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To my mother, who is no longer alive to witness my success that she dreamed for me in my childhood.

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Abstract

This study explored tolerance and intolerance in political discourse on Twitter during the U.S. 2016 election. It was a combination of social network analysis of four Twitter networks the day before the election, the day of the election, the day after the election, and four days after the election (November 7, 8, 9, 12) and content analysis of 1,114 tweets from 40 largest clusters of the four networks. The study found significant differences between content frames (tolerant, intolerant, and neither) in relation to out-degree centrality. However, there were no significant differences between tolerant and intolerant content in relation to in-degree centrality, betweenness centrality, and closeness centrality. Findings show similarities among the overall network structures across four days as all of the networks had low centralization (no hierarchical structure), low density, high modularity, and low reciprocity scores. The networks were not polarized; instead, they were divided into several small clusters with mixed conversations about both in-group and out-group candidates. This finding is in contrast with previous studies that found political discourse in online social networks is highly polarized (Adamic & Glance, 2005; Cha et al., 2010; Himelboim et al., 2013; Himelboim et al., 2017; Smith et al., 2014). Another major finding of this study was that Twitter users were more intolerant than tolerant and the percentage of intolerant tweets was doubled the day after and four days after the election.

Keywords: Tolerance, intolerance, social network analysis, Twitter, political discourse, the U.S., presidential election

Chapter 1: Introduction

Topic and Problem

Media and communication technologies have played a foundational role in the formation and development of modern societies (Castells, 2015; Lowrey & Gade, 2011a; Merrill, 2011). In order for democracy to function and justice to be maintained, citizens should actively take part in politics and political discussion (Castells, 1996; Fetzer & Weizman, 2006; Habermas, 2006; Huntington, 2006). Such political activities are highly dependent on communication and the related technologies, which play a crucial role in transmitting and shaping political information, beliefs, and opinions (Castells, 1996; Fetzer & Weizman, 2006; Gade, 2011; McLeod, Scheufele, & Moy, 1999; Shaw, 1996). Media and communication technologies are key for societal structures in providing the market place for free expression and exchange of opinions that shape political discourse (Castells, 1996; Laplante & Phenecie, 2010; Lowrey, 2011; Schmuhl & Picard, 2005).

With the rise of the Internet and growth of new forms of social networks, mediated political discourse has reached a new phase (Albrecht, 2006; Blumler & Kavanagh, 1999; Castells, 2015; Dahlgren, 2005; Larsson & Moe, 2012; Valenzuela et al., 2009). Networked media provide the opportunity for communication between many-to-many (Castells, 2009), which empowers the public to communicate instantly during important events not only in their local communities but also around the world (Muralidharan, Rasmussen, Patterson, & Shin, 2011). This function of networked media has toppled the hierarchal power of mass communication media, which was a communication between a one and many (Castells, 2009). Moreover, networked media

have provided people with a variety of media sources and choices anywhere, anytime, and in any format, which have empowered people to consume the kind of media that gratify them (Lowrey & Gade, 2011).

Social media are the most dominant networked media that exist independent of traditional media machines (Gainous & Wagner, 2014). Social media allow individuals to both frame and spread their own content in addition to building and maintaining relationships and getting involved in self-presentation activities (Boyd & Ellison, 2007; French et al., 2012). Not only do people use social media (such as Twitter, Facebook, YouTube, etc.) to take part in socio-political discussions, but also to form such discussions by creating, sharing, and spreading information online (Arceneaux & Johnson, 2013; Castells, 2015; Himelboim et al., 2013; Himelboim, Smith, Rainie, Shneiderman, & Espina, 2017; Muralidharan, Rasmussen, Patterson, & Shin, 2011). These political discussions do not exist free of social and ideological beliefs and values even though online networks are independent of geographic and time boundaries (Altheide, 2004; Boyd & Ellison, 2007; French et al., 2012).

Social media create what Mill (1861/1999) called the democratic environment for free expression where people can exchange ideas, debate over democratic priorities and learn different perspectives. News media have long been a vehicle for the product of free expression – political discourse (Merrill, 2011). In mass media age, news consumers were consumers only and their ability to participate in mediated political discourse was seldom visible (Baum & Groeling, 2008; Bennett, 2012; Domke et al., 1999; Kraus & Davis, 1990). However, online media, in particular social media, have changed these conditions, allowing almost everyone to express ideas and opinions and

participate in political discourse (Baum & Groeling, 2008; Bennett, 2012). In today's digital media, audiences have many choices of news and information, the ability to find news that fits their wants and biases, and engage through media with others who share their interests and views (Arceneaux & Johnson, 2013; Castells, 2015; Lowrey & Gade, 2011a). Thus, people can use media to create virtual communities, conversations and discourses, often with people like them (birds of a feather flock together) (Himmelboim et al., 2013; McPherson et al., 2001). The abundance of media choices, audience empowerment, and ability to network with like-minded people create some new dynamics in political discourse that bring into question the importance of diversity of views and the role of tolerance in political discourse (Brandt et al., 2014; Crawford et al., 2013; Graham et al., 2009; Jost et al., 2003; Sibley & Duckitt, 2008; Skitka & Bauman, 2008; Wetherell et al., 2013).

The concept of tolerance refers to willingness to respect differences in other people's beliefs, actions, and practices and to communicate with people from diverse backgrounds (Locke, 1690/1963; Mill, 1861/1999; Stepan, 2000; Sullivan et al., 1979). It is the duty of all individuals, institutions, and authorities to respect other people's rights to think, and believe in any way they want (Locke, 1963). In the virtual political discourse, people not only discuss the notions of tolerance and intolerance, but also they practice them in their online networking activities (Himmelboim et al., 2013; Lieberman, 2014). On the one hand, online networks are non-hierarchical platforms that encourage people from all backgrounds and demographics to join political discussions and reflect on other people's thoughts and ideologies (Castells, 2015; Gruzd & Roy, 2014). On the other hand, these networks foster homophily between like-minded groups of people

who group together against people with values and beliefs different from their own – questioning the extent to which mediated groups hear or are aware of each other’s veins of thought and are tolerant of them (or not) (Gruzd & Roy, 2014; Himelboim et al., 2013). In other words, based on the first argument, the Internet fosters diversity of thoughts, beliefs, and political activism among people across different virtual communities (Castells, 2012, 2015), which is very democratic and meets the notions of tolerance (Locke, 1963). However, the Internet also provides the opportunity for people to get connected to like-minded people on the basis of ideology, political view, religion, and so forth (Himelboim et al., 2013; Lieberman, 2014; Meraz, 2009; Tumasjan, Sprenger, Sandner, & Welpe, 2010), which enhances in-group homophily and intolerance for diversity and cross-group ties among online groups (Ali et al., 2011; Mislove et al., 2007; Yang & Self, 2015). Indeed, the new-found power and choice of digital media users also have a potential downside – that people are exposed to primarily those like them, seldom interact with those unlike them. Thus, digital media can be a fragmenting social force (Baum & Groeling, 2008; Lowrey & Gade, 2011; Sobieraj & Berry, 2011).

Studies have found political polarization and homophily in social media when people share their political views on issues and events – a divide of people into two big clusters based on political ideology and expression of it (Gruzd & Roy, 2014; Himelboim et al., 2013). For instance, Himelboim et al. (2013) found that Twitter users are polarized in the liberal and conservative blocks when they share their thoughts and reflections on social and political issues. Also, there is evidence for cross-ideological ties, discourses, and exchanges among groups on Twitter (Gruzd & Roy, 2014). This

means that digital media provide freedom of choice to users, and the opportunities for people to connect with all types of others to engage in political discourse, yet many people use this freedom to connect with those like them (Gruzd & Roy, 2014; Himelboim et al., 2013). The result is that – despite the potential of a more diverse and enlightening political discourse – many people may do the opposite, limiting their media exposure to people and ideas that they agree with, and throwing stones at those with other opinions (Bennett, 2012; Himelboim et al., 2009; Himelboim et al., 2013; Lieberman, 2014).

The U.S. presidential elections are the biggest political events that attract worldwide attention (Ankerson, 2015; Bezanson, 2012; Brousell, 2015; Adamic & Glance, 2005). The elections generate an abundance of political discourse, much of which is now created and shared through social media (Ankerson, 2015; Bezanson, 2012; Brousell, 2015). Presidential candidates use social media as platforms to communicate their messages and plans with the public as part of their campaign process (Brousell, 2015). “Candidates have discovered the quickest way to make news is to put out a statement or comment in a social media post and avoid paying for ad space (Lang, 2016, para.1).” Studies have shown evidence for tolerance and intolerance in political discourse on social media, which leads to polarization (Dunlap & McCright, 2008; Gruzd & Roy, 2012; Himelboim et al., 2013). The two-party political system in the U.S. (Republican vs. Democrats) is one of the main reasons behind polarization of American public in political discourse (Adamic & Glance, 2005; Haddadi, Benevenuto, & Gummadi, 2010; Hill & Hughes, 1988; Himelboim et al., 2009; Himelboim et al., 2013; Jansen et al., 2009; Kwak, Lee, Park, & Moon, 2010; Pak & Paroubek, 2010; Sakaki,

Okazaki, & Matsuo, 2010). Tolerance and intolerance among the two parties have roots in the basic differences in their values and beliefs within the party and toward each other (Dunlap & McCright, 2008; Habermas, 1994). Republicans view themselves as classic liberals, who emphasize individualism, limited government, and free enterprise (Habermas, 1994). Republicans are often associated with conservative/traditional views, who are change-resistant and believe in gradual progress with stable social and political structures and are more religious, anti-abortion, anti-homosexuality, and affirmative action (Dye & Zeigler, 1989; Levendusky, 2009). Democrats are known as contemporary liberals who favor bigger government and more regulation of businesses and social programs for under-privileged and poor (Dunlap & McCright, 2008; Dye & Zeigler, 1986; Freeman, 1986). Democrats tend to be less religious, pro-abortion, advocates for minorities, immigrants, and homosexuals (Levendusky, 2009; Uggen & Manza, 2002). The Republican vs. Democrat polarization reaches its peak during the presidential election time that not only creates the environment for discussing tolerance and intolerance, but also the expression of both types of beliefs (Brandt et al., 2014).

This dissertation is interested in exploring how online social network structure is associated with tolerance and intolerance in political discourse. In other words, the problem of this study is whether the network structure of online media contributes to social/political fragmentation and vice versa. The study will examine the relationship between social media network structure and the discourse of tolerance during the U.S. 2016 Presidential Election on Twitter. Digital technologies have provided the software tools that not only collect data from virtual communications, but also analyze the structure and patterns of relationships in addition to the content of messages (De

Maeyer, 2012; Hansen et al., 2011; Lieberman, 2014). The study of online social network's patterns and structure is also known as Hyperlink analysis, which explores how structure of network relations influences individual nodes and the whole system on the web (Barnett & Sung, 2006; Lusher & Ackland, 2011; Park, 2003). In recent years, more sophisticated software programs (e.g. NodeXL) have been developed, which have made online social network analysis easier, faster, and more comprehensive (Himmelboim et al., 2017; Hsu et al., 2013).

This study is a combination of social network analysis (SNA) and content analysis on political discourse on Twitter during the U.S. 2016 presidential election. Social network analysis explores the network structures, paths, centrality, and groupings between Twitter users during the election (Hansen, 2010; Hansen et al., 2011). Content analysis is used to analyze the content of tweets and find evidence for expression of tolerance and intolerance. Then, the study explores the connection between the network structure and tolerance/intolerance in the political discourse and measure of network centrality.

Rationale

This study seeks to explore the relationship between network structure and the discourse of tolerance. Previous studies have either focused on social network structure (Adamic & Glance, 2005; Cha et al., 2010; Himmelboim et al., 2009; Himmelboim et al., 2013; Himmelboim et al., 2017; Jansen, Zhang, Sobel, & Chowdury, 2009; Kwak et al., 2010; Pak & Paroubek, 2010; Sakaki et al., 2010) or discourse of tolerance (Caro & Schulz, 2010; Cote & Erickson, 2009; Coward, 1986; Nelson et al., 1997; Saito, 2011). Most of the social network studies on political discourse have explored political

homophily and polarization and have not considered tolerance and intolerance (Adamic & Glance, 2005; Himmelboim et al., 2013; Lieberman, 2014; Pak & Paroubek, 2010; Smith et al., 2014). At the same time, most of the studies on political tolerance and intolerance have focused on issues that are characteristics of tolerant or intolerant political behaviors such as political partisanship, incivility in electoral campaigns, political outrage, right vs. left-wing competitions, and so forth (Brandt et al., 2014; Crawford et al., 2013; Graham et al., 2009; Jost et al., 2003; Sibley & Duckitt, 2008; Skitka & Bauman, 2008; Sobieraj & Berry, 2011; Wetherell et al., 2013). This study attempts to fill the gap by connecting those areas of studies together and examining their relationships. Also, this topic is timely, because social media, in particular Twitter, are used extensively in political discourse during the election time. Presidential elections are the biggest political events in which social media have been used profoundly (Robertson, Vatrappu, & Medina, 2010). Candidates use their social media accounts during their campaign to an extent that most information and ideas from the candidates are spread on social media before reaching the news media (Lang, 2016). The news media often reflect on the candidates' social media posts and opinions later (Hjelmgaard, 2016; Lang, 2016). For instance, during the 2016 presidential election campaigns, Donald Trump was tweeting at 3:00 a.m., which was discussed in the news media several hours later after being shared and liked for several thousand times (Hjelmgaard, 2016).

The nomination of Hillary Clinton and Donald Trump as the presidential candidates for general election by Democrat and Republican parties heated the online political debates on the 2016 presidential election (Lang, 2016, Smith, 2016). Both

Clinton and Trump had controversial backgrounds and plans for future (Niose, 2016). Trump, for instance, is a multibillionaire Republican with a background in abuse of labor, groping women, using tax loopholes to avoid paying federal tax for many years, and refusing to make his tax returns public (Scherer, 2015; Zurcher, 2016). Clinton on the other hand, is an experienced democrat politician, who has been accused of betraying the American public as the Secretary of State by using her private email server for government business that includes emails on issues of national security (Graham, 2016; Rubin, 2016). She supported immigration reform that would provide a path to citizenship for undocumented immigrants and many of those who entered the U.S. illegally (Zurcher, 2016). In addition to these controversial backgrounds, the two candidates were flooded with thousands of posts on social media from their supporters and opponents, which included personal attacks from the candidates themselves on each other as well (DelReal, 2016; Hampson, 2016; Healy & Martin, 2016; Healy & Haberman, 2016; Walsh, 2016).

Purpose

The purpose of this study is to explore the relationship between online social network structure and tolerance and intolerance during the U.S. 2016 Presidential Election on Twitter. This is based on the assumption that with all of the egalitarian perspectives about online networks for being less hierarchal and more democratic environment for free expression and cross-group communication (Castells, 2003; 2015), there is evidence for homophilous activities among people in the online world (Ali et al., 2011; Mislove et al., 2007; Yang & Self, 2015). Previous research has demonstrated that the structure of the social networks may influence the extent to which political

discourse is tolerant or not (Brandt et al., 2014; Crawford et al., 2013; Graham et al., 2009; Jost et al., 2003; Sibley & Duckitt, 2008; Skitka & Bauman, 2008; Wetherell et al., 2013).

There are several factors that influence tolerance and intolerance in political discourse on social media, which have roots in broader notions of democracy, free speech, public sphere, and homophily. Social media provide the sphere for democratic political conversations among citizens, where anyone can say anything at anytime and in any format (Castells, 2015; Larsson & Moe, 2012; Tumasjan et al., 2010). Using social media, people can easily take part in political discourse by expressing their thoughts and opinions in relations to socio-political issues (Papacharissi, 2002). In such a democratic environment, everybody is expected to respect everybody else's ideas, beliefs, values, and other differences, and to not express discrimination against individuals and groups on the basis of demographic differences and social and political dominance (Habermas, 1991; Papacharissi, 2002; Post, 1990). The primary goal of political discourse is that heterogeneous communities communicate their ideas and beliefs, so together they can form a common public opinion (Post, 1990).

At the same time, factors such as the unlimited freedom of access to information, variety of media choices, and the empowerment of citizens as active participants of mediated communication encourage the citizens to largely engage in the communication activities that gratify them (Lowrey & Gade, 2011a). These factors are also related to socio-psychological factors such as homophilous and heterophilous beliefs and expressions toward people who are unlike one's self (Ali et al., 2011; Mislove et al., 2007; Yang & Self, 2015). Existing literature on homophily in social

networks indicates that individuals are more likely to be connected with their homogenous groups rather than with those who are different from them (Himmelboim et al., 2009; Himmelboim et al., 2013). Persisting in one's own group decreases the likelihood of information dissemination and cross-group discourses between demographically different people (Himmelboim et al., 2013). Studies have found homophily among users of social media, which can decrease cross-ideological ties between liberals and conservatives (Adamic & Glance, 2005; Himmelboim et al., 2013). That is why homophily is considered a barrier against expansion of networks or cross-group communications (Hargittai et al., 2008; Himmelboim et al., 2013).

Online political discourse creates virtual groups of people who identify themselves in relation to certain offline socio-political schools of thoughts, groups, and communities (Himmelboim et al., 2009; Himmelboim et al., 2013; Lieberman, 2014). Affiliation with certain socio-political groups increase the sense of in-group vs. out-group or US vs. THEM among people (Beatty & Walter, 1984; Coward, 1986; Caro & Schulz, 2010; Cote & Erickson, 2009; Peffley & Rohrschneider, 2003; Sullivan et al., 1993). Creation of such clusters provides the environment for expression of both tolerance and intolerance among citizens who take part in these discussions and express their thoughts and reflections either as individuals or as members of certain ideological, religious, political, and cultural groups (Bennett, 2012; Sobieraj & Berry, 2011). Therefore, even though the networked media environment has created an egalitarian space for communication, where people from different groups, ideologies, backgrounds, cultures, and geographies can get together, it has become a platform for people with diverse sets of values and beliefs to find their like-minded individuals and form

homophilous virtual groups and express intolerance toward out-groups (Castells, 2003, 2015; Himelboim et al., 2013).

Moreover, staying in a specific ideological circle can increase the tendency for relying on the information from the members of the same circle diminishes the chance of knowing about other groups and individuals, which can reduce in-group tolerance toward members of other groups whose values and beliefs are different from one's self (Beneke, 2006; Caro & Schulz, 2010; Cote & Erickson, 2009; Coward, 1986; Locke, 1963; Saito, 2011; Van Doorn, 2014). Studies have shown that members of conservative political groups tend to rely on conservative news sources for information more than liberal news sources; and similarly, members of liberal political groups are more likely to use liberal news sources than conservative ones (Himelboim et al., 2009; Himelboim et al., 2013). From social network perspective, the strength of social networks depends on the number of weak ties, which often bridge unconnected networks with each other (Granovetter, 1973; Ibarra, 1992). Even though strong in-group relationships increase the inner density of network, they decrease the chance of diverse relationships, which affect the flow of information across networks (Granovetter, 1973). Therefore, persistence in using partisan media as the primary source information can affect individuals' levels of tolerance and intolerance, which can impact their communication behavior within and between groups (Gruzd & Roy, 2014; Himelboim et al., 2013; Nelson et al., 1997).

Why Twitter?

Twitter is known as one of the top social media for news and political discourse (Hansen et al., 2011; Himelboim et al., 2009; Himelboim et al., 2013; Himelboim et al.,

2017). Twitter has become a powerful tool for political deliberation, in particular, during general elections and other political events (Tumasjan et al., 2010). Twitter is a media space for political news and discourse that includes citizen voices, not just news media (Himmelboim et al., 2013). So, these voices are not bound to neutrality of journalism, and given the user ability to determine their social networks (their ability to engage in conversation with those they want) and express their views on them, it is expected that the discourse will be more commentary, opinions and assessments of candidates and news media coverage of the campaign (Cha et al., 2010; Jansen, et al., 2009). Twitter is even called a news medium that hosts millions of social relations in addition to spreading information across the globe (Kwak et al., 2010). Jansen, et al. (2009) call tweets “the electronic word of mouth” (p. 2169). One of the main reasons behind Twitter’s popularity is microblogging, which is a very popular communication tool among internet users (Pak & Paroubek, 2010). Twitter’s microblogging is different from traditional live news coverage because it provides the opportunity for public debates on news events in addition to its real-time news coverage (Sakaki et al., 2010). In other words, Twitter can cover “anything from intimate friendships to common interests, or even a passion for breaking news or celebrity gossip” (Cha et al., 2010, p. 10). Twitter is the intersection between traditional news media and digital media for its usability as a news source and networked environment for connecting communities not only with each other, but also with news media, other social, political, economic organizations, and individuals and social and political actors (Hsu, Park, and Park, 2013; Verweij, 2012).

The sample of this study was collected from Twitter during the days surrounding the 2016 presidential election (November 7, 8, 9, and 12). The data was collected from Twitter through NodeXL. NodeXL is a software program designed as a template in Microsoft Excel, which not only retrieves network data from social media into an excel sheet, but also analyzes the network structures and visualizes them in graphs (Fay, 2016; Hansen et al., 2011; Himelboim et al., 2013). The sample for content analysis was collected from the 10 largest clusters of each of the four Twitter network.

Summary

The rise of digital media has brought revolutionary changes in the human communication and political discourse (Castells, 2015; Gade & Lowrey, 2011). In the networked media environment, there is a better chance for people from all places and demographics to form virtual discussion groups and play active role in politics (Castells, 2015; Skitka & Bauman, 2008; Wetherell et al., 2013), which includes expressions of tolerance and intolerance. Studies have found homophily among online groups on the bases of ideological beliefs and other social, political, and cultural values, which indicate degrees of intolerance in the virtual world (Himmelboim et al., 2013; Meraz, 2009; Tumasjan et al., 2010).

This study is a combination of social network analysis and content analysis. Social Network Analysis is a theoretical and methodological framework for examining social structures and people's activities including relationships patterns and implications of those relationships, information flow among individuals, groups and societies, and how these interactions and exchanges take place (Freeman, 2004; Kadushin, 2012;

Krebs, 2016; Van der Hulst, 2009). Another methodological framework that is used in this dissertation is content analysis, which is widely used in analyzing media content.

This dissertation explores how network structure explains the levels of tolerance in political discourses on Twitter social network during the 2016 Presidential Election. This is based on the assumption that with all of the egalitarian perspectives about online networks as less hierarchal and more democratic media, there is evidence that the structure of online networks can foster in-group homophily among online users against out-groups (Brandt et al., 2014; Crawford et al., 2013; Graham et al., 2009; Jost et al., 2003; Sibley & Duckitt, 2008; Skitka & Bauman, 2008; Wetherell et al., 2013).

This study is informed by a range of theories and literature on mediated communication, shift from mass media to digital media, social networks and social network analysis, political discourse, free speech, and tolerance and intolerance. This dissertation includes eight chapters. Chapter two focuses on the shift from mass media into digital media and ends with discussing online social media. Chapter three is on tolerance and intolerance in mediated political discourse. Chapter four reviews social network and social networks analysis and its main functions and features. Chapter five briefly summarizes the literature, connecting it to the problem of study that leads logically to the proposed study's research questions. Chapter six is about the methodologies of this study. Chapter seven is on the results of the research conducted in this dissertation. And finally, chapter eight discusses the findings of this study in relation to existing literature and proposes ideas for future research.

Chapter 2: From Mass to Digital/Networked Media

This dissertation seeks to understand the relationship between online social network structures and tolerance and intolerance as a political discourse on Twitter during the U.S. 2016 presidential election. Online social networks are one of the main outcomes of digital revolution in communication technologies through which not only can the public directly take part in political discussions, but also form political virtual discussion groups of diverse and like-minded members (Ankerson, 2015; Kietzmann, Hermkens, McCarthy, & Silvestre, 2011; Schwartz, 2015; van Dijck & Poell, 2015).

The advent of digital technology and growth of networked media have changed the dynamics of mediated political communication unlike any time in history (Castells, 2009, 2015). Networked media have empowered citizens to raise their voices and get heard (Merrill, 2011). Networked media mean more choices for the users, which provide the opportunity for use of sources that are from a variety of backgrounds, interests, values and beliefs (Arceneaux & Johnson, 2013; Castells, 2009, 2011). Meanwhile, networked media environment encourages people to form social groups of like-minded and communicate similar ideas and interests, which emphasizes in-group unity for such people (Gruzd & Roy, 2014; Himelboim et al., 2013). In other words, given the amount of choices people have, they choose media that gratify them and group with others like them (Lowrey & Gade, 2011a; Sobieraj & Berry, 2011). With the new-found power and choice of digital media, people are exposed to those primarily those like them, who have similar interest and media consumption habits (Arceneaux & Johnson, 2013; Gruzd & Roy, 2014; Himelboim et al., 2013). The trend to interact with like-minded people and stay in networks with individuals like one's self increases the

chance that people seldom interact with those unlike them (Granovetter, 1973; Gruzd & Roy, 2014; Himelboim et al., 2013). Thus, despite the fact that digital media and communication technologies have given birth to new forms of communication (Castells, 2003, 1015), they can be a fragmenting social force (Baum & Groeling, 2008; Lowrey & Gade, 2011a; Sobieraj & Berry, 2011).

