in the story, being influenced without needing to actually think about the input given while still being affected (M. Green & Brock, 2000). Additionally, the way in which narrative transportation is set up is also decoupled from traditional ways of persuading people, which usually happens through arguments that are formulated in a way that is made to give the listener something to think about (Green & Clark, 2002; cited in Green & Clark, 2013). Even though the way in which storytelling and narrative transportation has evolved since then, the way in which a kind of communication between a storyteller and a consumer happens has stayed the same (Van Laer et al., 2014). The format in which successful narrative transportation happens has been identified as having a clearly defined beginning in which the main characters and their problems are introduced, a middle, when the character arc is further developed, and an end in which a climax happens, the issues are resolved, and the moral of the story is revisited (M. Green & Brock, 2000; Van Laer et al., 2014). This structure can be seen across all different communication channels and in every piece of media released (M. Green & Clark, 2013).

There have been several studies that have found that when being on the receiving end of the story, the mood and activities of the listener and also their beliefs towards the topic of the story can change (Adaval et al., 2007; Adaval & Wyer, 1998; M. Green & Brock, 2000; M. Green & Clark, 2013). The way in which this effect is created is due to the person experiencing the story, from the teller, feeling as if becoming part of a new world and being able to put themselves into the shoes of the main character (Escalas & Stern, 2003; M. Green & Brock, 2000; Van Laer et al., 2014). Additionally, the transportation of the listener into the story is also improved through the possibility of them inserting themselves into the world that is created. This can happen by relating to the issues faced in the world, a common concept that is reflected in many famous movies (van Laer et al., 2018). As mentioned before, the role of the main character in a narration plays a significant role in increasing the believability of the story (Kreuter et al., 2007). The way in which the listener can put themselves into the shoes of the protagonist and relate to their struggles and feelings makes the message transported more believable (Cohen, 2006). This even might go as far as the receiver changing their appearance and their behavior to be more like a character that they felt connected to or look up to (Sestir & Green, 2010).

However, there is a side-effect that the transportation of the listener into a narrated world can have, which is them being lost in the story and delving too deep into it, which makes them accept the new "fictional world" as their reality, while also losing the sense of the actual world they live in and not accepting facts they have known to be true anymore (Gilbert et al., 1993; M. Green et al., 2009; M. Green & Brock, 2000; Strange & Leung, 1999). This is also backed by research that has shown that the more frequent humans are confronted by content that is knowingly false or unsupported by facts, the more likely they are to accept those facts (Arkes et al., 1989, 1991; Gerrig & Prentice, 1991; Gilbert et al., 1990; Hasher et al., 1977). As soon as this stage in convincing through narrative transportation is reached, it becomes increasingly difficult for people to get rid of those notions (J. R. Anderson, 1982; Ross et al., 1975; Wyer & Budesheim, 1987). This, of course, is also influenced by the feelings that are elicited through the narration, as feeling like being intensely involved with a character or the outcome of a story will be achieving a result easier (Fazio & Zanna, 1981; M. Green & Clark, 2013). The way in which the narrative and a possible persuasion towards one topic happen in narrative transportation can also occur in a very subtle way as the receiver might not even notice that the narrator is trying to push him towards a particular opinion on a topic (M. Green & Clark, 2013). This is also one of the main reasons subliminal messaging is used in all forms of media. The creation and growth that all social media platforms, as well as the internet and use of technology, have experienced in the past decades had a significant impact on the speed and frequency in which crafted stories that convey a purposefully placed message are created and shared (Greenfield, 2015 & Harris and Sanborn, 2013, cited in Gretter et al., 2016; Hobbs & McGee, 2014). This phenomenon is due to the prevalence of different interactive platforms and the possibility for every user to create their own narrative (Gee, 2015; Gleason, 2016). This is then used to intentionally influence the attitude and understanding of the world of users. This is also backed by the fact that users of social media platforms join them due to the nature of feeling like part of a group which is also an essential part of narrative transportation (M. Green et al., 2004). Until recently, one was able to decide for themselves when they want to be exposed to fictional or narrative transportation based stories; however, due to the overwhelming influence the internet has on humans, they are bombarded with different purposefully created stories in the different forms available to them online to sway their opinion on topics all the time (Gretter et al., 2016; Rossiter & Garcia, 2010). The concept of "transmedia storytelling" also applies to this phenomenon as through the internet, stories using narrative transportation can occur on different platforms at the same time and the impressions of it will follow the user across the different channels they are using online (Jenkins, 2007). This is especially prevalent at the moment in digital media advertising, as brands will operate across different internet platforms to showcase their products while trying to not make them look as advertisements (Clemons & Wilson, 2015). Further studies support these theories as narrative based advertisements can have a strong impact on the attitudes towards and perception of a brand (Brechman & Purvis, 2015; Phillips & McQuarrie, 2010; J. Wang & Calder, 2006).

In the context of the events that occurred on the 6th of January 2021 in front of the U.S. Capitol and the event leading up to it, for instance, the whole discussion about the election process and the legitimacy of Joe Biden becoming the 46th president of the United States, as well as the intentions to prevent the peaceful transfer of power, it is apparent that the messaging by people supporting Donald J. Trump, the 45th president of the United States, moved from a more subliminal messaging towards openly calling for the counting of votes to be stopped, as well as for the incumbent office holder to stay in power as they were not happy with the new candidate. This is backed by research that showcases that when messaging in the context of narrative transportation is moved into the obvious, people will not want to reject those views as it might break their own immersion in the world that they are transported in (M. Green & Clark, 2013).

2.4 Cognitive Dissonance and Selective Perception

The fact that a portion of American citizens, after the U.S. Presidental election in November 2020, did not believe that it had been won fairly and without external interventions caused some of them to push for the sitting government to not transfer the power of the presidential office so that Donald J. Trump would stay in office seems like a strict violation of many of their beliefs. Conservative members of the U.S. public are often perceived to adhere strictly to the American constitution. They are known to be defensive about their First Amendment Rights, which guarantee them the power to publicly state their opinions without being punished by the government for them, which they heavily relied upon when pedaling conspiracy theories. Additionally, Republicans often also defend their right to bear arms, which is stated in the second amendment of the constitution even though this amendment was written more than 200 years ago, which begs the question if the authors of the constitution had the way in which the public is using those guns for in mind. The constitution, however, also calls for a peaceful transfer of power after a certain period of days after the election, which should also be in the interests of the conservative members of the public as it is the basis for the democratic process which was set in stone after the United States became independent from the United Kingdom in 1776. The way in which members of the public, on the one hand, being vocal defenders of the constitution while, on the other hand, wanting to not adhere to what is written in it, dealing with their conflicting interests and their feelings towards their own behavior is explained through the concept of cognitive dissonance.

The theory of cognitive dissonance was first discussed by Festinger (1957), who proposed that when a person holds multiple beliefs about a topic and those beliefs result in conflicting emotions and attitudes for the person, something in the person's behavior or attitudes has to change to accommodate either only one belief remains or to reduce the deviation between the two until a state of comfort has been achieved (Festinger, 1968, pp. 260–266; Fischer et al., 2008). If a person has acted in a certain way and experiences cognitive dissonance afterward, research has found that it is more likely for them to change their beliefs to make the behavior appropriate and in line with their own beliefs (Festinger, 1964). This process happens in a person's cognitive system, which has been defined as a mental system in which different aspects of human cognition, like beliefs and attitudes, interact with each other (Littlejohn et al., 2017, p. 64). The way in which those beliefs and attitudes interact with each other was defined as being one of three ways. They can be in accordance with each other, they can be dissonant, or lastly, they can be irrelevant to each other, which means that they are not related and therefore do not influence each other (Littlejohn et al., 2017). The result of attitudes or beliefs not falling into the last category while also being dissonant creates cognitive dissonance in the cognitive system of a person and results in the aforementioned emotions.

A lot of research has been conducted that deals with cognitive dissonance in the field of decision-making as humans. When trying to make an informed decision that is in line with their values will rely on their beliefs to realize a satisfying result for themselves. The feeling of cognitive dissonance mostly happens, however, before a decision is made, and the person has to make a choice on what to act upon (Yahya & Sukmayadi, 2020). This, of course, is different for all humans, and the way they react will differ depending on their cognitive system and their internally saved beliefs and attitudes. However, as will be discussed later in the social media section, the way in which users of the internet are flooded with information on a constant basis, makes it even harder to end up with decisions that satisfy their need for cognitive balance (Yahya & Sukmayadi, 2020). It is also argued that, especially as people are faced with other peoples' opinions and stories through social media, it is even easier to be exposed to conflicting beliefs. If those beliefs then are found to have even a little piece of potential truth or are created with narrative transportation to change the readers' opinion, users are confronted with their internal cognitive dissonance. The emotions that are elicited through this effect often materialize themselves through anger, anxiety, and stress (Fontanari et al., 2012). The topic of political affiliation and beliefs, which this thesis also concerns itself with, is often the reason for cognitive dissonance. This has the effect that if their opinions about politicians they support are questioned, usually they will find a way to justify their beliefs and, through that, are okay with the possibility of supporting an objectively wrong opinion (Yahya & Sukmayadi, 2020). In line with the previously discussed concept of cognitive dissonance falls the theory of selective perception. It was first proposed in the 1950s when a study on the perception of rough play from supporters of different teams was done after a football game between the two teams happened. It became apparent that with different backgrounds, varying interpretations of the game, and its significance, everyone had different perceptions of what had actually transpired, who was to blame, and which team was the supposedly more rough one (Hastorf & Cantril, 1954). The theory, since then, has been expanded into many different aspects and fields, also tackling the bias that people might experience when it comes to religion or other beliefs that are set in stone for many people due to their upbringing (Walsh & Fahey, 1986).

2.5 The Far Right and QAnon

When talking about the storm on the U.S. Capitol on the 6th of January 2021, media outlets were quick to call the event a domestic terrorist attack on American freedom. To understand how the far-right was able to achieve such an attack on one of the American symbols of freedom, different aspects that are part of the ideology that its effects have to be understood.

Terrorism, in general, has been defined in many places and in many publications. However, the usage of the term has been used in day-to-day language through the media in which any act of aggression towards someone has often been titled terrorism. The most comprehensive meaning of terrorism is offered by defining it as an intentional usage of fear and violence to enable a change in either the political landscape or how organizations, countries, or entire societies are run (Hoffman, 2017, p. 71). Additionally, the usage of terrorism is linked to increasing doubt and fear in people who are not directly impacted by the act which was carried out. Through this, people who are carrying out terrorism acts intend to increase their own power and influence.

One aspect which has changed in which terrorism is carried out is also a change in lifestyle for the general public, as much of how the message of people using terrorism as a tool to intimidate people can now be controlled by terrorists themselves. Before the internet was prevalent and users were able to fill it with their own information, TV stations and newspapers were able to decide which information to print and, therefore, not instill fear and suppress information from which they assumed would cause panic. Through the switch towards the internet and social media, which will be discussed in the following section, terrorists are able to produce content and create their own style of narrative transportation through which fear is created in people that see it. Additionally, when uploaded to the internet, information spreads fast and cannot be deleted (Hoffman, 2017, pp. 276–277). The basis of this attack was laid through a political movement called neo-fascism that has existed as long as the end of the second world war. The names it has been called since then have changed quite often, but the terminology most often used now has been “far-right” and right-wing populism (Mudde, 2019, p. 4). Historically the terms left, and right have been around since the French Revolution, in which the supporters of the existing structure, which opposed a change to societal structures and wanted to keep the status quo, were sitting on the French king's right side, while the supporters of change and democracy were on the kings left. A definition for the “far-right” is given by Mudde (p. 6) as he describes the ideology of “far-right” being split into two sub-groups, one called “extreme right,” being the people opposing democracy itself, as well as the idea that the majority of people should hold power to govern everyone and would rather have a strong leader deciding for everyone, while the other, the “radical right” is in line with democracy while being against equal rights for minorities. This manifests itself in the concept of ethnocracy, through which the “far-right” wants to have citizenship and rights only for people of a certain ethnicity while stopping migration and getting rid of people who do not fit in with their standard. Another big part that often plays a role in right-wing ideology is antisemitism, which of course, has been one of the most prevalent topics for centuries (Mudde, 2019, p. 23).

Populism itself is based upon the assumption that the will of the people should always come before the will of the government and laws. Therefore, the ideology of populism is often anti-establishment and revolutionary in nature (Mudde, 2010). The way in which populists often argue includes the will of their supporters as the general will of the people that should be taken into account.

Through the means of populism, it was possible for Donald J. Trump to rally supporters ahead of the 2016 election and become president using topics that the "far-right" traditionally has ownership of, like immigration, opposition to globalization as well as the conspiracy theory of a ruling elite that controls everything in the country (Mudde, 2010).

These topics were the basis upon which the conspiracy theories of QAnon have been built upon. QAnon is often seen as a group of conspiracy theorists. One of the websites that QAnon thrives from to this day is 4chan, which is an online forum which is designed for anonymous posting (Knuttila, 2011). However, QAnon itself is a conspiracy theory that emerged from a messaging board on 4chan in 2016, which claimed that there was a child trafficking ring in the basement of a pizzeria from which the political elite and celebrities alike were profiting monetarily as well as using it as a sex cult and practicing cannibalism (Cernovich, 2016; Kang, 2016; LaFrance, 2020). This conspiracy theory was named Pizzagate.

Evolving from this theory, in 2017, an anonymous poster who claimed to be an insider of the U.S. government, receiving intelligence briefings through his clearance level Q, creating his name Q – his self-proclaimed intelligence clearing argued that Hillary Clinton, the opposing candidate to Donald J, Trump in the 2016 Presidential election, would be arrested due to her involvement with human trafficking (LaFrance, 2020). Combining his name and Anon, for anonymous therefore created QAnon. This, of course, was only a conspiracy theory, but since then, QAnon has gained millions of followers in the U.S. alone. Since its inception in 2017, the QAnon conspiracy theory has spread from 4chan into more and different social media platforms as well as traditional news stations (Zeeuw et al., 2020). As can be seen in Figure 2, starting in 2018, more and more news articles in different papers started to pick up on QAnon. The spike in media coverage was due to a video by CNN in Tampa Bay at a Trump rally in which they had discussions with believers of QAnon (CNN, 2018).

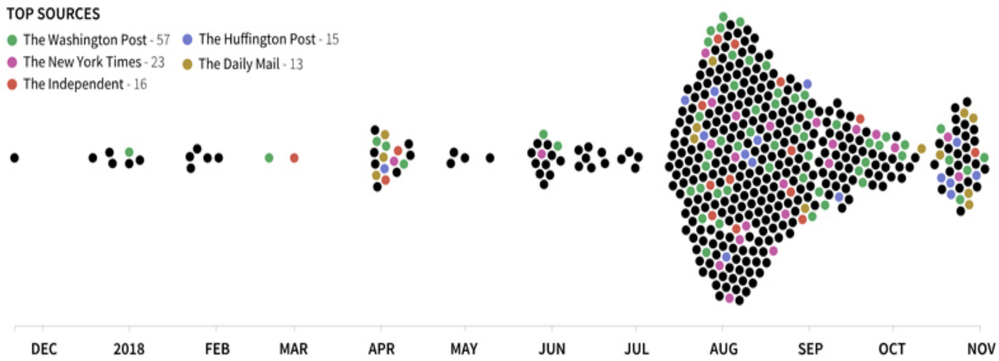

Figure 2 BeehiveGraph, QAnon mentioned in News Articles (Zeeuw et al., 2020)

As the followers of QAnon see the established political parties as a breeding ground for corruption and a worldwide elite that controls everyone's lives, they saw the president-elect of 2016, Donald J. Trump, as their champion to combat this perceived system of injustice and supported him (Miller et al., 2020). The terminology they used for this fictional system of a secret government ruling the world is the “deep state” (Rothschild, 2021, p. 11). According to user Q, Trump would lead a revolution to fight this deep state with the people part of the “deep state” being arrested and tried by military courts (Rosza, 2019; Rothschild, 2021, p. 106). Additionally, Trump, famous for his Twitter usage during his presidency, also used the social media platform to share ideas brought forward by the QAnon conspiracy movement (McIntire et al., 2019). As described earlier, when talking about the “far-right,” QAnon also shares the idea that a corrupt elite is ruling the world and therefore has to be destroyed (ADL, 2021). Even though the media has been doing a lot to debunk the theories set up by Q and provided an overview to people outside of the conspiracy theories grasp, people who believe in QAnon are unaffected, as they believe that the main-stream media is working for the “deep state” and are therfore part of the group that cannot be trusted (Hannah, 2021). As the conspiracy theory has grown so much, and the followers of QAnon have already shown their inclination to become violent, the FBI has classified them as a domestic terrorist threat (Rothschild, 2021, pp. 117–118; Winter, 2019). One of the major factors that make QAnon believable for many is the statement “do your own research,” which has been used by supporters in many contexts. For instance, when logical fallacies are pointed out, a defensive stance is taken, and no legitimate referencing can be given. However, when looking for a specific information on the internet, even the most ridicoulus ones, can be found after a short search, therefore supporting the claims made by QAnon believers. Another point that enables QAnon to endure logical fallacies and stay relevant througout widespread criticism is that connections between unrelated occurences are drawn and therefore "explained" by the posts that are sent by Q (Hannah, 2021). QAnon also played a large role in the storm on the U.S. Capitol as many of the supporters of the conspiracy theory were in attendance and identified themselves through flags and other symbols carried around with them (Howley, 2021).

2.6 Social Media

As a large chunk of the political discourse has shifted away from talking in person and open forums to social media, it is important to gain an insight into the ways in which people are interacting with each other through the means of the internet. The interactions which are happening in life itself but on social media as well, similarly to what was mentioned in the earlier chapter about narrative transportation, are inherent to humans and are used to share experiences, thoughts, and information (J. Berger, 2013). In the past, information if not shared through word-of-mouth between people on the streets, was generally shared through news networks for which the information was verified and then reprinted to reach as many people as possible (Ping Chiang et al., 2019). When looking at the way how the general public uses the internet, it has become an interactive platform in which information, opinions, or content can be shared by anyone, anywhere, and at any time (Ayeh et al., 2013; Cox et al., 2009). This fact, however, makes it harder to distinguish noteworthy information from ones that have been intentionally faked or are just plain inaccurate (C.-C. Wang, 2020; Westlund, 2013). This collaborative effort of filling the internet with information has been described as WEB 2.0 (Blank & Reisdorf, 2014). The definition of WEB 2.0 has been extended and also includes the possibility that content that has been uploaded can also be modified (Kaplan & Haenlein, 2010). Social media itself is a prime example of the application of WEB 2.0 in day-to-day usage. One of the main characteristics of social media is the sharing of user-generated content (UGC) (Gretzel, 2006; Kaplan & Haenlein, 2010). In research, it is argued that user-generated content has to fulfill three conditions to be accepted (Vickery & Wunsch-Vincent, 2007, p. 18). Firstly, the content has to be openly accessible for people on the same social media network to see. Secondly, there has to be some kind of creative effort to be put into the content which is uploaded, and thirdly, user-generated content has to be produced outside of ones work and without commercial interest. On the basis of these factors, Kaplan and Haenlein (2010) define social media as "*a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content.*" This definition has been criticised by researchers, arguing, that the impact of social networking sites as well as the importance of accounts on those sites (Boyd & Ellison, 2008). They offered their own definition of social media as a "*web-based services that allow individuals to (1)construct a public or semi-public profile within a bounded system, (2) articulatea list of other users with whom they share a connection, and (3) view and traversetheir list of connections and those made by others within the system.*" As can be seen from very differentiating opinions on the topic of social media, there has been no concesus on the definition. In accordance with that, Xiang and Gretzel (2010) argue that there is no widely accepted singular definition of the term of social media, this point of view is shared by Carr and Hayes (2015).