The audiences have more control over the flow of information across groups compared to the mass era by having many choices to access plenty of sources in different formats and products at anytime, anywhere, and in any format (Albrecht, 2006; Arceneaux & Johnson, 2013; Castells, 2015; Gurevitch et al., 2009; Lowrey & Gade, 2011a; Sobieraj & Berry, 2011). The same media that empower citizens also empower political interest groups to publish, promote and circulate their ideas. (Gainous & Wagner, 2014).

This chapter explores the transition from mass to digital media, focusing on online social networks and virtual communication, and political discourse among public. Overall, the growth of digital media has resulted in three main changes in mediated political communication: Empowerment of audience from a passive consumer into active participant; media fragmentation (Gade & Lowrey, 2011; Hindman, 2011; Merrill, 2011; Singer, 2011) and social networks and virtual communication among citizens where public/political debates take place (Bennett, 2012; Blanchard, 2004; Rheingold, 1993).

Audience Empowerment

The growth of networked media has shifted the exercise of control of information and relationship structure between news media and the audience (Singer,

2011). In the mass media era, the creation and flow of information were controlled by the news media and journalists (Gade & Lowrey, 2011). Journalists had access to the technology (e.g. printing press, production studios, etc.) that was not available for public (Gade & Lowrey, 2011; Singer, 2011). The mass era provided no basis for direct audience feedback; therefore, the public passively consumed the information they were provided by the mass media (Baum & Groeling, 2008; Bennett, 2012; Gade & Lowrey, 2011). News media were the agenda setters and the watchdogs of government institutions to public, and journalists had social and political influence because of having access to powerful people and the elites (Chaffee & Metzger, 2001; Gade & Lowrey, 2011; Singer, 2011). Journalists were powerful sources of information because they had control over the means for information production such as sources and tools and technologies for gathering, producing, and delivering information (Bennett, 2012; Gade & Lowrey, 2011).

However, digital media and communication technologies provide the opportunity for communication from many to many (Castells, 2003). In other words, the shift control to the audiences, made them active, interactive, and engaged in the entire process of information flow such as production, consumption, and spread (Castells, 2009; Gade & Lowrey, 2011). Nowadays, the news media, citizens, and officials all can use the online media to communicate directly with each other (Gade & Lowrey, 2011). The digital media allow everyone to publish, which creates peer-to-peer mediated communication that is no longer filtered by media professionals. These changes have reshaped the flow of creativity, innovation, political mobilization, information

gathering, and content dissemination (Friedman, 2005; Gade & Lowrey, 2011; Singer, 2011).

Castells (2009) argues that the era of digital communication is the era of mass-self communication, which includes new interactive communication processes. It is self-communication, because it is self-directed, self-selected, and self-defined. It is mass, because it can reach a global audience.

Online media have created flat platforms for communication among people, where anyone can create content – the rise of citizen-based media (Arceneaux & Johnson, 2013; Gade & Lowrey, 2011). With citizen-based media, everyone can be a content producer, which has led to the rise of “potent grassroots journalism” (Gade & Lowrey, 2011, p. 25). Nowadays “users are producers one moment and consumers the next” (Hansen, Shneiderman, & Smith, 2010, p. 13). The gratification of the online news on mobile phones provides opportunities for news consumption “anytime, anywhere, in any modality – audio, video, graphics, or text” (Dimmick, Powers, Mwangi, & Stoycheff, 2011, p. 177). The timeliness of communication activities is a transition from “prime-time” to “my-time” (Castells, 2009). The dramatic increase in the news sources have increased news consumption outside home than ever before (Dimmick et al., 2011). Online social integration and multitasking are other gifts of the Internet (Castells, 2009).

The Internet as a powerful democratic tool has blurred the wall between professional content producers/journalists and other content producers (Lowrey & Gade, 2011; Witschge & Nygren, (2009). At the same time, people specialize their news consumption in the online world on the basis of political ideology and personal interests (Mitchelstein & Boczkowski, 2010; Olmstead, Mitchell, & Rosenstiel, 2011;

van Cauwenberge, d'Haenens, & Beentjes, 2010). Changes in the public consumption of news in the age of information abundance have increased people's expectations to get content for free anywhere, anytime, and in any format (Gade & Lowrey, 2011).

Technology has created opportunities for audience to participate in journalism in ways that public journalism enthusiasts welcome (Arceneaux & Johnson, 2013). People are at the center of this paradigm, which has changed "the once-solid jar of elite media freedom" –shift from the hands of professional journalists to the hands of citizens (Merrill, Gade, & Blevens, 2001, p. 126).

In sum, in the mass media era, the only people who created mediated public discourse were journalists, or those who worked for media organizations (Singer, 2011). The public had no way to use media to actively question news gathering of journalists (Gade & Lowrey, 2011). The one-way top-down communication platforms made the public the kind of consumers who could not interfere in the information production process (Gade & Lowrey, 2011; Singer, 2011). Indeed, journalists and news media had no access to a mediated audience (Lowrey & Gade, 2011a). So, any feedback provided (letters to editor of newspaper, or to news directors of TV/radio stations) was: a) delayed for days, often weeks, so the issue context is lost or forgotten, and b) filtered through media – the editors and news directors decided which letters to publish or broadcast (Chaffee & Metzger, 2001; Gade & Lowrey, 2011; Singer, 2011). Nowadays, not only do the citizens have control over the kind of information they want to consume and produce, but also they have the power to decide the information sources and platforms that gratify them (Gade & Lowrey, 2011). These opportunities have emerged as a result of audience fragmentation, which will be discussed in the next section.

Audience Fragmentation

A major outcomes of the shift from mass media to digital media is demassification of audiences, which is also known as audience fragmentation (Gade & Lowrey, 2011; Sobieraj & Berry, 2011). Fragmentation is a result of technological developments that “allow and even encourage people to narrow the focus of their media consumption to pursue their individualized interests and needs” (Tewksbury, 2005, p. 332). It is about the relationship between the audience and information, which leads to increased choices and desires for personal gratification (Tewksbury, 2005). Overall, audience fragmentation has led to four main changes that are briefly discussed in the following paragraphs.

First, audience fragmentation has changed the status of news media as the biggest or the most dominant source of information into a major source of information (Gade & Lowrey, 2011; Lowrey & Gade, 2011a; Singer, 2011). Traditionally, news media were the agenda setters and people perceived the mass media as the primary sources of information (Gade & Lowrey, 2011; McCombs & Shaw, 1972; Mutz & Martin, 2001; Rogers & Kincaid, 1981; Wade & Schramm, 1969). However, with the rise of online media and the shift of power from journalists and media to the audience, citizens have unlimited access to diverse sources of information from all over the world from non-traditional sources – grassroots, organizations, other social, political, and economic institutions, and so forth – in addition to news media (Castells, 2003, 2009, 2015; Gade & Lowrey, 2011; Hindman, 2011). Nowadays, there are other dominant sources of information or alternative media (such as government and other social and political institutions’ websites, social media, etc.) alongside news media that people refer to for information (Atton & Hamilton, 2008; Downing, 1984; Himelboim et al., 2013;

Lievrouw, 2011; McKenzie et al., 2012; Singer, 2011; Vickery & Wunsch-Vincent, 2007).

Still, studies have shown that news media have maintained their position as one of the primary and trustful sources of information in the digital world – a major portion of online discourse starts with sharing links from the traditional news media (more than 30 percent) (Albrecht, 2006, 2007; Baum & Groeling, 2008; Gurevitch et al., 2009; Himelboim et al., 2013; Meraz, 2009; Tumasjan et al., 2010). This indicates that news media still play an important role in the agenda setting for public and political discourse (Albrecht, 2006, 2007; Baum & Groeling, 2008).

Second, access to diverse sources of information and production facilities have provided the citizens with the opportunity for better democratic participation in information flow (Gade & Lowrey, 2011; Turner, 2005). The online media environment is a nonhierarchical space for cooperation, collaboration, friendships, peer-to-peer culture (egalitarian), and businesses (Turner, 2005). Decentralization of institutional media has made information production more democratic, which is like a new phase of enlightenment that may help in the emergence of the truth in a more complete way (Gade & Lowrey, 2011).

Third, fragmentation of audience is also related to specialization of media outlets, which is about the kind of content or message media produce that meets the needs and wants of a certain group of people (Tewksbury, 2005). In other words, specialization is against the mass media era notion of producing a variety of media content and targeting large and diverse of groups of people (Sobieraj & Berry, 2011; Tewksbury, 2005). People specialize their news consumption in the online world based on their interests, ideologies,

and beliefs (Chafee & Metzger, 2001; Mitchelstein & Boczkowski, 2010; Olmstead et al., 2011; van Cauwenberge et al., 2010). Specialization is about people's narrow focus on specific content and ignoring other messages (Tewksbury, 2005).

Fourth, another outcome of audience fragmentation is the growth of partisanship among the public, which has increased the use of partisan information sources (Dimmick, 2002; Gade & Lowrey, 2011; Hindman, 2011; Tewksbury, 2005). With the access to infinite amount of content, people customize their media use to fit their wants and needs (Arceneaux & Johnson, 2013). They seek media that gratify them, and they expect to be gratified by the media they use (Gade & Lowrey, 2011; Hindman, 2011). In other words, the active audiences of the digital age have access to diverse sources of information and communication networks (such as news media, partisan sources of information, grassroots, etc.), which facilitate the opportunity to engage in partisan news consumption and communication activities (Dimmick, 2002; Hindman, 2011; Mitchelstein & Boczkowski, 2010; Olmstead et al., 2011; Tewksbury, 2005; van Cauwenberge et al., 2010). The infinite online media choices combined with people choosing media that fit their interests and biases, contribute to greater fragmentation (Chaffee & Metzger, 2001; Castells, 2009; Gade & Lowrey, 2011a; Hindman, 2011).

In short, the Internet has made political discourse more inclusive, less mass, more fragmented, polarized, and specialized (Bennett, 2012; Dimmick, 2002; Hindman, 2011; Mitchelstein & Boczkowski, 2010; Olmstead et al., 2011; Tewksbury, 2005; van Cauwenberge et al., 2010). The tendency toward engagement in polarized communication processes can increase the chances for people's involvement in interactions with like-minded people (Gurevitch et al., 2009; Himelboim et al., 2013; Meraz, 2009; Tumasjan

et al., 2010). In other words, people tend to choose media that gratifies them (Lowrey & Gade, 2011), which puts them in contact with others via media who tend to be like-minded, have similar interests and use media in similar ways (Himmelboim et al., 2013). These connections create mediated social networks, which have been widespread with the growth of social media (Blanchard, 2007; Castells, 2003, 2015; Himmelboim et al., 2013; Lieberman, 2014; Tumasjan et al., 2010). Social media are used as platforms for deliberation in political discourse, where citizens and political actors can directly communicate with each other (Bennett, 2012; Tumasjan et al., 2010). When people have access to so many sources of information that are in-line with their own (in-group) values, beliefs, and practice, they will be less likely to seek information elsewhere, from sources which they disagree with (Bennett, 2012; Himmelboim et al., 2013). Networks create groups that identify with a common idea, cause or interest (Himmelboim et al., 2013; Himmelboim et al., 2017; Lieberman, 2014).

Online Social Networks

Alongside other outcomes of the shift from mass media into digital media, the emergence of virtual communication has played a key role in the empowerment of audience as active participants in the public debates (Blanchard, 2007; Castells, 2003; Gleave, Welser, Lento, & Smith, 2009; Kietzmann, Hermkens, McCarthy, & Silvestre, 2011; Rheingold, 1993). Virtual communication refers to sets of interaction and information exchange between people via the Internet and computer mediated communication (CMC) (Castells, 2003; Jones, 1997). Virtual communication has redefined the notions of public discourse, which is one of the most powerful phenomena in the digital age (Arceneaux & Weiss, 2010; Kietzmann et al., 2011; Lieberman, 2014;

Mislove et al, 2007; Mangold & Faulds, 2009; Valenzuela et al., 2009). People use virtual space to discuss various issues and problems related to the social, political, economic, and cultural factors in their societies and around the world (Castells, 2015; Gleave et al., 2009; Hansen et al., 2011; Rheingold, 1993).

Common virtual communication includes emails, chat-systems, web-based discussions areas, sews groups, virtual communities, forums, social media discussions, and so forth (Jones, 1997; Reich, 2010). Social network websites such as Twitter, Facebook, Myspace, and Instagram are online platforms for virtual communication (Reich, 2010). Before the emergence of social media, in particular, Facebook and Twitter, online or virtual communication took place in certain websites and blogs where people got together and formed virtual communities (Rheingold, 1993; Castells, 2003; Gleave et al., 2009). Hence, before discussing social media networks, it is important to briefly review virtual communities.

Virtual communities. Virtual communities are “places where people meet” and are “tools” that facilitate communication between people who are physically and geographically far from each other (Rheingold, 1993, p. 50). The formation of virtual communities is related to four factors: 1) “a minimum level of interactivity,” 2) “a variety of communicators,” (3) “a minimum level of sustained membership,” and (4) “a virtual common public space (Jones, 1997, p. 5). Virtual communities gave birth to a new culture of socialization, which was different than the traditional friend-making processes. People started having new friends who did not live in their neighborhoods and were not necessarily from the same backgrounds as they were (Rheingold, 1993). Virtual communities connected isolated individuals from across the world to share their

thoughts, information, knowledge, problems, concerns, and so forth with each other (Rheingold, 1993).

The main difference between real communities and virtual communities is that virtual communities are not dependent on a physical location or geography (Jones, 1997; Reich, 2010). But other components of social communities such as kinship, shared values and religion can be part of online communities as well (Reich, 2010). Real communities are formed based on factors such as kinship, shared values and religion (Jones, 1997) among social groups who establish ties with each other in a geographic location (Reich, 2010). Virtual communities create the opportunity for the formation of social bonds across the globe without real physical settings (Katz et al., 2004; Rheingold, 1993).

In the physical world, sense of community (SOC) consists of “feeling of membership, influence, integration and fulfillment of needs, and shared emotional connections” (Blanchard, 2007, p. 827). Like real communities, developing the sense of community in the virtual world is necessary for bonding, and sharing thoughts, ideologies, feeling, happiness, sorrow, and so forth (Rheingold, 1993). Sense of virtual community (SOVC) is dependent on the feeling of membership, identity, belonging, integration, emotional attachment, and remaining in the community (Blanchard, 2007; Capece & Costa, 2010; Reich, 2010).

Virtual communities create the environment for information exchange, civic engagement, educational and scientific activities, and entertainment (Turner, 2005). People carry public discussions in the virtual world on various topics such as human relationships, data, wealth, power, so forth (Turner, 2005). Studies have shown that,

blogs attracted like-minded people who share similar ideologies, professions, and hobbies (e.g., political ideology, religion, cooking, loving food, etc.) (Blanchard, 2004, 2007; Yang & Self, 2015). In sum, virtual communities insist on certain levels of in-group belonging among members, which suggests these groups tend to be like-minded, have similar wants and needs, and may perceive non-group members as outsiders (Blanchard 2004, 2007; Capece & Costa, 2010; Reich, 2010; Turner, 2005).

With the rise of social media such as Twitter and Facebook, blogging and the trend of virtual communities declined, but they are still used by individuals and groups (not as much as social media) (Lenhart, Purcell, Smith, & Zickuhr, 2010). Social media are “a set of online tools that supports social interactions between users” (Hansen, Shneiderman, & Smith, 2010, p. 12). Social media have provided the opportunity for broader public discussions, which have bypassed the size, level, and capacity of virtual communities (Arceneaux & Weiss, 2010; Duggan et al., 2015; Hansen, Smith, & Shneiderman, 2011; Lieberman, 2014; Smith et al., 2014). Nowadays, people use social media to create more instant larger virtual networks than the earlier virtual communities (Lenhart et al., 2010; Lieberman, 2014; Duggan et al., 2015), which will be in the next section.

Social media networks. The term social media refers to digital internet-based technologies that are used as interactive platforms by individuals, groups, and entities to consume, create, share, and spread information, and engage in virtual public and private discussions (Arceneaux & Weiss, 2010; Kietzmann et al., 2011; Lieberman, 2014; Mislove et al., 2007; Valenzuela et al., 2009; Mangold & Faulds, 2009). Individuals and groups use social media to “share, cocreate, discuss, and modify user-generated

content” (Kietzmann et al., 2011, p. 241). Social media are used for different purposes such as social interaction, content production, sharing information from other sources as well as other social and political gatherings (Ankerson, 2015; Castells, 2015; Duggan, Ellison, Lampe, Lenhart, & Madden, 2015; Himelboim et al., 2013; Lieberman, 2014; Valenzuela et al., 2009).

Social media functions include an individual’s or entity’s presence by revealing all or portions of his/her identity, establishing relationships with others, sharing thoughts and information, establishing a reputation, engaging in conversation with others, and forming communities by creating or leading online groups (Kietzmann et al., 2011). Establishment of relationships on social media networks are defined as friendship, follower and following, and connections with whom the users interact through Posts, Tweets, Likes, Favorites, Comments, Messages, Retweets, Replies to, and Post Shares, (Ankerson, 2015; Cha et al., 2010; Himelboim et al., 2013; Himelboim et al., 2017; Hansen et a., 2011; Lieberman, 2014; Smith et al., 2014).

According to a study, the top 10 most dominant and popular social media in October 2016 were: Facebook (more than 1.7 billion users), YouTube (more than 1 billion users), Instagram (500 million users), Twitter (313 million users), Reddit (234 million users), Vine (200 million users), Ask.fm (160 million users), Tumbler (115 million users), Flickr (112 million users), and Google+ (111 million users) (Hainla, 2016). In addition to being a social practice, social media deal with notions of personalities and other social factors (Hansen et al., 2010). Not only do people use social media to share their good moments with others, but also to raise their voices against institutions, governments, companies, and politicians, and other individuals

(Ankerson, 2015; Castells, 2015; Duggan et al., 2015; Kietzmann et al., 2011). As a result, the reputations of individuals, in particular celebrities and politicians, and companies and institutions have become associated with social media (Kietzmann et al., 2011). Social media differ from each other on the basis of size of producer and consumer, pace of interactions, genre, control of basic elements, types of connections, and retention of content (Hansen et al., 2010).

Political organizations and politicians are among the most dominant users of social media as an attempt to reach their public and gain their trust (Ankerson, 2015; Cha et al., 2010; Lenhart et al., 2010; Lieberman, 2014; Smith et al., 2014). In addition, social media inform people about the most recent, trending, and viral issues, events, and individuals from around the world via news feeds (Kaplan & Haenlein, 2010).

Therefore, social media discussions have become the most popular and the biggest form of social and political discourse in the virtual world (Arceneaux & Weiss, 2010; Duggan et al., 2015; Hansen et al., 2011; Lieberman, 2014; Smith et al., 2014). People widely use hashtags on social media to talk about topics and events around them or the issues they are interested in (Arceneaux & Weiss, 2010; Hansen et al., 2011). Hashtags are created by users based on the issues related to events, ideas, and people that interest them (Lieberman, 2014). These conversations are different from virtual communities, because they occur at a certain time on certain issues, people, and events among individuals who are not necessarily friends or followers of one another (Arceneaux & Weiss, 2010; Hansen et al., 2011; Lieberman, 2014; Smith et al., 2014). In other words, people do not need to be members of a certain virtual community in order to communicate with members of that group (Lenhart et al, 2010). A simple tag

(mention) and hashtag can connect people and ideas from different parts of the world (Kaplan & Haenlein, 2010; Lieberman, 2014).

Despite all these facilities and opportunities for democratic free exchange of ideas among citizens, social media network structures are mixed products of their designers' innovative-business models (Castells, 2003; Sunstein, 2017; Xiang & Gretzel, 2010). In other words, different kinds of social media are designed by their developers in ways that shape people's communication patterns differently. For instance, Twitter has been designed as a microblog in which people can express their opinions in less than 140 characters, while YouTube is designed for video sharing, and Facebook is designed for a wide range of socialization. All of the social media platform operate under certain algorithmic systems that specialize the users' exposure to different kinds of content and sources, which technically deprive them from seeing content from sources they are not visiting a lot (Agichtein, Castillo, Donato, Gionis, & Mishne, 2008; Aggarwal & Zhai, 2012). These kinds of technological programs, help social media businesses to find patterns of communication and interests among their users, and sell them on advertisers (Romero, Galuba, Asur, & Huberman, 2011; Xiang & Gretzel, 2010). However, these programs and designs act against the main arguments about the Internet being a flat space for free and democratic exchange of thoughts and ideas among people free of all kinds of filters (Isaac, 2017; Sunstein, 2017).

At the same time, social media owners claim they are advocates of democracy and freedom of expression in their platforms. Twitter even sued the government in order to block the government's demand for unmasking of accounts that were critical of Trump (Isaac, 2017). Scholars like Sunstein (2017) suggest that social media owners

should act responsibly in relation how social media are used. Social media owners cannot just say they are platforms, because they are more than just free platforms for exchange of information.

Social media structures were widely used by some organizations and individuals for the spread of fake news during the U.S. 2016 presidential election (Isaac, 2017). The abundance of fake news during the U.S. 2016 election resulted in some serious actions by social media entrepreneurs such as Facebook's Zuckerberg to hire a high profile editor to handle the fake news problem (Benton, 2017; N.A., 2017).

Twitter. Twitter is the most popular microblogging medium, which has become a virtual hub for communication and a dominant platform for political dialogues among heterogeneous groups of people (Arceneaux & Weiss, 2010; Himelboim et al., 2013). Twitter was established by three young technologists in 2006 as a medium in which posts/Tweets are limited to 140 characters (Arceneaux & Weiss, 2010; Himelboim et al., 2013; Hsu et al., 2013). Twitter is a media space for political news and discourse that includes citizen's voices in addition to links from news media (Himelboim et al., 2013). It is even called a news medium that hosts billions of social relations in addition to spreading information across the globe (Kwak et al., 2010). Twitter can cover "anything from intimate friendships to common interests, or even a passion for breaking news or celebrity gossip" (Cha et al., 2010, p. 10). But it is a powerful tool for political deliberation, in particular, during general elections and other big political events (Tumasjan et al., 2010). Twitter's microblogging is different from traditional live news coverage of political events because it provides the opportunity for public debates on news events in addition to its real-time news coverage (Sakaki et al., 2010). According

to Lieberman (2014), polarized networks are among the most popular forms of Twitter networks, which are often formed on politics and political issues. Political polarization occurs when people are split into two groups on an issue –two dense clusters with little interconnections (Lieberman, 2014). During such political polarizations in online political discussions, members of one cluster demonstrate intolerance toward members of the opposing cluster through Tweets, Retweets, and information sharing. Such expressions emphasize the notions of US versus THEM among members of two clusters (Himmelboim et al., 2013; Lieberman, 2014).

Twitter users have both in-degree (being followed, retweeted, mentioned, or replied to) and out-degree (following, mentioning, or replying to) ties (Himmelboim et al., 2013; Himmelboim et al., 2017; Lieberman, 2014). The existence of in-degree and out-degree ties not only demonstrate the kind of ties established between the users, but also they give information about dominance and popularity of certain actors in the network (Hsu, Park, & Park, 2013; Krebs, 2016; Kadushin, 2012). Some Twitter profiles tend to be more dominant than most accounts and their tweets are more likely to be circulated by other users (Hsu et al., 2013).

In short, social media networks are the most popular and interactive forms of virtual communication (Arceneaux & Weiss, 2010; Duggan et al., 2015; Hansen et al., 2011; Lieberman, 2014; Smith et al., 2014). Not only have they enabled citizens to easily and actively take part in the information production process, but also to form and lead public and political debates on issues, events, and people (Kwak et al., 2010; Tumasjan et al., 2010). Twitter is one of the top social media that has been used for social and political discourse, in particular during big political events such as elections

(Arceneaux & Weiss, 2010; Duggan et al., 2015; Hansen et al., 2011; Lieberman, 2014; Smith et al., 2014).

Summary

This chapter reviewed the shift from mass media to digital media. Overall, the transition from mass into digital media includes audience empowerment, fragmentation, and emergence of social media networks (Bennett, 2012; Gade & Lowrey, 2011a; Mitchelstein & Boczkowski, 2010; Singer, 2011). The emergence of online social networks is a major outcome of the shift from mass media to digital media, which has provided the public with a new space for social and political discourse, and playing active role in political decision makings (Gleave et al., 2009; Reich, 2010). Social media have given a new face to the public discourse by providing the people with highly interactive platforms for communicating their ideas, problems, and concerns with other citizens, actors, and organizations (Arceneaux & Weiss, 2010; Duggan et al., 2015; Hansen et al., 2011; Lieberman, 2014; Smith et al., 2014). Factors such as empowerment of audience, abundance of choices, and audience fragmentation – all may impact public discourse and the level of tolerance on social media (Himmelboim et al., 2013; Lieberman, 2014). The next chapter will explore mediated political discourse, freedom of speech as a democratic right in relation to tolerance in online political conversations.

Chapter 3: Tolerance and Intolerance in Online Political Discourse

This dissertation explores how online social network structures contribute to tolerance and intolerance among people in political discourse on Twitter. “Political tolerance is greater in stable democracies that have endured over time,” with well-developed socioeconomic status, where the citizens have more opportunities to involve and use their civil liberties for democratic activism and where free speech is guaranteed as a right of citizens (Peffley & Rohrschneider, 2003, p. 2). The two-party system in the U.S. has created natural basis for two-pronged discourse – Republican vs. Democrat or Conservative vs. Liberal (Hill & Hughes, 1988; Himelboim et al., 2013). Tolerance and intolerance among the two parties have roots in the basic differences in their values and beliefs, which leads to political polarization among the U.S. public that reaches its highest level during the presidential election (Adamic & Glance, 2005; Dunlap & McCright, 2008; Gruzd & Roy, 2012; Habermas, 1994; Wallace, 2009). In the U.S. 2016 election, the candidates campaigned in ways that highlighted the political system in the country (Berenson, 2016; Bradner, 2016; Tumulty, Rucker, & Gearan, 2016). The way the candidates for the general election, Hillary Clinton and Donald Trump, were interacting with each other reflected the deep intolerance between parties (Bradner, 2016; Tumulty, Rucker, & Gearan, 2016).

Mediated political discourse has evolved with the shift from mass media to digital media. Traditionally, mediated political discourses such as presidential election campaigns and debates were solely handled by journalists and news media (Baum & Groeling, 2008; Bennett, 2012; Domke, McCoy, & Torres, 1999; Kraus & Davis, 1990). Nowadays, political discussions find their ways into social media where people

continue talking and reacting over the problems and issues of their interests related to the elections and campaigns (Baum & Groeling, 2008; Bennett, 2012). As a result, the notions of free speech, public sphere and political discourse have also evolved with the dramatic growth of digital communication technologies (Vergeer, 2012; Bennett, 2012). Not only can citizens actively and directly take part in political discourse with other citizens, but also they can interact with political actors and the news media at very large scales (Vergeer, 2012; Wallace, 2009).

The virtual sphere is a new marketplace of ideas in which citizens engage in exchanging their thoughts and opinions with each other in order to bring changes in their real societies (Schmuhl & Picard, 2005). It is a place for self-expression (Jones, 1997), where ordinary individuals and groups directly reach out to each other (Grossman, 1995; Papacharissi, 2002; Rash, 1997). The emergence and use of virtual space in public discourse have changed the structure of public affairs (Castells, 2015; Grossman, 1995; Jones, 1997; Papacharissi, 2002; Rash, 1997). Free speech and factors such as tolerance and intolerance are prominent components of political discourse in virtual sphere (Beneke, 2006; Bezanson, 2012; Caro, 2011; Caro & Schulz, 2010; Drucker & Gumpert, 2009). Like the real world, political discourse in the virtual space is associated with expression of ideas and thoughts that foster democracy and freedom of speech among diverse groups of people. At the same time, people use the virtual space to express their prejudice and hatred toward those different from them on the basis of ideology, political view, and so forth (Cha et al., 2010; Himelboim et al., 2013; Lieberman, 2014; Pak & Paroubek, 2010; Smith et al., 2014).

Considering the free speech and democracy, political discourse in the virtual world becomes a way for expression of both tolerance and intolerance. This chapter first, discusses the importance of freedom of speech and then tolerance and intolerance in political discourse in virtual political sphere and the role of framing in expression of tolerance and intolerance. The next part of the chapter briefly reviews the U.S. political discourse and the media. The last part of the chapter is an overview of the U.S. 2016 presidential election and the political discourse on it.

Free expression and democratic political discourse

The term freedom of expression or free speech refers to speaking, seeking, receiving, and spreading any information and ideas through any medium (Beneke, 2006; Barendt, 2005). The philosophical notions of free speech deal with the idea that human beings are rational creatures who are created equal, and that they should be granted unlimited freedom to express their ideas and thoughts even if those thoughts are against the dominant beliefs and practices in a society (Caro, 2011; Gordon, 1993; Mill, 1861/1999; Siebert, Peterson, & Schramm, 1956; Sullivan et al., 1993). Locke (1713/1988) argued that free expression is a natural right, as much an inherent right of humanity as the air we breathe. Milton (1918) defined freedom of speech as a multi-faceted right that includes the right to express, seek, receive, impart, and disseminate information and ideas by any medium. Milton emphasized that truth emerges from open discussions when people freely put their ideas and knowledge in open encounter.

Freedom of speech, as a democratic right, enables citizens to actively take part in political discourse and communicate their thoughts and opinions without the fear of government retaliation or censorship or social pressure from other people (Akdeniz,

2002; Bhuiyan, 2011; Emerson, 1963; Post, 1990; van Mill, 2002). Discourse is a form of interaction that plays an important role in political communication among people, which is related to individuals' access to certain referential power and control of it (van Dijk, 1997). Such power and control enables individuals and groups to shape public opinions and dominant ideologies (van Dijk, 1997). Political discourse is a form of public discourse that deals with socio-political issues in a democratic society (Wodak, 1989). Connolly (1993) defined the term political discourse as political thought consisted of framing of political reflection, and "judgments or commitments that are conventionally sanctioned when these criteria are met" (p. 2). Some of the most influential political discourse occurs in informal communications among family, friends, and peers, in classrooms, restaurants and bars, even churches (Van Renesse, Birman, & Maffeis, 1996). It also takes place in the form of political debates, speeches, hearings, and other kinds of interactions (Connolly, 1993; Wodak, 1989). In the United States, the First Amendment guarantees freedom of speech for all citizens, which encourages the citizens to express all kinds of ideas and beliefs in public (Beneke, 2006).

Considering the right of free speech, the idea that the public should be closely involved in societal issues has roots in democratic ideals and active participation of citizens in public affairs (Papacharissi, 2002). These roots grew from 17th and 18th century Enlightenment philosophers' thoughts that individuals should be allowed to speak their thoughts and opinions freely so the truth emerges as a result of confrontation of different kinds of information (Locke, 1690/1963; Milton, 1918). The primary goal of political discourse is that heterogeneous communities communicate their ideas and

beliefs freely “so that a common democratic and public opinion maybe formed” (Post, 1990, p. 603). Political discussions involve exposure to politically dissimilar perspectives (Sullivan et al.,1993). According to Mill (1884/1973), “It is hardly possible . . . to overstate the value . . . of placing human beings in contact with other persons dissimilar to themselves, and with modes of thought and action unlike those with which they are familiar” (p. 594). Discussion partners should have different opinions and views so they can communicate those differences (Mill, 1884/1973). The Founding Fathers of the United States took these ideas into practice by encouraging the American colonies for outspoken political criticism in order for the colonies to get their independence (Schudson & Tifft, 2005).

In order for political discourse to happen, there is a need for a marketplace, public sphere, where people can freely exchange their ideas and thoughts and standpoints (Papacharissi, 2002; Schmuhl & Picard, 2005). The idea of public sphere first emerged in the 18th century when citizens began discussing their problems in social gatherings and made their voices heard by the authorities (Habermas, 1991). Before that time, all issues related to public life were controlled or belonged to the state, authorities, and the ruling class (Fraser, 1990; Habermas, 1991). The term public sphere was coined by the Frankfurt School philosopher, Jurgen Habermas, in 1962 in his book: *The structural transformation of the public sphere: An inquiry into a category of bourgeois society*. He defined public sphere as a domain of social life where public opinion is formed via rational public debate. According to Habermas, informed and rational discussions can lead to public agreement and decision making that best represent democracy. Democratic governments provide the sphere for political discourse where

all citizens, from different backgrounds and demographics can equally participate in public affairs and raise their voices for development and change in society (Habermas, 1994). In such an ideal public sphere, everybody respects everybody else's ideas, beliefs, values, and other differences, and there is no discrimination against individuals and groups on the basis of demographic differences and social and political dominance (Papacharissi, 2002). The public sphere is a place where ideas are expressed and debated (Merrill, 2011).

Media and communication technologies play a crucial role in political discourse by providing the public with the marketplace or sphere to communicate their thoughts, problems, and concerns (Castells, 2015; Merrill, 2011). The public media are often seen to serve for citizens' participation in public policies and issues in a democratic society (Merrill, 2011; Schudson & Tiftt, 2005). From the early days of the print and broadcast media, the media played crucial roles in informing and educating the public about issues and events – social, political, economic, cultural, and so forth (Dimmick et al., 2011; Schudson & Tiftt, 2005; Sobieraj & Berry, 2011). In American society, the print media played a foundational in mobilizing American colonies to get their independence, form a new nation, and develop as new form of politics (Schudson & Tiftt, 2005). The invention of the telegraph enhanced the quality, speed, and spread of news media and information flow during the Civil War politics in the second half of the 19th century (Schudson & Tiftt, 2005). In the early 20th century, the advent of radio led to the emergence of broadcast media, which brought political leaders and their voices to households and people could hear political elites' voices on public issues (Schudson & Tiftt, 2005). A decade later, the development of the television gave a new dimension to

broadcast media and political discourse (Adams, 1983; Albrecht, 2006; Schudson & Tift, 2005). The television pioneered hosting political debates between the candidates for political positions among which the presidential election debates have been one of the most watched broadcast shows of all time (Adams, 1983; Albrecht, 2006; Druckman, 2003; Jamieson, 2011).

Despite the services of mass media, the public could not directly participate in mediated political discourse due to lack of direct access to mediated communication process and flow of information (Gade, 2011; Merrill, 2011). Mass media communication was largely a one-way process – media spoke, audience listened, with little opportunity for providing feedback (Lowrey & Gade, 2011). In other words, the public mainly listened, viewed, or read the mediated political discourse, but they could not directly take part in it or form their own political discourse beyond their family and friends' circles (Castells, 2015; Jones, 1997; Papacharissi, 2002).

Networked media have provided the public with the communication tools, spaces, and platforms through which they can form public and political debates beyond geographic, cultural, and other physical boundaries (Blumer & Gurevitch, 2001; Castells, 2015). This new public sphere is called cyberspace, virtual space, online space, and social media environment, where traditional mythic narratives of progress meet the desire toward self-fulfillment and development (Ankerson, 2015; Grossman, 1995; Jones, 1997; Rash, 1997). Virtual sphere is a place for interaction among individuals and groups who exchange their ideas and beliefs regarding real life events and issues (Castells, 2015).

There are two ideas about the potentials of digital communication technologies for democracy. First, virtual space is a new marketplace of ideas where people engage in exchanging their thoughts and ideas with each other for social, political, and economic benefits (Schmuhl & Picard, 2005). Virtual space can create the environment for formation of virtual town squares where conversation among citizens and citizens and authorities can take place in a matter of seconds (Ankerson, 2015; Papacharissi, 2002; Vergeer, 2012). The virtual public sphere is a place for self-expression (Jones, 1997), where little-known individuals and groups directly reach out to citizens and change the structure of public affairs (Papacharissi, 2002). “Acquiring and dispersing political communication online is fast, easy, cheap, and convenient (p. 14).

The second idea suggests that the potential of digital communication technologies can easily be undermined. The digital age with its endless choices and citizen activities, encourages people to seek media they want (Albrecht, 2006; Gurevitch et al., 2009; Lowrey & Gade, 2011a; Sobieraj & Berry, 2011). This kind of empowerment has made the citizens to expect much more from these media and often consume the kind information that fits their ideologies and beliefs (Adamic & Glance, 2005; Himelboim et al., 2013; Mislove et al., 2007; Wojcieszak, 2011). This results in the formation of clusters of people with common interests communicating together online (Cha et al., 2010; Lieberman, 2014; Pak & Paroubek, 2010; Smith et al., 2014). They communicate with like-minded others, which can easily mean they seldom hear views that conflict with their own, or know that they can express views that others in network will agree with (Adamic & Glance, 2005; Himelboim et al., 2013). The

network structure of online discourse, especially social media networks, can easily – and for many does – become an echo chamber (Lieberman, 2014; Smith et al., 2014).

The majority of participants tend to remain in the groups with similar political/ideological orientations (Himmelboim et al., 2009; Himmelboim et al., 2013; Wallace, 2009). Such groupings of people with like-minded others create the idea of in-group vs. out-group perception among people (Caro & Schulz, 2010; Cote & Erickson, 2009; Saito, 2011). The concept of in-group vs. out-group in political discourse on social media is discussed in how people of opposing political ideologies interact with each other in political discourse (Adamic & Glance, 2005; Himmelboim et al., 2013; Lieberman, 2014; Himmelboim et al., 2017).

There are clusters of liberals versus conservatives, where members of one group show less patience for expressions of the opposite group (Himmelboim, et al., 2013; Lieberman, 2014). Such impatience toward expressions of opposition groups' thoughts conflicts with the notions of freedom of speech and democratic political debates. In other words, the virtual space can create the environment for expression of hate speech that facilitates discriminatory conversations among people (Arthur, 2011; Fisher, 2001). These ideas regarding the virtual space a public sphere for free expression of ideas and political discourse bring up the discussion of tolerance and intolerance in the online world, which is discussed in the following section.

Tolerance

The word tolerance is synonymous with acceptance, endurance, open-mindedness, patience, fortitude, stamina, indiscrimination, and unprejudiced (Merriam Webster Dictionary, n. d.). According to Merriam Webster's Dictionary, the word

tolerance means the “willingness to accept feelings, habits, or beliefs that are different from your own,” or “the ability to accept, experience, or survive something harmful or unpleasant.” From a Lockean perspective, tolerance is about respecting other people’s “inward beliefs” (e.g. religion) and providing an environment for free practice of religion rather than prosecuting or punishing other individuals because of their faiths (Locke, 1690/1963, p. 12). Tolerance is “the result of experiences which are characterized by heterogeneity of ideas, or direct or various exposure to other ways of life and other ways of defining situations” (Borhek, 1965, p. 89). Tolerance is about “a willingness to ‘put up with’ those things that one rejects” (Sullivan et al., 1979, p. 785). Thus, “one is tolerant to the extent one is prepared to extend freedom to those ideas one rejects, whatever these ideas might be” (Sullivan et al., 1979, p. 784). Moreover, “tolerance is a person’s willingness to support the civic and political rights of fellow citizens with whom [he or] she disagrees” (Hiskey, 2013, p. 1).

Cote and Erickson (2009) define tolerance as “complex, stemming from a combination of social networks, voluntary association activities, and individual attributes” (p. 1664). Cote and Erickson argue that tolerance is a form of social capital. While “Social capital is a social network experience producing some positively valued outcome” tolerance is often considered the result of such an outcome (p. 1665). This means that more contacts with different groups of people encourage individuals to “interact, cooperate, share valued experiences, come to like” members of those groups and think positively about them (p. 1665).

Furthermore, tolerance is about rejection of prejudice at the cognitive level and acceptance of differences at the social level (Habermas, 2004). Prejudice often consists

of stereotyping the beliefs of out-groups, negative evaluation of the members of the out-group, and “a predisposition to act negatively toward the group” (Sullivan et al., 1993, p. 5). Tolerance fosters co-existence of communities and reciprocity between them including respect for freedom of expression, freedom of association, and self-obligation to behave tolerantly (Habermas, 2004). Also, tolerance entails the “acceptance of the differences between others and ourselves that we would rather fight, ignore, or overcome” (Van Doorn, 2014, p. 905). It refers to accepting that our own world views are not the only versions of the truth, and “we must also tolerate those who express the ideas, despite their ‘otherness’” (Lewis, 1988, p. 17).

In addition, tolerance refers to cross-group communication among diverse groups of people (Cote & Erickson, 2009; Sullivan et al., 1993). Cross group interaction increases the opportunity for people to learn about groups different from them and become more tolerant toward those people (Cote & Erickson, 2009). Cross-group interaction can increase tolerance among people (Caro & Schulz, 2010; Cote & Erickson, 2009). Interaction with diverse groups of people results in individuals’ positive social orientations toward out-group people and the individuals tend to become more willing to accept people different from themselves (Caro & Schulz, 2010; Cote & Erickson, 2009; Saito, 2011). Tolerant individuals are willing to cooperate with out-group people, support them in their socio-political activities, value their socio-political efforts, accept them in their own group, and like them –tolerance (Cote & Erickson, 2009; Sullivan et al., 1993). Voluntary association activities widen individuals’ social network and increase interaction and flow of information across different groups (Cote & Erickson, 2009; Putnam, 2000). Voluntary associations are viewed as “schools for

democracy' where people learn a range of civic skills and virtues as they take part in and govern their special interest groups" (Cote & Erickson, 2009, p. 1671). It is also true that associations are established on the basis of a certain identity, belief, and other characteristics and demographics that can foster competition with groups different from one's own, which can increase intolerance for out-group members (Cote & Erickson, 2009). In other words, voluntary associations are often established to enforce homogeneity among people –churches, neighborhood organizations, etc. (Mutz & Mondak, 2006).

Furthermore, political tolerance among people differs on the basis of education, (Peffley & Rohrschneider, 2003). Studies have shown that people with higher levels of education tend to be more tolerant toward people who are different from them (e.g. minorities) compared to those who have less education (Beatty & Walter, 1984; Cote & Erickson, 2009; Gex-Collet, 2012; Hazama, 2011; Hiskey, 2013; Sullivan et al., 1993). As democratic citizens, if people want to enjoy their own freedoms, they need to be equally tolerant of others' freedoms as they themselves expect those other individuals to be tolerant of theirs (Mill, 1861/1999).

Drawing from the above literature, in this study, tolerance is a form of cognitive and emotional social capital, which enables individuals to endure each other's ideologies, social and cultural values and beliefs, and biological and physical differences, and do not express discriminatory ideas, attitudes, and behaviors toward them.

In the virtual world, tolerance refers to cross-group communication and expression of acceptance, openness to interact and make friends with diverse people and

sources of information, and respect toward people different from one's self on the basis of ideology, personal beliefs, and demographics (Adamic & Glance, 2005; Himelboim et al., 2013).

Intolerance

Tolerance and intolerance are at the two ends of a spectrum –meaning they are the opposite of one another (Lewis, 1988; Locke, 1690/1963). Intolerance includes all those behaviors and actions that are in violation with tolerance –unwillingness to accept those who have different beliefs and values from one's self (Locke, 1690/1963; Sullivan et al., 1979). For instance, interfering in other individuals' ideological or religious beliefs is an act of intolerance, which can also include discrimination and prejudice against them only because of their personal opinions and values (Coward, 1986; Yang & Self, 2015).

There is no clear definition for intolerance in the existing literature. Reviewing some court cases and literature on tolerance, intolerance can be defined as unwillingness to accept (rejecting) those who have different beliefs and values from one's self (Locke, 1690/1963; Sullivan et al., 1979), which deals with discrimination and prejudice against other people (Coward, 1986; Yang & Self, 2015). It can be expressed in different forms of defamation, hate speech, name calling, attempt to attack violently, attempt to provoke outrage, cursing and swearing at someone, discriminating against one's demographics or beliefs and values, and the use of fighting words (Smith, N.A; Chaplinsky v. New Hampshire, 1942; Snyder v. Phelps, 2011; Teeter & Loving, 2008; Texas v. Johnson, 1989). It also refers to an intent to threaten, display of symbols that arouses anger, alarm or resentment, invasion of privacy, infliction of emotional

distress, accuse someone of a crime, and attack their personal business and reputation (Snyder v. Phelps, 2011; Smith, N.A; Teeter & Loving, 2008; Texas v. Johnson, 1989). Or it refers to the rejection of views/acts of either in-group or out-group and resorts to language that expects or demands the group to think or act differently (Locke, 1690/1963; Mill, 1861/1999; Sullivan et al., 1979).

Intolerance increases social distance among groups and communities and decreases the chance for formation of cross-group ties (Coward, 1986; Lewis, 1988). This is because getting stuck in one's own group decreases the motivation for being involved in diverse social networks and associations (Cote & Erickson, 2009).

Intolerance in the virtual world refers to the tendency to communicate and make friends predominantly with those like one's self (Yang & Self, 2015). Such tendency for grouping with likeminded people often results in the usage of like-minded sources of information, and expressing dislike and discrimination toward those different from them (Himmelboim et al., 2013; Yang & Self, 2015).

Levels of tolerance and intolerance vary among people on the basis of individual attributes and characteristics such as political ideology, sociocultural beliefs, attitudes, religion, education, and membership in minority groups (Cigler and Joslyn, 2002; Cote & Erickson, 2009; Erickson, 2004; Habermas, 2003; Peffley & Rohrschneider, 2003).

There is a strong association between religion and political intolerance that even the discourse of tolerance began from religious intolerance in the 17th century (Beatty & Walter, 1984). Religion has been a key source of intolerance in the history of humanity (Coward, 1986). Religion has given birth to religious discriminations and formal persecution (Coward, 1986; Fichtner, 2008; Kaplan, 2009). Religious discrimination is

different from other types of discrimination, because it is not on the basis of biological or physical differences (e.g. race, gender, or physical disabilities), rather, it is about differences in people's inward values and beliefs (Coward, 1986). From a psychological perspective, even though most people follow the faiths of their parents and ancestors, individuals choose whether to be part of a religious group or not (Coward, 1986). Such individual pride can be a symptom of blindness to others or others' perspectives (Coward, 1986; Djupe, 2015; Hiskey, 2013).

Intolerance can be observed in the expression of ideological differences between individuals or groups (Brandt et al., 2014; Coward, 1986; Caro & Schulz, 2010; Cote & Erickson, 2009; Djupe, 2015; Graham et al., 2009; Hiskey, 2013; Saito, 2011; Skitka & Bauman, 2008; Van Dijk, 2003; Wetherell et al., 2013). Van Dijk (2003) defines ideologies as belief systems used "as the basis of the social representations of groups" that include "any kind of socially shared mental representation" (p. 207). Ideological differences play important roles in individuals' and groups' perceptions, expressions, and behaviors toward those who are different from them (Berry, Ringquist, Fording, & Hanson, 1998; Brandt et al., 2014; Jussim et al., 2013). The main political ideologies in the last two centuries have been socialism, liberalism, conservatism, communism, green politics, and so forth (van Dijk, 2003). Contemporary political ideologies in the U.S. are often defined in relation to broad dimensions of liberal and conservative or left-wing and right-wing (Brandt et al., 2014; Graham et al., 2009; Sibley & Duckitt, 2008; Wetherell et al., 2013). Individuals tend to group with those who follow political ideologies and parties that fit their own thoughts and beliefs and oppose those who

choose groups and parties that are different from their own (Berry et al., 1998; Brandt et al., 2014; Sullivan et al., 1993; van Dijk (2003).

Whether members of one group have tolerance or intolerance toward a group different from them can influence the group to respond accordingly (Cote & Erickson, 2009; Kawakami, Dovidio, Moll, & Russen, 2000; Pettigrew, 1998). Such response is called reciprocity in social psychology, which suggests that satisfaction of individuals from other people in social relationships encourage the individuals to offer similar response in exchange (Rook, 1987). In other words, if members of group A are tolerant toward group B, the members of group B will also show tolerance toward group A – meaning tolerance increases tolerance and intolerance increases intolerance (Cote & Erickson, 2009). Therefore, if the first group shows intolerance toward the other group, the response will more likely be the same (Cote & Erickson, 2009). People who hold conflicting ideologies see each other as opponents (Benhabib, 1996). If people limit their social interactions with like-minded others, it will lead to polarization and growth of extremism due to lack of knowledge about multiple political perspectives (Sunstein, 2001).

Competition and lack of personal contact foster intolerance among individuals and groups, because they see each other as threat (Cote & Erickson, 2009). Political intolerance includes disliking or discriminating against individuals and groups who have dissimilar values, threatening their security and safety, and violating their moral values (Brandt et al., 2014). For instance, people agree that members of their opposing groups should be banned from a public office (e.g. being the U.S. president), banned from speaking out their ideas and organize public rallies, and banned from teaching in

public schools (Sullivan et al., 1979; Sullivan et al., 1993). People also agree that members of their opposing groups get fired from their jobs or outlawed, their communications are monitored by government, and books written by them are removed from libraries (Sullivan et al., 1979; Sullivan et al., 1993). Intolerant individuals tend to have pessimistic views about the future of their out-groups and are resistant toward accepting members of the out-group in their own groups. In other words, people often have double standards when it comes to out-group people in relations to themselves—fostering the US versus THEM or liking the in-group and disliking the out-group (Cote & Erickson, 2009). However, the perceptions toward their own beliefs and practices (e.g. ideological, political, religious, etc.) are more positive compared to the perceptions toward others' beliefs (e.g. atheists, communists, homosexuals, militarists, racists, etc.) (Beatty & Walter, 1984). Another factor that plays a key role in shaping tolerance and intolerance in political discourse is framing (Peffley & Rohrschneider, 2003), which is discussed in the following section.

The Role of Framing in Discourse of Tolerance

Tolerance and intolerance in political discourse involve framing of in-group versus out-group people, in which individuals express liking or disliking and support or discrimination toward people who are different from them (Peffley & Rohrschneider, 2003; Sullivan et al., 1979; Sullivan et al., 1993). Framing refers to the process by which people develop a particular conceptualization of an issue or reorient their thinking about an issue (Chong & Druckman, 2007, p. 104). Framing is the process of describing or defining certain attributes of issues, people, or events (Coleman & Banning, 2006; Entman, 1993; Goffman, 1974; Lang and Lang, 1983; McCombs &

Estrada, 1997; Wanta and Wu, 1992; Wanta, Golan, & Lee, 2004). Framing can be used in “making new beliefs available about an issue, making certain available beliefs accessible,” or making beliefs applicable or “strong” in people’s evaluations (Chong & Druckman, 2007, p. 111). Entman (1993) argues that framing “involves selection and salience,” as he says:

To frame is to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation for the item described. (p. 52)

Frames are aspects of issues that can contain both verbal and nonverbal attributes, which make communication more effective (Coleman & Banning, 2006; McCombs & Estrada, 1997). Friedland and Mengbai (1996) define frames as “bridge[s] between... larger social and cultural realms” (p.13). Frames “prescribe” an issue, then “define the problems” based on “common cultural values” and then make “moral judgments” about the problems (Entman, 1993, p. 52).