When communicating through social media, users generally type what they want to say rather than communicate through spoken word. This enables users to not immediately answer based on their true feelings and knowledge but are able to alter their written text after deliberation with themselves or someone else before sending it (J. Berger, 2013). The fact that users are able to consult other information sources outside of their current knowledge makes it also possible for them to showcase themselves in a better light (Walther, 2011). Additionally, communication through social media or the means of the internet can offer anonymity for users. This fact removes a lot of the reservations and inhibitions that people might have to discuss topics more freely compared to when their real-world name is known to the other people in the discussion (Chen & Berger, 2013). This, of course, also enables people to spread fake news and defamatory statements about others as they will not be identified.

Looking at what benefits users receive from social media usage is twofold. On the one hand, they are part of a large group of other users which satisfies the desire specified in the network effect, which describes that users are more willing to participate in an activity or a service and see this participation as more valuable when many others are also participating in it (Blank & Reisdorf, 2014). On the other hand, when provided with a functional platform on which interactions between users are possible, as well as the uploading of UGC, users are able to stay in close contact with people they already know, get to know new people, as well as discover opinions from people that are similar to theirs (Ben-Shaul & Reichel, 2018; Blank & Reisdorf, 2014). Especially when it comes to differing or similar opinion holders, the user is faced with a lot of choices when it comes to selecting the network that they want to be part of, as there are different social media that cater to different views and desires of users and might fulfill a certain role in their life (Ben-Shaul & Reichel, 2018). The way that social media platforms work can vary from platform to platform, with some requiring users to enter their accounts into some kind of connection with other accounts to be able to see their content.

Additionally, when using the internet to broadcast ideas or content, the group to which they are exposed is a lot larger than when information is exchanged in a group of friends or with colleagues. The way in which this influences the decision-making process of the sharer has been recognized as the larger the group is that people share with, the more likely they are to think about how what they are saying can be perceived and increases their attention to the way in which they present themselves (Barasch & Berger, 2014). Even though the number of people that messages are broadcasted to is large in comparison to day-to-day life, users who do regularly share on social media can forget that the potential reach of their posts can be a lot higher than what they expect and be unaware of the potential implications that might have on them. Therefore, releasing more information than they had planned (J. Berger, 2013). The issue with this is often that through the fact that social media is part of the internet, written statements, even after they are deleted, can be found using archives, and therefore a lot of the information will exist for a longer time than intended.

2.6.1 Parler

When talking about social media, the biggest platforms in the world, Facebook, Instagram, Twitter, and Youtube, often come to mind. As mentioned previously, Twitter was the most prevalent communications platform of Trump before and during his presidency. During this time, then President Trump and his supporters also flocked to the platform Parler, which advertised itself as a "free-speech" platform that would not infringe on the First Amendment rights of its users. This, of course, is appealing to users who feel like they are being censored on traditional social media platforms due to their political views, which is often the case for supporters of far-right ideology (Aliapoulios et al., 2021). Parler itself was first introduced in 2018, portraying itself as a place where people are able to post any of their ideas and beliefs anonymously while not being under scrutiny for them (Herbert, 2020). Parler itself works similarly to most other social media networks, with users having to sign up, then being able to establish connections with other people they want to be associated with. Users are able to make posts, comment on other peoples' posts, and are able to vote on the quality of posts through a like-system. Additionally, one feature that is taken from Reddit is the possibility to collect monetary donations or rewards for posts that were made (Aliapoulios et al., 2021). After Parler was introduced, especially people that are aligned with far-right views started participating in the

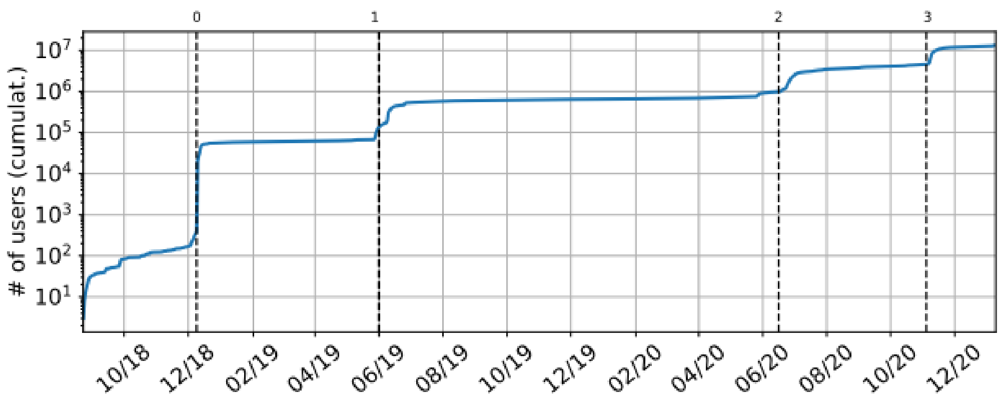

Figure 3 Logarithmic Cumulative number of Parler Users (Aliapoulios et al., 2021)

community. Through several endorsements of right-wing commentators and political figures during 2020, Parler increased its user numbers significantly.

This can be seen clearly in Figure 3, which describes the follower growth from late 2018 to the end of 2020. The 0 and 2 event lines, which are indicated on the graph, represent the endorsements by leading right-wing political figures Candace Owens and Dan Bongino in the U.S. Event line 1 describes an influx of Saudi Arabian users who started using the service due to apparent censorship of monarchy-critical voices. The influx around line 3 was due to the presidential election in November 2020, in which many of the conspiracy theories about a stolen election were construed and shared on Parler (Aliapoulios et al., 2021). The influx of the users can be explained by the network effect, as users might have felt an increasing need to be part of this platform while also achieving a higher benefit from using it as they felt like their ideology was being represented without the fear of being reprimanded for it (Aggarwal & Yu, 2012).

After the storm on the U.S. Capitol, President Trump was blocked from Twitter, and even more, users started to move to Parler as their social media of choice to share their opinions and ideology

2.6.2 Filter Bubble and Echo Chamber

Traditional news media has been a major influence on public opinion, selecting the way news is framed as well as the timing and scope of all information that would be included. Through the shift toward a more digitalized world, users are not dependent anymore on big budgets to create print versions of shared information. Nowadays, people are able to broadcast their opinions freely to all recipients who have unrestricted access to the internet, , aided by search engines which make it easy to reach any type of information that people desire, may it be factual or fiction (Flaxman et al., 2016). According to research, the fact that humans will often seek out information that confirms previously held beliefs, combined with the advancements in algorithms and machine learning used by social media and search engines, creates echo chambers and filter bubbles (Hannak et al., 2013; Munson & Resnick, 2010; Pariser, 2011, p. 10; Sunstein, 2007, p. 60). Pariser (2011) introduced the concept of filter bubbles in the online world to the mainstream and attributed three key factors to the concept of filter bubbles. Firstly, in online filter bubbles, even though there are other people who share the same or at least similar interests to oneself, the user is alone. The way in which filter bubbles are enabled through algorithms, each person has small differences in it and will be delivered unique content that is to their liking. Additionally, when being online, users are not aware of the category that they are placed by the algorithm. They are also not able to change the affiliation that the algorithm chose for them. In comparison to that, when consuming traditional media, the receiver was able to decide what ideology or at least what kind of take on an issue he would like to consume as they have a free choice regarding what paper to buy or which TV station to watch. Lastly, the user never opted into being subjected to an algorithm that decides what they see. Therefore, the user had no ability to decide not to be inside a filter bubble (p. 10-11).

In accordance with this, studies have shown that users are more prone to share a complying piece of information if it matches their opinions or beliefs (Spears et al., 1990). This can be a hindrance to the democratic process, as even though the internet is a medium in which many different opinions can be accessed, which is the basis for all educated decisions, ranging from purchasing decisions and political ideology to opinions about different groups of people, information that already appeases the readers opinions are the ones seen on the internet. The influence that filter bubbles on the opinion of voters can have has been discussed in the media quite extensively in the context of the U.S. 2016 Presidential election when the way in which news and information were shared was influenced willingly or not by algorithms, as well as detailed advertiser targeting on the internet (Funk, 2016; McCormick, 2016). In the context of the political world.

Similar to filter bubbles which are algorithm-driven and therefore a technological interference happens to curtail diversity of opinions, the concept of echo chambers also describes a lack of opposing views to the same topic on social media. However, in contrast to filter bubbles, echo chambers are created through a lack of social diversity surrounding a person (Sunstein, 2007, p. 60). As mentioned before, the way in which the personality of a person might influence the likelihood of finding themselves in a filter bubble or an echo chamber has been researched as well. The theory of the five-factor model of personality has been used to analyze users and to correlate the results of the personality test with the likelihood of filter bubbles. The studies have shown that there are several personality factors that might influence this behavior. The findings show that the age and gender of a person, as well as the conscientiousness and extraversion scores, might influence the chance of being caught in an echo chamber (Brailovskaia & Margraf, 2016; Ryan & Xenos, 2011; Sindermann et al., 2020). A study has shown that the effects of the echo chamber are also enhanced by the desire of a user to read pieces of information that support their views while also spending an increased amount of time on it (Garrett, 2009). Furthermore, research has also shown that the way in which social media is used, mostly to follow opinion holders that carry the same beliefs you do as well as to interact with people with who you either have an interpersonal connection or a connection through a shared ideology or belief system, creates high efficient echo chambers due to the homogeneity of the connected people (Himelboim et al., 2013). This can happen online as well as offline. In the case of online echo chambers, Parler is a good example as many of the people flocking towards it due to right-wing opinion holders being present on the platform, the network was dominated by a far-right-leaning ideology. The way in which people joined Parler after a political event had happened has been previously covered in the research when the online behavior of politically left and right-leaning people was surveyed. In 2015, a scandal involving Hillary Clinton and the usage of an unauthorized e-mail server outraged a lot of right-leaning people and drove them to visit the far-right news medium, Breitbart. This same effect, a scandal involving someone on the opposing side of the political spectrum in 2020, the "stolen" election, and the storm on the U.S. capitol had similar effects, as users wanted people that reinforced their strong opinions about the topic surrounding them on social media (Sunstein, 2017, pp. 100–101). Research has described a connection between the concept of filter bubbles and echo chambers with the previously mentioned theory of cognitive dissonance. Users seek out information that is aligned with their previous views and will avoid pieces of information that could cause them dissonance (Garrett, 2009).

Research has also covered the topic of how banning people that hold a certain worldview might change the continuing online behavior of those people. The study focused on the supporters of ISIS usage of Twitter and dedicated itself to analyzing the effects that a mass ban had on the usage of the social media platform. Even though there was a measurable decline in activity of ISIS supporters as well as a decline in content that showcased propaganda material, the authors also warn that the removal of people from one social media might increase the chance of them resurfacing somewhere else with a higher degree of radicalization as well as an increase in likelihood for echo chambers (J. M. Berger & Morgan, 2015). This effect might also be observed in the switch of users from Twitter to Parler. People felt as if their First Amendment rights were infringed upon and as if they were discriminated against by removing their accounts or by removing users or content that they supported.

2.7 Electronic Word-of-mouth

When information is received, this can happen through many different channels ranging from print media, online sources, the TV, or the radio. However, no channel reaches the same level of trust in the information learned as being told information on an interpersonal level (Godes & Mayzlin, 2005). This interpersonal and informal communication between two or more people transferring information is called word-of-mouth (WOM) (E. W. Anderson, 1998). The way in which WOM occurs is highly dependent on the way in which the interaction takes place and also on how the information between the participants in the exchange interacts (Allsop et al., 2007; Sweeney et al., 2012). There have been several studies that showcased the importance of personal recollections of information in the buying decision of people, as well as the value that people place on the messages shared by others (Banerjee, 1993). This can also have an effect on the listeners' general opinion about a topic and might change their attitude towards a product, political party, event, or general piece of information (Bikhchandani et al., 1992). One aspect of WOM that describes the speed at which information is traveling through word-of-mouth has been discussed in the concept of weak and strong ties between people participating in the communication chain (Granovetter, 1973). In his paper, Granovetter discusses the linkages inside communities as well as connections between different communities and comes to the conclusion that information that is shared within a group, through strong links, will travel a lot faster than between groups, on weaker connections between people. The reason why word-of-mouth is sought by people is described by Allsop et al. (2007) as perceiving this information more valuable due to the fact that the person giving the information has had first-hand experience with a topic. There have been various studies that have come to conflicting results when it comes to the question if people are more inclined to share negative or positive information about a topic (Donavan et al., 1999; East et al., 2007; Heskett & Sasser, 2010; Keller, 2007).

Research has shown that there is a distinction between sharing positive and negative WOM depending on if the information was generated by oneself or if the information was received from someone else (De Angelis et al., 2012). In their paper, the authors come to a conclusion that, on the one hand, if word-of-mouth is generated by a person, it is more likely that the sentiment of this information is positive due to them wanting to be perceived positively through self-enhancement. On the other hand, if a piece of information is transmitted through word-of-mouth that has not been generated between one of the parties involved but rather had only been received, the transmission will more likely have a negative sentiment towards the topic. The topic of self-enhancement through WOM also has to do with the fact that people will want to improve their own image in other peoples' opinions by seeming interesting, therefore sharing positive information about interesting topics (Wojnicki & Godes, 2008). Research has shown that there is an influence on how much WOM is generated and transmitted depending on the qualities of the topic it pertains to. Generally, more highly interesting topics are discussed frequently at the time they turn up, but topics that are in the vicinity of the communicators constantly, even without being interesting per se, get more ongoing WOM over time. This also is a factor in the context of social media, especially in the political spectrum, as users are confronted with politics on a daily basis, which is the case due to the increase in social media and constant news coverage about the presidential election in the United States, will have politics in their head all the time. Combining this with the earlier discussed factor that negative WOM is transmitted more often, social media can become a pool of negative emotions which are enhanced by filter bubbles which will be discussed in the following section.

As mentioned before, the emergence of Web 2.0 has changed the way in which people communicate with each other. This, of course, also changes the way in which word-of-mouth occurs in day-to-day life. Communication has been made a lot easier as it can happen with anyone, anywhere in the world, at any time (Allsop et al., 2007). Electronic word-of-mouth (eWOM) has taken the definition of traditional word-of-mouth and expanded it to include the fact that the communication happens through an electronic, web-based format (Litvin et al., 2008). eWOM can happen through different types of UGC, ranging from pictures and videos to text-based posts on social media (Chu & Kim, 2018). On the one hand, this opens up communication to a new format as people are able to decide if they want to broadcast their opinions and beliefs to only a selected group of people, as in the traditional word of mouth, often with known people, or they are able to increase this group to everyone around the world, which of course, also includes strangers (Ip et al., 2012). One aspect that might also increase the possibility of negative word-of-mouth, especially in the context this thesis is set in, is the possibility of anonymity across the internet. Parler, as mentioned previously, marketed itself as being anonymous and preserving First Amendment rights, therefore being a platform for sharing information, correct or not, that people wanted to listen to due to it transferring word-of-mouth. The shift towards online communication, however, also enables researchers to better understand word-of-mouth, as it keeps records of open communication for everyone to see and, therefore, makes it measurable and revisitable at a later stage to run analyses on. A comparison in importance between the two different ways of word-of-mouth has been of interest to researchers. However, different studies have shown conflicting results, with some arguing that eWOm is trustworthy, while others argue that eWOM lacks credibility due to the anonymity and the lack of established relations between users (Bronner & de Hoog, 2011; Dickinger, 2011). This has prompted a study that showcased that a generalization cannot be made to rank the two in terms of importance (Tan & Tang, 2013). The application of electronic word-of-mouth also has shown a major influence on the way marketing is conducted, as users of the internet are now also an effective tool for marketers of products, ideas, or ideologies to promote their preferred option or, at the same time discouraging people through negative word-of-mouth to follow opposing products or views (Berthon et al., 2008).

Studies have shown that electronic word-of-mouth is also associated with cognitive dissonance, as users who are adamant about their own experiences might become frustrated when reading about other users' experiences, and they are not congruent with their own (Dellarocas, 2006). This input of conflicting information and the users' discomfort with the discrepancy between their own experience compared to another user's shared information, in turn creates dissonance (Matz & Wood, 2005). If this dissonance is experienced, users are inclined to "correct" the opinion that they feel this dissonance with and post their own perceived experiences to persuade others (Shin et al., 2014).

This can be observed on social media, especially on Parler, which is known to be a platform especially used by people with far-right-leaning ideologies. If more moderate users posted something that was against the general opinion of the community, it was flooded with comments with the consensus opinions of the community, and any type of moderate approach to a topic was silenced immediately as it did not fit in with the ideas and sentiment of the general population of the platform, which does not fit in with their propagation of free speech.

2.8 Fake News and Conspiracy Theories

Fake news has existed for centuries; however, it has been known under different names until now. The concepts of propaganda and misinformation have been around since before humans started counting years in 44BC, Octavian was already using coins to convey his defamation of Mark Anthony throughout the Roman Empire (Posetti & Matthews, 2018). Posetti and Matthews offer a comprehensive review of the main events in which intentionally or unintentionally made up facts played a large role in the portrayal of events and how the public was to be swayed by them. Since then, the term fake news has been defined as pieces of information that have been made up with the intent to make readers believe in them and discredit something or someone else while being objectively false (Allcott & Gentzkow, 2017). In accordance with this definition, it has been expanded to also include that fake news is made to have the looks of a traditional journal article or news piece (Egelhofer & Lecheler, 2019). With the invention of the internet and the establishment of WEB 2.0, the way in which those types of information can spread has only been accelerated and made easier. Data has shown that nearly half of the outgoing traffic from major social media network Facebook is skewed towards one or the other ideology and, most of the time, also contains false information (Wong, 2016). One factor that contributes to the fact that fake news can spread easily on the internet is one that it has in common with filter bubbles, as people who want to share information are now free to do so while not needing a large scale media operation to spread their beliefs (Allcott & Gentzkow, 2017).

The way in which fake news are construed is often through purposefully created media websites. The ways in which they are run are either to offer a platform for fake news to be spread or to be a mix of verifiably true articles with misinformation being spread in between. Some examples for websites that offer this content are “rense.com” and “thereligionofpeace.com”. There are two main motivators for why fake news websites are created, money and ideology. A reason for people to create fake news stories or to host them is often a financial decision, as the way fake news is spread is often through sharing of eWOM on social media, which drives traffic to the hosting website and therefore generates a lot of revenue from advertising (Dewey, 2016; Subramanian, 2017). The other reason why fake news is hosted and shared is due to the belief that the creation and transmission of those stories will impact the results of events and promote their own ideology (Allcott & Gentzkow, 2017). The lack of ethics and journalistic process then results in a piece of information that is not comparable to traditional media in terms of believability and accuracy (Lazer et al., 2018).

A theory on how the bias towards media and inside media itself has been construed and discusses the way in which suppliers of pieces of media will change their perspective and bias towards certain topics to fit with the demand. The theory also mentions that when the readers and consumers will ask for bias, the suppliers are happy to change their stances as it increases the sales of the media (Gentzkow et al., 2014). The authors also discuss the effects that quality of reporting might have on the reception of the consumer. However, it is mentioned that users will often accept a piece of information to be of high quality as it confirms their previously held ideas. When applying this concept to fake news, it becomes apparent that companies that are responsible for the creation and spread of fake news are either not intending to be long-lasting and well respected but rather to make money quickly or that they want to be perceived as high quality and are therefore not differentiated from mainstream media and are able to satisfy the needs for negative reports on an opposing candidate or a belief system (Allcott & Gentzkow, 2017).