In the communication process, frames are produced by communicators in the context of keywords, concepts, metaphors, stereotyped terms, symbols, phrases, and images (Bliss-Carroll, 2016; Entman, 1991,1993; Pavalanathan & Eisenstein, 2015). Words and images have the capacity to stimulate the media message in favor or against political competitors (Entman, 2004). These words and images can frame world events as highly “understandable,” “memorable” and culturally influential (p. 6). Furthermore, Chong and Druckman (2007) call frames “adjectives” that are stronger, “superior,” applicable, and often convey “exaggerations,” “symbols, endorsements, and links to

partisanship and ideology” (p. 111). Political frames are used to emphasize problems without discussing the solutions, or to reinforce negative aspects of an issue more than the positive sides of it (Entman, 2003).

Studies have shown that in the framing of in-group versus out-group, people tend to express their tolerance and intolerance as following. First, people often have positive tone in talking about in-group individuals by expressing their support, respect, acceptance, pride, love, good wishes, and excitement toward them (Hardisty, Johnson, & Weber, 2009; Schubert & Otten, 2002; Shah, Brazy & Higgins, 2004; Powell, Branscombe, & Schmitt, 2005; Tropp & Wright, 2001). Second, in contrast to in-group framing, people often tend to have negative tone toward out-group by expressing discrimination, criticism, disrespect, rejection, jittery, hatred, dislike, hostility, and shame (Hardisty et al., 2009; Schubert & Otten, 2002; Shah et al., 2004; Powell et al., 2005; Tropp & Wright, 2001). For instance, people from one group framed members of other groups as outsiders and dangerous terrorists and criminals who should not be allowed to exercise their democratic rights (Brandt et al., 2014; Peffley & Rohrschneider, 2003; Sullivan et al., 1979; Sullivan et al., 1993; Yang & Self, 2015). The next section reviews tolerance and intolerance in the U.S. political discourse.

U.S. Political Discourse

In the U.S., political discourse is centered around two main schools of thoughts that usually define the interests of the two parties. The two-party political system in the U.S. (Republican and Democrat) often creates polarized political discourse among public (Hill & Hughes, 1988; Himelboim et al., 2013). Tolerance and intolerance between the two parties have roots in the basic differences in their values and beliefs

(Dunlap & McCright, 2008; Habermas, 1994). Republicans are known as conservatives who trace their roots to classical liberalism of the 18th century, in which philosophers like John Locke, Adam Smith, and Tomas Jefferson “affirmed their faith in the rational abilities of humans to determine their own destinies” (Dye & Zeigler, 1986, p. 33). Based on this school of thoughts, “all men are created equal, that they are endowed by their Creator with certain alienable Rights [and] that among these are Life, Liberty and pursuit of Happiness” or property (p. 33). Classic liberalism “asserted the dignity and worth of the individual” and suggested a limited government formed with the consent of the governed people to protect their individual liberty (p. 33). This school of thoughts is also closely related to capitalism as an economic ideology and emphasizes the rights of individuals to make contracts, trades, and bargains with very limited government intervention (Dye & Zeigler, 1986). As a result, Republicans claim they are true liberals, because they emphasize individualism, limited government, and free enterprise (Dye & Zeigler, 1986). Also, Republicans tend to be more religious, antiabortion, anti-homosexuality, and resistant to affirmative action (Levendusky, 2009).

On the other hand, Democrats are known as contemporary liberals that emerged in the 20th century who value “individual dignity, civil rights, due process of law, and equality of opportunity” (Dye & Zeigler, 1986, p. 34). Democrats recognize that some people are not as capable or motivated to exercise their talents or intellects toward individual development or economic gain (Dunlap & McCright, 2008). Furthermore, not all individuals are created economically equal, nor are there equal opportunities for people of different socio-economic strata (Dunlap & McCright, 2008; Freeman, 1986). These are the reasons for the positive power of government and why Democrats tend to

favor more government regulation of businesses and more social programs for under-privileged and poor (Dye & Zeigler, 1986; Freeman, 1986). Democrats tend to be less religious, pro-abortion, advocates for minorities, immigrants, and homosexuals (Uggen & Manza, 2002).

Following the two-party ideology, individuals, political actors, and groups and organizations express their ideas, reflections, and beliefs toward each other that include elements of tolerance and intolerance as listed above (Himmelboim et al., 2009; Himmelboim et al., 2013; Hill & Hughes, 1988; Wallace, 2009). Studies have shown that both liberals and conservatives show similar intolerance toward each other (Adamic & Glance, 2005; Brandt et al., 2014; Himmelboim et al., 2013). Conservatives are more likely to consume conservative news media and grassroots media and get involved in the conversations with like-minded people online (Himmelboim et al., 2009; Yang & Self, 2015). In contrast, liberals tend to consume more traditional news media (Himmelboim et al., 2009). Also, there are differences among liberals and conservatives in their discussions of news articles, social, political, and economic topics, and political figures (Adamic & Glance, 2005). For instance, conservatives tend to refer to conservative news media and grassroots information sources, while liberals largely use mainstream news media as their sources of information (Adamic & Glance, 2005).

These differences and disagreements between Republicans and Democrats lead to a stronger in-group agreement within each party (Cote & Erickson, 2009; Habermas, 2004; Lewis, 1988; Van Doorn, 2014). News media largely cover political issues and events in accordance with Republican vs. Democrat analogies, which reinforces political polarization in political discourse –e.g. CNN and FoxNews (Hindman, 2011).

Moreover, in recent decades, the number of partisan news media has increased and these outlets cover issues and events in ways that is in favor of their own party and against the opponent party (Hindman, 2011). According to Hindman, by such emphasis on polarized ideologies and values by the mainstream news media, the citizens are exposed to polarized information even if they do not identify as Republican or Democrat. For instance, the coverage of elections in news media largely takes place like a horse-race, in which the main focus is on winning and losing of candidates (Farnsworth & Lichter, 2010).

Thus, most political discussions in the U.S. become polarized, and such polarization not only creates the environment for discussing tolerance and intolerance, but also for expressing them (Adamic & Glance, 2005; Brandt et al., 2014; Gruzd & Roy, 2012). Political polarization reaches its peak during the last week of presidential election (Adamic & Glance, 2005; Gruzd & Roy, 2012). Himelboim et al. (2013) studied cross-ideological political discussions on Twitter during 2010 midterm elections and found that there are not many cross-ideological political discussions on Twitter.

Presidential Elections and Mediated Political Discourse

The news media are regarded as the fourth branch of government alongside executive, judiciary, and legislative branches (Farnsworth & Lichter, 2010; Merrill, 2011). Political campaigns and elections are among the biggest events covered by the news media in the forms of political debates, news, and entertainment (Farnsworth & Lichter, 2010). Media are important means of communication for political events such as elections and candidates largely dependent on the media in order to directly communicate their messages with citizens (Bezanson, 2012; Kraus & Davis, 1976).

Since the mid-1900s, the candidates have largely used news media to spread their messages to voters (Farnsworth & Lichter, 2010). The primary work of traditional media in mediated political discourse has been hosting political debates, political talk shows, and coverage of election campaigns and the elections (Farnsworth & Lichter, 2010). The advent of digital media and audience fragmentation for traditional media have led to a dramatic decline of the audiences of mass media (Hindman, 2011). Nowadays, presidential election campaigns largely take place in the virtual world, where the candidates and political actors can directly target their publics (Scharl & Weichselbraun, 2008; Schwartz, 2015; Vergeer, 2012; Wallace, 2009).

In the digital age, citizens have substantially different access to candidates and other citizens than the mass media age, when citizens had to rely more on legacy news media for information (Kushin & Yamamoto, 2010; Vergeer, 2012). Nowadays, citizens have direct access to information about candidates and their advocates, which enables them to not only become informed about the candidates and their goals and strategies, but also to express their personal thoughts and reflections regarding the candidates (Scharl & Weichselbraun, 2008; Vergeer, 2012; Wallace, 2009). This is why political actors, organizations, parties, and candidates all try to have an existence on social media in order to have a voice among the public (Kushin & Yamamoto, 2010; Vergeer, 2012). In general, media consumption and engagement in socio-political discussions on social media are related to people's ideological, political, religious, and cultural beliefs, which can influence their tolerance and intolerance toward others (Agiesta, 2016; Lieberman 2014; Smith et al., 2014; Yang & Self, 2015). The discussions on political issues, events, and actors on social media often lead to the emergence of two dense clusters of

people, with little interconnection between them, who are split in their opinion on certain issues (Lieberman, 2014).

The U.S. 2004 presidential election was the first election in the United States in which blogs were used profoundly during the campaigns (Adamic & Glance, 2005; Kushin & Yamamoto, 2010; Scharl & Weichselbraun, 2008; Vergeer, 2012; Wallace, 2009). The 2008 presidential election in the U.S. was the first presidential election in which social media such as Facebook and Twitter were used for political campaigns (Kushin & Yamamoto, 2010). Young adults, especially, first voters, used video sharing websites not only for getting campaign information but also for sharing the information, exchanging ideas and viewpoints, and expressing support for their favorite candidates (Kohut, 2008; Smith & Rainie, 2008). Most observers viewed Barak Obama's success as an outcome of his social media campaign (Gruzd & Roy, 2012; Kushin & Yamamoto, 2010).

Twitter has become one of the most popular social media for political discourse during presidential elections (Ankerson, 2015; Cha et al., 2010; Conover et al., 2011; Gruzd & Roy, 2012; Jansen et al., 2009; Kwak et al., 2010; Pak & Paroubek, 2010; Sakaki et al., 2010; Schwartz, 2015). Political discourse on Twitter often takes shape around users' political affiliations, which create the environment for debating against the opposing groups and in favor of one's own group (Himmelboim et al., 2013; Meraz, 2009; Tumasjan et al., 2010). Twitter tags and hashtags (#) are largely used by Twitter users through which the users associate themselves with people, issues, and events either as advocates or opponents (Cha et al., 2010; Lieberman, 2014; Pak & Paroubek, 2010; Smith et al., 2014).

The 2016 U.S. Presidential Election and Political Discourse

The 2016 election was the 58th presidential election in the United States for electing the 45th president of the country (Jackson, 2017). Hillary Clinton was the candidate from the Democratic Party (from six candidates) and Donald Trump was the Republican Party candidate (from among seventeen candidates) (Andrews, Bennett, & Parlapiano, 2016a; Andrews, Lai, Parlapiano, & Yourish, 2016b). The success of Clinton and Trump in the primary elections helped them come out as their parties' candidates for the general election highlighted the political division in the country (Killough, 2016; Niose, 2016). The candidates carried on a campaign with nasty personal attacks, in which much of their own discourse revealed little tolerance for the other (Killough, 2016). Given that such tone was set by the candidates themselves, it would appear logical that the same negative, personal and out-group attacks appeared in the citizens' discourse (Killough, 2016; Niose, 2016). According to a CNN/ORC Poll, 8-in-10 Americans said that during 2016 election the country was divided more than anytime in the past several decades (Agiesta, 2016). More than 200 newspapers endorsed Clinton and less than 20 newspapers endorsed Trump (Sillito, 2016).

Both Clinton and Trump had controversial backgrounds and plans for future (Killough, 2016; Niose, 2016). Some voters called both Clinton and Trump "evils," and preferred to vote for the one that looked "the lesser of two evils" (Long, 2016, para. 1). Trump for instance, is a multibillionaire who did not release his finances, in particular tax papers (Barstow, Craig, Buettner, & Twohey, 2016). Documents investigated by *The New York Times* indicate that in 1995, Trump declared a \$916 million loss on his income tax returns, which "could have allowed him to legally avoid paying any federal

income taxes for up to 18 years” (Barstow et al., 2016, p. 1). He has been the first Presidential election candidate in the U.S. history who hid his finances from the public. Also, Trump did not distance himself from his businesses during the presidential election campaigns (Venook, 2016).

Trump was accused of sexual assault and abuse of labor (Scherer, 2015). During the campaigns, Trump proposed plans for refugees and immigration in the U.S., which included building a wall on the U.S. border with Mexico as a way of preventing South Americans from entering the U.S. soil illegally (Scherer, 2015; Zurcher, 2016). He also suggested a temporary ban on entrance Muslims to the U.S. for national security of Americans (Zurcher, 2016). Trump’s immigration policy was a response to the Democrats’ immigration policy (during Obama’s presidency) that helped five million undocumented immigrants from South America and accepted more than 2,000 Muslim immigrants from Syria and Iraq (Berman, 2014; Shear & Cooper, 2017).

Clinton on the other hand, was accused of betraying the American public as the Secretary of State by using her personal email dealing with controversial international issues such as the attack on the U.S. embassy in Libya (Graham, 2016). Clinton not only supported friendly immigration policies, but also suggested that the number of Syrian refugees settled in the U.S. should increase from 10,000 to 65,000 (Zurcher, 2016). Clinton supported racial equality, in particular, she advocated regulations that could benefit African Americans (e.g. laws that reduce police brutality) (Zurcher, 2016).

The majority of Republicans supported Trump, which helped him get the GOP support for representing the Republican Party (Roberts & Owen, 2016). Some of the

high-profile Republicans who supported Trump were Sarah Palin, John A. Boehner, Dick Cheney, Mitch McConnell, and Rand Paul (Krishnakuma & Bellantoni, 2016). It was not until the release of a tape from 2005 on October 7, 2016, on mainstream media that some top Republican politicians distanced themselves from Trump (Fahrenheit, 2016; Roberts & Owen, 2016). In the tape, Trump used misogynist terms about kissing, grabbing, and having sex with women without their permission (Fahrenheit, 2016). In his conversation with Billy Bush on the tape, Trump says that “when you’re a star, they let you do it...you can grab them by the pussy” (para. 1). Hours after the release of the tape, prominent members of Republican Party started backing away from Trump and said they were not supporting Trump for presidency (e.g. Paul Ryan, Condoleezza Rice, and so forth) (Samuels, 2016). Some major Republican donors even asked Trump to give them their donated money back (Samuels, 2016). Furthermore, seventy-eight Republican politicians, donors and officials announced their support for Hillary Clinton (Blake, 2016).

Both Trump and Clinton heavily relied on social media, in particular Twitter, during their campaigns (McCormick, 2016; Rubin, 2016). However, Trump heavily relied on social media, especially Twitter, to discuss his standpoints regarding the issues and topics discussed in mainstream media and among the public (Rubin, 2016). He used social media as a direct platform to communicate with his target public that he even argued that “social media has more power than the money they spent” (McCormick, 2016, para, 2). He even tweeted at 3 a.m., which became a time for his controversial attacks on his political rival and her supporters (Rubin, 2016).

The primary election campaign began in April 12, 2015, in which 23 candidates (6 candidates from Democratic Party and 17 from Republican Party) started campaigning (Berenson, 2016; Bradner, 2016; Tumulty, Rucker, & Gearan, 2016). Over the coming months, Hillary Clinton and Bernie Sanders came out as the top candidates running for the Democratic Party nomination, and Donald Trump, Ted Cruz, Marco Rubio, and John Kasich as the top candidates for the Republican Party who competed in the primary elections (Andrews et al., 2016a; Berenson, 2016; Bradner, 2016; Tumulty, Rucker, & Gearan, 2016). Among the Democratic Party candidates, Clinton won in 34 states and Sanders won in 23 states, which led to Clinton's victory in the Democratic National Convention by winning 2,220 delegate counts while Sanders only won 1,831 (Andrews et al., 2016a). Therefore, on July 26, 2016, the Convention officially nominated Clinton for 2016 presidential election and Tim Kaine as the nominee for vice president (Chaves, Stracuqlursi, Kelsey, 2016).

Among the top four candidates from Republican party, Trump won in 41 states, Cruz in 11 states, Rubio in three states, and Kasich in one state, which led to Trump's victory in the Republican National Convention by winning 1,447 delegate counts while Cruz, Rubio, and Kasich only won 551, 167, and 161 delegate counts (Andrews et al., 2016a). Thus, on July 22, 2016, the Convention officially nominated Trump for 2016 presidential election and Mike Pence as the nominee for vice president (Brander, 2016).

During the campaign for general election between Clinton and Trump, both indulged in personal attacks on each other's characters, values, and moralities (Healy & Martin, 2016; Walsh, 2016). For example, Trump attacked Clinton using the allegations against her husband, former president, Bill Clinton, arguing "Hillary Clinton was

married to the single greatest abuser of women in the history of politics” (Healy & Haberman, 2016, para. 8). Trump called her a “nasty” woman who criticized the women claimed to be victims of sexual misconduct with her husband (Healy & Haberman, 2016). He also called her an unstable, incompetent, liar, criminal, and robot who does not look presidential (DelReal, 2016). He named her “crooked Hillary” (Hampson, 2016, p. 19) and questioned her mental health (DelReal, 2016). Clinton on the other hand, attacked on Trump’s past comments on women and minorities such as his comments on the former Miss Universe (Wolfgang, 2016).

Despite all the controversial issues and scandals, Trump became the 45th president of the United States by winning more than 30 states including nine swing states (Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, North Carolina, Pennsylvania, and Wisconsin) (Bradner, 2016). Clinton only won in more than 20 states while winning the popular vote by nearly 3 million people (Bradner, 2016; Berenson, 2016). The election results were unlike what polls predicted –Clinton’s victory (Berenson, 2016; Bradner, 2016; Tumulty, Rucker, & Gearan, 2016). Trump’s win led to street protests across U.S., and the protestors chanted that Trump is “not my president” (Ali & Hassan, 2016, para. 2). Some protestors demonstrated against Trump’s victory by shutting down a major highway in Los Angeles and some Interstate 5 in Oregon and burning an American flag in Washington (Ali & Hassan, 2016). Social media, in particular Twitter, was inundated with posts and conversations expressing concerns about the election results. Some celebrities like Katy Perry and Rosie O’Donnell even uploaded “simple black profile and header photos to their Twitter timelines to protest President-elect Donald Trump” (Gibbs, 2016, para. 2). Hashtags

were created on Twitter that demonstrated the creators' reaction toward the election results –such as #Twitterblackout, #NotMyPresident, and #StillWithHer (Gibbs, 2016).

Summary

In the discussion of political discourse in a democracy, free expression becomes an essential element (Mill, 1861/1999). Tolerance is a foundational component of freedom and free expression in political discourse in a democracy (Bezanson, 2012; Caro, 2011; Caro & Schulz, 2010). The two-party system in the U.S. has created natural basis for two-pronged discourse – Democrat vs. Republican, which leads to political polarization among the U.S. public, in particular, during the presidential elections (Adamic & Glance, 2005; Dunlap & McCright, 2008; Gruzd & Roy, 2012; Habermas, 1994; Hill & Hughes, 1988; Himelboim et al., 2013; Wallace, 2009). Such polarization shows tolerance and intolerance among the followers of the two parties in how they view themselves in comparison to the opposing group (Adamic & Glance, 2005; Dunlap & McCright, 2008; Gruzd & Roy, 2012; Habermas, 1994; Wallace, 2009).

Traditionally, mediated political discourses such as presidential elections' campaigns and debates were solely handled by journalists and news media (Baum & Groeling, 2008; Bennett, 2012; Domke, McCoy, & Torres, 1999; Kraus & Davis, 1990). Nowadays, political discussions find their ways into social media where people continue talking and reacting over the problems and issues of their interests related to the elections and campaigns (Baum & Groeling, 2008; Bennett, 2012). As a result, the notions of free speech, public sphere and political discourse have evolved with the dramatic growth of digital communication technologies (Vergeer, 2012; Bennett, 2012). Not only can citizens actively and directly take part in political discourse with other

citizens, but also they can interact with political actors and the news media at very large scales (Vergeer, 2012; Wallace, 2009).

In the U.S. 2016 election, the candidates represented the very polarized political system and the deep intolerance between parties (Bradner, 2016; Tumulty, Rucker, & Gearan, 2016). The 2016 election was also the most popular political event on social media, and the candidates predominantly used Twitter to communicate with their public rather than traditional media (Ali & Hassan, 2016; Berenson, 2016; Bradner, 2016; Gibbs, 2016; Tumulty, Rucker, & Gearan, 2016). Yet, social media have enabled the public to recreate similar polarized and homophilious social networks based on certain political and ideological values (Brandt et al., 2014; Jussim, Cain, & Cohen, 2013; Wetherell et al., 2013). The next chapter explores social networks and the structural features of online social networks.

Chapter 4: Social Network Analysis (SNA)

This dissertation explores the relationship between online social network structure and the Twitter users' tolerance and intolerance toward each other in political discourse during the U.S. 2016 presidential election. Previous chapters reviewed the evolution of mediated political communication as a result of the shift from mass media to networked media, and tolerance as a form of free speech in mediated political discourse, in particular on virtual political sphere. This chapter focuses on social networks and social network analysis (SNA), and explores the important functions and features of social media networks. The chapter begins with a broad discussion about social networks. Next, it talks about online social networks and their key functions and features based on the existing literature.

Social Networks

Social networks have been the foundation of human societies since the beginning of human civilization, without which human relationships cannot exist (Hanneman & Riddle, 2005; Scott, 2012). A social network is “a set of relationships,” which contains a set of objects or nodes and the description of relationships between them (Kadushin, 2012, p. 14). Social networks are made of actors (individuals, groups, entities, etc.) or nodes that communicate with each other and establish relationships (Kadushin, 2012; Wasserman & Faust, 2009). Traditionally, networks exist in all social ties from family, village, and kinship to society and the entire world system (Kwak et al., 2010). Networks exist in many formats such as natural (e.g. neural networks) and human-made such as group and cross group networks, inter-organizational networks, and so forth (Monge & Contractor, 2003).

Social network analysis (SNA) is the study of interactions, ties, and exchange of information and goods between individuals, groups, communities, organizations, societies and so forth (Scott, 2012; Kadushin, 2012). Study of networks goes back to centuries ago (Barabasi, 2002; Milgram, 1967; Wellman & Hampton, 1999). In 1736, mathematician Leonhard Euler was one of the first individuals who used graphs in order to solve problems for bridges and land masses (Barabasi, 2002). The second half of the 20th century was a time of dramatic progress for SNA. In physical social networks, geographic location, class, profession, co-working, nationality, school, and so forth are among the core predictor variables for the formation of social ties between individuals (Kadushin, 2012). The study of social networks explores patterns of relationships among interacting units in social, political, and economic systems (Wasserman & Faust, 2009). Understanding about the patterns of relationships in these systems helps in explaining how and why social network structures form in certain ways that influence social and political discourses (Adamic & Glance, 2005; Bodin & Crona, 2009; Dunlap & McCright, 2008; Gruzd & Roy, 2012; Himelboim et al., 2013; Wallace, 2009).

The Internet has given birth to new forms of social networks that have expanded social relationships beyond physical and geographic boundaries (Valenzuela et al., 2009). Online social networks not only help the existing social relationships, but also provide the basis for new types of social ties, which enable people to find new friends; relationships and locate sources of information and spread them, and form virtual discussion groups and communities (Arceneaux & Johnson, 2013; Gruzd & Roy, 2014; Mislove et al., 2007).

One of the foundational factors in social networks is the power law distribution (Adamic & Huberman, 2000; Barabási & Albert, 1999). Power is a process in society, which enables actors to influence the decisions of other actors (Castells, 2009). Power law is a relationship between two quantities in a self-regulating and interactive system, in which a relative change in one quantity brings in a proportional relative change in the other quantity (Adamic & Huberman, 2000). Power law distribution is not like a normal distribution, in which the mode, median, and mean are the same and the majority of the cases fall one standard deviation below and above the average (Barabasi, 2002). Instead, in power law distributions, the mode, median, and mean are very different from each other (Barabási & Albert, 1999). The majority of nodes fall below the average and with an increase in the population, and a few get a vast share of the audience (Adamic et al., 2001). The distance between the highest and the lowest positions will go up with an increase in the sample size (Barabasi, 2002).

Foundational Features in Social Network Structure

All networks consist of nodes and their ties in the forms of groups and subgroups that are known as clusters, cliques, and sub-groups (Hanneman & Riddle, 2005; Wasserman & Faust, 2009). A node is a connection point, an intersection, an individual, an actor, or an entity that establishes ties with other nodes and form a social network (Scott, 2012). There are two kinds of social networks based on the kinds of actors (Hanneman & Riddle, 2005). First, one-mode network refers to the networks that have actors of the same level or general type – e.g. a friendship network of 6 people (Kadushin, 2012). Second, in two-mode or binary networks ties are established between nodes that belong to two different sets (Wasserman & Faust, 2009). Two-mode

networks are also known as network affiliation – e.g. a group of people are members of different clubs (Kadushin, 2012).