The effects of fake news on politics, as mentioned before, have been around for a long time. However, the increased ability that social media gives has been analyzed only recently in the context of the U.S. Presidential election in 2016. A review of the performance of content was done by Buzzfeed News which analyzed the virality of fake news compared to mainstream news stories. They found that posts and content regarding fake news stories in partisan media gained more and more traction when getting closer to the election while also being shared 18% more than news from more moderate information sources (Silverman, 2016). The review of content also identified the most shared pieces of fake news regarding Donald J.Trumps' opponent in the election, Hillary Clinton, which tied her to ISIS as well as accused her of conspiracy to murder. In line with this analysis, Ipsos Public Affairs, a polling company, analyzed the way in which fake news was received by the American public after the 2016 election and found that three-quarters of respondents thought that fake news headlines, which they were able to remember, were accurate (Silverman & Singer-Vine, 2016). Allcott and Gentzkow (2017) offer a variety of reasons for the increase in the popularity of fake news, as they attribute it to the loss in trust of the American population in mainstream media as well as the increase in negative sentiment toward the opposing ideologies.

The presidency of Donald J. Trump increased the presence of fake news even more as he propagated that criticism in general as well as of his persona and his politics by the mainstream media were to be considered fake news. This also increased the distrust of his followers in traditional media and turned them to alternative news sources which held a more partisan view (Benkler et al., 2018, p. 4; Lazer et al., 2018). The drop in trust in traditional media was quantified by the Gallup institute as only 14% of Republicans trust mass media as a source (Lazer et al., 2018).

In contrast to fake news, conspiracy theories are often seen as difficult to confirm or deny while also having a passionate following regarding their truthfulness. Defining conspiracy theories has been contested, but a definition has been found by Sunstein and Vermeule (2009), who explained them as the explanation of an event through the involvement of a higher power, often in the form of a social or political elite, whose participation is to remain hidden until a certain goal has been reached. This is supported by research by Imhoff, Dieterle, and Lamberty (2021). Additionally, it is stated that conspiracy theories often involve the participation of different people who are able to control everything and everyone around them to not be discovered.

One aspect of conspiracy theorists' beliefs has been analyzed by Karl Popper as he stated that it is in human nature to believe that there has to be a connection between an event benefitting a group of people and the cause for the event (Sunstein & Vermeule, 2009). In contrast to the previously mentioned fake news, which propagates false information to influence people to believe in the creators' opinion, conspiracy theories are often something people accept as true and result in a lack of trust in politics, and therefore the person excludes themselves from participating in the democratic process. Research has shown that people who have fallen into the grasp of a conspiracy theory are of the opinion that the democratic process is useless as every decision is predetermined by a ruling and controlling elite (Wood, 2016). Interestingly, in contrast to that, even though the previously mentioned QAnon is a conspiracy theory, its supporters are of the opinion that former President Trump was a champion of their beliefs and was fighting this ruling elite and was therefore trying to support him through voting, which, by the given research by Wood (2016) should not have been the case. Interestingly, even though participation in democracies is seen as declining in people believing in conspiracy theories, the willingness to attempt some sort of crime is increased by their beliefs as they argue that they should be able to exploit the system as the ruling elites are doing (Jolley et al., 2019).

Research has connected extremist views with the likelihood of believing in conspiracy theories as well as people aligning themselves with right-wing ideology (Krouwel et al., 2017; Wood & Gray, 2019). Which fits in with the beliefs in the QAnon and Pizzagate conspiracy theories.

3 Methodology

This chapter will deal with the methodology that is behind the analysis done to better understand the sentiment and opinions that occurred on Parler around the time of the 6th of January. Firstly, the way how the data was sourced and cleaned to be able to work with the dataset will be explained. Secondly, the way in which the data was worked with and what types of analysis were undertaken will be discussed. The results of the data analysis, as well as the graphs that were created, will be discussed in the following chapter of the thesis.

The worldview of this thesis is to better understand the way in which the users of Parler have viewed the world and what their experiences and opinions are which they shared on the social media platform. This has been defined as the social constructivist worldview (Creswell, 2009). He argues that the way in which social constructivists conduct their research can be qualified as qualitative research. Even though no subjects were studied directly in this research, the author puts the idea forward that the way in which users interact through posting and sharing their beliefs on social media warrants an even better understanding of real feelings as the users are not aware that they are being subjected to analysis and they are therefore not concerned with filtering themselves as they are in a comfortable environment that they are used to. Creswell (2009) interprets that the social constructivist worldview, in conjuncture with qualitative research, places a focus on the context in which interactions happen. The intention of the researcher should be to try and understand as well as find meaning in the answers or statements that the researched subject gave.

3.1 Data Sourcing and Cleaning

The data used was downloaded from a repository that was created by Aliapoulis et al. (2021) for their research. The dataset contains over 40.000.000 posts from the social media network Parler and has a size of 148GB. The posts present in this dataset spanned from October 2018 until March 2021. Parler was used as a connecting platform for users to communicate their thoughts and ideas and conspire to meet before the events. As the data encompasses the posts made on Parler, the researched population is the platform's users. The dataset was comprised of 166 individual .ndjson files, which common text analysis tools are not able to process directly. Therefore, each dataset was converted to .txt files, of which seven at a time were combined by using PowerBI as conventional tools like Excel were not strong enough to process the amount of data. The original dataset contained 35 columns which were: "Comments, Body, Body with URLs, Created at, Created at Formatted, Creator, Datatype, Depth, Depthraw, Followers, Following, Hashtags, ID, Last Seen TS, Links, Media, Posts, Sensitive, Share Link, Upvotes, URLs, Domain, Long, Metadata, Modified, Short, Username, Verified, Article, Impressions, Preview, Reposts, and State." The data then was reduced to only include 4 columns, which were "Body, Created at Formatted, Hashtags, and Username." This was done due to limitations due to computing power.

Additionally, all messages that were sent out automatically due to people joining Parler as well as bot posts, as for instance, a welcome message was sent out from the account of the founder of Parler to each new member that joined. The data of the 40.000.000 posts were then filtered to only include posts between the 1st of November 2020 and the 6th of November 2020, being two days each before and after the election of the U.S. President, as well as between the 3rd of January 2021 and the 7th of January being before and after the storm on the U.S. Capitol. This cleaning process resulted in a final dataset with 974.479 sets of text body, date, hashtags used, and the username of the person that created it. The code with which the data was processed to be readable in PowerBI and Excel is attached in appendix A.

From this on, all data was read into a .csv file which was then read into RStudio using the readr() package. When importing, the data was also converted to fit the standard UTF-8 format (Welbers et al., 2017). The data was then processed in RStudio using a custom code that was written by the author with the aid of his supervisor, as well as using code that is available from GitHub (Orduz, 2018). The code used can be found in appendix B.

3.2 Data Analysis

The data analysis was carried out in R through RStudio. The programming language was designed to aid researchers and data scientists in statistical analysis as well as to do text analysis (Welbers et al., 2017). It was developed to aid researchers with these types of analyses due to increased demand and interest in the field of text mining and analysis (Grimmer & Stewart, 2013). The research approach to the code was deductive, as it was written to understand patterns and important topics that were posted on Parler, which were decided on beforehand (Welbers et al., 2017). The intention behind the analysis was to understand which topics were prevalent in the defined timeframes as well as to understand the sentiment that could be found during the time (Mostafa, 2013).

To analyze the number of posts that were made in the two previously defined timeframes, the dataset was split, and the number of posts was graphed out. To carry out the analysis, the format of the dates had to be adjusted to be in the POSIXct format. The most frequent words that occurred in the posts were graphed in two different ways to visualize the data accordingly. The body of the posts was cleaned using standard processing methods for the bag-of-words model by implementing a function removing the stopwords, punctuation, whitespaces, numbers, and stemming the words. The process of stemming words is used to detect underlying words in a body of text by reducing the variation of words that have the same basis, this ranges from singulars and plurals, but also from synonyms. In stemming, words are shortened by truncating the end of the word and removing any aditional letters that come after the core word. After stemming words, the term created has to be interpreted (Xu & Croft, 1998). The resulting data was then used to create a barplot and a word cloud to showcase the most frequently used words.
The hashtag column was converted into a string which then was split using several delimiters and converted into a data frame. The frequency of those was counted using a stringr() function and mapped using a word cloud.

Additionally, bi-, tri-, and skip grams were created to understand which words were used together most frequently and to gain insight into the messages that were transported in the posts. This was done through tokenization using the ngrams() package. By using this, the body text was split into pairs and trios to be analyzed, respectively. The bigram and trigram words then were weighted so that the networking functions were able to pick up on a threshold. Different networks were created, which can be seen and will be analyzed in the following chapter. Using networks in text analysis is a common technique when trying to visualize the connection between different variables or nodes. Through analyzing the way in which they are interconnected, one can create sub-communities that showcase how several smaller systems will exist in a larger network (Fortunato & Castellano, 2009). The learnings from these steps were then taken to create a membership network using the Louvain clustering technique. The technique uses modularity, which defines the strength of connections between different nodes, and finds subcommunities in larger communities. This is done by calculating the change in modularity when introducing one node into a community of other nodes repeatedly. If the change in modularity is positive, the node is introduced, if it is negative, the node is not. This step is repeated over and over until the nodes have been tried in all different communities, which results in sub-communities. They were then clustered again, and a network with several communities was created with some edges between the different membership groups but a high interconnectedness inside the group (Blondel et al., 2008).

For several analysis methods, the content of the dataset had to be converted to document term matrices (DTM), using the tm() package, as it allows to run matrix analysis tools as it shifts the way the data is handled from characters to numerical (Welbers et al., 2017). While the usage document term matrix was used for word association as well as when analyzing the sentiment of the posts, another package that was used in the sentiment analysis, which is traditionally an alternative to the DTM, which is tidytext(). In contrast to the document term matrix, it does not create a matrix but rather enables the data to be read as a long string in rows (Silge & Robinson, 2016).

Following this, the correlation between the words in the body text was calculated using pairwise correlation. To enable this, the preprocessed data was tokenized again while removing stopwords. These then were used to create a matrix using three topic words which were defined as “Trump,” “Vote,” and

“Democrat.”

Next, word associations were calculated using the findAssocs() function. This was done for the terms “Trump,” “Republican,” “Capitol,” and “Investig.” Finally, the sentiment of the posts was analyzed, and the polarity of the posts during the timeline was plotted. This was done separately for both timeframes, the one around the U.S. election of 2020 and the second one for the dates around the storm on the Capitol. Finally, a sentiment analysis was done to understand the emotions which were shared throughout the posts on Parler. This was done using a sentiment database which is based on the NRC dictionary, which parses each word into different columns, which are named after the corresponding emotions in which the code deemed the word to be in. The emotions tracked are "anger", "anticipation", "disgust", "fear", "joy", "sadness", "surprise", "trust", "negative", and "positive" (Mohammad & Turney, 2010). The most frequent words were plotted in comparison clouds for both timeframes.

The findings will also be supported by the insertion of some of the posts that correspond to the findings made. This is done to aid the contextualization of the analysis as well.

4 Results & Discussion

This section of the paper will deal with the results of the analysis that were achieved with the code that was written. The focus will be placed on the explanation of content as well as the contextualization of this content.

4.1 Post per day

Firstly, the posts were mapped out along a timeline to analyze the number of posts that were in the dataset in the timeframes, the first being 1st November 2020 – 8th November 2020, which encompasses the Presidential election on the 3rd of November.

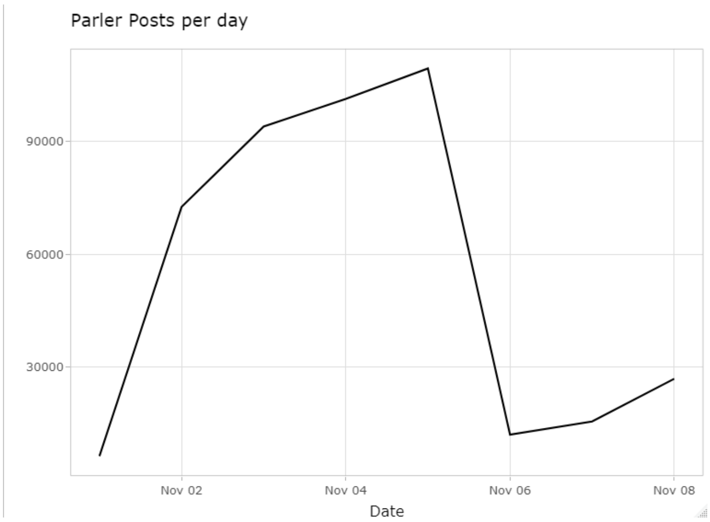

Figure 4 Posts Per Day - Election

In figure 4, one can see a strong increase in posting activity in the days leading up to the election and continuing until the 5th of November. The election in 2020 was so close that it took certain states 3 days until a result was announced. Donald J. Trump and his supporters were adamant that the election was going to be stolen through the aid of foreign powers and the hidden secret elite that was previously mentioned in the section regarding conspiracy theories. The increase in posting activity during that time might be related to this conspiracy as well as the demand to "Stop the Count," which was a slogan that Trump and his supporters created as they felt that there were invalid votes being counted. Those, however, were mail-in ballots that were being counted after all in-person votes had been counted. There is a sharp drop in posting activity on the 6th of

November 2020. This might be due to incomplete data or the fact that during that time, the election results came out, and people might have been so shocked that they did not post immediately. The figure also shows an uptick in posts on the 8th of November back to a more moderate posting activity.

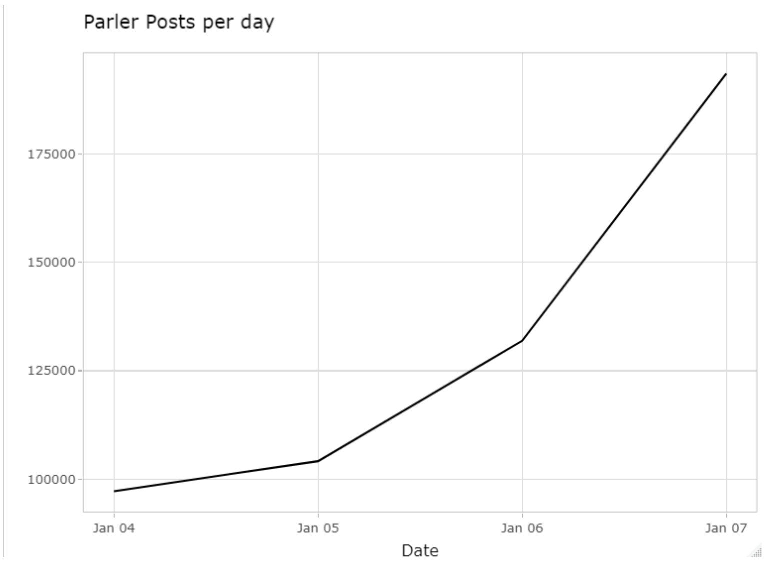

Figure 5 Posts per Day - Storm on Capitol

The second timeframe, 4th January 2021 – 07th January 2021, which is 2 days prior to and one day after the storm on the U.S. Capitol, can be seen as a graph in figure 5. It showcases the increase in posts leading up to the storm on the U.S. Capitol as well as the following day. Even though the posts were already at a higher level compared to the days of the election, the number increased even more the day after the incident. During the 6th of January, many posts were made regarding the state of the protests, and they were even more aggressive when certain conspiracy theories about the protest were spread on Parler. What exactly those were will be discussed later on.

4.2 Most Frequent Words

When looking at the top 20 most frequently used words, which can be found in figure 6, one can see that "trump," of course, had the highest frequency. Second, third, and fourth were words that can be seen in conjuncture, as "will," "vote," and "people" were the following. A lot of the posts that were made during the course of the election period, as well as the process of certification, which was happening during the storm on the capitol, included claims of the "will of the

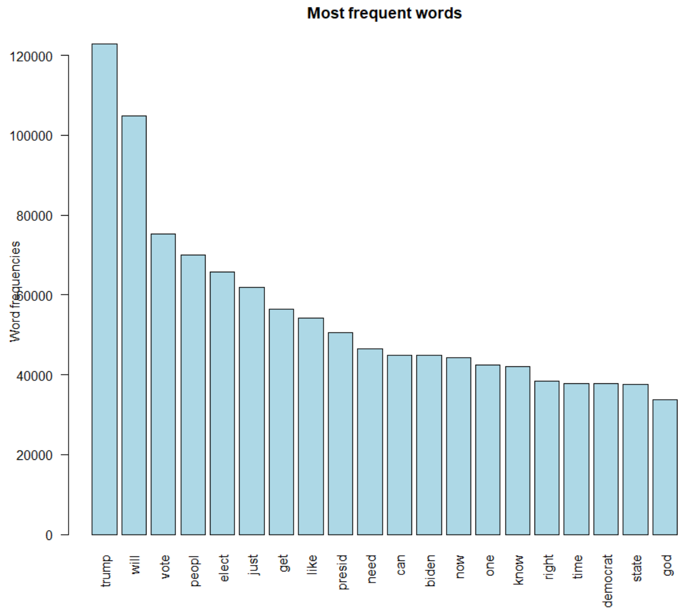

Figure 6 Most Frequent Words, Barchart

people" and the "people's vote." Many of the remaining words are stopwords that can not be analyzed when only looking at a bar chart.

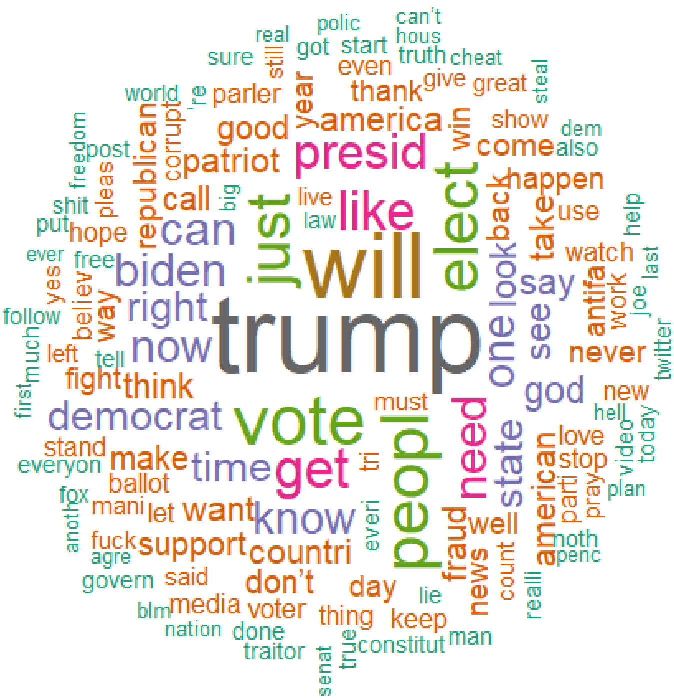

Figure 7 Most Frequent Words, Wordcloud

When looking at a word cloud that represents more than the 20 most frequently used words, a lot of other important information can be seen. In figure 7, the 200 most used words are displayed. Aside from the previously mentioned 20, the words “corrupt,” “fight,” “ballot,” “fraud,” and “Antifa” can be seen in orange, which attributes them a medium frequency. The users of Parler, which of course, were stern believers in Donald J. Trump, believed that corruption was one of the reasons that their desired outcome would not happen. In response to that, a sense of urgency to defend their country from this corruption was created. Donald J. Trump himself, on the morning of the 6th of January, in his speech in Washington D.C., rallied his followers by telling them to “fight like hell,” further increasing the prominence of the thought that a fight had to be had.

> *“\you'll see what's going to happen...they're not taking this white house, we're going to fight like hell\ #presidenttrump at monday night's rally in #georgia.\n\n#trump #maga #kag #stopthesteal #marchtosaveamerica”* (rossr2878, Dataset, 05.01.2021)

A lot of the controversy about the election came from the first time shift towards mail-in ballots in several states of the U.S. due to the COVID-19 pandemic. The traditional way of vote counting, therefore, had been changed, and instead of all the votes being counted on the night and the day after the election, several states took considerably longer. For the supporters of Trump and other Republicans, this was a sign of fraud due to the new nature of the vote counting, and even though Donald J. Trump was ahead in several states, the mail-in ballots, which were predominately skewed towards Democratic voters, meaning that the margin in select states became smaller and smaller and he even got overtaken in some of them by Joe Biden (Levine & Chang, 2020).