Relational ties or edges are connections between nodes, which show an activity, bonding, or exchange between them (Hanneman & Riddle, 2005). Ties show activities between actors such as sharing, delivery, and exchange of resources (Kadushin, 2012; Wasserman & Faust, 2009). Relational ties can be formed for resources including information, cooperation, social support, advice, money, and so forth (Kadushin, 2012). There are two kinds of ties in social networks: directed and non-directed relationship ties (Kadushin, 2012; Wasserman & Faust, 1994). Directed ties show in-degree and out-degree relationships and whether or not they are reciprocal (Wasserman & Faust, 2009). In-degree refers to the number of ties coming to the node and out-degree is the number of ties from a node to outside (Wasserman & Faust, 2009). Directional ties are the ones that indicate whether a connection is coming to a node (in-degree tie) or going to a node (out-degree ties). In-degree and out-degree ties in directional networks are shown with arrows (Hanneman & Riddle, 2005; Kadushin, 2012). Non-directed ties indicate dichotomous relationships that do not show the direction of the flow (Hanneman & Riddle, 2005). They just show whether a relationship exists or not (Kadushin, 2012). On Twitter, ties are directed that include following and being followed, retweeting and being retweeted, mentioning and being mentioned, replying and being replied to, which create short paths of connection between people with long distances from each other (Himmelboim et al., 2017; Lieberman, 2014). These short paths of connections are established through a few people who connect the otherwise disconnected clusters or groups in a network (Himmelboim et al., 2017).

Geodesic distance among the nodes in a network is an important factor that shows how close they are to each other (Choi, Thomee, Friedland, Cao, Ni, Borth, & Poland, 2014; Ghosh & Lerman, 2010; Kadushin, 2012; Wasserman & Faust, 2009). Geodesics or short paths are often used to measure network metrics in order to make assumptions about the flow of information through the network's shortest paths (Krebs, 2016). Different paths give different interpretations about information flow in a network. Thus, "it is important to be on many efficient paths in networks that reach out to various parts of the extended network (Krebs, 2016, para. 9)." The well-integrated nodes in a network of paths have both local and distant information from different sources (Krebs, 2016).

The smallest sub-set in a social network is a dyad, in which two nodes are connected to each other. Cliques are subgroups with three or more nodes (Wasserman & Faust, 2009). Cliques are sub-sets of networks, in which actors are more closely connected to each other than they are to other members of the network (Hanneman & Riddle, 2005; Kadushin, 2012). Clusters are subgroups in a network, which have more connected nodes with one another compared to other nodes outside the subgroups (Scott, 2012). Clusters form areas of high density in social networks based on similarity of social behaviors and interactions (Scott, 2012; Schaeffer, 2007). Clustering coefficient measures the degree to which nodes or individuals in a network tend to bond together (Zhou & Wang, 2005).

Network centrality. Centrality is a key factor in social network structure, which is about actors' location in a network and is synonymous with importance and prominence (Wasserman & Faust, 2009). Network centrality is the "relationship

between the centralities of all nodes can reveal much about the overall network structure” (Krebs, 2016, para. 7). But “networks of low centrality fail gracefully” (para. 7). There are different kinds of degree centrality: In-degree and out-degree centrality (for directed ties), degree centrality (for undirected ties), betweenness centrality, and closeness centrality (Krebs, 2016; Wasserman & Faust, 2009).

In-degree and out-degree centrality. In-degree and out-degree centrality measures mean different things in different networks (Freeman, 1979; Kadushin, 2012; Wasserman & Faust, 2009). For instance, in a mutual-tie network, in-degree and out-degree centrality are equal (Wasserman & Faust, 2009). But in a communication network, in-degree centrality is associated with popularity, which deals with the identification of the most active and important actors based on the number of in-coming connections an actor receives in a network (Barnett & Sung, 2006; Freeman, 1979; Kadushin, 2012; Wasserman & Faust, 2009). The actor is more powerful if those in-degree connections are also powerful actors (Kadushin, 2012). Such actors are the recipients of the highest number of incoming links (Wasserman & Faust, 2009). On the other hand, out-degree centrality in such a network denotes less popularity, because the people with highest out-degree centrality scores are the ones who nominate so many people as their friends but those people may not respond mutually (Wasserman & Faust, 2009). In Twitter networks for instance, people with high in-degree centrality are the ones with the highest number of followers and people with high out-degree centrality scores are the ones who follow others. People who heavily follow others on Twitter are the ones who are exposed to tweets from those they follow while those messengers do

not directly see the posts of their followers (Himmelbiom et al, 2013; Himmelbiom et al, 2017; Lieberman, 2014).

At the same time, in a trade relationship between countries, the most powerful countries are the ones with the highest scores for out-degree centrality, because they are the biggest exporters (Wasserman & Faust, 2009). In contrast, countries with the highest in-degree centrality are the biggest importers, which often does not stand for economic power in trade (Wasserman & Faust, 2009).

Degree centrality. Degree centrality is a measure for undirected ties, which is about the number of links or direct connections of a node in a network (Freeman, 1979; Wasserman & Faust, 2009). It deals with the number of opportunities and alternatives a node has compared to other nodes (Hanneman & Riddle, 2005). The actor with the most direct connections in a network is called the hub, who is the most active node of the network, which gives him/her the maximal centrality index (Krebs, 2016; Wasserman & Faust, 2009). Where the connections lead and how they connect the otherwise disconnected are important factors and if a node has so many direct connections with those who are already connected to each, it is not so powerful for the central node (Krebs, 2016). Simply, the number of in-degree and out-degree ties of the nodes suggests that certain actors are more central than others (Hanneman & Riddle, 2005).

Based on Freeman's approach, degree centrality is measured according to in-degree and out-degree and the overall centralization of the graph (Freeman, 1978). But having the same degree does not necessarily make actors equally important (Hanneman & Riddle, 2005). Bonacich (1987) proposed that more connections do not necessarily mean more power for the central node; instead, nodes become more central and

powerful when they are connected to other powerful nodes. A node is central when it has more connections in its neighborhood (Bonacich, 1987). If there are fewer connections in an actor's neighborhood, the actor is more powerful (Hanneman & Riddle, 2005).

$$C_{D(n_i)} = d(n_i) = \sum_j X_{ij} = \sum_j X_{ji}$$

$C_{D(n_i)}$ is the actor level degree centrality index, which indicates the number of lines incident with the node in the graph (in-degree) (Wasserman & Faust, 2009).

Betweenness centrality. Betweenness centrality is number of times a node or an actor acts as a bridge along the shortest path between two other nodes or actors (Krebs, 2016; Wasserman & Faust, 2009). It is about a node having a tie to each node in the network and that there is no third actor involved in between this node and all other nodes – or how likely an individual is to be the most direct route between two people in a network (Hanneman & Riddle, 2005). Nodes that are located between two important constituencies play the brokers' role in the network –connecting to people who are disconnected otherwise (Krebs, 2016). Without such nodes, the ties between important actors will be cut off – affecting the information and knowledge flow from other networks and clusters (Hanneman & Riddle, 2005; Krebs, 2016). “A node with high betweenness centrality has great influence over what flows – and does not – in the network” (para. 5).

$$C_B(n_i) = \sum_{j=i} g_{jk}(n_i)/g_{jk}$$

In the above formula, betweenness centrality equals to sum of the number of geodesic links between that contains I number of actors or nodes, n_i , divided by the number of geodesic links between j and k.

Closeness centrality. Closeness or distance is the average length of the shortest path between a node and all other nodes in a network. When an actor is closer to all nodes compared to other actors, he/she reaches everyone in a network faster than others (Hanneman & Riddle, 2005; Lieberman, 2014). Such nodes have the shortest paths to all other nodes and therefore are closer to everyone (Krebs, 2016). Such positions give these nodes the chance to monitor the information flow in the network, because they have the best visibility in “what is happening in the network” (para. 6). When the number of paths between the central nodes and other nodes goes up, the centrality scores of the central nodes decrease (Wasserman & Faust, 2009). An actor is central when he/she can quickly interact with all other actors in the network (Wasserman & Faust, 2009).

$$C_c (n_i) = \left[\sum_{j=i}^g d(n_i, n_j) \right]^{-1}$$

In the above formula, $d(n_i, n_j)$ is the number of lines in the geodesic linking of actors i and j. And $\sum d(n_i, n_j)$ is sum of distance from all other actors, which is taken over all $j \neq i$ (Wasserman & Faust, 2009).

Network density. Network density deals with interconnectivity among individuals in a network (Himmelboim et al., 2017). It is “a function of pairwise ties between actors or between events,” which is at the heart of a community, social support,

and high visibility (Wasserman & Faust, 2009, pp. 29-315). Density helps with the transmission of information, ideas, rumors, and diseases (Kadushin, 2012). Dense communities are cohesive, good sources of social support, and effective transmitters (Kadushin, 2012). Network density is about the proportion of all possible ties – sum of all ties divided by the number of possible ties. It gives insight about the speed of information flow among nodes, social capital of actors and social constraint (Hanneman & Riddle, 2005).

Network reciprocity. Reciprocity is about whether the relationship between actors are two-way (Lieberman, 2014). It is the ratio of the number of pairs with reciprocal ties with the number of pairs with any ties (Hanneman & Riddle, 2005). Reciprocity is an important factor in directional ties, because one person may have a relationship with another person, but that person may not have the same relationship with him/her (Hanneman & Riddle, 2005). For instance, a Twitter tie is reciprocal when two users follow each other, which will enable both sides to have each other's tweets on their Twitter pages (Lieberman, 2014). In non-directional ties, when person A becomes friend with person B, both of them are connected. Facebook relationships are examples of non-reciprocal ties (Conroy et al., 2012; Reich, 2010; Schwartz, 2015; Xenos et al., 2014).

Homophily in Social Networks

Homophily is an important factor in the structure and flow of information in both offline and online social networks (Kadushin, 2012; McPherson et al., 2001; Valenzuela et al., 2009). Homophily refers to the preference of individuals in building social ties with those individuals and groups whom they have certain similarities (e.g.

race, sex, age, ethnicity, religion, ideology, class, culture, education, geographical location, and so forth) (French et al., 2012; Kwak et al., 2010; Louch, 2000).

Homophily is the tendency of people to connect with those who have similar demographics, ideological, and behavioral characteristics as their own – embedding the folk proposition that “birds of a feather flock together” (Kadushin, 2012; McPherson et al., 2001; Valenzuela et al., 2009). Being in certain social networks and staying away from others networks influences individuals’ personal characteristics and behavioral patterns, because they are only exposed to certain resources and social ties that are not much diverse (Ibarra, 1992). At the individual level, homophily occurs on the basis of ideology, religion, age, sex, race, and so forth, when people group with those who follow the same political view, religious belief from similar age, sex, and race (Lazarsfield & Merton, 1978). At the group level, the definition of homophily depends on whether companies, groups, and organizations are friends or competitors (Kadushin, 2012). For instance, people from different Christian denominations come together under the umbrella of Republican party (Kadushin, 2012).

Political ideology is a prominent factor for homophily in online social networks (Adamic & Glance, 2005; Himelboim et al., 2013; Wojcieszak & Mutz, 2009). Adamic and Glance studied the linking patterns and discussion topics of political bloggers during the last two months before the U.S. 2004 presidential elections. They analyzed top-40 political blogs to explore the degree of interaction between liberal and conservative blogs, and there were differences in the structure of the two communities. They also studied single day snapshots of over 1,000 political blogs. Adamic and Glance found that conservatives were more interconnected and dense compared to

liberals because of linking to each other more than liberals (Adamic & Glance, 2005). Wojcieszak and Mutz (2009) studied how online discussion spaces facilitate exposure to political disagreement among groups in political discourse. They surveyed more than 1000 Americans reporting participation in chat rooms or message. Their findings suggested that cross-cutting political discourse in online groups occurs only incidentally, because politics is not the central purpose of the discussion space. Additionally, religion can also influence individuals' behaviors in social relationships, and religiosity of friends affects people's self-religiosity, which helps in predicting their antisocial behavior (French et al., 2012). Race and ethnicity are other predictors of homophily in online networks although online environment is less dependent on socio-cultural boundaries (Ellison et al., 2007).

Online Social Networks

The Internet and its related technologies have elevated human communication into a new stage –virtual communication – which is based on social networking in the online world (Castells, 2015; Papacharissi, 2002; Katz & Rice, 2002). Formation of online social networks are dependent on users who create their own presence, decide and define how to present themselves in social contexts (Cheung et al., 2011). Online networks play important roles in the formation of ties with strangers in addition to maintaining social relationships among old friends who know each other in real life (Mislove et al., 2007).

Social media are the most dominant and popular platforms for online social networking (Lieberman, 2014; Valenzuela et al., 2009). Social media are used for different purposes such as social interaction, content production, and sharing

information from other sources in addition to social and political gatherings on pages and events (Ankersen, 2015; Himelboim et al., 2013). People widely use tags and hashtags on social media to talk about topics and events around them or the issues (Hansen et al., 2011).

Social media have enabled users to not only connect with friends and acquaintances, but also raise their voices on any issues and ideas they are concerned about (Arceneaux & Weiss, 2010; Himelboim et al., 2013). Facebook and twitter are the top social media for political communication, which have attracted a lot of attention in big political events such elections from politicians, citizens, and the news media (Arceneaux & Johnson, 2013; Castells, 2015; Himelboim et al., 2013; Muralidharan et al., 2011). Donald Trump even claimed that his victory in the U.S. 2016 election was because of his heavy use of Facebook and Twitter (McCormick, 2016).

Facebook was originally developed as social network platform for college students in 2004 and soon became a global phenomenon with more than 1.5 billion users (Conroy, Feezell, & Guerrero, 2012). The structure of relationships on Facebook is in the form of friends, followers, groups, and tags, which help people not only help people connect with each other, but also share their thoughts, reflections, and all kinds of content (e.g. text, photos, videos, graphics, hyperlinks, etc.) with others (Conroy et al., 2012; Reich, 2010; Schwartz, 2015; Xenos et al., 2014). In a comparative study of Facebook users in Australia, U.S. and the UK, Xenos, Vromen, and Loader (2014) found that Facebook use has a strong positive correlation with political engagement.

Twitter as the most popular microblogging medium has become a virtual hub for political discourse (Arceneaux & Weiss, 2010; Himelboim et al., 2013). Twitter has

received an enormous amount of attention of social network analysis scholars, who focus on phenomena such as hashtags, Twitter accounts, brand, public policy, and so forth (Lieberman, 2014). Twitter users have both the Indegree (the people following) and Outdegree (friends the person follows) ties (Lieberman, 2014).

In online social networks, more diverse ties between groups, clusters and cliques, represents tolerance (Caro & Schulz, 2010; Cote & Erickson, 2009; Himelboim et al., 2017). In contrast, dense clusters and groups of homophilious actors who are willing to mainly communicate with those like themselves are evidence for intolerance (Himmelboim et al., 2013; Lieberman, 2014). Himmelboim et al. (2013) studied Twitter networks of 10 controversial political topics during the 2010 midterm election, and discovered several homogeneous clusters of self-connected users based on their political orientations. The content analysis of the tweets of the clusters' members showed that Twitter users are unlikely to be exposed to cross-ideological content. Himmelboim and colleagues found that Democrats and Republicans do not communicate with each other on Twitter on controversial political topics.

Summary

This chapter was an overview of the social networks and social network analysis, and the main factors and features in social networks and online social networks. Social networks are at the core of human relationships and consist of nodes that establish ties and relationships in the forms of cliques, clusters, groups, and communities (Hanneman & Riddle, 2005; Kadushin, 2012; Scott, 2012). Homophily is another factor in social networks that refers to individuals' tendency to build social ties with those like them (Kadushin, 2012; McPherson et al., 2001; Valenzuela et al., 2009).

Online social networks are new phenomena developed with the rise of digital communication technologies, which have played an important role in public political discourse. Similar to offline social networks, online network structures are influenced by factors such as power and previous social relationships and ties, which lead to formation of homophilous and less tolerant groups and clusters in the online world (Himmelboim et al., 2013; Lieberman, 2014). The next section of the literature review restates the research problem, and poses the research questions.

Chapter 5: Research Questions

This dissertation explores the relationship between social media networks and tolerance and intolerance in political discourse during the days surrounding the U.S. 2016 presidential election campaigns. First, this study explores the structure of the social networks, and then, it explores how the discourse on the networks is framed in relation to tolerance (or intolerance).

Literature suggests that communication in social media often occurs in homophilous ways, in which like-minded people stay connected to each other and stay away from those different from them (Gruzd & Roy, 2014; Himelboim et al., 2013; Lieberman, 2014). In political discourse on social media, people of similar ideologies tend to be friends and followers of each other, not of those from opposing camps (Gruzd & Roy, 2014; Himelboim et al., 2013). The problem of this study is whether the network structure of online media contribute to social/political fragmentation.

To study the problem, the first three chapters (after the introduction) explored literature in several relevant areas including sociology, mass communication, political communication, and social network analysis. Chapter 2 was an overview of the shift from mass media to digital media has changed the dynamics of political discourse by empowering citizens to not only take part in political decisions, but also to form virtual political discussion networks (Castells, 2009, 2015; Merrill, 2011). Networked media provide the public with more choices and variety of information anywhere, anytime, and at any platform, which gives more control to consume the kind of media that gratify them (Arceneaux & Johnson, 2013; Castells, 2009, 2011; Lowrey & Gade, 2011a; Sobieraj & Berry, 2011). The empowerment of citizens by the networked media and

abundance of media choices create the opportunity for them to stay in the virtual groups with like-minded people, interact with them, and consume information from like-minded sources (Arceneaux & Johnson, 2013; Gruzd & Roy, 2014; Himelboim et al., 2013). The tendency to interact with people whom one shares certain values, beliefs, and demographics with increases the chance that the people seldom interact with those unlike them (Gruzd & Roy, 2014; Himelboim et al., 2013). Social media as the new communication platforms have increased the chance that people often communicate with close friends and those like them rather than those different from them (Gainous & Wagner, 2014). A new phenomenon that has emerged with the birth of social media is virtual public (political) discourse, a new market place of ideas, in which citizens directly and actively form and participate in important public and political discussions by expressing their ideas with other citizens and political actors (Gruzd & Roy, 2014; Himelboim et al., 2013).

Chapter 3 reviewed literature on free speech and tolerance and intolerance in political discourse in general, and the U.S. political discourse and the 2016 presidential election in particular. Political discourse is a form of public discourse that deals with socio-political issues in a democratic society, which includes public action and reaction, reflection, judgment and commitment toward or against certain issues, events, and actors (Connolly, 1993; Habermas, 1994; Wodak, 1989). Free speech is a key element of democratic rights that allows individuals to communicate their thoughts and opinions without the fear of government and other sources' retaliation or censorship (Akdeniz, 2002; Bhuiyan, 2011; Emerson, 1963; van Mill, 2002). For a democratic political discourse to take place there is a need for a free public sphere where people can freely

demonstrate their ideas and opinions even if those ideas and opinions are controversial (Habermas, 1994; Mill, 1999; Post, 1990). The need for a democratic and free public sphere brings the ideas of free speech and tolerance (Caro, 2011; Gordon, 1993; Mill, 1999; Siebert, Peterson, & Schramm, 1956; Sullivan et al., 1993). Tolerance among citizens creates the sphere for acceptance and respect toward those different from one's self and expand the diversity of ideas and thoughts among individuals and groups (Bezanson, 2012; Caro, 2011; Caro & Schulz, 2010; Drucker & Gumpert, 2009). Tolerance and intolerance have been visible in mediated political discourse during the U.S. presidential elections (Adamic & Glance, 2005; Himmelboim et al., 2013). Online social networks on such political discourse have been polarized in previous elections (Himmelboim et al., 2013; Lieberman 2014; Smith et al., 2014).

Chapter 4 focused on social networks and social network analysis (SNA) as well as key functions and features of online social networks. Social networks have been the foundation of human societies since the beginning of human civilizations, which consists of interconnected relationships between nodes or entities in the form of groups, communities, and so forth (Hanneman & Riddle, 2005; Kadushin, 2012; Scott, 2012; Wasserman & Faust, 2009). Online social networks are pretty much like the offline social networks except for the fact that online communication is not dependent on physical and geographic space (Arceneaux & Weiss, 2010; Blanchard, 2007; Castells, 2003; Ellison et al., 2007; Lieberman, 2014; Mislove et al., 2007; Papacharissi, 2002; Singer, 2005; Valenzuela et al., 2009). Homophily is a factor in online social networks, which is about the tendency of people to stick with the groups and individuals who share values and beliefs as their own (Ellison et al., 2007; French, Purwono, & Rodkin,

2012; Ibarra, 1992; Kwak et al., 2010; Louch, 2000; McPherson, Smith-Lovin, and Cook, 2001; Rogers & Kincaid, 1981; Shalizi & Thomas, 2011). Emphasizing on being close to like-minded people and establishing homophilious networks can improve in-group intolerance against outgroups and decreases tolerance to diversity of thoughts in the online world (French et al., 2012; Kadushin, 2012; Kwak et al., 2010; Louch, 2000; McPherson et al., 2001; Valenzuela et al., 2009). While staying with like-minded people who one already knows can increase in-group ties, it makes the group deprived of better diverse connections and sources of information (Caro & Schulz, 2010; Cote & Erickson, 2009; Ellison et al, 2007; Saito, 2011).

Other topics discussed in chapter four were the main features social network structure such as centrality, density, and reciprocity. Network centrality is about actor's location in the network, which indicates that the powerful actors in a network are the ones with highest number of in-degree ties (Hanneman & Riddle, 2005; Kadushin, 2012; Krebs, 2016). Network density is about the proportion of all possible ties in network, which shows the interconnections between nodes (Hanneman & Riddle, 2005; Kadushin, 2012). Reciprocity refers to whether relationships between nodes are two-way or not (Hanneman & Riddle, 2005; Lieberman, 2014).

To explore the relationship between social media network structure and tolerance and intolerance during the U.S. 2016 election, the research questions are proposed in two different categories. The first category consists of research questions about the network structure and group/cluster structures. The second category of research questions are about the content and relationship of content with network structure.

Social network structure is identified by nodes and edges, centrality or location of actors in the network, direction of ties, and network reciprocity and density (Hanneman & Riddle, 2005; Kadushin, 2012; Wasserman & Faust, 2009). In other words, actors become powerful in a social network based on the number of incoming ties (in-degree connections), direction of connections (betweenness centrality), closeness to all nodes (closeness centrality), and closeness to the most important nodes (Krebs, 2016; Barnett & Sung, 2006; Freeman, 1979; Kadushin, 2012; Wasserman & Faust, 2009). Thus, the following research questions are posed for the Twitter network structure during the 4-day sample on the U.S. 2016 presidential election.

RQ1a: How was the Twitter network structured the day before the U.S. 2016 presidential election?

RQ1b: How was the Twitter network structured on the day of the U.S. 2016 presidential election?

RQ1c: How was the Twitter network structured the day after the U.S. 2016 presidential election?

RQ1d: How was the Twitter network structured four days after the U.S. 2016 presidential election?

Previous studies have found that because of political homophily in online social networks, online discourse takes shape in the form of clusters or groups within a network, in which individuals tend to communicate with like-minded others (Adamic & Glance, 2005; Himelboim et al., 2013; Himelboim et al., 2017; Lieberman, 2014). People group together on the basis of ideology, political opinions, cultural values, and so forth (Hill & Hughes, 1988; Himelboim et al., 2013; Wallace, 2009). In these

clusters, people often talk about issues, events, and individuals by using in-group and out-group frames, which distinguish them from other groups (Adamic & Glance, 2005; Himelboim et al., 2013; Himelboim et al., 2017; McPherson; Mislove et al., 2007; Wojcieszak, 2011). Hence, the following research questions are posed:

RQ2a: The day before the U.S. 2016 presidential election, what were the in-group characteristics of dominant clusters within the network?

RQ2b: On the day of the U.S. 2016 presidential election, what were the in-group characteristics of dominant clusters within the network?

RQ2c: The day after the U.S. 2016 presidential election, what were the in-group characteristics of dominant clusters within the network?

RQ2d: Four days after the U.S. 2016 presidential election, what were the in-group characteristics of dominant clusters within the network?

Online political discourse consists of frames between people in the form of in-group vs. out-group expression of thoughts and opinions (Brandt et al., 2014; Peffley & Rohrschneider, 2003; Yang & Self, 2015). Twitter political discussions often take shape around users' political views and interests, which create the environment for debating against the opposing groups and in favor of one's own group through their tweets, replies, retweets, mentions, and information sharing (Himmelboim et al., 2013; Lieberman, 2014; Meraz, 2009; Tumasjan et al., 2010). The following research questions are on the frames of tolerance and intolerance in the U.S. 2016 presidential election.

RQ3a: The day before the U.S. 2016 presidential election, how was the content framed in terms of tolerance and intolerance in the 10 largest clusters?

RQ3b: On the day of the U.S. 2016 presidential election, how was the content framed in terms of tolerance and intolerance in the 10 largest clusters?

RQ3c: The day after the U.S. 2016 presidential election, how was the content framed in terms of tolerance and intolerance in the 10 largest clusters?

RQ3d: Four days after the U.S. 2016 presidential election, how was the content framed in terms of tolerance and intolerance in the 10 largest clusters?

Staying in like-minded group often decreases tolerance of outgroup individuals, which can result in less involvement in diverse social networks and associations (Cote & Erickson, 2009). In contrast, interacting with diverse groups of people who are different from one's own group increases tolerance in individuals, which can increase one's positive feelings toward out-group people (Caro & Schulz, 2010; Cote & Erickson, 2009; Saito, 2011). Based on social network theory, in-degree, out-degree, and betweenness centrality can explain how the location of certain individuals in social networks make them either foster cross group communication or decrease it (Hanneman & Riddle, 2005; Krebs, 2016; Wasserman & Faust, 2009).

In-degree centrality measures in a communication network, such as conversational networks on twitter, is associated with popularity, which deals with the identification of the most active and important actors based on the number of in-degree connections (Barnett & Sung, 2006; Freeman, 1979; Kadushin, 2012; Wasserman & Faust, 2009). These in-degree connections are established when other people retweet, reply to, or mention these popular users (Hansen et al 2011; Himelboim et al 2017; Lieberman, 2014). In contrast, out-degree centrality in such a network denotes less popularity, because the people with highest out-degree centrality scores are the ones

who retweet or mention others or reply to their tweets (Hansen et al 2011; Himelboim et al 2017). Such users are heavily exposed to tweets from those they follow while those messengers do not directly see the posts of their followers (Himelbiom et al, 2017; Lieberman, 2014). From a tolerance and intolerance point of view, users with higher in-degree centrality might be more tolerant than those with low in-degree centrality, because they are connected with more diverse groups of people compared to users with higher out degree centrality. This is because people with higher out-degree centrality actively choose to communicate with those they want to while those with high in-degree centrality are being chosen (Hansen et al 2011; Himelboim et al 2017). Based on the existing literature, online media users tend to interact with like-minded people more than those different from them (Hansen et al 2011; Himelboim et al., 2013; Lieberman, 2014), which denotes intolerance toward outgroup.

Nodes that are located between two important constituencies have higher score for betweenness centrality and play the broker's role in the network, which makes them powerful (Hanneman & Riddle, 2005; Krebs, 2016). Without such nodes, the ties between important actors will be cut off –affecting the information and knowledge flow from other networks and clusters (Krebs, 2016). Betweenness centrality can predict how tolerant or intolerant people are in their interactions with in-group and out-group people.

Political tolerance includes individuals' interactions with people from different ideological beliefs and backgrounds and respecting them (Cote & Erickson, 2009; Coward, 1986; Yang & Self, 2015), which suggests that such individuals will have higher betweenness centrality acting as a bridge between two otherwise disconnected

nodes or actors (Krebs, 2016; Wasserman & Faust, 2009). Without such nodes, the ties between important actors will be cut off – affecting the information and knowledge flow from other networks and clusters (Hanneman & Riddle, 2005; Krebs, 2016). Considering tolerance and intolerance in relation to degree centrality and betweenness centrality, the following research question is asked.

Closeness or distance is the average length of the shortest path between the node and all other nodes in a network. Actors with higher closeness centrality are closer to all nodes compared to other actors and can reach everyone in the network faster than others (Hanneman & Riddle, 2005; Lieberman, 2014). Closeness centrality enables nodes to monitor the information flow in the network, because they have the best visibility in what is going on in the network (Krebs, 2016). Lower closeness centrality means more distance or paths between the central nodes and other nodes and that the actor cannot interact quickly with other actors in the network (Wasserman & Faust, 2009).

RQ4: What is the association between tolerance and intolerance and measures of network centrality such as in-degree and out-degree, betweenness centrality, and closeness centrality?

Chapter 6: Methodology

This dissertation seeks to explore the relationship between online social network structure and tolerance and intolerance in political discourse on Twitter during the U.S. 2016 presidential election. This multi-method approach is a combination of social network analysis or hyperlink analysis and content analysis. Social network analysis is used to explore the network structures and relationships between Twitter users during the U.S. 2016 election. Content analysis is conducted on the tweets to find evidence for tolerance and intolerance in political discourse during four days around the election, including election day election. Then, the relationships between the network structure of the discourse and the content of the discourse itself are explored. This chapter, first explains the procedures for social network analysis including data collection and sampling. The second part of the chapter focuses on identifying network clusters and the in-group characteristics of the largest clusters in the networks. The third part of this chapter explains the process for content analysis of the tweets and the measures and variables.

Social Network Analysis

The first part of this study is social network analysis, which explores structural relations of online networks (De Maeyer, 2012; Himelboim et al., 2013). Social network analysis for online networks was originally developed for measuring scholarly or academic activities on the web – using regression analyses (ordinary least squares) to measure structural bonding of hyperlinks and characteristics of websites and their actors (Lusher & Ackland, 2011). Online social network analysis is used to examine the structural relationships between individuals and how their positions in the network

affect their attitudes and behaviors (Par, 2003). Using hyperlinks, SNA predicts how the structure of network relations influences individual nodes in online network (Barnett & Sung, 2006; Lusher & Ackland, 2011; Park, 2003). This study analyzes the structural properties of the Twitter networks during four days surrounding the 2016 presidential election. Some of the main concepts that help in understanding the structure of social networks are centralization, density, modularity, and isolates, which are briefly explained in the following section.

Network centralization. Network centralization is an aggregate metric, which describes how centralized a network is (Freeman 1979; Hansen et al 2010). It is “the degree to which the centrality of the most central point exceeds the centrality of all other points” (Freeman, 1979, p. 227). In other words, centralization, as a measure, shows how central the most centralized nodes networks are compared to other nodes (Freeman 1979; Himelboim et al., 2017). Centralization is calculated by dividing the differences between the largest value and every centrality point over the maximum possible sum of differences of “n” points in a network (Freeman 1979). Centralization score ranges from 0 to 1, with 1 indicating the most centralized network and 0 being non-centralized network (Kadushin, 2012; Wasserman & Faust, 2009). A more centralized network has one or a few very central nodes and if these nodes are damaged or taken away, the network will be divided into sub networks (Krebs, 2016). Centralized networks often have many edges coming from a few nodes and spread across the entire networks, which indicate network hierarchy (Hansen et al., 2010; Himelboim et al., 2017). This means that a few people are the hubs in the network who play the role of gatekeepers. In contrast, there is little variation between the number of nodes and edges

in decentralized networks – non-hierarchical (Hansen et al., 2010). Less centralized networks can sustain even if they lose some of their nodes (Krebs, 2016). In-degree centralization means that one or a few nodes in the network receive a lot of connections from many other nodes in the network or have more in-coming ties (e.g. followers, retweets, mentions, replies, etc.) than the rest of the nodes in the network (Freeman 1979; Himelboim et al., 2017). A high out-degree centralization means that one or a few users initiate a large proportion of the links or ties by following, retweeting, mentioning, and replying to others (Himmelboim et al., 2017).

Density. Network density is an aggregate metric that describes the level of interconnectedness in the overall network (Hansen et al., 2010; Himelboim et al., 2017). It is the ratio of the number of observed connections in the network divided by the number of possible connections (Hansen et al., 2010). It is a quantitative measure for showing cohesion, solidarity, and membership among the nodes (Hansen et al 2010). A low density score means loosely connected nodes, and high density score means highly interlinked nodes (Himmelboim et al., 2017). More interconnectivity (greater density) means a higher chance of information exchange and more interaction among users (Hansen et al 2011; Himelboim et al., 2017). Low density can either be a result of “sparse but connected set of users or a network of isolated with a few clustered subgroups of users” (Himmelboim et al., 2017, p .6).

Modularity. Network modularity is a measure of quality of clustering that measures the extent to which nodes within clusters are interconnected with themselves but the clusters are disconnected from other clusters in the network. Modularity measure ranges from 0 to 1 – a 0 modularity meaning the nodes are very divided within

their clusters and 1 meaning the nodes are very unified. Network density and modularity, together, explain how divided or unified a network is. A network with a high density score and low modularity is a single dense group or a unified community. Conversely, a network with low density and high modularity has “a few highly intraconnected clusters that are loosely interconnected” (Himmelboim et al., 2017, p. 4).

Isolates. Isolates are important elements of a network structure, which are users that are not connected to other users in the network (Himmelboim et al., 2017). In Twitter networks, isolates are the users who tweet about a certain topic, but do not mention or reply to others and are not retweeted, mentioned or replied to by others. The proportion of isolates in a network is calculated by dividing the number of isolate users over the total number of users in the network (Himmelboim et al., 2017). The proportion of isolates varies from 0 to 1 – 0 meaning no isolates and 1 meaning a total of divided network.

Research population and sample. The U.S. 2016 presidential election was on Tuesday, Nov. 8. The population of this study includes all of the Tweets related to the U.S. 2016 election on November 7, 8, 9, 12. The current software programs are not able to draw a random sample from the millions of online Tweets; they can only collect a snapshot of the most recent posts or tweets at a specific point of time (Himmelboim et al., 2013). Therefore, the data sampling of this study is not based on traditional sampling methods.

Twitter is a network for conversation based on topic rather than users (e.g., Facebook, YouTube, etc.) and sampling on networks is determined by key search terms (Himmelboim et al., 2013; Himmelboim et al., 2017). For the purpose of this study, the

term “election” was chosen because it is broad enough to be included in almost every political tweet during the days surrounding the election. Also, the term election is neutral and it decreases the possibility that the sampling emphasizes partisanship. The reason for not collecting the sample using partisan terms is because such terms create a degree of homophily just by their names, and if the goal is to see how discourse creates itself organically, then the partisan terms are not the best. It is important to search based on topics instead of hashtags, because not all Twitter users are aware of those hashtags when they post – “a hashtag is announced for planned events, not everyone knows about it” (Hansen et al., 2011, p. 9).

The time frame of this study includes four snapshots: the day before election (November 7, 2016), election day (November 8, 2016), the day after the election (November 9, 2016), and four days after the election (November 12, 2016). The reason for including three other days to the sample’s time frame was to see the differences in political discourse immediately before the election, during the election, and after the election. In other words, people continued talking about election, voting, and election results the days after the election (Berenson, 2016; Bradner, 2016; Tumulty et al., 2016). In addition, the 2016 presidential election was followed by a range of anti-Trump protests across the U.S. that generated an abundance of ongoing election-related public discourse on Twitter, some of which are part of the sample collected after the election day (Ali & Hassan, 2016; Berenson, 2016; Bradner, 2016; Gibbs, 2016; Tumulty et al., 2016). In particular, the reason for including November 12 in the sampling time frame was that this day was the first Saturday after the election with numerous planned protests across the

country (Bradner, 2016; Gibbs, 2016). Therefore, these protests would create additional election-related discourse on social media, in particular Twitter.

At the beginning, it was unclear which time of the day was the most appropriate to draw the sample. Thus, using the term election, five samples of election networks were collected at five different times on November 7, 8, 9, 12. These sample snapshots were collected at 8:00 a.m., 12:00 p.m., 4:00 p.m., 8:00 p.m., and the final minutes of the day (11:50 p.m.) central time. As Table 6.1 shows, in all four days, the samples from 8:00 a.m., 12:00 p.m., 8:00 p.m., and 11:50 p.m. are consistently smaller than the samples from 4:00 p.m. In other words, the snapshots from 4:00 p.m. are consistently the largest throughout the four days. In addition to the consistency in network size, the data at 4 p.m. would capture the discourse from various regions of the country during the day. The 4:00 p.m. sample was used because it had the most election discourse compared to the samples from other times of the four days.

Table 6.1: Twitter Networks in 5 Points of Time Four Days around the Election

	8 a.m.	12 p.m.	4 p.m.	8 p.m.	11:50 p.m.
Nov. 7	6,397 (5 minutes)	4,203 (2 minutes)	7,957 (4 minutes)	7,650 (3 minutes)	1,527 (1 minute)
Nov. 8	1,762 (3 minutes)	491 (1 minute)	13,826 (3 minutes)	4,860 (5.2 minutes)	10,999 (2 minutes)
Nov. 9	3,705 (1 minute)	1,673 (1 minute)	10,402 (4 minutes)	3,823 (2 minutes)	1,247 (6 minutes)
Nov. 12	3,457 (3 minutes)	1,632 (2 minutes)	6,462 (4 minutes)	170 (1 minute)	2,150 (3 minutes)

Note: the minutes in parentheses indicate the amount of time each data set was retrieved via NodeXL

NodeXL. NodeXL software was used for data collection from Twitter. NodeXL is a software program designed as a template in Microsoft Excel, which can retrieve

data from online networks (Hansen et al., 2011). It is a powerful tool for social network analysis not only by importing the structure of the networks created on social media into an excel sheet, but also analyzing and visualization of the data (Fay, 2016; Hansen et al., 2011; Himelboim et al., 2013; Himelboim et al., 2017). NodeXL also includes features for summarizing and manipulating the data (Fay, 2016). It was initially released in 2008 as a free tool for analyzing social media networks, and since 2015, NodeXL Pro has been released with a fee and more features for importing larger data sets (<http://NodeXLcodeplex.com>, 2015). NodeXL Pro can collect up to 20,000 tweets at a time, analyze the structure of social networks, information flow, and the measures and algorithms needed for understanding the networks (Fay, 2016). Also, NodeXL can calculate both general graph metrics of the data (e.g. density, number of components and isolates) and node-specific metrics (e.g. in-degree, out-degree, betweenness, and closeness centrality) (Hansen et al., 2011; Himelboim et al., 2017). Structural factors such as in-degree, out-degree, degree (in undirected networks), betweenness, and closeness centrality help in finding whose posts reach the most users in the network, who are the most active actors in the conversation, who are the peripheral members in the network, and who bridges across the groups in the network (Hansen et al., 2011; Himelboim et al., 2017).

The network data retrieved from Twitter via NodeXL includes tweets, mentions, and replies (Hansen et al., 2011). Public/political discourse on Twitter communication platform often occurs either by retweeting/reposting or sharing other people's posts or mentioning or replying to them (Himelboim et al., 2017). A tweet is a content consisting up to 140 characters including words, mentions, hashtags, pictures, stickers,

emojis, and URLs (Bliss-Carroll, 2016; Himelboim et al., 2013; Himelboim et al., 2017; Pavalanathan & Eisenstein, 2015). A retweet is reposting of a tweet by another Twitter user, which starts with the RT@ sign and the name of the original author (e.g. RT @nytimes, RT @Realdonaldtrump, RT @wikileaks, etc.). A reply is a tweet that is written in response to someone else's tweet, which starts with .@ sign and the receiver's name (e.g. .@Hillary Clinton, .@GlobeEdmonton, etc.).

Phases of Analysis

Analyzing network structure. As mentioned earlier, the first part of this dissertation research is on the overall network structure in the four networks. The overall network structure deals with issues such as network size, edges, centralization, density, modularity, and isolates. NodeXL can calculate all of the above measures except centralization. Network centralization was calculated on UCINET after copying each of the network edge lists from NodeXL into UCINET. UCINET is a software program used widely for social network analysis (Hanneman & Riddle, 2005).

There were a total of 38,647 nodes (or individual users) and 34,800 edges (or connections among nodes) in the entire four-group sample. All of these nodes and edges generated 7,434 tweets, 1,382 replies, 9,817 mentions, and 20,014 retweets, 8,025 of which are unique retweets (See Table 6.2). As shown in Table 2, 22.82 percent of the data was unique content (Tweets and retweets). However, 51.79 percent of the content was duplicate and 25.40 percent of the data were mentions, which made a total 77.19 percent of data.

Table 6.2: Total Population, Nodes, Edges, Tweets, Replies, Mentions, and Retweets

Day	Nodes	Edges	Tweets	Replies	Mentions	Retweets
Nov. 7 Percentage	7,957	7,054	1,550 19.48%	233 2.93%	2,100 26.39%	4,074 51.20%
Nov. 8 Percentage	13,826	12,554	2,966 21.45%	416 3.01%	3,480 25.17%	6,964 50.37%
Nov. 9 Percentage	10,402	9,264	1,839 17.68%	428 4.11%	2,561 24.62%	5,574 53.59%
Nov. 12 Percentage	6,462	5,928	1,079 16.70%	305 4.72%	1,676 25.94%	3,402 52.65%
Total	38,647	34,800	7,434	1,382	9,817	20,014
Percentage			19.24%	3.58%	25.40%	51.79%

Clusters. The second part of network analysis was about identifying the in-group characteristics of the clusters. Applying Wakita-Tsurumi algorithm on NodeXL identifies clusters in each of the four networks (Wakita & Tsurumi, 2007). Wakita-Tsurumi algorithm is an improved version of Clauset Newman Moore (CNM) algorithm, which identifies network clusters by putting members in the clusters that they best fit based on their patterns of interactions and interconnections (Himmelboim et al., 2013). But CNM is designed for small networks while Wakita-Tsurumi algorithm is developed for larger networks (Wakita & Tsurumi, 2007). This method puts the majority of users in a few major clusters and some smaller ones (Himmelboim et al., 2013). As Table 3 shows, there are 13,177 clusters in the entire four-group sample, in which 2,762 clusters belong to the sample on November 7, 5,004 clusters belong to November 8, 3,437 clusters to November 9, and 1,974 clusters belong to the sample on November 12.

In addition to identifying clusters, some calculations were done on Microsoft Excel to find out the type of content in the data. These calculations found that more than

half of the data in all four networks were retweets or duplicates. Duplicate content is the shared information that people repost from other sources without adding or deleting anything in them. Table 6.3 illustrates that on November 7, about 30 percent of the content was unique (26.46 percent tweets and 3.98 percent replies) and 59.56 percent of were retweets, 28.92 percent of which were unique retweets and 40.64 percent were duplicates. This means that from all of the content on November 7, 59.36 percent was unique and 40.46 percent was duplicate. On November 8, about 32 percent of the content was unique (28.67 percent tweets and 4.02 percent replies) and 67.31 percent of it was duplicate, 28.32 percent of which consisted of unique retweets and 38.99 percent duplicate. This means that from all of the content on November 8, 61 percent of them were unique and 39 percent of them were duplicates.

Table 6.3: *Total Nodes, Clusters, Tweets, Replies, Retweets and Unique Tweets*

Day	Clusters	Tweets	Replies	Retweet	Tweets + Replies + Retweets	Unique RTs	Duplicate RTs	Total Sample (Tweets + Replies + Unique RTs)
7-Nov	2,762	1,550	233	4,074	5,857	1,694	2,380	3,477
Percentage		26.46%	3.98%	69.56%	100.00%	28.92%	40.64%	59.36%
8-Nov	5,004	2,966	416	6,964	10,346	2,930	4,034	6,312
Percentage		28.67%	4.02%	67.31%	100.00%	28.32%	38.99%	61.01%
9-Nov	3,437	1,839	428	5,574	7,841	2,122	3,452	4,389
Percentage		23.45%	5.46%	71.09%	100.00%	27.06%	44.02%	55.98%
12-Nov	1,974	1,079	305	3,402	4,786	1,279	2,123	2,663
Percentage		22.54%	6.37%	71.08%	100.00%	26.72%	44.36%	55.64%
Total	13,177	7,434	1,382	20,014	28,830	8,025	11,989	16,841
Percentage		25.79%	4.79%	69.42%	100.00%	27.84%	41.59%	58.41%

On November 9, about 29 percent of the content was unique (23.45 percent tweets and 5.46 percent replies) and 71.09 percent of it were retweets, 27.06 percent of

which were unique retweets and 44.02 percent were duplicates. Thus, from all of the content on November 9, 55.98 percent of them were unique and 44.02 percent of them were duplicates. On November 12, about 29 percent of the content was unique (22.54 percent tweets and 6.37 percent replies) and 71.08 percent of them were retweets, 26.72 percent of which were unique retweets and 43.36 percent were duplicates. Hence, from all of the content on November 12 network, 58.41 percent were unique and 44.36 percent were duplicates.

In sum, more than 58 percent of the content was unique, and more than 41 percent of it was duplicate. This indicates that much of the discourse was shared, retweeted and duplicated without adding any additional content (Himmelboim et al., 2017). Since the goal of this study was to analyze the content of the discourse, the repeated or duplicated content in the network was excluded from the sample – it was not original content or discourse. The focus was on the original content, which was unique and not duplicated. As result, in order to code every tweet (unit of analysis) once, only the unique retweets were included in the sample.

After identifying the network clusters, a general graph metrics of clusters were calculated on NodeXL and then the clusters were ordered in descending order based on the number of Twitter users in each one of them (Himmelboim at al., 2013). NodeXL's algorithm allows the researchers to identify the largest clusters in the entire social network (Hansen et al., 2010). Thus, a sample of the 10 largest clusters from each four-day sample was chosen for analysis. These 10 clusters represented the largest and most active groups in the network with the most nodes and edges, which means they were

most representative of the primary Twitter discourse for the networks sampled (Himmelboim et al., 2013).

The 10 largest clusters made almost 3 percent of the total data and more than 6.7 percent of the unique content in the four-group data. The 40 clusters that contain 1,132 tweets, replies, and unique retweets. As shown in Table 4, there were a total of 269 tweets, replies, and unique retweets in the ten largest clusters on November 7, 377 on November 8, 270 on November 9, and 198 on November 12. From the total of 1,132 tweets, replies, and unique retweets, 18 of them were not in English, which were excluded from the sample and the sample size decreased to 1,114 cases (See Table 6.4).

Table 6.4: Total Tweets, Retweets and Unique Tweets Across Ten Largest Clusters

Clusters	Tweets	Replies	Retweets	Total Tweets + Replies + RTs	Unique RTs	Duplicate RTs	Total (Tweets + replies + Unique RTs)
7-Nov Percentage	46 4.02%	22 1.84%	1077 94.14%	1,144 100.00%	201 17.57%	876 76.57%	269 23.43%
8-Nov Percentage	53 2.70%	42 2.14%	1,869 95.16%	1,964 100.00%	282 14.36%	1,587 80.80%	377 19.20%
9-Nov Percentage	31 2.25%	50 3.63%	1,296 94.12%	1,377 100.00%	189 13.73%	1,107 80.39%	270 19.61%
12-Nov Percentage	33 3.30%	40 4.00%	927 92.70%	1,000 100.00%	125 12.50%	802 80.20%	198 19.90%
Total Percentage	163 2.97%	153 2.79%	5,169 94.24%	5,485 100.00%	797 14.53%	4,372 79.71%	1,114 20.29%

For more details of the original content within each cluster in the 10 largest clusters of each network, see Appendix A.

In order to answer RQ2a-d about the in-group characteristics of the 10 largest clusters of each of the four networks, two sets of analyses were conducted. First, a 3-step method was used to identify in-group and out-group in each cluster by looking at

(1) the most common words, (2) the most common word pairs, and (3) the most retweeted messages.

First, the most frequent words among the tweets in each cluster were selected from the list of 10 words and word pairs calculated on NodeXL. Second, each cluster's main themes were identified based on the 10 words and word pairs, excluding words that did not explain any characteristics of the cluster such as RT, election, news, etc. The third stage included looking at the top retweets in each cluster and finding the patterns that matched the themes and choosing the most appropriate category for the cluster. For instance, in cluster nine of the network from November 8, the top 10 most frequent words were Wikileaks, election, statement, Clinton, Hillary, Julian, campaign, Assange's, and Assange, which gave information about the names and broad topics discussed in the group such as Clinton, Julian Assange, and Wikileaks. Second, the top 10 most frequent words in pairs were: Rt Wikileaks, Clinton campaign, Julian Assange's, Assange's statement, Wikileaks Wikileaks, Wikileaks editor, editor Julian, statement today, today election, and Wikileaks Assange, which indicate the discussion in the group was about Clinton and the editor of Wikileaks, Julian Assange. Third, the top retweets in this cluster were about the release of Clinton's campaign documents by Wikileaks. From this process, the nature of the discourse – that Wikileaks was connected to the Clinton campaign and editor Julian Assange had issued a statement about material the website posted – could be identified. But these procedures could not clear whether the retweets were only on Assange's statement about Clinton or they contained negative frames. For more details about this step, see Appendix B.

This process was helpful, but it did not produce a definitive picture of the network's in-group and out-group characteristics. In other words, the words alone could not help in identifying the in-group, because there were a lot of overlaps between the tweets from Trump's and Clinton's supporters and nonpartisans that the repeated words, word pairs and retweets could not help in identifying as supportive a specific candidate or political ideology. The words and retweets were a mixture of messages from different groups including news media. Thus, another step was added.

Because the first step for identifying the in-group cluster characteristics was not definitive, a second method was used to identify the in-group/out-group in each network. The second set of analysis for clusters' in-group characteristics included coding of tweets (N = 1,114) for positive and negative frames toward the candidates. Framing the tweets produced three categories of Clinton, Trump, and Neither. Each tweet was coded for frames toward the candidate into three categories –positive, negative, and neither.

Positive frames included words such as support, praise, love, happy for victory, respect, hopeful, excited, proud, prayer for favorite candidate, partying for election, congratulating others for their victory (Adamic & Glance, 2005; Andreoni, 1995; Bae & Lee, 2012; Russell & Carroll, 1999; Watson et al., 1988; Wojcieszak, 2011; Wolsko et al., 2000). Negative frames included words and phrases such as hostile, hate, shut up, bigot, guilty, not happy, criticize, upset, not hopeful, afraid, jittery, ashamed, bored, ridiculous, sick, crazy, disappointed, election odds, cannot enjoy life, against the opposing party, upshot, victory, distressed, and nervous (Adamic & Glance, 2005; Andreoni, 1995; Bae & Lee, 2012; Russell & Carroll, 1999; Watson, Clark, & Tellegen,

1988; Wojcieszak, 2011). Neither frames included words and phrases that were neither positive nor negative such as casting vote, watching the election results, reporting facts about election, etc.

After coding for positive, negative, and neither frames, the in-group for each cluster was identified using the following steps. First, the positive tweets for candidate A and the negative tweets for candidate B were summed. Second, the positive tweets for candidate B and the negative tweets for candidate A were summed up. Third, the sums of $(\text{posCandA} + \text{negCandB})$ and $(\text{posCandB} + \text{negCandA})$ were compared, and the candidate with the largest sum was identified as the in-group. For example, Cluster 1 in November 8 network was identified as a Clinton in-group, because in this cluster, the sum of Clinton's positive tweets and Trump's negative tweets was 38 while the sum of Trump's positive tweets and Clinton's negative tweets was 31. If neither of the candidates had a total of 5 tweets (e.g., $\text{posCandA} + \text{negCandB} < 5$), then the cluster was coded as neither (no clear in- or out-group).