4.3 Hashtags

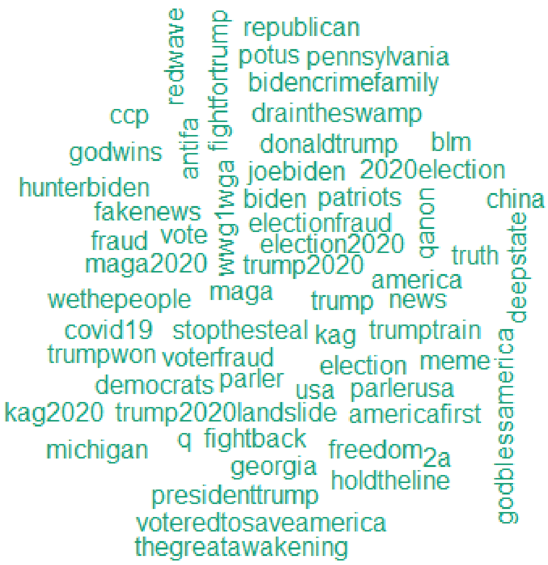

Figure 8 Most Frequent Hashtags, Wordcloud

The hashtags give a nice indication of what moved the users of Parler, as it gives the opportunity for them to combine several words into one to showcase an opinion. In figure 8, the most frequently used hashtags are shown. One can see that there is no standout usage of one hashtag. However, the ones are shown here give an indication of the general opinion during the defined timeframes.

The hashtags "trump2020landslide", "voteredtosaveamerica," and "redwave" describes the desired election outcome of Republicans, red being their color. The goal of the 2020 election was to achieve majorities in the Senate, the House of Representatives, and of course, to have a Republican President.

> *"i don't think it, i know it. #trump2020landslide"*(nailnhead, Dataset, 08.11.202)

The "CCP," which is the ruling Communist Party in China, is seen by Trump supporters as one of the medelling governments that wanted to stop the reelection. The same context also applies to the hashtags "china", and "deepstate," which is the term that conspiracy theorists use for the ruling elite that suppresses everybody that is not with them.

A hint towards another one of the conspiracy theories that was made up in the lead up to the election can be found in "hunterbiden" as well as “bidencrimefamily.” Hunter Biden is the son of Joe Biden, the opposing candidate of Donald J. Trump. The theory claims that Joe Biden while being the vice-president of the U.S., participated in corruption to get a position for his son in one of the major companies in Ukraine. The theory went as far as claiming that Joe Biden withheld funding for Ukraine to pressure the government of Ukraine to get rid of a prosecutor that was investigating the alleged corruption (Collins & Zadrozny, 2020).

Of course, “qanon,” “q,” and “qtrummp” are also some of the most frequently used hashtags. As mentioned before, QAnon, the conspiracy theory about the ruling elite and Trump’s presidency are strongly interconnected. Also connected with those hashtags are “thegreatawakening”, and “draintheswamp” which is the cleansing of the ruling elite that “Q” claims will happen through Donald Trump.

Additionally, the previously discussed fake news are also represented in the word cloud in figure 8, as the Trump supporters claimed that the election was also rigged by the mainstream media, which can also be seen in conjuncture with “electionfraud”, “voterfraud”, “trumpwon” and “stopthesteal”, which was a trending hashtag during the 6th of January with the users of Parler wanting Mike Pence to overturn the electoral college votes to help Trump to become President again.

“Fightback” and “holdtheline” were also prevalent, which were representative of the stance that Trump tried to impose on his followers on the day of the storm on the U.S. Capitol. This also had implications for the “2a” hashtag that describes the second amendment of the U.S. Constitution, which guarantees the right to bear arms to U.S. citizens.

Lastly, “georgia” and “pennsylvania” were also under the most used hashtags, as Pennsylvania was the most closely contested state with Republicans sending their own slate of electoral college votes even though having lost, and Georgia having another election as it was too close, and both Democratic candidates winning, guaranteeing a Senate majority for the Democrats.

4.4 Bigram Network

Figure 9 Bigram Network (Threshold = 1500)

The bigram network showcases which words were next to each other when being posted on Parler. Figure 9 shows a visualization of this network. Some of the words that appeared together give the opportunity to analyze the opinions that were shared and also to see the connections that some words shared. For instance, on the outside of the figure, one can see connections like “lin-wood,” which is one of the lawyers that tried to have the election overturned on several occasions. Of course, he was also active on Parler, and people spoke about him a lot as he was furthering Trump’s agenda. Close to it, one can also find “mail-ballot” this again is an indication that the concept of mail-in ballots was frequently discussed on Parler as it was seen as one of the reasons that alleged election fraud happened.

“Suprem-court” can also be found close to it, as many of Trump's supporters and Parler users claimed that the election would be voided by the U.S. supreme court as the sitting President had been able to nominate three new judges who were seen as Trump-friendly. This, of course, did not happen.

> *“reclaiming a superpower\n americans prepare for war\n\nwhere is the fbi? whereis the cia? where is the doj? where is the supreme court?\n they no longer serve the american people. it is our right, it is our duty, to throw off such government and to provide new guards for our future security. \nhere is the 15 page pdf outlining election fraud #stopthesteal #patriots #election2020 #trump”* (diligent512, Dataset, 05.01.2021)

As mentioned previously, “mike-penc”, representing the then vice-president Mike Pence, was seen as an important piece in overturning the election as he was responsible for counting the electoral college votes. Trump supporters, lawyers, and some experts on the U.S. constitution claimed that the vice-president holds power to either accept a slate of electoral college votes or to refuse them. The counting of the electoral college votes was also a heavily discussed topic which can be seen in the connections “college-elector-count”.

An interesting connection in the followers of Donald J. Trump, religion, and the country, in general, can also be drawn from this data, as “constitution-godgiven-speech-free” is also represented in figure 9, referencing the 1st amendment to the U.S. constitution, being free speech. Additionally, this can be seen in “bless-god” and “christ-jesus”.

A connection that a special focus has to be put on is “antifa-blm”. Antifa, a left-wing movement that is often seen as the instigator for riots and violence in protests by the far-right, has been accused by Trump supporters as having been present at the events on January 6th and being the reason for the storm on the capitol. Antifa is seen as the nemesis of the right-wing agenda that many of the Trump supporters subscribe to and is often claimed to be the reason for anything that goes against the desires of the Republicans. The connection to “blm” (Black Lives Matter) is interesting as apparently, the users of Parler saw a connection between a racially motivated movement towards equality and a group that they see as the evil in the U.S.. The Black Lives Matter movement is also seen as an issue to the previously mentioned “radical right” as they oppose equal rights for minorities and fear a change in societal status.

The way in which “civil-war” is also connected shows the frustration and fearmongering that Parler users were exposed to. One of the talking points that were spread around the social network was the expectation that when Joe Biden would be elected President, he would take away the guns of Trump supporters and that this would end up in a rise against the power of the government and therefore end in a civil war.

The different connections between “elect-fraud-voter” as well as “steal-elect” demonstrate the way in which users of Parler saw the election process and that they did not perceive it as a just election.

“Biden-hunter” and “biden-joe” again showcase what has been seen in the hashtags previously. The conspiracy theory of Hunter Biden and his ties to Ukraine, as well as his father's intervention, were highly discussed topics during the defined timeframes.

Lastly, one has to look at the different connections that emerge from “trump.” They are “win,” “support,” and “won.” This again showcases the disbelief in the actual results of the election and their non-acceptance of accepting Joe Biden as the new President.

4.4.1 Bigram Wordcloud

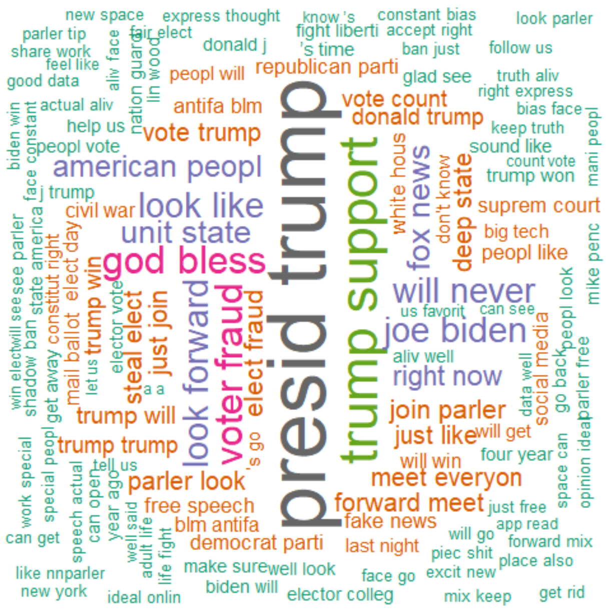

Figure 10 Bigram Wordcloud

As shown in figure 10, the bigrams that were created earlier can also be displayed in the format of a word cloud. This showcases the frequency in which the bigrams have occurred together. The word cloud was created to incorporate the 200 most frequently used words.

As can be expected, “presid-trump” was the bigram occurring with the highest frequency as well as “trump-support.” The group of bigrams shown in pink, “voter-fraud” and “god-bless,” are an indication of two of the biggest talking points on Parler, as the claim for voter fraud often occurred as well as the relation of the cause and ideology of Republicans to god as their guidance. The frequencies of “joe-biden” and “will-never” occurred similarly as often as “look-forward,” “fox-news” and “look-forward.” One can see that many of the bigrams that are surrounding the most frequently used ones are related to conspiracy theories, which fits in with the idea that Parler was a breading and spreading ground for them as they were echoed, which is the Parler specific term for sharing information, frequently.

4.4.2 Trigram Wordcloud

Figure 11 Trigram Wordcloud

When looking at the trigrams that were created resulting from the dataset in figure 11, deeper insight can be gained into what the previously mentioned bigrams meant. Most of the trigrams that are shown in the middle of the graph revolve around free speech, and that the users of Parler apparently see them as godgiven rights through the constitution. A lot of the trigrams concern themselves with other social media and online content platforms, as they are talks about "throtteling shadow bans" as well as "shadow banning free speech," which corresponds to their claims that Twitter, Facebook, and Youtube would not display and share their content through its algorithm just because of their ideology. This can also be seen in connection with the previously mentioned free speech argument, as they feel their rights are violated.

> *"i like not being censored! i ran out of email address to feed to twitter. most of the people on here seem to be like-minded. good to know free speech still exists and there are true patriots out here like you and others."* (firefather24, Dataset, 07.01.2021)

4.5 Memebership Clustering

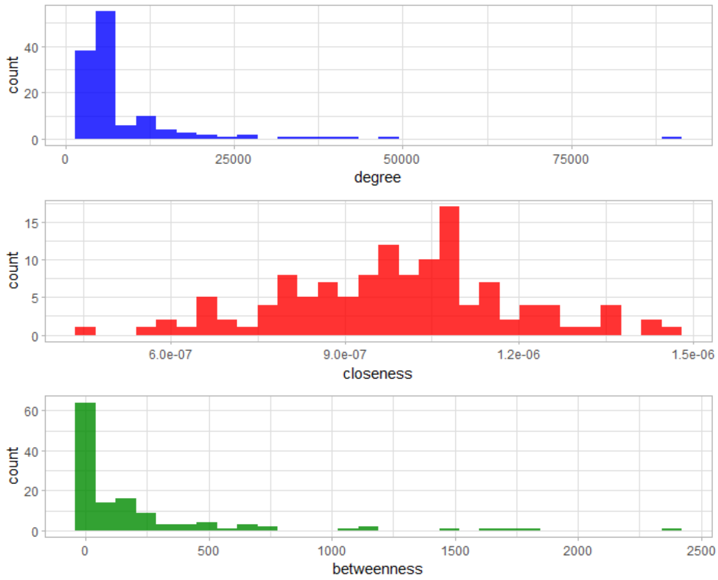

Figure 12 Cluster Analysis

Before creating the clustered graph, the betweenness, closeness, and degree between the clusters had to be calculated.

The degree variable, shown in figure 12, describes the importance factor that each node holds due to the number of edges. This shows how many links one variable or node has to other variables in the whole network (Zhang & Luo, 2017). In the corresponding figure, the degree between the different variables shows that most of the nodes have a very low score in degree. However, there are still some in the medium range of the scale. Towards the higher end, there are only a few nodes that reach a high score in the degree variable.
The closeness variable also graphed out in figure 12, showcases how close the different nodes are in comparison to the other nodes in the same network. This is showcased through a calculation of the shortest way between the different nodes (Zhang & Luo, 2017). As one can see in figure 12, the closeness between the nodes is on a very constant albeit very low level. Therefore, the nodes are very close together. Lastly, the betweenness variable demonstrates the frequency of how often a node is between two other nodes and is, therefore, connectors or bridges. To achieve this value, the calculation is to find the shortest path between different nodes and checking how often a node falls on this path (Zhang & Luo, 2017). The figure shows that the nodes in this network

mostly have a score of low betweenness; however, there are some variables that show at least a medium score in the variable.

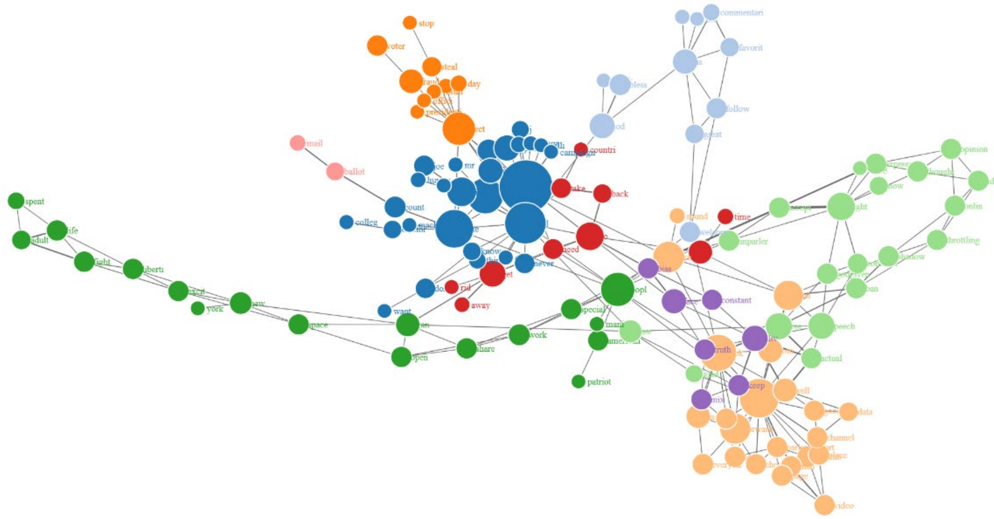

Figure 13 Louvain Method Cluster

Using the previously described method of Louvain clustering, one can see the interconnectedness between the different communities as well as the connection between the discussed bigrams. Figure 13 is a 3D network representation of this clustering and showcases that the bigrams which were discussed in the previous section are shared between communities that also are interconnected. This enables to understand the way in which certain words, even though not connected in bigrams, might still be in relation to another.

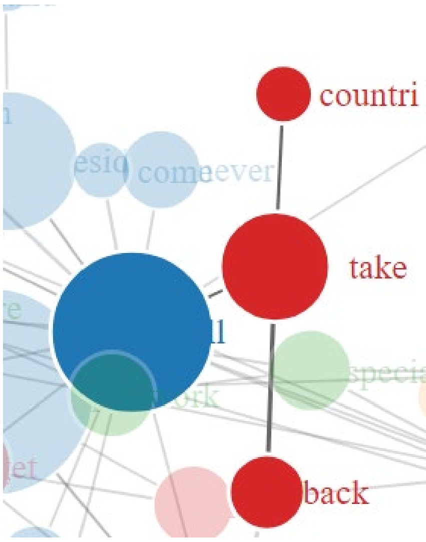

Figure 14 Clustering (Will)

One interesting connection which could not previously be discovered is the one between "will-take-back-countri" which can be seen in Figure 14, showcasing the ideology and intent of the supporters of Donald Trump to take the country back from their opponents.

Figure 15 shows the connection between "vote" and its surrounding notes of "machine," "colleg-elector," and "mail-ballot-count." This displays the previously described but not visible connection that Trump supporters claimed to see

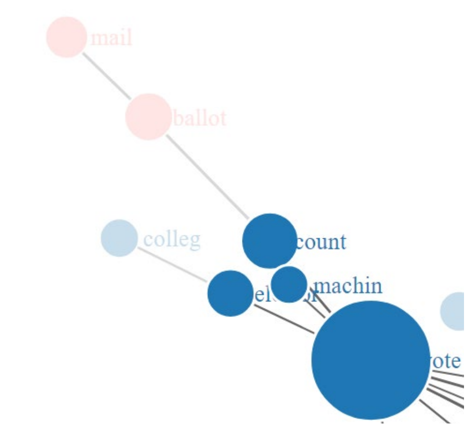

Figure 15 Clustering (Vote)

between mail-in ballots and the counting of the votes. As mail-in ballots were and are not common practice in the U.S., the way in which they were counted was unfamiliar to the general public and many of the users in Parler perceived it as a major security risk for the election.

Another interconnectedness between different communities that is apparent in figure 10 is between “will,” “people,” “take,” “god,” and “elect.” Describing the connection between the “will of the people,” as well as “will elect,” with elect being strongly linked to “trump” again. Another connection that can be seen in “will-god” is the previously mentioned belief that it is gods will for Donald Trump to be reelected as president.

> *“god used david in the old testament and god will continue to use donald trump for his good. #trump2020 fight. pray. win.”* (mscaz2012, Dataset, 04.11.2020)

To showcase the two largest groups or communities in the data, please refer to figure 16. When looking at the largest community, most of the connections have been discussed in the text until now. However, there are two connections that should be mentioned here as well. The first being “maga,” which describes the slogan that Donald Trump used in the 2016 election, Make America Great Again. Republicans who are also supporters of Trump refer to themselves as “maga” when discussing their political affiliation. This showcases that they do not associate themselves with the Republican party itself as they believe them to be elitist as well but rather align themselves with Trump.

```
> comm.det.obj
IGRAPH clustering multi level, groups: 8, mod: 0.66
+ groups:
  $`1`
   [1] "presid"   "trump"   "joe"     "vote"     "donald"  "mail"    "biden"   "elector" "support"
  [10] "hunter"   "count"   "j"       "mr"       "ballot"  "stand"   "win"     "won"     "colleg"
  [19] "maga"     "machin"  "ralli"   "campaign"

  $`2`
   [1] "god"        "help"       "follow"     "great"      "welcom"     "favorit"    "us"         "thank"
   [9] "tell"       "bless"      "commentari"
```

Figure 16 Biggest Clusters

The second node that should be mentioned in the largest community is “ralli,” referring to the rally that was held on the 6th of January. The event was held by

Trump and his allies in the morning of the day of the storm on the U.S. Capitol, where he enticed his followers to fight for their country. The event in the morning was titled by Trump and his team as "Save America Rally," in which he not only called them to fight for the country but also to take back America, which was also shown in figure 14.

4.6 Word Correlation

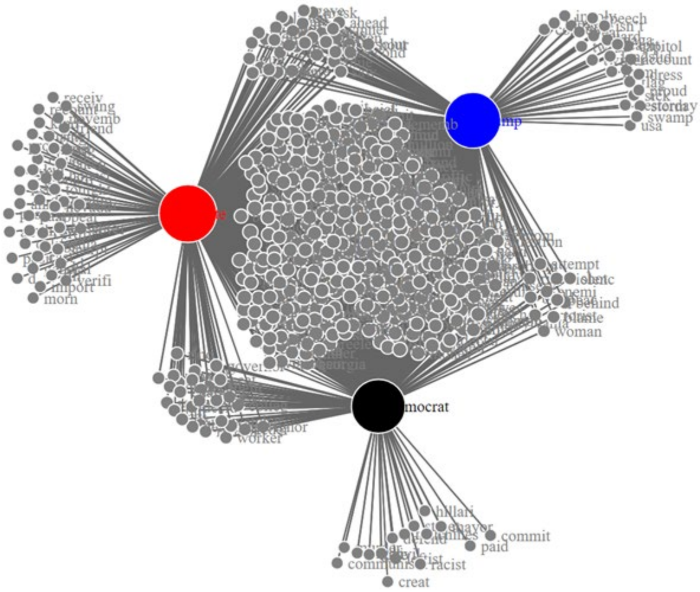

Figure 17 Word Correlation (Full)

The word correlation with the three topic words "democrat", "trump", and "vote" was calculated and graphed out, which can be seen in figure 17. As the graph was created to imply a 3D network, it is optimized for interactiveness. For clearer vision purposes, certain segments will be specially shown in the following figures.