Content analysis. The third part of this study was content analysis of tweets. In order to find answers for RQ3a-d about tolerance and intolerance in political discourse on the U.S. 2016 presidential election, a content analysis of the unique content from the largest 10 clusters over a four-day period surrounding the election (40 total clusters) was conducted. Framing is a methodological framework that is widely used for content analysis (Adamic & Glance, 2005; Himelboim & Gleave, 2009; Himelboim et al., 2013; Lewis, Zamith, & Hermida, 2013). Frames are words, adjectives, phrases, concepts, and symbols that are used to describe attributes of issues (Coleman & Banning, 2006; Entman, 1991, 1993). First, frames “prescribe” an issue, then they “define the

problems” based on “common cultural values” and then make “moral judgments” about the problems and suggest “remedies” for them (Entman, 1993, p. 52). Framing is key in “making new beliefs available about an issue, making certain available beliefs accessible,” or making beliefs applicable or “strong” in people’s evaluations” (Chong and Druckman, 2007, p. 111).

Operationalization of tolerance and intolerance. This study sought to explore how tolerance and intolerance in political discourse on Twitter are associated with Twitter network structure. Tolerance and intolerance on Twitter were examined by content analyzing 1,114 tweets from a total of 40 largest clusters from four different networks on November 7, 8, 9, and 12.

Before discussing measures and variables, it is noteworthy to briefly talk about how the codebook was developed. This study was the content analysis of tolerance and intolerance. Previous studies of tolerance have been survey analyses with different measures and variables. As a result, despite drawing a lot of ideas about how tolerance has been defined from the existing literature, these ideas were not definitive for operationalizing the frames to measure the tolerance and intolerance variables. Therefore, using the tolerance literature, the researcher identified definitions for tolerance and intolerance. Some other concepts were derived from legal cases and civic discourse such as democracy, freedom, and so forth. Reading the literature and relevant sources, a list of terms, words, and phrases was identified on tolerance and intolerance. Then, samples of tweets were used to identify how to apply the terms from the literature to the actual tweets. Doing so, several revisions were made in the codebook. The process of developing the codebook also included recoding and refining the codebook,

which took approximately thirty hours over one month. The researcher and her dissertation advisor worked closely in developing the codebook and pre-coding hundreds of tweets from other times of the days from the days in the samples. First, they were coding the tweets together and discussing their thoughts about coding in relation codebook and revising it. Second, they coded sets of 30 to 60 tweets separately three times and compared their coding for reliability until they reached 90.3 percent agreements. Then, the researcher coded all of the tweets (N = 1,114) based on the following operationalization.

Tolerance was defined based on the idea of being willing to accept the ideas, expressions and actions (non-violent) of people who are unlike one's self or whose views differ from one's own (Locke, 1690/1963; Mill, 1861/1999; Sullivan et al., 1979). Thus, tolerance refers to the acceptance of diversity of views, which is beyond the acceptance of in-group views (Locke, 1690/1963; Mill, 1861/1999).

Tolerance was identified in relation to acceptance of broad concepts such as democracy, social justice, equality, diversity, etc. (Locke, 1690/1963; Mill, 1861/1999; Sullivan et al., 1979), which are explained as following.

- **Acceptance of all people** regardless of their demographics (Adamic & Glance, 2005; Andreoni, 1995; Bae & Lee, 2012; Russell & Carroll, 1999; Watson et al., 1988; Wojcieszak, 2011; Wolsko et al., 2000).
- **Acceptance of America as a whole** (Locke, 1690/1963; Mill, 1861/1999).
Example, "Let's vote to better serve our civic duty."

- **Acceptance of those who disagree or reject the communicator's views** (Locke, 1690/1963; Sullivan et al., 1979). Example, "I am a Democrat voting for Trump."
- A tweets was **not coded tolerant** when it contained **frames for acceptance of in-group** or group of which one is expected to agree with. Example: Trump cluster – "I support Trump."
- If attempt at **promotion or persuasion** toward in-group (campaign slogans) was expressed as a broad appeal, then it was coded as **neither**. Examples: "Let's all support Trump to save the 2nd Amendment, Make America Great Again (MAGA), Strong together." In the above examples, "Make American Great Again" or "MAGA" is Trump's campaign slogan and "Strong together" is Clinton's campaign slogan. Even though these phrases seem very tolerant on the surface, they stand for promoting and persuading of people to support and vote a specific political ideology. Therefore, words and phrases like in the above examples were not coded as tolerant.

Intolerance was identified in relation to any group, person, or set of ideas based on the following themes. The reason that coding for intolerant frames included any group and tolerant frames only include the out-group was that people often tend to show intolerance toward anyone that they disagree with. Even though people often express intolerance toward out-group, sometimes they show signs of prejudice and rejection toward their in-group individuals or ideas as well. Whereas, tolerance refers to acceptance of people, ideologies, and values regardless of the notions of in-group and out-group.

- Creating the sense of **us** vs. **them** competition (Hardisty, Johnson, & Weber, 2009; Schubert & Otten, 2002; Shah, Brazy & Higgins, 2004; Powell, Branscombe, & Schmitt, 2005; Tropp & Wright, 2001). Examples, “this is an election of Good vs. Evil,” or “I am sure you will choose hope over fear.”
- **Name calling** (Smith, N.A; Chaplinsky v. New Hampshire, 1942; Snyder v. Phelps, 2011; Teeter & Loving, 2008; Texas v. Johnson, 1989): Calling someone Hitler, Crooked Hillary, stupid, Drump, ghost, corrupt, hipster, criminal, liar, bereaved, ass hole, afraid, evil, zodiac killer, deplorable, immoral, whine, Nazi misogynist president, a bunch of fat-bags; sore losers, and “misled pigs”.
- **Rejecting**: Denying a person, group, ideology, etc. (Locke, 1690/1963; Sullivan et al., 1979). Examples: “Let’s drain the swamp,” “not my president,” “never Hillary,” “I don’t want to hear your opinion,” “vote NO in gun control,” forcing anti-Trump celebrities out the country, “I won’t accept this election,” take someone down, and expressing distrust on someone.
- **Punishing**: Go to jail, imprison, (Smith, N.A; Chaplinsky v. New Hampshire, 1942; Snyder v. Phelps, 2011; Teeter & Loving, 2008; Texas v. Johnson, 1989). Examples, impeach, assassinate, block, “Trump was dropped out of school.”
- **Attacking**: Threatening, warning, display of symbols that arouse anger, and use of fighting words (Snyder v. Phelps, 2011; Smith, N.A; Teeter & Loving, 2008; Texas v. Johnson, 1989).

- **Accusing someone of Corruption:** Rigging, deceiving, lying, suspicion, attempting to fix/manipulate (Snyder v. Phelps, 2011; Smith, N.A; Teeter & Loving, 2008; Texas v. Johnson, 1989). Examples, blowing the election, Dems posing as Republicans, cheating, stealing, slight of hand, gutting the voting rights
- **Cursing/swearing** (Snyder v. Phelps, 2011; Smith, N.A; Teeter & Loving, 2008; Texas v. Johnson, 1989): “F*** Donald Trump,” shame on the candidate/party, “the bitch nigga Trump.”
- **Discriminating:** Expressing prejudice, **disgust** and **hate** on the basis of race, ethnicity, sex, sexual orientation, religion, political ideology (Adamic & Glance, 2005; Bae & Lee, 2012; Coward, 1986; Russell & Carroll, 1999; Wojcieszak, 2011; Wolsko, Park, Judd, & Wittenbrink, 2000; Yang & Self, 2015). Examples, “sick of Dems,” or people of this group are stupid.”
- **Humiliating** (Snyder v. Phelps, 2011; Smith, N.A; Teeter & Loving, 2008; Texas v. Johnson, 1989): “Democrats, people scoff at you,” “Dems sat on their butts and lost,” and “Trump will turn into pumpkin.”
- **Using hashtags:** Hashtags that contain intolerant words. Examples: #nastywoman, #neverhillary, and #Drump
- **Using negative Emojis:** Angr face, thumbs down or dislike, middle finger, crying face
- If protests were **clearly directed toward a specific person or group**, the tweet was coded as **intolerant** (e.g., Hundreds of people took part in a

protests/riots to express anger against Trump, Lady Gaga protests against Trump in front of Trump Tower).

- If protests were reported with **no clear subject and object**, the tweet was coded as **neither** (e.g., Hundreds of protestors took streets after election).

If the tweets did not include expressions of tolerance and intolerance, they were coded as neither.

The coding process included reading the entire tweet including mentions (@words) and hashtags (#words), identifying the subject and the object of the tweet, and traits associated with the object. If the subject had no direct/indirect objects (any person or group), then the traits associated with the subject were coded. If the tweet had more than one sentence (complete or clause), then a) it was coded for the first appearance of tolerance or intolerance, and b) if no tolerance or intolerance in the first clause, the second clause was considered, etc. If tweets had questions in them, they were coded as follows: a) If the whole tweet was a question, it was coded as neither tolerant nor intolerant. Except if subject of the tweet was called names or accused of prejudice, corruption, or deceiving. For example, “All that drama before the election! ? ?Racist Trump close?” If the whole tweet ended with a question, it was coded as neither. But if there was a question with an answer in the tweet, it was coded for the answer. For example, ““Do you know who rigged the election? Nigga Trump, not Hillary” If the tweets could not be understood, they were coded as neither. Example: “While ur following @wikileaks & election duality 24/7 -7th gen prophecy happenin- Elders smoked from Crazy horse,Geroni?”

Inter-Coder Reliability. The researcher coded all the of the tweets (N = 1,114) from the 40 largest clusters based on the number of users in each network and was the primary coder of the content. To ensure a level of consistency in coding and that another researcher would apply the same standards and definitions of the codebook as the primary researcher, an inter-coder reliability test was conducted (Wimmer & Dominick, 2011). Inter-coder reliability measures "the extent to which the different judges tend to assign exactly the same rating to each object" (Tinsley & Weiss, 2000, p. 98). According to Lacy and Riffe (1996), at least 10 percent of the research sample should be re-coded for the reliability test. Therefore, a second coder was trained to recode a random sample of at 10 percent of data (n = 112) of the entire tweets (Himmelboim at al., 2013). In order to test the inter-coder reliability, Cohen's Kappa test was conducted. Cohen's Kappa test measures the agreement between two coders of non-parametric variables while accounting for the likelihood the coders agree by chance; in this way, it is a robust test of multiple coder reliability (Riffe, Lacy & Fico, 2005). Cohen's Kappa coefficient ranges from 0 to 1, and is acceptable at .75 or higher (Wimmer & Dominick, 2011). The Cohen's Kappa coefficient for the tolerance/intolerance variable was .877, which is good.

In order to answer RQ4 about the association between tolerance and intolerance in the Twitter discourse and the network structure, scores from four measure of network centrality (in-degree, out-degree, betweenness, and closeness centrality) were analyzed in relation to framings of tolerance, intolerance, and neither. Before comparing network content with network structure, the network data was normalized, because network data are distributed based on power law, which is like a J-curve rather than a normal curve (Adamic & Huberman, 2000; Barabási & Albert, 1999). Transforming a non-normal

distribution into a normal distribution on SPSS is about making it useful for comparison with data that are normally distributed (Tabachnick, Fidell, & Osterlind, 2006).

According to Tabachnick et al., transformation of data is about making the mean nearly equal to the median, because in skewed distributions, the median is often “a more appropriate measure of central tendency” than the mean (p. 86). There are three different ways of normalizing skewed data: Square root transformation, log transformation, and inverse transformation. Square root transformation is used when the distribution differs moderately from normal. If the distribution substantially differs from normal, a log transformation should be used. If the transformation differs severely from normal (J curve), an inverse transformation should be tried.

All three transformations were conducted for all four centrality measures (in-degree, out-degree, betweenness, and closeness centrality) to find out which one can produce skewness and kurtosis values near zero. Based on Tabachnick et al. (2001), the transformed data in which the median and mean values are very close and have the smallest skewness and kurtosis values should be chosen. Thus, for in-degree centrality, inverse transformation produced the smallest skewness (-.420) and Kurtosis (-1.520) with a mean of 6.6608 and median of 1.0. For out-degree centrality, inverse transformation produced the most normalized distribution – .390 skewness and -1.548 kurtosis, and mean of .7363 and median of 1.0. Log transformation produced the most normalized distribution for betweenness centrality with -1.488 skewness, 7.622 kurtosis, a mean of 4.0432 and a median of 3.9036.

After transforming the data, two-way ANOVA analyses were run to explore the significance of relationships between tolerance and candidate in-group cluster and

network centrality measures: In-degree, out-degree, betweenness, and closeness. Two-way ANOVA compares the mean differences between groups that are split on two independent variables (Tabachnick et al., 2001). A two-way ANOVA analysis also helps in explaining whether there is an interaction between the two independent variables on the dependent variable (Tabachnick et al., 2001). In this analysis, tolerance and cluster were the independent variables and in-degree centrality, out-degree centrality, betweenness centrality, and closeness centrality were the dependent variables. Each of these four centrality measures reveal a node's position within the network structure, which can show the relative importance of nodes within the network. Hence, comparing tolerance and intolerance of a Twitter user with his/her centrality score (position in the network) can help in examining the relationship between Twitter content and network structure. A two-way ANOVA test for tolerance and cluster as IVs and each of the centrality measures as DVs will examine whether there are significant differences among the group means of the four network centrality measures based on tolerance and cluster.

Summary

This chapter was on the methods and procedures of the analyses conducted in this dissertation research. The chapter was mainly divided into three parts. The first part of the chapter focused on how the social network analysis was done in this research, which included details on data collection, sampling, and analyzing the social network data. The second part of the chapter was about clusters and identifying the in-group characteristics of the 10 largest clusters in each of the four networks in the sample, which included sampling and coding for positive, negative, and neither frames in

tweets. The third part of the study was on content analysis of tweets for tolerance and intolerance, which consisted operationalization of tolerance and intolerance and examining the relationship of tolerance and cluster with four measure of network centrality –in-degree, out-degree, betweenness, and closeness.

Chapter 7: Results

This study was a combination of social network analysis and content analysis of political tolerance and intolerance in political discourse on Twitter during the U.S. 2016 presidential election. Using these two methods, this dissertation explored the relationship between social network structure and framing of tolerance and intolerance in political discourse on social media. The digital media have empowered citizens to not only make active decisions about their media use, but also to form political discussion groups independent of traditional media and communicate their thoughts and opinions with others. Despite the opportunities for cross-group communication, studies have shown that users tend to form homophilous communication networks, in which they interact with like-minded people in terms of political orientation (Himmelboim et al., 2013; Liberman et al., 2014).

The time period of the Twitter discourse included four days surrounding the election day (November 7, 8, 9, and 12) in order to explore whether there were differences among the networks before, during, and after the election. A total of 1,114 tweets from 40 largest clusters from the four networks were analyzed to explore the relationship between social network structure and expression of tolerance and intolerance in people's tweets. This chapter presents findings from social network analysis and content analysis answering four sets of research questions. The first part of the results chapter briefly summarizes the finding about the structures of the social networks over a four day-period surrounding the election – answering RQ1a-d. The second part of this chapter answers RQ2a-d about the in-group characteristics of the largest clusters in the networks during this period and the nature of the discourse in

these clusters. In part three of the chapter, RQ3a-2 explored the relationships between tolerant and intolerant content frames in the tweets with the in-group candidate characteristics of the largest clusters. The last part of this chapter answers RQ4 on the association between tolerance, in-group cluster characteristics and four measures of network centrality – in-degree, out-degree, betweenness, and close centrality.

RQ1a-d explored the network structure of the election discourse on Twitter during the four-day period surrounding the election. The following graphs belong to the four networks from the four days surrounding the election, which show the network structures visually.

Figure 7.1: Election Network on Nov. 7

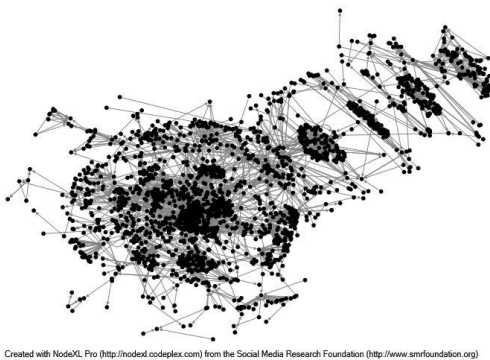


Figure 7.2: Election Network on Nov. 8

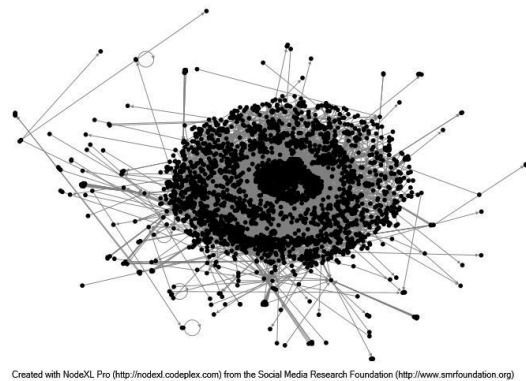


Figure 7.3: Election Network on Nov. 9

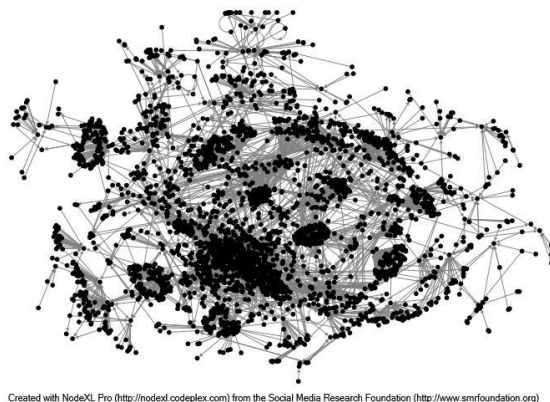
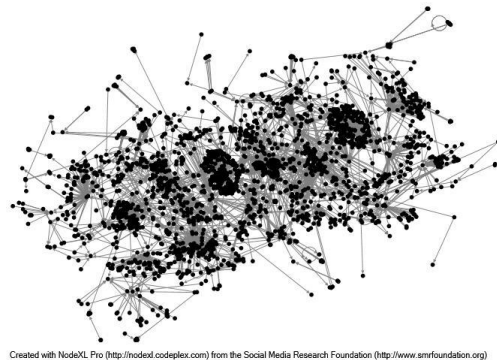


Figure 7.4: Election Network on Nov. 12



RQ1a asked about how was the Twitter network structured on November 7, the day before the U.S. 2016 presidential election. There were a total of 7,959 nodes or vertices, 7,054 edges in the election network on November 7. This means there were 7,959 Twitter users (i.e., nodes) who generated 7,054 ties (6,803 unique and 251 duplicate ties) or Twitter interactions in the form of tweets, retweets, mentions, and replies. A unique edge or tie is created with only one tweet, retweet, mention, or reply between two users, but duplicate edges (number of repeated vertex pairs) are established when there is more than one tweet, retweet, mention or reply between users (Hansen et al., 2010). There were 2,733 connected components in the November 7 network. A connected component is a set of nodes or sub-networks that are connected to each other but are disconnected from the rest of the network (Hanneman & Riddle, 2005; Hansen et al., 201). In other words, a component refers to “the portion of the network that remains intact after removing isolates” (Lee, Kim, & Piercy, 2016, p. 10). A component can contain several clusters (Hanneman & Riddle, 2005; Hansen et al., 201). There were 1,262 isolates or single-vertex connected components that were not connected to any other vertices in the entire network. Moreover, the number of connected components in this Twitter network was twice as the number of isolates, indicating that about two-thirds of the users were connected to at least one other user in the network (see Figure 7.1). As Figure 1 illustrates, the biggest component is in the left side of this network with 2,005 nodes and 2,313 edges, which looks denser and more connected than the rest of the network. The largest connected component contained more than a quarter of the whole network.

As shown in Figure 7.1, the November 7 network was not centralized. Centralization measures the extent to which a social network structure is hierarchical or non-hierarchical (Wasserman & Faust, 2009). In a hierarchical network, one or a few users are extremely more popular than others with the most number of connections (Freeman, 1979; Himelboim et al., 2017). In contrast, in a non-hierarchical network, users' connections are distributed more or less evenly across the network (Wasserman & Faust, 2009). Centralization score ranges from 0 to 1, with 0 being a completely flat and decentralized network and 1 being the most hierarchical and centralized network (Freeman, 1979; Kadushin, 2012; Wasserman & Faust, 2009).

In-degree centralization of the November 7 network was 0.016, meaning the most popular users received 1.6 percent of the overall in-coming connections in the network. This in-degree centralization indicates a low level of hierarchy in the network. Out-degree centralization was also low (0.001), even lower than the in-degree centralization. An out-degree centralization of 0.001 indicates that the most central users initiated 0.1 percent of communication on the total communication connections in form of mentioning, retweeting, and replying. Network density was 0.00008, which showed a low level of interconnectivity among nodes. Considering that network density shows ranges from 0 to 1 (Hanneman & Riddle, 2005; Wasserman & Faust, 2009), a density score of 0.00008 means that 8 out of a 1,000 users were interconnected in this network.

The modularity score in this network was 0.883. Network modularity score ranges from 0 to 1 with 0 indicating no interconnectivity among nodes within clusters and 1 indicating the highest level of interconnectivity among nodes within clusters

(Himmelboim et al., 2017). A modularity score of 0.883 means that 88.3 percent of the users were connected to those within their own clusters, not with nodes from other clusters. A high level of modularity and low level of density, together, indicate that nodes were not interconnected in the network, they were disconnected across clusters, but connected within their own clusters.

Maximum geodesic distance (e.g., diameter) in the network was 24. Geodesic distance is the shortest path between two users (Kadushin, 2012). The maximum geodesic distance is the farthest distance between two users in the network (Wasserman & Faust, 2009). In this network, the average geodesic distance was 9.3, which means that on average, there were more than 9 paths between two nodes in this network. The reciprocity score in this network is 0.001, meaning that Twitter users responded to only 0.1 percent of the total number of tweets in the network. Network reciprocity scores range between 0 and 1 (Hanneman & Riddle, 2005), and a reciprocity of .001 indicates that one of 1,000 tweets drew a response, or interaction. This showed a low level of interaction in the network.

RQ1b asked about the structure of Twitter network on the day of the U.S. 2016 presidential election. On November 8 network, there were 13,826 nodes and 12,554 edges (11,837 unique and 717 duplicate edges). This means that 13,826 Twitter users on the November 8 election network generated 12,554 ties or interactions (e.g., tweets, retweets, mentions, and replies). There were 4,956 connected components or subnetworks and 2,413 isolates in the November 8 network. This means that the network had twice as many connected components as isolates. Figure 7.2 shows that November 8 network was very connected, the largest component located at the center

of the network has 3,678 nodes and 4,376 edges – making a quarter of the whole network. As a result, the network was shaped central and compact and the nodes look interconnected.

Figure 7.2 shows that the November 8 network looks centralized, but the centralization scores were slightly higher than zero in the network. In-degree centralization of the network was 0.059, which suggests that the most popular users in this network received only 5.9 percent of the total in-coming connections (retweets, mentions, and replies). Likewise, out-degree centralization was 0.001, which was 0.1 percent of hierarchy in the network based on out-going ties. In other words, the most central users' retweets, mentions and replies accounted for 1 out of 1,000 connections in the network.

The density of the network was 0.00004, which revealed 0.004 percent interconnectivity in the entire network. This suggests that just 4 of 1,000 users in the network were inter-linked with each other. Modularity score was 0.833 that demonstrates a high level of interconnectivity within clusters. The low density and high modularity scores show the Twitter users were loosely connected in the November 8 network, rarely interacted beyond their clusters, but they were interconnected within their own clusters. The maximum geodesic in the network was 22 and the average geodesic distance was 6.6, indicating that on average, there were more than 6 paths between two nodes in this network and the longest distance was 22 paths between two nodes. The reciprocity score in this network was 0.003, meaning 3 out of 1,000 tweets, or .3 percent, were replied to, revealing a low level of interactivity in the network.

RQ1c asked how was the Twitter network structured the day after the U.S. 2016 presidential election. On November 9, the network had 10,402 nodes, 9,264 edges (8,938 unique and 326 duplicate edges). There were 3,396 connected components and 1,536 isolates in the network, which means that the network had more than twice as many nodes as the number of isolates. As Figure 7.3 shows, the biggest component in this network is located in the lower left side of the network with 2,857 nodes and 3,289 edges.

The in-degree centralization of the network was 0.018, which means 2 percent hierarchy in the network structure based on in-coming ties. In other words, the most central nodes in this network received 1.8 percent of the total in-coming ties in the network –retweets, mentions, and replies. This means that out-degree centralization score was 0.001, which suggests that only 0.1 percent of the popular nodes retweeted, mentioned, and replied to other people’s tweets. This is 1 reply for every 1,000 tweets.