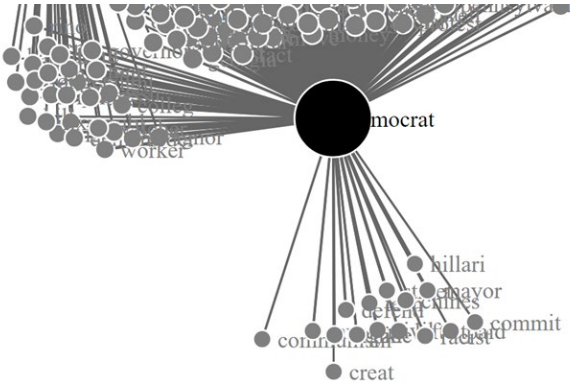

Figure 18 Word Correlation (Democrat)

In figure 18, the words that are only correlated with “democrat” are shown. The standout words that require further explanation and contextualization are “leftist,” “communism,” and “murder.” “Communism” in the context of democrats is often referred to by Republicans as they see even slightly left-leaning social policies as communist. As now-President Biden and his democratic party have been trying to introduce healthcare for everyone, increase the minimum wage, and introduce other policies that, from a republican standpoint, are left-wing, they refer to this as communism. Additionally, a shared sentiment for supporters of Trump was that if Biden had been voted president, the United States would have become a communist government. This can then also be seen in conjunction with the term “leftist,” as most of the policies that are seen as basically democratic in most countries are perceived as leftist by Republicans and their supporters. “Murder” is a strong word that, in connection with “democrat,” showcases the apparent beliefs of what would be necessary to save the country by the users of Parler. Additionally, during the storm on the U.S. capitol, a supporter of Donald Trump was shot by security personnel which railed up the users of Parler as they claimed this to have been murder.

> *“the democract leaders and party all of them, allowed rioting, looting, burning of buildings and police precincts, and tearing down of our national monuments and even murder for an entire year! what did they think the end result would be?? it reached their own doorsteps, now they are outraged! what phony and dishonest hypocrites. you (democracts and media) are the people responsible for yesterday chaos, not trump.”* (duillu, Dataset, 07.01.2021)

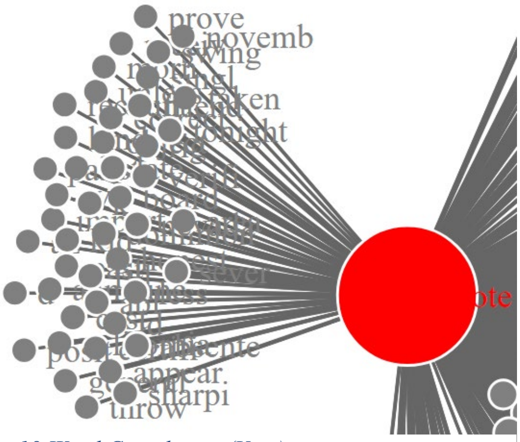

Figure 19 Word Correlation (Vote)

Figure 19 shows the words that are correlated solely to “vote.” The words that need to be examined further, in this case, are “sharpi,” “certifi,” “verifi,” “absente,” “dominion,” “recount,” and “rig.” Most of these words can be grouped together for explanatory purposes. “Verifi” and “absente” were both parts of talking points among the users of Parler as well as the general republican followers. Especially the absentee ballots that were cast through mail-in voting were one of the aspects that Republicans criticized and argued that they could be a way in which votes could have been falsified as it could not be verified that the actual person filled them out. Another aspect that Republicans claimed after the election was that ballots were cast by relatives of dead people, as well as some people were casting their votes twice. Interestingly, most of the ballots that were either falsified or cast in the name of dead family members were made by Republican voters.

> *“???????? judicial watch: over 4,700 of georgia's absentee votes in november election tied to non-residential addresses”* (gholland04, Dataset, 05.01.2021)

“Sharpi”, refers to a conspiracy theory that was spread among the followers of Donald Trump. “Sharpiegate” which refers to the claims that ballots filled out with sharpie pens were not counted in the state of Arizona, after a video claiming this had spread on social media. In previous elections, ballots marked with sharpie were disqualified; however, in the 2020 election, they were allowed. As in-person voting was preferred by Republicans, they claimed that their ballots were not counted as the polling stations were only providing sharpies, which made them claim that they were cheated out of their vote and therefore disenfranchised.

> "*please echo! georgians please! take your own black or blue ball point ink pens, and extras for others. remember \no sharpies\ of any color, and no \red ball point ink pens\ !!!!!!!!!!!! don't let them tell you other wise. it says on the ballot not to... thank you."* (ssnevada, Dataset, 05.01.2021)

Another conspiracy theory that has been circulating since the days of the election and has been discussed in courts, as well as the media has been the company "dominion," which is providing voting machines to several states in the U.S. The claim by conspiracy theorists as well as Trump's aids and team was that dominion machines were tied to the government of Venezuela and the previously mentioned Antifa movement. This conspiracy theory was then also brought forward to the media by Trump's lawyers, while they now face lawsuits for defamation.

After the election results started to come in, in the days following the election and Republicans saw in the news that their candidate lost, many of them called for a "recount" of the votes, which can also be seen in the data.

Finally, "rig" referring to rigged also refers to the previously discussed claims that the election was rigged to make sure that Donald Trump lost and Joe Biden, the Democratic candidate, would win. There is no substantial evidence for those claims. Claiming that the election was rigged by the ruling elite, which again is connected to the QAnon conspiracy theory, also furthered the disbelief in the mainstream media.

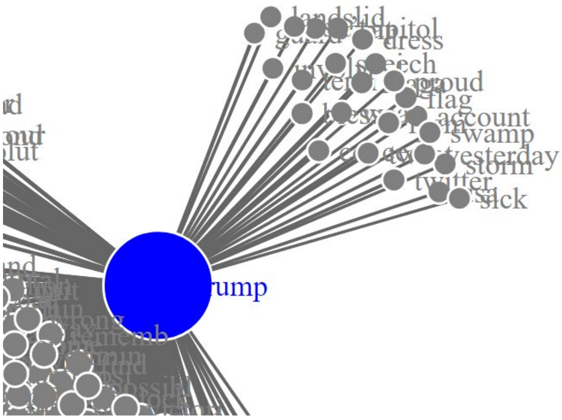

Figure 20 Word Correlation (Trump)

Looking at figure 20, one can see the words that were solely correlated with "trump." The term "landslide," as mentioned before, was the preferred outcome the Republicans wanted to see, as they wanted to hold and even increase the majorities in all governing bodies. However, they lost all 3 governing bodies in the 2020 election.

The connection of "conced" with "trump" refers to the claim that Trump and his followers would never concede their country to the democrats.

> *"i think it means there will be a big orderly transition for his new administration and it is a play on words. it marks the end of the greatest first term in history- not his last! the words trump concedes is not there! trump is not a quitter and he doesn't roll over- he's playing chess and they just put all their checkers back in the box! ????"* (sunshineandroses77, Dataset, 07.01.2021)

"Maga" again appears here as well, showcasing the way in which the followers of Trump see themselves not as Republicans per se but rather as maga. The terms "swamp" and "storm" are connected through conspiracy theories. As mentioned previously in the hashtag analysis, "draintheswamp" refers to the QAnon conspiracy theory, which claims that Donald Trump would be the one to fight back against the ruling elite and therefore drain the metaphorical swamp. "Storm" in the context of the users of Parler does not refer to the storm on the U.S. Capitol, but rather is the name of the event, which will be the end of the ruling elite. As discussed in the previous section about QAnon, they believe that the "storm" will be the day the elite will be arrested, thrown into prisons, and publicly held trials will start, resulting in a free and utopian world.

> *"they have to put on a show. the storm is coming. calm down, get a grip and get ready. \worry destroys focus.\ ~ donald j. trump 2013. eye on the prize. your energy flows where your focus goes. make it positive energy for the outcome we all know is going to be the truth. do you really think you can take down a global cabal of satan lovers and the most powerful people and governments in a few months? or days? you cannot be that stupid. big picture! he is ridding the world, ill say again, the world of this evil and corruption."* (huskyhawkhouse, Dataset, 07.01.2021)

Some further nodes that need to be mentioned, while not easily extracted from the 3D network, are "rino," "socialist," "tax," and "gun," which are correlated to "democrat" and "vote." "Rino" refers to an acronym for "Republicans In Name Only," which is a derogatory term used by maga supporters who see their ideology as the premier one that should be followed by the whole Republican party. Politicians who are elected as Republicans but do not support Trump are therefore labeled as "rino" to showcase that they might be elected; however, they do not support the cause that maga is fighting for.

"Socialist," which in the U.S. is interchangeable with "communist," also appeared in the correlation regarding "democrat." Users of Parler were afraid of the U.S. becoming a socialist state which would increase taxes. The supporters of Trump and Republicans in general also believed that their guns would be taken away to aid the transition towards a socialist state and to deter any kind of insurrection.

> *"you are the communist , socialist. soon as the forensic audits are done of machines . it will show all . even this run off . no surprise. our republicans running high then no surprise , mail out fraud ballots are counted and numbers changed . audit those ballots closely . one county , corrupt all the way !!"* (chrisdesilvio, Dataset, 06.01.2021)

The fear of the government taking away the public's guns has been around for quite some time. Most Republican voters do support relaxed gun laws as they argue they need to defend themselves from the government, which is a baseless claim.

Lastly, "winner," which is correlated to "trump" and "vote," also has to be looked at and contextualized. On the one hand, users of Parler claim that Donald Trump did win the 2020 Presidential election. Even though recounts and analysis of ballots have shown that those claims are not founded in reality. Additionally, they also dispute the fact that Joe Biden won the popular vote. A statement that Trump himself has made several times is that he received more popular votes than any other President before him, which is true. However, Joe Biden received even more votes and therefore also makes this claim false as well.

4.7 Word Associations

The next step in the analysis was to look at the word associations between 5 different terms that were defined by the author. Those terms are "Trump," "Republican," "Investigate," and "Capitol." The findAssocs() function uses correlation to investigate if certain words appear together. The value which is shown for the correlation then describes the score on how often words appear together. A score of 1 indicates that the terms are always together, while a score of 0 shows that the words never appear together.

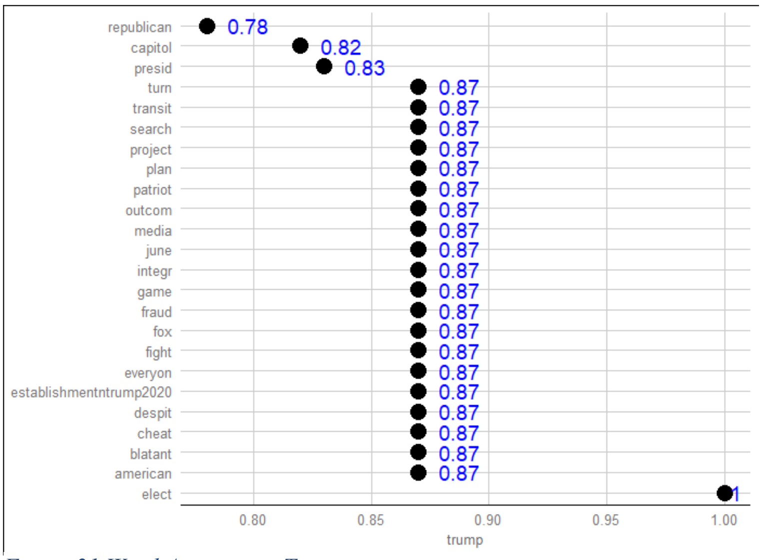

Figure 21 Word Association Trump

As shown in figure 21, the term “trump” always appeared together with “elect.” Either talking about the election or referring to him as the president-elect. A further high correlation was found between “trump,” “blatant,” “cheat,” and “fraud,” which, of course, refers to the claims by his supporters that there was blatant cheating and fraud regarding the election, as well as “integr” which is the stemmed version of integrity which the maga supporters claimed the election to not have. Another word that frequently appeared with “trump” was “fox.” The news and media company Fox News, which is owned by the Murdoch family, has historically been supportive of Trump and his political ambitions. They were also the media source he consumed most while being President. A lot of the conspiracy theories that he and his supporters were talking about were also shared on Fox News. Additionally, some of the hosts of the talk and news shows on the channel were also used by Trump as aides. However, Fox News was also the first media company that called the state of Arizona for Joe Biden during the election, which was a highly discussed topic for the users of Parler.

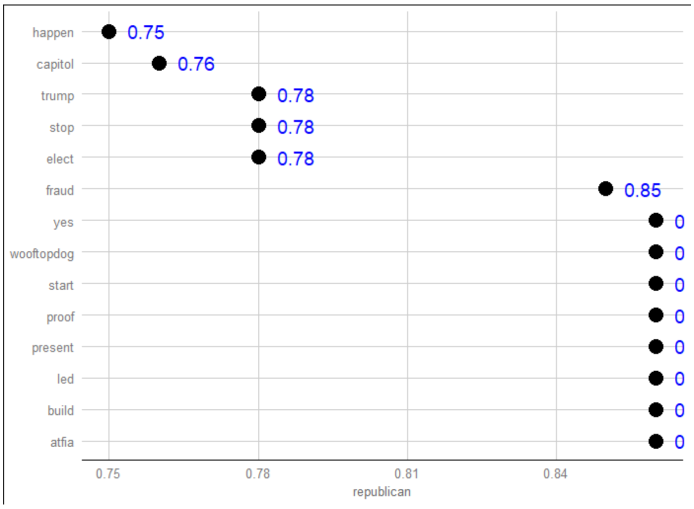

Figure 22 Word Association Republican

When looking at the terms associated with “republican” in figure 22, the terms that need further inspection are “present,” “proof,” “stop,” “elect,” and “fraud.” A claim that trumps lawyers and Republicans alike made frequently was that they would present proof of the stolen election and election interference which then was echoed by the users in Parler. Additionally, the terms “stop,” “election,” and “fraud,” of course, were also often used by the supporters of Trump and users of Parler to voice their opinion about the validity of the election as well. Another term that is associated with “republican” is “capitol,” which, on the one hand, of course, refers to the U.S. capitol, which was the finish of the rally that Trump held on the 6th of January as well as the place where all senators and representatives were at the same time, democrats and republicans alike.

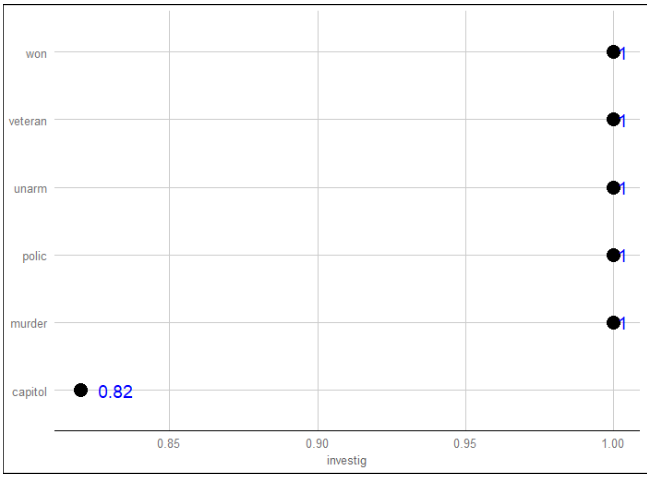

Figure 23 Word Association Investig

As many of the users of Parler called for investigations of the election, they also called for the investigation of the claimed murder of Ashley Babbit. A woman stormed the U.S. capitol and tried to get close to a room in which Senators were located. A security guard shot her when trying to breach into a secured area. Therefore, the terms “murder,” “capitol,” and “unarm” are related, which can be seen in figure 23.

> *“unarmed young lady killed by a police officer. it's called a cold blooded murder.”* (mlgnwgeorgia, Dataset, 07.01.2021)

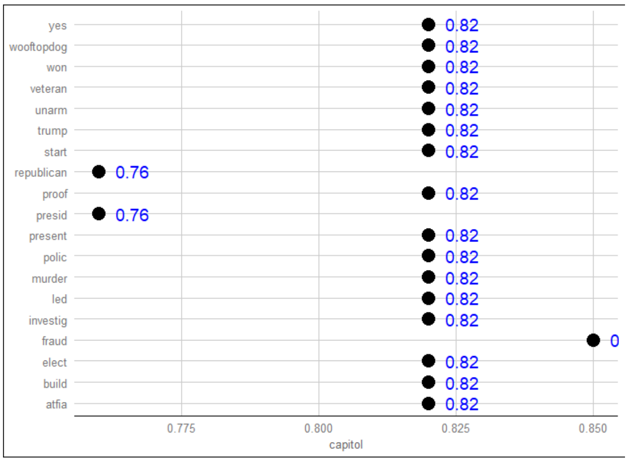

Figure 24 Word Association Capitol

As can be seen in figure 24, the term with the highest association with “capitol” is “fraud.” As mentioned previously, fraud was one of the allegations that supporters of Donald Trump claimed had happened at the election. Additionally, “atfia” as well as “proof” were highly associated with the term “capitol” as well. “Atfia,” the stemmed version of Antifa, was claimed to be the reason that the storm on the U.S. capitol had happened, as maga supporters argued that busses full of Antifa supporters were carried into Washington D.C. by the government to instigate a riot and to breach the capitol to make Donald Trump’s supporters look bad. The term “proof” was mostly used in the context of proof being brought up by Trump and his supporters of the stolen election, as well as the proof for Antifa being the ones instigating the storm on the capitol.

> *“but those are mostly peaceful protests, like when cnn reporter was standing with burning cars and storefronts behind him. what happened when so called rioters stormed the us capital was to establish the new narrative. the dc police escorted buses of antifa/blm dressed in maga clothing waving trump flags and permitted them to breach security. there is video proof of dc police escorting rioters into capital, even permitting them to pose while taking selfies. it was planned to ensure damaging video/photos to support msm’s narrative and hurt trump’s maga movement.”* (russelkinzie, Dataset, 07.01.2021)

4.8 Polarity Analysis

For analyzing the polarity in the posts on Parler, the split dataset was used to showcase the data in the election timeframe separately compared to the one in the timeframe of the storm on the Capitol. Looking at the unsmoothed polarity for the election period, one can see steep drops in polarity towards the middle of figure 25. The throughs reach a negative polarity up to -8 while only reaching a maximum positive score of 5.

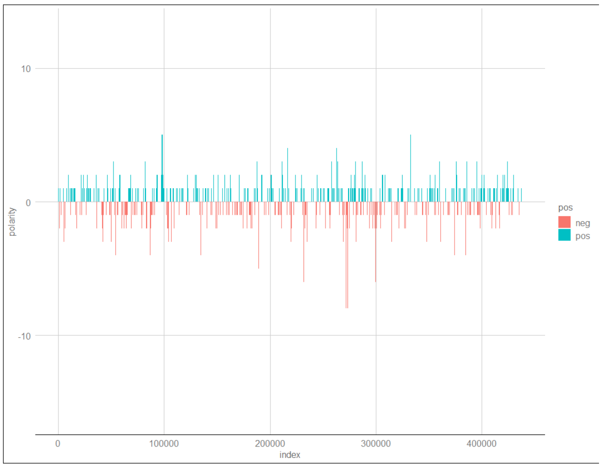

Figure 25 unsmoothed Polarity, election

Comparing this to the unsmoothed polarity around the storm on the capitol, which is shown in figure 26, the polarity levels never achieve maximums in the positive or negative spectrum as they did around the election. To achieve a clearer picture, the data was smoothed.

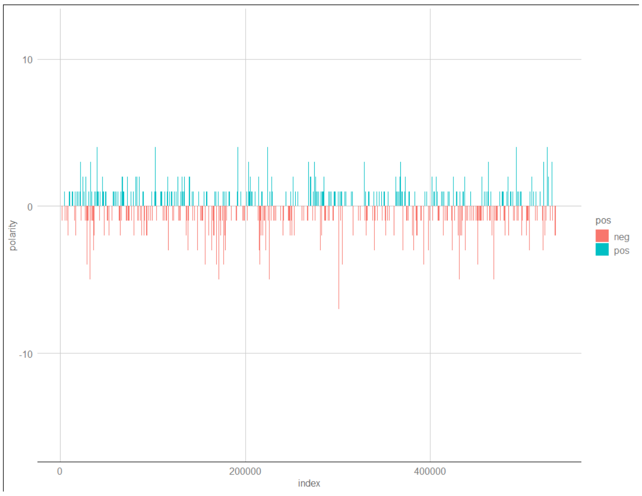

Figure 26 unsmoothed Polarity, storm

In figure 27, one can see a strong wave form along with the number of posts, therefore, the emotions got stronger and weaker along the timeframe. This is

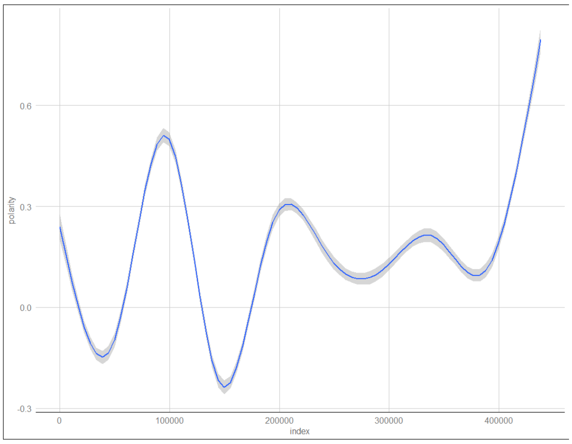

Figure 27 smoothed Polarity, election

due to the results of the election in the different stages of the counting process being either favorable or unfavorable to Trump. Towards the tail of the dataset, the sentiment shows the highest value of positivity. However, the positivity never achieved the same level of sentiment as it did with the negative emotions. The lowest level it reached was under -0.2, while it barely reached +0.2.

In comparison to this, during the timeframe of the storm on the Capitol, which can be seen in figure 28, there was never the same wave motion of the graphed line. The positivity reached its peak around the 1.7 value, while the negative polarity reached lower than for the election period. Additionally, the emotions were constantly in the negative range during the storm on the Capitol period. This is due to the fact that the day on which the storm happened, the electoral college vote count was also occurring, which would be the end of the term of Donald Trump and the start of Joe Bidens.

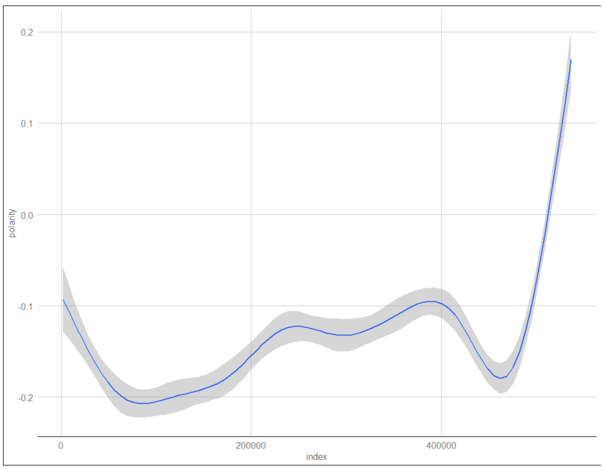

Figure 28 smoothed Polarity, storm

4.9 Sentiment

Firstly, bar charts with the frequency of the different emotions for the two timeframes were created. As can be seen in figure 29, there are more positive emotions than negative ones. Positive emotions achieved a score of over 800, while negative ones reached around 780. Additionally, there was a high value of trust at 650 during this time. However, anticipation, fear, and anger can be seen closely behind in the most frequent emotions. Surprise, sadness, and joy are on the same level, while disgust is the lowest.

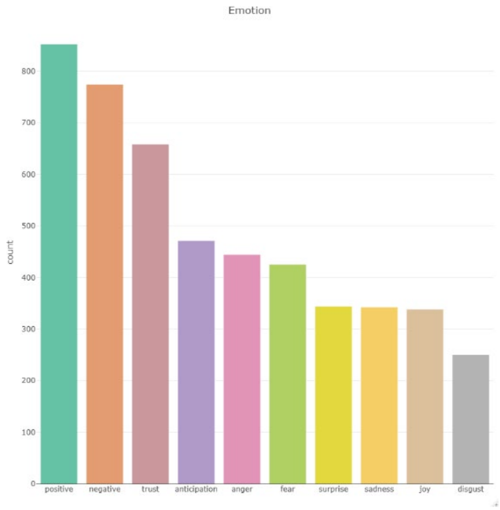

Figure 29 Emotion Barchart, Election

Comparing the values found around the election to the ones found around the storm on the capitol, in figure 30, one can see immediately that during the second timeframe, negative emotions were overwhelmingly more persistent.

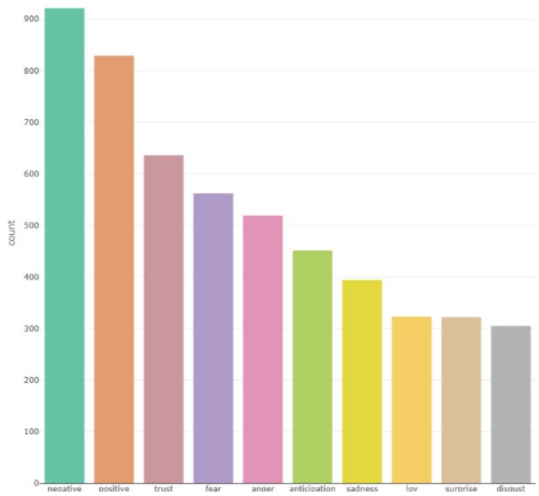

Figure 30 Emotion Barchart, Storm

The negative emotions during the timeframe of the storm on the Capitol reached a value of over 900, while the positive emotions were lower than the score it achieved during the first timeframe. The amount of trust was also reduced in the timespan of 2 months. However, fear and anger reached higher scores in the second set of the data. Additionally, the level of disgust was at the same amount as joy and surprise compared to the election period when disgust was far behind the others. Lastly, two comparison clouds were created that each sort the most used terms respective of the emotions that they were assigned to by the algorithm used. Firstly, the comparison cloud of the time around the election was created, which can be seen in figure 31 and figure 32.

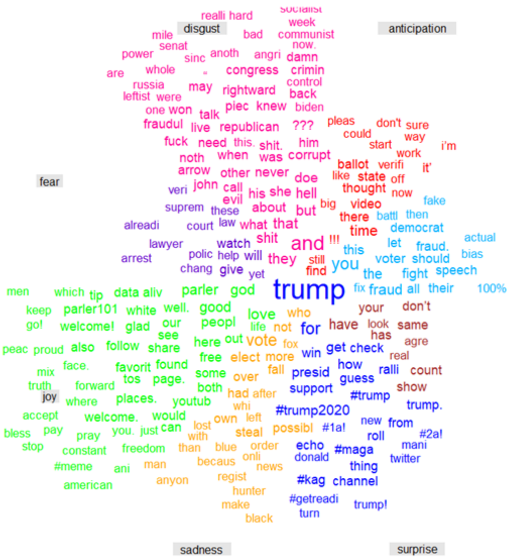

Figure 31 Comparison Cloud, election

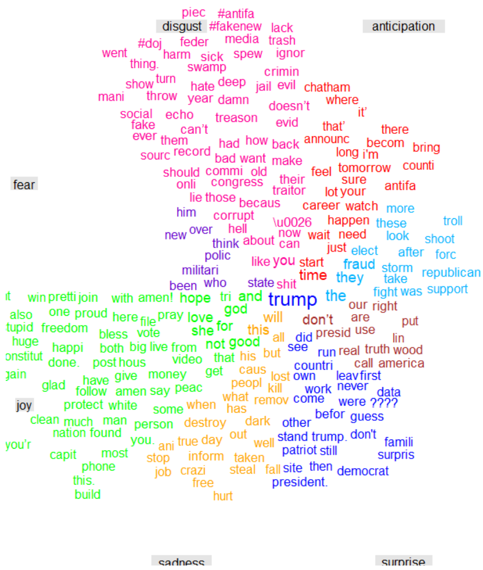

Figure 32 Comparison Cloud, storm

5 Conclusion and Future Work

The final part of this thesis will deal with a conclusion that will be drawn, and the findings will be contextualized using the literature that was reviewed earlier. Additionally, it will give an overview of how research could advance the understanding of the far-right ideology field and Parler users using the same methods of social media listening and text as well as sentiment analysis. Furthermore, the limitations of this study will be addressed.

5.1 Conclusion

The findings of this study align with its research goal, to analyze the posts on Parler to give scientific backing to the discussion around conspiracy theories as well as the general sentiment on the far-right social media platform. An analysis of the most frequently used words as well as an analysis of bi- and trigrams was conducted to draw from the body of text that was available, and the main talking points were extracted.

The results and claims made in the data analysis section were supported by showcasing some of the posts that included the keywords that were discussed and showcased some of the insanity and disbelief in reality that many of the users of Parler demonstrated.

This study aimed to give context to the emotions and beliefs that were shared on Parler, which was carried out. Additionally, the emotions and the sentiment of the users of Parler during two key timeframes for the American political system were analyzed and compared. Putting the findings in context, one can see how Parler acted as a social media bubble for many users as they quit their subscriptions and accounts to mainstream media as well as traditional social media networks.

Conspiracy theories were widely shared, which was also demonstrated when analyzing the most frequent hashtags and bigrams. The concept of cognitive dissonance was found in many pieces of text when a user attacked another one for writing differing beliefs compared to their own. The concept of fake news was the basis for much of the conspiracy theories that were shared while also being a key talking point which was also shown in the analysis. The emotions that were analyzed were shown to have shifted towards a more negative sentiment between the two timeframes, which happened to be around 2 months.

A comparison not only between positive and negative sentiment was done between the timeframes but also of the other emotions that are tracked using the NRC library.

Linking this thesis to the field of study that the author pursues comes through the use of the techniques that were used to run the analysis. The concept of social media listening and sentiment analysis has already been part of marketers' tools for quite some time now. In marketing, social media listening and sentiment analysis are often used to understand the feelings towards a product or a brand and how they change when a new marketing campaign is launched (Schweidel & Moe, 2014).

The usage of those tools also allows marketers to rely on a statistical analysis of sales numbers and the analysis of sales funnels. It aids them in understanding the mood and impact that marketing campaigns have, which would otherwise not be possible (Stavrakantonakis et al., 2012). However, the means to run those analyses are often behind the paywalls of major companies that offer the technology for rent to smaller companies.

Additionally, sentiment analysis is used for crisis mitigation and understanding if an issue is slowly coming up with social media users when it comes to brands. Suppose the analysis can be done close to real-time. In that case, companies can identify the issues users have with their products or services and are able to proactively address the problem or communicate in a way that satisfies the consumers and other social media users. The mentioned real-time tracking would have also enabled law enforcement to address the issues that arose around the 6th of January 2021 and prevent the events.

When using social media listening tools to understand customers' sentiments, it can also be used to monitor what potential competitors are doing and how their marketing campaigns alter the state of emotions in customers. Analyzing and tracking the hashtags used in connection with a specific topic, as was also done in this thesis, gives additional information that can easily be extracted. When understanding and tracking the interactions in which products are mentioned or the field in which a company works is talked about also allows marketers and companies to be part of that conversation. Therefore, it also allows the brand to increase and target their engagement with their current and potential customers (Schweidel & Moe, 2014).

The text analysis tools used in this thesis could also contribute to understanding customers' needs and worries as bi- and trigrams enable marketers to understand talking points and ideas that consumers share on a large scale.

The code used for this thesis is replicable, and any company that has access to an API of a social media platform that downloads the data to a server or database can easily be analyzed. If the analysis conducted by an agency or a company themselves can be done in real-time, using cloud computing and real-time API access, then it enables them to broaden the impact that they can have on the users and the sentiment towards their product.

5.2 Future Work

Future research should be conducted using more advanced coding as well as the usage of natural language processing. This could result in an even clearer picture regarding how conspiracy theories spread and where to address this to improve the understanding of true versus fake news. Additionally, a qualitative study regarding users of Parler would also offer a deeper insight into the psyche and behavior of the people that joined the network because of their following of Donald Trump. Conducting a similar analysis around the time of the 2022 midterm elections in the U.S. and comparing the findings with this study might also give a clearer picture of what might be a reason for shifting the talking points on social media as well as the impact a more positive result for the maga supporters might have on their sentiment. Doing analysis like the one conducted here in real-time might also improve chances for law enforcement and researchers alike to detect shifts in sentiment and predict events that might happen in the near future, which would enable them to stop attacks or other events.

5.3 Limitations

Looking at the potential ethical issues that come with the type of research done, one has to look at the origin of the analyzed data. The data was leaked through hacking of an API of the social media platform servers, which already puts the research under scrutiny. This also eliminates the possibility of asking the users for consent and voluntary participation. However, the data is publicly available. Additionally, there are datasets of the same content, including the real-world name of the user who posted the information. This makes the data not anonymous, which might also be a topic that could be considered unethical.

There are limitations of the study that need to be considered as well. Firstly, the scope of the research needs to be addressed. As the downloaded dataset is extensive, the timeframe in which the posts were made must be decided upon. This might reduce the validity of some results as a narrative creation and transportation might have already happened before this timeframe. Additionally, the posts which fall into the timeframe might also be related to events that transpired before the beginning of the time set. Secondly, the results of the study are highly dependent on the quality of the coding done and the correctness of the coding.

A limitation that became apparent during the processing and analysis of the data was that the limitation of computing power, even after an upgrade during the time of the analysis, was still too limited to process all data that was available. Therefore, the thesis focused on certain parts of the data.

Lastly, the results that occurred after the storm on the Capitol have been well documented in the media. Therefore, there might be a problem with inductive thinking and analysis rather than deductive one.

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7 Appendix

Appendix A

Power Bi Code

```
let
    Source = Folder.Files("C:\Users\sebas\Desktop\Uni\Modul\MSc\Thesis\Parler Data txt\Part 
13"),
    #"Filtered Hidden Files1" = Table.SelectRows(Source, each [Attributes]?[Hidden]? <> 
true),
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File (4)", each #"Transform File (4)"([Content])),
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"Source.Name"}),
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Column1",{{"Source.Name", type text}, {"Column1", type text}}),
    #"Removed Columns" = Table.RemoveColumns(#"Changed Type",{"Source.Name"}),
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Columns",",""body",";""body",Replacer.ReplaceText,{"Column1"}),
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Value1",",""hashtags",";""hashtags",Replacer.ReplaceText,{"Column1"}),
    #"Replaced Value3" = Table.ReplaceValue(#"Replaced 
Value2","],""id""","];""id""",Replacer.ReplaceText,{"Column1"}),
    #"Split Column by Delimiter" = Table.SplitColumn(#"Replaced Value3", "Column1", 
Splitter.SplitTextByDelimiter(";", QuoteStyle.Csv), {"Column1.1", "Column1.2", 
"Column1.3", "Column1.4", "Column1.5", "Column1.6"}),
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Delimiter",{{"Column1.1", type text}, {"Column1.2", type text}, {"Column1.3", type text}, 
{"Column1.4", type text}, {"Column1.5", type text}, {"Column1.6", type text}}),
    #"Replaced Value4" = Table.ReplaceValue(#"Changed 
Type1","],username:","];username:",Replacer.ReplaceText,{"Column1.6"}),
    #"Split Column by Delimiter1" = Table.SplitColumn(#"Replaced Value4", "Column1.6", 
Splitter.SplitTextByEachDelimiter({";"}, QuoteStyle.Csv, false), {"Column1.6.1", 
"Column1.6.2"}),
    #"Changed Type2" = Table.TransformColumnTypes(#"Split Column by 
Delimiter1",{{"Column1.6.1", type text}, {"Column1.6.2", type text}}),
    #"Split Column by Delimiter2" = Table.SplitColumn(#"Changed Type2", "Column1.6.2", 
Splitter.SplitTextByEachDelimiter({","}, QuoteStyle.Csv, false), {"Column1.6.2.1", 
"Column1.6.2.2"}),
    #"Changed Type3" = Table.TransformColumnTypes(#"Split Column by 
Delimiter2",{{"Column1.6.2.1", type text}, {"Column1.6.2.2", type text}}),
    #"Split Column by Delimiter3" = Table.SplitColumn(#"Changed Type3", "Column1.4", 
Splitter.SplitTextByEachDelimiter({","}, QuoteStyle.Csv, false), {"Column1.4.1", 
"Column1.4.2"}),
```

```
    #"Changed Type4" = Table.TransformColumnTypes(#"Split Column by Delimiter3",{{"Column1.4.1", type text}, {"Column1.4.2", type text}}),

    #"Removed Columns1" = Table.RemoveColumns(#"Changed Type4",{"Column1.1", "Column1.3", "Column1.4.2", "Column1.6.1", "Column1.6.2.2"}),

    #"Replaced Value5" = Table.ReplaceValue(#"Removed Columns1","body:","",Replacer.ReplaceText,{"Column1.2"}),

    #"Replaced Value6" = Table.ReplaceValue(#"Replaced Value5","createdAtformatted:","",Replacer.ReplaceText,{"Column1.4.1"}),

    #"Replaced Value7" = Table.ReplaceValue(#"Replaced Value6","UTC","",Replacer.ReplaceText,{"Column1.4.1"}),

    #"Replaced Value8" = Table.ReplaceValue(#"Replaced Value7","hashtags:","",Replacer.ReplaceText,{"Column1.5"}),

    #"Replaced Value9" = Table.ReplaceValue(#"Replaced Value8","username:","",Replacer.ReplaceText,{"Column1.6.2.1"}),

    #"Renamed Columns" = Table.RenameColumns(#"Replaced Value9",{{"Column1.2", "Body"}, {"Column1.4.1", "CreatedAt"}, {"Column1.5", "Hashtags"}, {"Column1.6.2.1", "Username"}}),

    #"Changed Type5" = Table.TransformColumnTypes(#"Renamed Columns",{{"CreatedAt", type datetime}}),

    #"Removed Errors" = Table.RemoveRowsWithErrors(#"Changed Type5", {"CreatedAt"}),

    #"Changed Type6" = Table.TransformColumnTypes(#"Removed Errors",{{"CreatedAt", type date}}),

    #"Filtered Rows" = Table.SelectRows(#"Changed Type6", each [CreatedAt] > #date(2020, 11, 1) and [CreatedAt] < #date(2020, 11, 6) or [CreatedAt] > #date(2021, 1, 3) and [CreatedAt] < #date(2021, 1, 8)),

    #"Filtered Rows1" = Table.SelectRows(#"Filtered Rows", each [Body] <> null and [Body] <> ""),

    #"Filtered Rows2" = Table.SelectRows(#"Filtered Rows1", each [Username] <> null and [Username] <> ""),

    #"Reordered Columns" = Table.ReorderColumns(#"Filtered Rows2",{"CreatedAt", "Body", "Hashtags", "Username"})

in

    #"Reordered Columns"
```

Excel Code

```
let

    Source = Excel.CurrentWorkbook(){[Name="Table1"]}[Content],

    #"Changed Type" = Table.TransformColumnTypes(Source,{{"Created At#(tab)Body#(tab)Hashtags#(tab)Username", type text}, {"Column1", type any}, {"Column2", type any}, {"Column3", type any}}),

    #"Split Column by Delimiter" = Table.SplitColumn(#"Changed Type", "Created At#(tab)Body#(tab)Hashtags#(tab)Username", Splitter.SplitTextByEachDelimiter({"#(tab)"}, QuoteStyle.Csv, false), {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.1", "Created At#(tab)Body#(tab)Hashtags#(tab)Username.2"}),

    #"Changed Type1" = Table.TransformColumnTypes(#"Split Column by Delimiter",{{"Created At#(tab)Body#(tab)Hashtags#(tab)Username.1", type date}, {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2", type text}}),

    #"Split Column by Delimiter1" = Table.SplitColumn(#"Changed Type1", "Created At#(tab)Body#(tab)Hashtags#(tab)Username.2", Splitter.SplitTextByEachDelimiter({"#(tab)"}, QuoteStyle.Csv, false), {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.1", "Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2"}),

    #"Changed Type2" = Table.TransformColumnTypes(#"Split Column by Delimiter1",{{"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.1", type text}, {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2", type text}}),

    #"Split Column by Delimiter2" = Table.SplitColumn(#"Changed Type2", "Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2", Splitter.SplitTextByEachDelimiter({"#(tab)"}, QuoteStyle.Csv, false), {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2.1", "Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2.2"}),

    #"Changed Type3" = Table.TransformColumnTypes(#"Split Column by Delimiter2",{{"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2.1", type text}, {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2.2", type text}}),

    #"Removed Columns" = Table.RemoveColumns(#"Changed Type3",{"Column1", "Column2", "Column3"}),

    #"Renamed Columns" = Table.RenameColumns(#"Removed Columns",{{"Created At#(tab)Body#(tab)Hashtags#(tab)Username.1", "Created At"}, {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.1", "Body"}, {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2.1", "Hashtags"}, {"Created At#(tab)Body#(tab)Hashtags#(tab)Username.2.2.2", "Username"}}),

    #"Filtered Rows" = Table.SelectRows(#"Renamed Columns", each not Text.Contains([Username], "WashTimesOpEd")),

    #"Filtered Rows1" = Table.SelectRows(#"Filtered Rows", each [Username] <> null and [Username] <> ""),

    #"Filtered Rows2" = Table.SelectRows(#"Filtered Rows1", each not Text.Contains([Username], "JoePags")),

    #"Filtered Rows3" = Table.SelectRows(#"Filtered Rows2", each not Text.Contains([Username], "ronpaul")),

    #"Filtered Rows4" = Table.SelectRows(#"Filtered Rows3", each not Text.Contains([Username], "John")),

    #"Filtered Rows5" = Table.SelectRows(#"Filtered Rows4", each [Body] <> "Thank you"),

    #"Filtered Rows6" = Table.SelectRows(#"Filtered Rows5", each [Body] <> "Thank you!"),

    #"Filtered Rows7" = Table.SelectRows(#"Filtered Rows6", each [Body] <> "Welcome")
```

```
in
    #"Filtered Rows7"
```

Appendix B

R Code

```
library(tm)
library(dplyr)
library(magrittr)
library(lubridate)
library(wordcloud)
library(SnowballC)
library(glue)
library(cowplot)
library(magrittr)
library(plotly)
library(tidyverse)
library(widyr)
library(hms)
library(ngram)
library(lubridate)
library(networkD3)
library(igraph)
library(naniar)
library(purrr)
library(slam)
library(stringr)
library(tibble)
library(tidyr)
library(corrplot)
library(tidygraph)
library(tidytext)
library(tidyselect)
library(anytime)
library(rjson)
library(ggthemes)
library(widyr)
library(SnowballC)
library(readr)
options(stringsAsFactors = FALSE)

#Import Data
Parler_all_posts_final <-
read_delim("C:/Users/sebas/Desktop/Uni/Modul/MSc/Thesis/RStudio/Parler_all_posts_final.csv",delim
= ";", escape_double = FALSE, trim_ws = TRUE)
posts <- Parler_all_posts_final
posts <- posts[-c(5:13)]

#Clean up Dates
```

```
posts$Date <- as.character.Date(posts$Date)
posts$Date <- dmy(posts$Date)

#Put as tables and dataframes
content <- as.character(posts$Body)
posts.tbl <- as_tibble((posts))
Username.df <- tibble(posts$Username)

#Rename Usernames to ID
names(Username.df)[1] <- "ID"

#Date Analysis
posts %>% pull(Date) %>% min()
posts %>% pull(Date) %>% max()

#Posts per Date
after.election <- as.POSIXct(x = '2020-11-10')
before.storm <- as.POSIXct(x = '2021-01-01')
posts.a.el <- posts %>%
  filter(posts$Date < after.election) %>%
  select(Body, Date)
plt.a.el <- posts.a.el %>%
  count(Date) %>%
  ggplot(mapping = aes(x = Date, y = n)) +
  theme_light() +
  geom_line() +
  xlab(label = 'Date') +
  ylab(label = NULL) +
  ggtitle(label = 'Parler Posts per day')
plt.a.el %>% ggplotly()
before.storm <- as.POSIXct(x = '2021-01-03')
posts.b.st <- posts %>%
  filter(posts$Date > before.storm) %>%
  select(Body, Date)
plt.b.st <- posts.b.st %>%
  count(Date) %>%
  ggplot(mapping = aes(x = Date, y = n)) +
  theme_light() +
  geom_line() +
  xlab(label = 'Date') +
  ylab(label = NULL) +
  ggtitle(label = 'Parler Posts per day')
plt.b.st %>% ggplotly()

# Introduce Function to Clean up Post Body
```

```
preprocess <- function(feedtext){
  feedtext %>%
    tolower() %>%
    removeWords(stopwords()) %>%
    removePunctuation() %>%
    stripWhitespace() %>%
    removeNumbers() %>%
    stemDocument() %>%
    return()
}

#Apply Function
pre <- preprocess(content)
prex <- as_tibble(pre)
contentx <- as_tibble(content)

#Hastags
hashtags.str <- as.character(posts$Hashtags)
hashtags.str <- gsub(",", " ", hashtags.str)
hashtags.str <- tibble(hashtags.str)
hashtags.str %>% head()
hashtag.count <- str_split_fixed(hashtags.str$hashtags.str, " ", 15)
hashtag.count <- str_c(hashtag.count)
hashtag.count <- tibble(hashtag.count)
hashtag.count <- hashtag.count %>% count(hashtag.count)
hashtag.list <- hashtag.count %>% count(hashtag.count)
wordcloud(
  words = str_c(hashtag.list$hashtag.count),
  scale = c(2,1),freq = hashtag.list$n,
  min.freq = 500, max.words = 200, random.order=FALSE,
  colors=brewer.pal(8, 'Dark2')
)
#BiGram
bi.gram.words <- prex %>%
  unnest_tokens(
    input = value,
    output = bigram,
    token = 'ngrams',
    n = 2
  ) %>%
  filter(! is.na(bigram))
bi.gram.words %>%
  select(bigram) %>%
  head(10)
```

```
st <- as_vector(stopwords("english"))
bi.gram.words %<>%
  separate(col = bigram, into = c('word1', 'word2'), sep = ' ') %>%
  filter(! word1 %in% st) %>%
  filter(! word2 %in% st) %>%
  filter(! is.na(word1)) %>%
  filter(! is.na(word2))
bi.gram.count <- bi.gram.words %>%
  count(word1, word2, sort = TRUE) %>%
  # We rename the weight column so that the
  # associated network gets the weights (see below).
  rename(weight = n)
bi.gram.count %>% head()
threshold <- 1000

# For visualization purposes we scale by a global factor.
ScaleWeight <- function(x, lambda) {
  x / lambda
}
network <-  bi.gram.count %>%
  filter(weight > threshold) %>%
  mutate(weight = ScaleWeight(x = weight, lambda = 2E3)) %>%
  graph_from_data_frame(directed = FALSE)
plot(
  network,
  vertex.size = 1,
  vertex.label.color = 'black',
  vertex.label.cex = 0.85,
  vertex.label.dist = 0.35,
  edge.color = 'gray',
  main = 'Bigram Count Network',
  sub = glue('Weight Threshold: {threshold}'),
  alpha = 50
)

# Store the degree.
V(network)$degree <- strength(graph = network)

# Compute the weight shares.
E(network)$width <- E(network)$weight/max(E(network)$weight)
plot(
  network,
  vertex.color = 'lightblue',
  # Scale node size by degree.
  vertex.size = 2*V(network)$degree,
```

```
  vertex.label.color = 'black',
  vertex.label.cex = 0.6,
  vertex.label.dist = 1.6,
  edge.color = 'gray',
  # Set edge width proportional to the weight relative value.
  edge.width = 3*E(network)$width ,
  main = 'Bigram Count Network',
  sub = glue('Weight Threshold: {threshold}'),
  alpha = 50
)
clusters(graph = network)

# Select biggest connected component.
V(network)$cluster <- clusters(graph = network)$membership
cc.network <- induced_subgraph(
  graph = network,
  vids = which(V(network)$cluster == which.max(clusters(graph = network)$csize))
)
cc.network

# Store the degree.
V(cc.network)$degree <- strength(graph = cc.network)

# Compute the weight shares.
E(cc.network)$width <- E(cc.network)$weight/max(E(cc.network)$weight)
plot(
  cc.network,
  vertex.color = 'lightblue',
  # Scale node size by degree.
  vertex.size = 0.8*V(cc.network)$degree,
  vertex.label.color = 'black',
  vertex.label.cex = 0.6,
  vertex.label.dist = 1.6,
  edge.color = 'gray',
  # Set edge width proportional to the weight relative value.
  edge.width = 3*E(cc.network)$width ,
  main = 'Bigram Count Network (Biggest Connected Component)',
  sub = glue('Weiight Threshold: {threshold}'),
  alpha = 50
)

# Treshold
threshold <- 2000
network <-  bi.gram.count %>%
```

```
  filter(weight > threshold) %>%
  graph_from_data_frame(directed = FALSE)

# Store the degree.
V(network)$degree <- strength(graph = network)
# Compute the weight shares.
E(network)$width <- E(network)$weight/max(E(network)$weight)

# Create networkD3 object.
network.D3 <- igraph_to_networkD3(g = network)
# Define node size.
network.D3$nodes %<>% mutate(Degree = (1E-2)*V(network)$degree)
# Degine color group (I will explore this feature later).
network.D3$nodes %<>% mutate(Group = 1)
# Define edges width.
network.D3$links$Width <- 10*E(network)$width
forceNetwork(
  Links = network.D3$links,
  Nodes = network.D3$nodes,
  Source = 'source',
  Target = 'target',
  NodeID = 'name',
  Group = 'Group',
  opacity = 0.9,
  Value = 'Width',
  Nodesize = 'Degree',
  # We input a JavaScript function.
  linkWidth = JS("function(d) { return Math.sqrt(d.value); }"),
  fontSize = 12,
  zoom = TRUE,
  opacityNoHover = 1
)
skip.window <- 2
skip.gram.words <- prex %>%
  unnest_tokens(
    input = value,
    output = skipgram,
    token = 'skip_ngrams',
    n = skip.window
  ) %>%
  filter(! is.na(skipgram))
skip.gram.words$num_words <- skip.gram.words$skipgram %>%
  map_int(.f = ~ ngram::wordcount(.x))
skip.gram.words %<>% filter(num_words == 2) %>% select(- num_words)
skip.gram.words %<>%
```

```
  separate(col = skipgram, into = c('word1', 'word2'), sep = ' ') %>%
  filter(! word1 %in% st) %>%
  filter(! word2 %in% st) %>%
  filter(! is.na(word1)) %>%
  filter(! is.na(word2))
skip.gram.count <- skip.gram.words  %>%
  count(word1, word2, sort = TRUE) %>%
  rename(weight = n)
skip.gram.count %>% head()
threshold <- 1500
network <-  skip.gram.count %>%
  filter(weight > threshold) %>%
  graph_from_data_frame(directed = FALSE)

# Select biggest connected component.
V(network)$cluster <- clusters(graph = network)$membership
cc.network <- induced_subgraph(
  graph = network,
  vids = which(V(network)$cluster == which.max(clusters(graph = network)$csize))
)

# Store the degree.
V(cc.network)$degree <- strength(graph = cc.network)
# Compute the weight shares.
E(cc.network)$width <- E(cc.network)$weight/max(E(cc.network)$weight)

# Create networkD3 object.
network.D3 <- igraph_to_networkD3(g = cc.network)
# Define node size.
network.D3$nodes %<>% mutate(Degree = (1E-2)*V(cc.network)$degree)
# Degine color group (I will explore this feature later).
network.D3$nodes %<>% mutate(Group = 1)
# Define edges width.
network.D3$links$Width <- 10*E(cc.network)$width
forceNetwork(
  Links = network.D3$links,
  Nodes = network.D3$nodes,
  Source = 'source',
  Target = 'target',
  NodeID = 'name',
  Group = 'Group',
  opacity = 0.9,
  Value = 'Width',
  Nodesize = 'Degree',
```

```
  # We input a JavaScript function.
  linkWidth = JS("function(d) { return Math.sqrt(d.value); }"),
  fontSize = 12,
  zoom = TRUE,
  opacityNoHover = 1
)
node.impo.df <- tibble(
  word = V(cc.network)$name,
  degree = strength(graph = cc.network),
  closeness = closeness(graph = cc.network),
  betweenness = betweenness(graph = cc.network)
)
node.impo.df %>%
  arrange(- degree) %>%
  head(10)
node.impo.df %>%
  arrange(- closeness) %>%
  head(10)
node.impo.df %>%
  arrange(- betweenness) %>%
  head(10)
plt.deg <- node.impo.df %>%
  ggplot(mapping = aes(x = degree)) +
  theme_light() +
  geom_histogram(fill = 'blue', alpha = 0.8, bins = 30)
plt.clo <- node.impo.df %>%
  ggplot(mapping = aes(x = closeness)) +
  theme_light() +
  geom_histogram(fill = 'red', alpha = 0.8, bins = 30)
plt.bet <- node.impo.df %>%
  ggplot(mapping = aes(x = betweenness)) +
  theme_light() +
  geom_histogram(fill = 'green4', alpha = 0.8, bins = 30)
plot_grid(
  ... = plt.deg,
  plt.clo,
  plt.bet,
  ncol = 1,
  align = 'v'
)
comm.det.obj <- cluster_louvain(
  graph = cc.network,
  weights = E(cc.network)$weight
)
comm.det.obj
```

```
V(cc.network)$membership <- membership(comm.det.obj)
network.D3$nodes$Group <- V(cc.network)$membership
forceNetwork(
  Links = network.D3$links,
  Nodes = network.D3$nodes,
  Source = 'source',
  Target = 'target',
  NodeID = 'name',
  Group = 'Group',
  opacity = 1,
  Value = 'Width',
  Nodesize = 'Degree',
  # We input a JavaScript function.
  linkWidth = JS("function(d) { return Math.sqrt(d.value); }"),
  fontSize = 12,
  zoom = TRUE,
  opacityNoHover = 1
)
membership.df <- tibble(
  word = V(cc.network) %>% names(),
  cluster = V(cc.network)$membership
)
V(cc.network)$membership %>%
  unique %>%
  sort %>%
  map_chr(.f = function(cluster.id) {

    membership.df %>%
      filter(cluster == cluster.id) %>%
      # Get 15 at most 15 words per cluster.
      slice(1:15) %>%
      pull(word) %>%
      str_c(collapse = ', ')

  })

#CORRELATION
prex <- as_tibble(pre)
prex %<>% bind_cols(Username.df)
prex.df <- as.data.frame(prex)
stopwords.df <- tibble(
  word = c(stopwords(kind = "en"))
)
prex.unnest <- prex.df %>%
```

```
  unnest_tokens(input = value, output = word) %>%
  anti_join(y = stopwords.df, by = "word")
cor.prex <- prex.unnest %>%
  group_by(word) %>%
  filter(n() > 200) %>%
  pairwise_cor(item = word, feature = ID)
cor.prex <- as_tibble(cor.prex)
head(cor.prex)
cor.filter <- cor.prex %>% filter(correlation > 0.75)
table(cor.filter)
topic.words <- c('trump', 'vote', 'democrat')
threshold = 0.1
network <- cor.prex %>%
  rename(weight = correlation) %>%
  # (relevant nodes)
  filter((item1 %in% topic.words | item2 %in% topic.words)) %>%
  filter(weight > 0.1) %>%
  graph_from_data_frame()
V(network)$degree <- strength(graph = network)
E(network)$width <- E(network)$weight/max(E(network)$weight)
network.D3 <- igraph_to_networkD3(g = network)
network.D3$nodes %<>% mutate(Degree = 5*V(network)$degree)

# Define color groups.
network.D3$nodes$Group <- network.D3$nodes$name %>%
  as.character() %>%
  map_dbl(.f = function(name) {
    index <- which(name == topic.words)
    ifelse(
      test = length(index) > 0,
      yes = index,
      no = 0
    )
  }
  )
network.D3$links %<>% mutate(Width = 10*E(network)$width)
forceNetwork(
  Links = network.D3$links,
  Nodes = network.D3$nodes,
  Source = 'source',
  Target = 'target',
  NodeID = 'name',
  Group = 'Group',
  # We color the nodes using JavaScript code.
  colourScale = JS('d3.scaleOrdinal().domain([0,1,2]).range(["gray", "blue", "red", "black"])'),
```

```
  opacity = 1,
  Value = 'Width',
  Nodesize = 'Degree',
  # We define edge properties using JavaScript code.
  linkWidth = JS("function(d) { return Math.sqrt(d.value); }"),
  linkDistance = JS("function(d) { return 550/(d.value + 1); }"),
  fontSize = 18,
  zoom = TRUE,
  opacityNoHover = 1
)

#WORD EMBEDDING
library(tensorflow)
library(keras)
# making tokenizer
tokenizer <- text_tokenizer(num_words =  18000) # maximum number of word to keep (based on
frequency)
# tokenize data
tokenizer %>% fit_text_tokenizer(contentx$value)
library(reticulate)
library(purrr)
skipgrams_generator <- function(text, tokenizer, window_size, negative_samples) {

  gen <- texts_to_sequences_generator(tokenizer, sample(text))

  function() {
    skip <- generator_next(gen) %>%
      skipgrams(
        vocabulary_size = tokenizer$num_words,
        window_size = window_size,
        negative_samples = 1
      )

    x <- transpose(skip$couples) %>% map(. %>% unlist %>% as.matrix(ncol = 1))
    y <- skip$labels %>% as.matrix(ncol = 1)

    list(x, y)
  }

}

# determine model tuning inputs
embedding_size <- 256  # dimension of embedding vector
skip_window <- 2       # number of skip-gram
```

```
num_sampled <- 1       # number of negative sample for each word

# making architecture
input_target <- layer_input(shape = 1)
input_context <- layer_input(shape = 1)
embedding <- layer_embedding(
  input_dim = tokenizer$num_words + 1,
  output_dim = embedding_size,
  input_length = 1,
  name = "embedding"
)
target_vector <- input_target %>%
  embedding() %>%
  layer_flatten() # to return the dimension of the input
context_vector <- input_context %>%
  embedding() %>%
  layer_flatten()
dot_product <- layer_dot(list(target_vector, context_vector), axes = 1)
output <- layer_dense(dot_product, units = 1, activation = "sigmoid")
model <- keras_model(list(input_target, input_context), output)
model %>% compile(loss = "binary_crossentropy", optimizer = "adam")
summary(model)
model %>%
  fit(
    skipgrams_generator(prex$value, tokenizer, skip_window, negative_samples),
    steps_per_epoch = 100, epochs = 30
  )

#obtaining word vector
embedding_matrix <- get_weights(model)[[1]]
words <- dplyr::tibble(
  word = names(tokenizer$word_index),
  id = as.integer(unlist(tokenizer$word_index))
)
words <- words %>%
  dplyr::filter(id <= tokenizer$num_words) %>%
  dplyr::arrange(id)
row.names(embedding_matrix) <- c("UNK", words$word)
dim(embedding_matrix)

library(text2vec)
find_similar_words <- function(word, embedding_matrix, n = 5) {
  similarities <- embedding_matrix[word, , drop = FALSE] %>%
    sim2(embedding_matrix, y = ., method = "cosine")
```

```
  similarities[,1] %>% sort(decreasing = TRUE) %>% head(n)
}

find_similar_words("trump", embedding_matrix)
find_similar_words("biden", embedding_matrix)
find_similar_words("election", embedding_matrix)
find_similar_words("presidential", embedding_matrix)
find_similar_words("republican", embedding_matrix)
find_similar_words("democrat", embedding_matrix)
find_similar_words("antifa", embedding_matrix)
find_similar_words("gop", embedding_matrix)
find_similar_words("maga", embedding_matrix)

# combining the two vectors and putting them into a corpus data type
corpus <- VCorpus(VectorSource(pre))

# make the necessary transformations into a Vector Space
dtm <- TermDocumentMatrix(corpus)
#dtmmatrix <- as.matrix(dtm)

tdm <- TermDocumentMatrix(corpus)
m <- removeSparseTerms(tdm, 0.99)
v <- sort(row_sums(m), decreasing=TRUE)
d <- data.frame(word = names(v), freq=v)
head(d, 10)

#Most Frequent Words
barplot(d[1:20,]$freq, las = 2, names.arg = d[1:20,]$word,
        col ="lightblue", main ="Most frequent words",
        ylab = "Word frequencies")
wordcloud(words = d$word, freq = d$freq, min.freq = 1,
          max.words=200, random.order=FALSE, rot.per=0.35,
          colors=brewer.pal(8, "Dark2"))

#Word Association

#Association Trump
associations.trump <- findAssocs(tdm,terms="trump", corlimit=0.70)
associations.trump <- as.data.frame(associations.trump)
associations.trump$terms <- row.names(associations.trump)
associations.trump$terms <- factor(associations.trump$terms, levels=associations.trump$terms)
ggplot(associations.trump, aes(y=terms)) + geom_point (aes(x=trump), data=associations.trump, size=5)
+
  theme_gdocs()+ geom_text(aes(x=trump, label=trump),
```

```
                         colour="blue", hjust=-.5, size=5)+
  theme(text=element_text(size=10),
        axis.title.y=element_blank())

#Association Republican
associations.republican <- findAssocs(tdm,terms="republican", corlimit=0.75)
associations.republican <- as.data.frame(associations.republican)
associations.republican$terms <- row.names(associations.republican)
associations.republican$terms <- factor(associations.republican$terms,
levels=associations.republican$terms)
ggplot(associations.republican, aes(y=terms)) + geom_point (aes(x=republican),
data=associations.republican, size=5) +
  theme_gdocs()+ geom_text(aes(x=republican, label=republican),
                         colour="blue", hjust=-.5, size=5)+
  theme(text=element_text(size=10),
        axis.title.y=element_blank())

#Association Capitol
associations.capitol <- findAssocs(tdm,terms="capitol", corlimit=0.75)
associations.capitol <- as.data.frame(associations.capitol)
associations.capitol$terms <- row.names(associations.capitol)
associations.capitol$terms <- factor(associations.maga$terms, levels=associations.capitol$terms)
ggplot(associations.capitol, aes(y=terms)) + geom_point (aes(x=capitol), data=associations.capitol,
size=5) +
  theme_gdocs()+ geom_text(aes(x=capitol, label=capitol),
                         colour="blue", hjust=-.5, size=5)+
  theme(text=element_text(size=10),
        axis.title.y=element_blank())

#Association Investigation
associations.investig <- findAssocs(tdm,terms="investig", corlimit=0.75)
associations.investig <- as.data.frame(associations.investig)
associations.investig$terms <- row.names(associations.investig)
associations.investig$terms <- factor(associations.maga$terms, levels=associations.investig$terms)
ggplot(associations.investig, aes(y=terms)) + geom_point (aes(x=investig), data=associations.investig,
size=5) +
  theme_gdocs()+ geom_text(aes(x=investig, label=investig),
                         colour="blue", hjust=-.5, size=5)+
  theme(text=element_text(size=10),
        axis.title.y=element_blank())
associations.antifa <- findAssocs(tdm,terms="antifa", corlimit=0.75)
associations.antifa <- as.data.frame(associations.antifa)
associations.antifa$terms <- row.names(associations.antifa)
associations.antifa$terms <- factor(associations.maga$terms, levels=associations.antifa$terms)
ggplot(associations.antifa, aes(y=terms)) + geom_point (aes(x=antifa), data=associations.antifa, size=5)
+
  theme_gdocs()+ geom_text(aes(x=antifa, label=antifa),
```

```
                    colour="blue", hjust=-.5, size=5)+
  theme(text=element_text(size=10),
        axis.title.y=element_blank())

#BIGRAM
library(RWeka)

# bigram function, to make another gram type, you have to change the min and max value
bi.gram.words <- prex %>%
  unnest_tokens(
    input = value,
    output = bigram,
    token = 'ngrams',
    n = 2
  ) %>%
  filter(! is.na(bigram))
bi.gram.words %>%
  select(bigram) %>%
  head(10)
st <- as_vector(stopwords("english"))
bi.gram.words %<>%
  separate(col = bigram, into = c('word1', 'word2'), sep = ' ') %>%
  filter(! word1 %in% st) %>%
  filter(! word2 %in% st) %>%
  filter(! is.na(word1)) %>%
  filter(! is.na(word2))
Bigram_Tokenizer <- function(x){
  NGramTokenizer(x, Weka_control(min=2, max=2))
}

# create a bigram matrix
bitdm <- TermDocumentMatrix(corpus, control = list(tokenize = Bigram_Tokenizer))

# remove some sparsity
bitdms <- removeSparseTerms(bitdm, 0.999)
corpus.dtm <- DocumentTermMatrix(corpus)
bi.gram.words <- bi.gram.words %>%
  unnest_tokens(
    input = word1,
    output = bigram,
    token = 'ngrams',
    n = 2
  ) %>%
  filter(! is.na(bigram))
```

```
bi.gram.words %>%
  select(bigram) %>%
  head(10)
bitdmsx <- bitdm %>%
  count(bitdm$j, sort = TRUE) %>%
  rename(weight = n)

# transform into a regular matrix
bitdmsm <- as.matrix(bitdms)
v <- sort(rowSums(bitdmsm), decreasing=TRUE)
d <- data.frame(word = names(v), freq=v)

# create the bi-gram word cloud
wordcloud(words = d$word, freq = d$freq, min.freq = 1,
          max.words=200, random.order=FALSE, rot.per=0.35,
          colors=brewer.pal(8, "Dark2"))
library(dplyr)
library(tidyr)
library(igraph)

# separate the dataframe bigrams into two distinct words
d.separated <- d %>% separate(word, c("word1", "word2"), sep = " ")
head(d.separated)

# build a filtered word network from the above created dataframe
word.network <- d.separated %>% filter(freq > 700) %>% graph_from_data_frame()

# visualize the created word network
word.network
library(ggraph)

# the formatting of the arrow in the directed graph
a <- arrow(angle = 20, length = unit(0.05, "cm"), ends = "last", type = "open")

# visual print of the graph
ggraph(word.network, layout = "fr") + geom_edge_link(aes(color = freq, width = freq), arrow = a) +
  geom_node_point() + geom_node_text(aes(label = name), vjust = 0.5, hjust = 0.5) + labs(title = "Word
network")



#TriGram
tri.gram.words <- prex %>%
  unnest_tokens(
    input = value,
    output = trigram,
    token = 'ngrams',
```

```
    n = 3
  ) %>%
  filter(! is.na(trigram))
tri.gram.words %>%
  select(trigram) %>%
  head(10)
st <- as_vector(stopwords("english"))
tri.gram.words %<>%
  separate(col = trigram, into = c('word1', 'word2', 'word3'), sep = ' ') %>%
  filter(! word1 %in% st) %>%
  filter(! word2 %in% st) %>%
  filter(! word3 %in% st) %>%
  filter(! is.na(word1)) %>%
  filter(! is.na(word2)) %>%
  filter(! is.na(word3))
tri.gram.words %>%
  select(trigram) %>%
  head(10)

library(RWeka)

# bigram function, to make another gram type, you have to change the min and max value
TriGram_Tokenizer <- function(x){
  NGramTokenizer(x, Weka_control(min=3, max=3))
}
corpus1 <- tm_map(corpus, removeWords, c("parler", "just", "join", "look", "forward", "meet"))

# create a bigram matrix
tritdm <- TermDocumentMatrix(corpus1, control = list(tokenize = TriGram_Tokenizer))

# remove some sparsity
tritdms <- removeSparseTerms(tritdm, 0.999)
tri.gram.words %>%
  select(trigram) %>%
  head(10)

# transform into a regular matrix
tridmsm <- as.matrix(tritdms)
v <- sort(rowSums(tridmsm), decreasing=TRUE)
d <- data.frame(word = names(v), freq=v)

# create the bi-gram word cloud
wordcloud(words = d$word,scale = c(1,0.1), freq = d$freq, min.freq = 1,
      max.words=600, random.order = FALSE, rot.per=0.15,
```

```
          colors=brewer.pal(8, "Dark2"))
library(dplyr)
library(tidyr)
library(igraph)

# separate the dataframe bigrams into two distinct words
d.separated <- d %>% separate(word, c("word1", "word2"), sep = " ")
head(d.separated)

# build a filtered word network from the above created dataframe
word.network <- d.separated %>% filter(freq > 700) %>% graph_from_data_frame()

# visualize the created word network
word.network
library(ggraph)

# the formatting of the arrow in the directed graph
a <- arrow(angle = 20, length = unit(0.05, "cm"), ends = "last", type = "open")

# visual print of the graph
ggraph(word.network, layout = "fr") + geom_edge_link(aes(color = freq, width = freq), arrow = a) +
  geom_node_point() + geom_node_text(aes(label = name), vjust = 0.5, hjust = 0.5) + labs(title = "Word
network")

# Sentiment
library(textdata)
library(tidytext)
library(syuzhet)
library(plotly)
library(tidyr)
data("sentiments")
get_sentiments("nrc")
corpus.dtm <- DocumentTermMatrix(corpus)
corpus.tidy <- tidy(corpus.dtm)
corpus.tidy[200:220,]
corpus.tidy$count <-as.numeric(corpus.tidy$count)
colnames(corpus.tidy)[2]<- 'word'
corpus.tidy$document <- as.numeric(corpus.tidy$document)

# Construct a polarity timeline
corpus.sentiment <- inner_join(corpus.tidy, sentiments)
corpus.sentiment <- count(corpus.sentiment, sentiment, index=document)
corpus.sentiment <- spread(corpus.sentiment, sentiment, n, fill=0)
corpus.sentiment[15:16,]
corpus.sentiment$polarity <- corpus.sentiment$positive - corpus.sentiment$negative
corpus.sentiment
```

```
corpus.sentiment$pos <- ifelse(corpus.sentiment$polarity >=0, "pos", "neg")
ggplot(corpus.sentiment, aes(x=index, y=polarity, fill=pos))+geom_bar(stat="identity",
position="identity", width=1)+theme_gdocs()
corpus.smooth <- ggplot(corpus.sentiment, aes(index, polarity))
corpus.smooth + stat_smooth() + theme_gdocs()

# Sentiment Election
data("sentiments")
get_sentiments("nrc")
content.election <- as.character(posts.a.el$Body)
pre.election <- preprocess(content.election)
corpus.election <- VCorpus(VectorSource(pre.election))
corpus.election.dtm <- DocumentTermMatrix(corpus.election)
corpus.tidy.election <- tidy(corpus.election.dtm)
corpus.tidy.election[200:220,]
corpus.tidy.election$count <-as.numeric(corpus.tidy.election$count)
colnames(corpus.tidy.election)[2]<- 'word'
corpus.tidy.election$document <- as.numeric(corpus.tidy.election$document)

# Construct a polarity timeline
corpus.sentiment.election <- inner_join(corpus.tidy.election, sentiments)
corpus.sentiment.election <- count(corpus.sentiment.election, sentiment, index=document)
corpus.sentiment.election <- spread(corpus.sentiment.election, sentiment, n, fill=0)
corpus.sentiment.election[15:16,]
corpus.sentiment.election$polarity <- corpus.sentiment.election$positive -
corpus.sentiment.election$negative
corpus.sentiment.election
corpus.sentiment.election$pos <- ifelse(corpus.sentiment.election$polarity >=0, "pos", "neg")
ggplot(corpus.sentiment.election, aes(x=index, y=polarity, fill=pos))+geom_bar(stat="identity",
position="identity", width=1)+theme_gdocs()
corpus.smooth <- ggplot(corpus.sentiment.election, aes(index, polarity))
corpus.smooth + stat_smooth() + theme_gdocs()
options(scipen = 100)

# Sentiment Storm
content.storm <- as.character(posts.b.st$Body)
pre.storm <- preprocess(content.storm)
corpus.storm <- VCorpus(VectorSource(pre.storm))
corpus.storm.dtm <- DocumentTermMatrix(corpus.storm)
corpus.tidy.storm <- tidy(corpus.storm.dtm)
corpus.tidy.storm[200:220,]
corpus.tidy.storm$count <-as.numeric(corpus.tidy.storm$count)
colnames(corpus.tidy.storm)[2]<- 'word'
corpus.tidy.storm$document <- as.numeric(corpus.tidy.storm$document)
```

```
# Construct a polarity timeline
corpus.sentiment.storm <- inner_join(corpus.tidy.storm, sentiments)
corpus.sentiment.storm <- count(corpus.sentiment.storm, sentiment, index=document)
corpus.sentiment.storm <- spread(corpus.sentiment.storm, sentiment, n, fill=0)
corpus.sentiment.storm[15:16,]
corpus.sentiment.storm$polarity <- corpus.sentiment.storm$positive - corpus.sentiment.storm$negative
corpus.sentiment.storm
corpus.sentiment.storm$pos <- ifelse(corpus.sentiment.storm$polarity >=0, "pos", "neg")
ggplot(corpus.sentiment.storm, aes(x=index, y=polarity, fill=pos))+geom_bar(stat="identity",
position="identity", width=1)+theme_gdocs()
corpus.smooth.storm <- ggplot(corpus.sentiment.storm, aes(index, polarity))
corpus.smooth.storm + stat_smooth() + theme_gdocs()

#Emotion Election
set.seed(12345)
content.election.2 <- sample(as.character(content.election), 1000)
emotions.election <- get_nrc_sentiment(content.election.2)
emo.election_bar <- colSums(emotions.election)
emo.election_sum <- data.frame(count=emo.election_bar, emotion=names(emo.election_bar))
emo.election_sum$emotion <- factor(emo.election_sum$emotion,
levels=emo.election_sum$emotion[order(emo.election_sum$count, decreasing = TRUE)])

#Emotion Barchart

plot_ly(emo.election_sum, x=~emotion, y=~count, type="bar", color=~emotion) %>%
  layout(xaxis=list(title=""), showlegend=FALSE,
         title="Emotion")
wordcloud_corpus <- c(
  paste(content.election.2[emotions.election$anger > 0], collapse=" "),
  paste(content.election.2[emotions.election$anticipation > 0], collapse=" "),
  paste(content.election.2[emotions.election$disgust > 0], collapse=" "),
  paste(content.election.2[emotions.election$fear > 0], collapse=" "),
  paste(content.election.2[emotions.election$joy > 0], collapse=" "),
  paste(content.election.2[emotions.election$sadness > 0], collapse=" "),
  paste(content.election.2[emotions.election$surprise > 0], collapse=" "),
  paste(content.election.2[emotions.election$trust > 0], collapse=" ")
)

corpus.2 <- Corpus(VectorSource(wordcloud_corpus))

# remove punctuation, convert every word in lower case and remove stop words
corpus.election.2 <- tm_map(corpus.2, tolower)
corpus.election.2 <- tm_map(corpus.2, removePunctuation)
corpus.election.2 <- tm_map(corpus.2, removeWords, c(stopwords("english")))
corpus.election.2 <- tm_map(corpus.2, stemDocument)
```

```
# create document term matrix
tdm.election.2 <- TermDocumentMatrix(corpus.election.2)

# transform into a regular matrix
tdm.election.2 <- as.matrix(tdm.election.2)
tdm.election.new <- tdm.election.2[nchar(rownames(tdm.election.2)) < 11,]

# column name binding
colnames(tdm.election.2) = c('anger', 'anticipation', 'disgust', 'fear', 'joy', 'sadness', 'surprise', 'trust')
colnames(tdm.election.new) <- colnames(tdm.election.2)
comparison.cloud(tdm.election.new, random.order=FALSE,
        colors = c("#00B2FF", "red", "#FF0099", "#6600CC", "green", "orange", "blue", "brown"),
        title.size=1, max.words=250, scale=c(2.5, 1.0),rot.per=0.0)

#Emotion Storm
content.storm.2 <- sample(as.character(content.storm), 1000)
emotions.storm <- get_nrc_sentiment(content.storm.2)
emo.storm_bar <- colSums(emotions.storm)
emo.storm_sum <- data.frame(count=emo.storm_bar, emotion=names(emo.storm_bar))
emo.storm_sum$emotion <- factor(emo.storm_sum$emotion,
levels=emo.storm_sum$emotion[order(emo.storm_sum$count, decreasing = TRUE)])

#Emotion Barchart
plot_ly(emo.storm_sum, x=~emotion, y=~count, type="bar", color=~emotion) %>%
  layout(xaxis=list(title=""), showlegend=FALSE,
    title="Emotion")
wordcloud_corpus <- c(
  paste(content.storm.2[emotions.storm$anger > 0], collapse=" "),
  paste(content.storm.2[emotions.storm$anticipation > 0], collapse=" "),
  paste(content.storm.2[emotions.storm$disgust > 0], collapse=" "),
  paste(content.storm.2[emotions.storm$fear > 0], collapse=" "),
  paste(content.storm.2[emotions.storm$joy > 0], collapse=" "),
  paste(content.storm.2[emotions.storm$sadness > 0], collapse=" "),
  paste(content.storm.2[emotions.storm$surprise > 0], collapse=" "),
  paste(content.storm.2[emotions.storm$trust > 0], collapse=" ")
)
corpus.2 <- Corpus(VectorSource(wordcloud_corpus))

# remove punctuation, convert every word in lower case and remove stop words
corpus.storm.2 <- tm_map(corpus.2, tolower)
corpus.storm.2 <- tm_map(corpus.2, removePunctuation)
corpus.storm.2 <- tm_map(corpus.2, removeWords, c(stopwords("english")))
corpus.storm.2 <- tm_map(corpus.2, stemDocument)
```

```
# create document term matrix
tdm.storm.2 <- TermDocumentMatrix(corpus.storm.2)

# transform into a regular matrix
tdm.storm.2 <- as.matrix(tdm.storm.2)
tdm.storm.new <- tdm.storm.2[nchar(rownames(tdm.storm.2)) < 11,]

# column name binding
colnames(tdm.storm.2) = c('anger', 'anticipation', 'disgust', 'fear', 'joy', 'sadness', 'surprise', 'trust')
colnames(tdm.storm.new) <- colnames(tdm.storm.2)
comparison.cloud(tdm.storm.new, random.order=FALSE,
        colors = c("#00B2FF", "red", "#FF0099", "#6600CC", "green", "orange", "blue", "brown"),
        title.size=1, max.words=250, scale=c(1.5, 1.0),rot.per=0.0)
```