Graph density of the network was 0.00006, which demonstrates that users were only 0.006 percent interconnected with each other across this network. This means that 6 out of 1,000 users were inter-linked in this network. The modularity score in November 9 network was 0.874, which demonstrates high interconnectedness among nodes within clusters. Comparing the low density and high modularity scores shows that the nodes were loosely interconnected across the network, but densely interconnected within clusters. Maximum geodesic distance in the network was 20 – meaning – the longest distance between two nodes was 20 steps or users. The average geodesic distance was 8.3, which suggests that on average, 2 Twitter users were 8 steps far from each other in this network. The reciprocity score in this network was

0.003, which suggests every 3 of 1,000 tweet generated replies (0.3 percent of the total content in the network).

RQ1d asked how was the Twitter network structured 4 days after the U.S. 2016 presidential election. In the election network on November 12, there were 6,462 nodes 5,928 edges (5,664 unique and 264 duplicate edges). There were 1,937 connected components and 845 isolates in the November 12 network suggesting that the network nearly 2.5 as many connected nodes as isolates. Figure 7.4 demonstrates that the largest component is spread across the central areas on the network with 2,317 nodes and 2,669 edges, which includes nodes from more than four clusters. In-degree centralization of the network was 0.033, which indicates that the most central nodes received 3.3 percent of in-coming connections such as retweets, mentions, and replies – not hierarchical. At the same time, out-degree centralization was 0.001, which means that only 0.1 percent out-going ties were started by the most central nodes in the network. Network density was 0.0001, which demonstrates 0.01 percent of interconnectivity among nodes across the network. This also mean that 10 out of 1,000 users in this network were interconnected with each other. Modularity score were 0.871 that shows the clusters were disconnected from each other, but the nodes were interconnected within the clusters. Such a low density score and high modularity score indicate that the nodes were loosely interlinked in the network and clusters disconnected from each other, but cluster members were interrelated within themselves. The maximum geodesic distance (diameter) in the network was 24 and the average geodesic distance was 8.97, which suggests that on average, there were about 9 paths between two nodes in this network and the longest distance between two nodes

was 24 steps. The reciprocity score in this network was 0.005, indicating that 5 out of 1,000 tweets were replied to, which makes 0.5 percent of the total communication in the network.

Compare and Contrast the Four Networks

Before comparing and contrasting the four networks, it is noteworthy to mention that the comparisons between network structures were based on descriptive differences and similarities among the networks (See Table 7.1).

As Table 7.1 shows, there were similarities between the four networks in the four days around the election, including the election day. In all four networks in-degree centralization was low and non-hierarchical and out-degree centralization was lower than in-degree centralization. Also, density scores were low in all four networks while the modularity scores were high. Maximum and average geodesic distance scores were similar across the network. Reciprocity was also low in all four networks.

Despite the similarities between the four networks, there were patterns in the data across the four days in terms of networks size, connectedness, centralization, density, geodesic distance, and density. These patterns showed how the networks changed over the four days surrounding the election.

The network on November 8 was the biggest network in terms of number of nodes (13,826) and edges (12,554) followed by November 9 (10,402 nodes and 9,264 edges), November 7 (7,957 nodes and 7,054 edges), and November 12 (6,462 nodes and 5,928 edges). Accordingly, the differences in the network size impacted the sizes of components, isolates, and levels of density in the four networks. Like the network size, number of connected components was bigger on November 8 and 9 compared to

November 7 and 12. Similarly, the number of isolate nodes was larger in November 8 and 12 network than November 7 and 9 networks (See Table 7.1).

The density scores were low in all four networks, which indicates that nodes in all four networks were loosely interconnected. November 12 network had slightly higher density score (0.0001) among the four networks followed by November 7 (0.00008), November 9 (0.00006) and November 8 (0.00004) networks. There were differences in density scores because nodes in bigger networks are often loosely connected to each other than they in smaller networks – as a network gets smaller, it becomes denser (Hanneman & Riddle, 2005). This being said, because November 8 network is the biggest among the four networks and it has lower density score than November 12, 7, and 9 networks.

The differences in the density scores among the four networks also mean that there were more interactions among Twitter users in November 12 network compared to other three networks; November 8 network – election day – was the least interconnected network among the four. This indicates that on November 12 and other days surrounding the election, people were more interconnected compared to the day of election. Even though the network size on November 8 was bigger than the other three days, the users were less interconnected with each other in this network compared to other three networks (low density).

Although centralization scores were low in all of the four networks, the network on November 8 had the highest centralization score (0.059) followed by November 12 (0.033), November 9 (0.018), and November 7 (0.016). Looking at Figure 7.2, the election network on November 8 looks more central compared to the other three

networks. This means that the network on November 8 was more hierarchical – more structured around a few key users – than the other three networks. These central users were the candidates (Trump and Clinton), news media (CNN, *The Washington Post*, and *The New York Times*), high profile politicians (Bernie Sanders and Mike Pence), candidate’s family members (e.g., Donald Trump Jr. and Eric Trump), celebrities (Bill Mitchel and Lady Gaga), and WikiLeaks.

Table 7.1: Network Structures on November 7, 8, 9, and 12

Network	Vertices	Total Edges	Unique Edges	Edges With Duplicates	Connected Components	Isolates or Single-Vertex Connected Components	Maximum Vertices in a Connected Component	Maximum Edges in a Connected Component	In-degree Centralization	Out-degree Centralization	Density	Modularity	Maximum Geodesic	Average Geodesic Distance	Reciprocity
Nov. 7	7,957	7,054	6,803	251	2,733	1,262	2,005	2,313	0.016	0.001	0.00008	0.883	24	9.33	0.001
Nov. 8	13,826	12,554	11,837	717	4,956	2,413	3,678	4,376	0.059	0.001	0.00004	0.833	22	6.67	0.003
Nov. 9	10,402	9,264	8,938	326	3,396	1,536	2,857	3,289	0.018	0.001	0.00006	0.874	20	8.36	0.003
Nov. 12	6,462	5,928	5,664	264	1,937	845	2,317	2,669	0.033	0.001	0.0001	0.871	24	8.97	0.005

The modularity scores were high in all four networks starting from November 7 (0.883) followed by November 9 (0.874), November 12 (0.871), and November 8 (0.833). The high modularity scores indicate the existence of highly disconnected clusters in all four networks. This can also mean that clusters on different topics were very disconnected from each other even if they supported the same candidate. The election network on November 8 had the lowest modularity score among the four networks, which means there were more cross-group interactions among clusters in this network compared to other three networks.

There were some patterns in the geodesic distance and reciprocity across the four network. The average geodesic distance on November 7 was high, it got smaller on

November 8, increased on November 9, and again decreased on November 12. The average geodesic distance in the November 8 network was the smallest (6.67) among the four networks. November 8 election network reveals that users were closer together on the election day than on other three days. This means that on average there were of six nodes (or users) between the two users in November 8 network. This is what social network scholars have called six degrees of separation (Travers & Milgram, 1967; Watts, 2004). Milgram (1967) was the first researcher who conducted a study called “The Small World Problem,” which found that in any given country, it only takes six steps of acquaintances for a resident to know another resident. This also suggest that people live in clusters, which facilitate the linkage among them and makes it easy to connect them to each other even without their awareness (Barabasi, 2002). Kwak et al. (2010) found that the average distance between two users on Twitter is 4 paths. The finding of this study is different from Kwak and colleagues in that the average geodesic distances in the four networks range between 6 to 9 steps.

Overall, reciprocity was very low in all of the four networks, but November 7 network had the lowest reciprocity (0.001), followed by November 8 (0.003), 9 (0.003), and 12 (0.005) networks. November 7 revealed the lowest level of reciprocity, suggesting that on the day before the election people in the network were either following election news or expressing their own views, as opposed to responding or interacting with others. The networks on November 8 and 9 had the same levels of reciprocity, which suggest that people were replying to others’ tweets on the election day and the day after in similar manner. However, the higher reciprocity on November 12 indicates that people were more interactive in their Twitter communication after the

election compared to time before the election. Reciprocity might be low due to the structure of the platform, because Twitter is a medium of the moment and the Twitter networks are conversational. It might also be due to the time frame of the data collection (1-5 minutes).

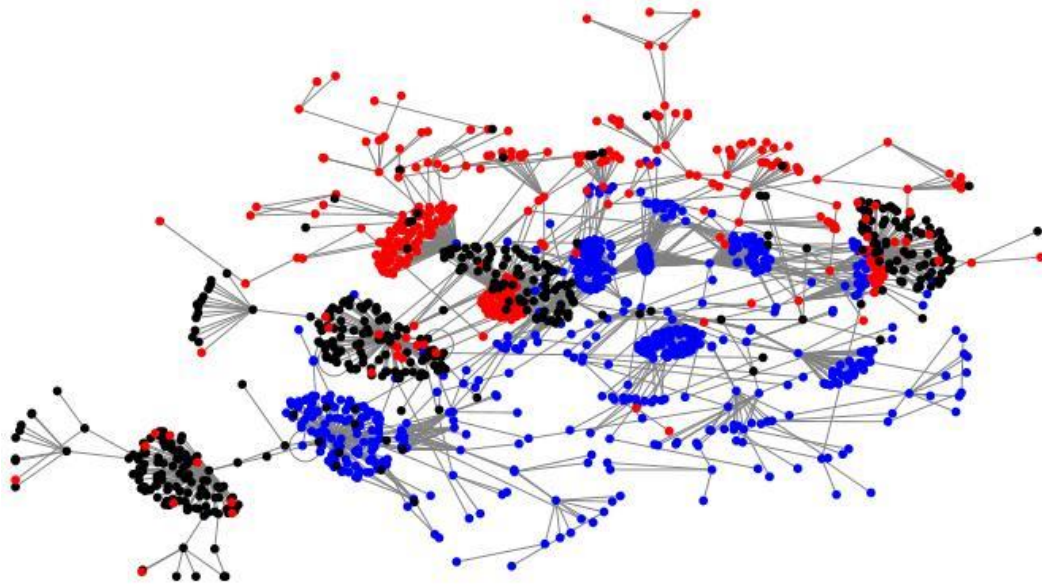
RQ2a-d asked about the candidate in-group characteristics of each of the 10 largest clusters for the four days sampled. To do this, two sets of analyses were used. First, a 3-step method was used to identify candidate in-group in each cluster by looking at (1) the most common words, (2) the most common word pairs, and (3) the most retweeted messages in the cluster. The 3-step process could help in identifying the candidates and topics discussed in the clusters, but it was not able to identify how these topics were framed and which candidates were primarily supported or not in the tweets. The repeated words, word pairs and retweets overlapped in most clusters, which made it confusing to decide which candidate or political ideology was dominant in a specific cluster (See Appendix B).

Because the first set of analyses was not useful in identifying the in-group and out-group of clusters, the second analysis of clusters included coding of all tweets (n = 1,114) for positive, negative and neither frames toward each candidate and neither of the candidates. Positive tweets included frames in support for the candidate, the political party, or campaign. Negative tweets included frames against the candidate, the political party, or issues related to the political ideology. Neither tweets included those in which the subject or topic of the tweets did not include either candidate or the frame of the tweets did not reflect positively or negatively toward either candidate.

After coding for positive, negative, and neither frames, the in-group for each cluster was identified by summing up the positive tweets of Clinton with negative tweets of Trump and positive tweets of Trump with negative tweets of Clinton. If the sum of Clinton's positive tweets and Trump's negative tweets was more than the sum of Trump's positive tweets with Clinton's negative tweets, Clinton was identified as the in-group for the cluster. If the sum of Trump's positive tweets with Clinton's negative tweets was more than Clinton's positive tweets and Trump's negative tweets, the cluster was identified as Trump in-group. If the sum of neither candidate's positive tweets with the opposing candidate's negative tweets was more than 5, the clusters was identified as neither. The following section briefly explains the in-group characteristics of each of the 10 largest clusters in the four networks on November 7, 8, 9, and 12.

RQ2a asked about the in-group characteristics of dominant clusters within the network the day before the U.S. 2016 presidential election. There were 269 original tweets in the 10 largest clusters in November 7 network. After analyzing the tweets for positive, negative, and neither frames and comparing the sums of positive tweets of one candidate with the negative tweets of the other candidate, 3 clusters were identified as Clinton in-group, 3 as Trump in-group, and 4 as neither. Figure 7.5 illustrates the 10 clusters based on their in-group characteristics, in which blue stands for Clinton's clusters, red for Trump's clusters and black for neither clusters.

Figure 7.5: The 10 Largest Clusters from Nov. 7 Network Colored based on Political Ideology



Created with NodeXL Pro (<http://nodexl.codeplex.com>) from the Social Media Research Foundation (<http://www.smrfoundation.org>)

In cluster 1 (the largest cluster) in the November 7 network there were 77 original tweets. This cluster was identified as Clinton in-group, because the sum of Clinton’s positive tweets and Trump’s negative tweets (Clinton positive + Trump negative) was 37 tweets, which was higher than the sum of positive tweets about Trump and the negative tweets about (Clinton Trump positive + Clinton negative), 21 tweets. As Table 7.2 shows, a total of 19 tweets were neither positive nor negative toward the two candidates.

Table 7.2: Cluster1: Clinton

	Positive	Negative	Neither	Total
Trump	11	14	1	26
Clinton	23	10	2	35
Neither	2	3	11	16
Total	36	27	14	77

The results of the next nine largest clusters in November 7 network are summarized in the following bullet points. The number of original tweets in each cluster is noted parenthetically:

- Cluster 2: Clinton in-group (n = 66); Clinton positive + Trump negative = 21; Trump positive + Clinton negative = 10; neither = 35
- Cluster 3: Clinton in-group (n = 33); Clinton positive + Trump negative = 6; Trump positive + Clinton negative = 2; neither = 25
- Cluster 4: Neither in-group (n = 8); Clinton positive + Trump negative = 1; Trump positive + Clinton negative = 0; neither = 7
- Cluster 5: Trump in-group (n = 15); Clinton positive + Trump negative = 2; Trump positive + Clinton negative = 8; neither = 5
- Cluster 6: Neither in-group (n = 5); Clinton positive + Trump negative = 1; Trump positive + Clinton negative = 0; neither = 4
- Cluster 7: Trump in-group (n = 36); Clinton positive + Trump negative = 6; Trump positive + Clinton negative = 14; neither = 16
- Cluster 8: Neither in-group (n = 7); Clinton positive + Trump negative = 1; Trump positive + Clinton negative = 0; neither = 6
- Cluster 9: Trump in-group (n = 21); Clinton positive + Trump negative = 0; Trump positive + Clinton negative = 11; neither = 10
- Cluster 10: Neither in-group (n = 1); Clinton positive + Trump negative = 0; Trump positive + Clinton negative = 0; neither = 1

As shown on Table #, from the 10 largest clusters about election on November 7, the day before the election, three Clinton in-group, three Trump in-group, and four

neither in-group clusters emerged. For the three Clinton in-group clusters, there were 64 tweets that identified her as the in-group (the sum of Clinton positive + Trump negative in the three clusters). There were also 33 tweets that were not positive toward Clinton (sum of Trump positive and Clinton negative in these clusters). There were 79 tweets in these Clinton in-group clusters that identified neither candidate as the in-group.

Table 7.3: In-group Characteristics in the 10 Largest Clusters of November 7 Network

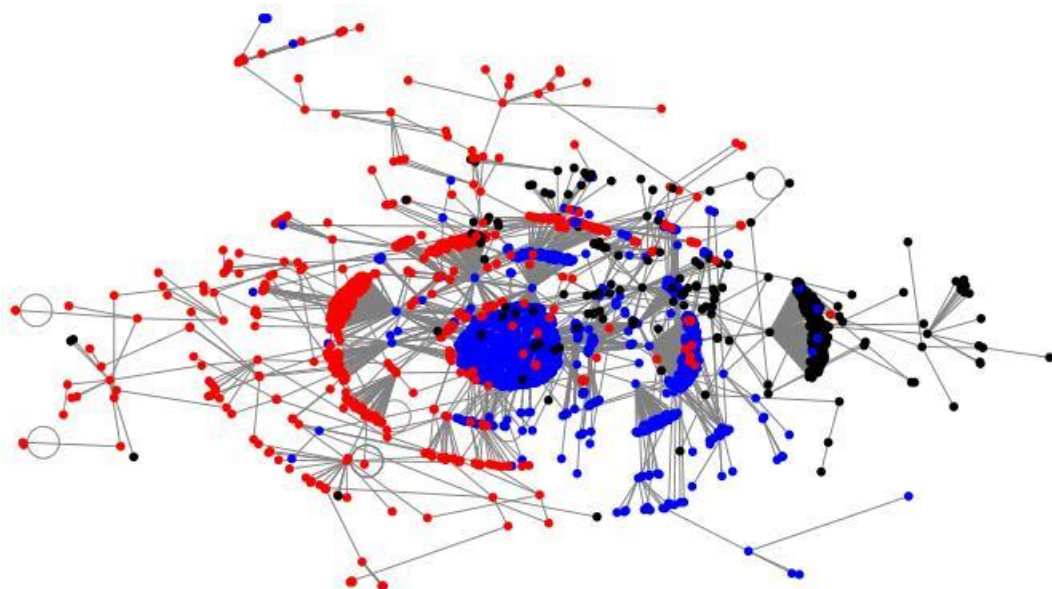
	Clinton positive +	Trump positive +		
	Trump negative	Clinton negative	Neither	Total
Clinton	37	21	19	77
	21	10	35	66
	6	2	25	33
	64	33	79	176
Trump	2	8	5	15
	6	14	16	36
	0	11	10	21
	8	33	31	72
Neither	1	0	7	8
	1	0	4	5
	1	0	6	7
	0	0	1	1
	3	0	18	21
Total	75	66	128	269

As shown on Table 7.4, in the three Trump in-group clusters, there were 33 tweets that identified Trump as in-group (sum of Trump positive and Clinton negative in these clusters) and 8 tweets were not positive toward him (the sum of Clinton positive +

Trump negative in the three clusters). There were 31 tweets in these clusters that were about neither of the candidates. In the three neither clusters, the sum of Clinton's positive and Trump's negative tweets was 3 and sum of Trump's positive and Clinton's negative tweets was zero. In these clusters, 18 tweets identified neither of the candidates as in-group.

RQ2b asked about in-group characteristics of the dominant clusters within the Twitter network on the day of the U.S. 2016 presidential election. There were 377 original tweets in the 10 largest clusters of November 8 network. The framing analysis for positive, negative, and neither frames revealed three clusters as Clinton in-group, 5 as Trump in-group, and 2 as neither. Figure 7.6 shows the in-group characteristics of clusters in different colors, in which blue stands for Clinton in-group clusters, red for Trump in-group clusters, and black for neither clusters.

Figure 7.6: The 10 Largest Clusters Colored in November 8 Network



Created with NodeXL Pro (<http://nodexl.codeplex.com>) from the Social Media Research Foundation (<http://www.smrfoundation.org>)

The results of the 10 largest clusters' in-group characteristics are presented in the below bullet points, in which the total number of original tweets are written in parentheses.

- Cluster 1: Clinton in-group (n = 99); Clinton positive + Trump negative = 38;
Trump positive + Clinton negative = 31; neither = 30
- Cluster 2: Neither in-group (n = 17); Clinton positive + Trump negative = 3;
Trump positive + Clinton negative = 2; neither = 12
- Cluster 3: Clinton in-group (n = 45); Clinton positive + Trump negative = 14;
Trump positive + Clinton negative = 3; neither = 28
- Cluster 4: Trump in-group (n = 25); Clinton positive + Trump negative = 1;
Trump positive + Clinton negative = 18; neither = 6
- Cluster 5: Trump in-group (n = 34); Clinton positive + Trump negative = 3;
Trump positive + Clinton negative = 10; neither = 21
- Cluster 6: Trump in-group (n = 32); Clinton positive + Trump negative = 2;
Trump positive + Clinton negative = 14; neither = 16
- Cluster 7: Trump in-group (n = 28); Clinton positive + Trump negative = 1;
Trump positive + Clinton negative = 13; neither = 14
- Cluster 8: Neither in-group (n = 34); Clinton positive + Trump negative = 2;
Trump positive + Clinton negative = 1; neither = 31
- Cluster 9: Trump in-group (n = 30); Clinton positive + Trump negative = 4;
Trump positive + Clinton negative = 12; neither = 14
- Cluster 10: Clinton in-group (n = 33); Clinton positive + Trump negative = 11;
Trump positive + Clinton negative = 1; neither = 21)

From the 10 largest clusters about election on November 8, the election day, three clusters were identified as Clinton in-group, five clusters as Trump in-group, and two clusters as neither. In the three Clinton in-group clusters, 63 tweets were recognized as Clinton in-group (the sum of Clinton positive + Trump negative in the three clusters). In these three clusters, 33 tweets were not positive toward Clinton (sum of Trump positive and Clinton negative in these clusters). There were 79 tweets that identified neither candidate as the in-group in these Clinton in-group clusters.

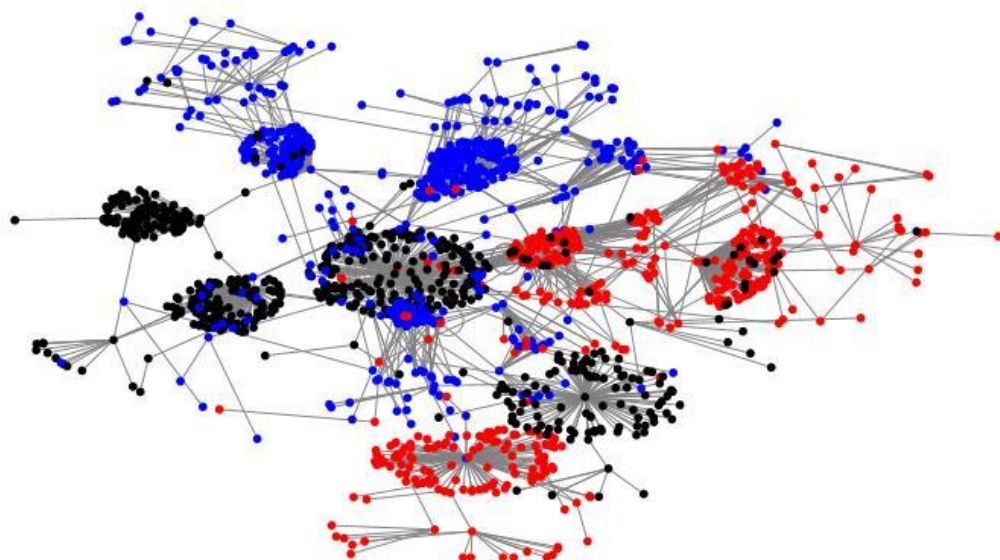
Table 7.4: In-group Characteristics in the 10 Largest Clusters of November 8 Network

	Clinton positive + Trump negative	Trump positive + Clinton negative	Neither	Total
Clinton	38	31	30	99
	14	3	28	45
	11	1	21	33
	63	35	79	177
Trump	1	18	6	25
	3	10	21	34
	2	14	16	32
	1	13	14	28
	4	12	14	30
	11	67	71	149
Neither	3	2	12	17
	2	1	31	34
	5	3	43	51
Total	79	105	193	377

As shown on Table 7.5, in the five Trump in-group clusters, 67 tweets identified Trump as in-group (sum of Trump positive and Clinton negative in these clusters) and 11 tweets were not positive toward him (the sum of Clinton positive + Trump negative in the three clusters). In these five clusters, 71 tweets recognized neither of the candidates as in-group. In the two neither clusters, the sum of Clinton positive and Trump negative were 5 tweets and sum of Trump positive and Clinton negative was 3. In these clusters, 43 tweets identified neither of the candidates as in-group.

RQ2c asked about in-group characteristics of the dominant clusters within the network the day after the U.S. 2016 presidential election. In the 10 largest clusters in November 9 network, there were 270 original tweets. The analysis of positive, negative, and neither frames in these tweets revealed that there were 3 in-group clusters for Clinton, 3 for Trump, and 4 for neither. The clusters' in-group characteristics are shown in figure 7.7 in three colors – blue for Clinton in-group clusters, red for Trump in-group clusters, and black for neither clusters.

Figure 7.7: The 10 Largest Clusters Colored in November 9 Network



Created with NodeXL Pro (<http://nodexl.codeplex.com>) from the Social Media Research Foundation (<http://www.smrfoundation.org>)

The findings for in-group characteristics of clusters are summarized in bullet points below, and the total number of original tweets in each cluster are written in parentheses.

- Cluster 1: Clinton in-group (n = 67); Clinton positive + Trump negative = 22;
Trump positive + Clinton negative = 19; neither = 26
- Cluster 2: Trump in-group (n = 84); Clinton positive + Trump negative = 25;
Trump positive + Clinton negative = 38; neither = 21
- Cluster 3: Neither in-group (n = 3); Clinton positive + Trump negative = 3;
Trump positive + Clinton negative = 0; neither = 0
- Cluster 4: Clinton in-group (n = 34); Clinton positive + Trump negative = 21;
Trump positive + Clinton negative = 5; neither = 8
- Cluster 5: Neither in-group (n = 4); Clinton positive + Trump negative = 3;
Trump positive + Clinton negative = 0; neither = 1
- Cluster 6: Clinton in-group (n = 49); Clinton positive + Trump negative = 21;
Trump positive + Clinton negative = 14; neither = 14
- Cluster 7: Trump in-group (n = 10); Clinton positive + Trump negative = 1;
Trump positive + Clinton negative = 8; neither = 1
- Cluster 8: Trump in-group (n = 12); Clinton positive + Trump negative = 3;
Trump positive + Clinton negative = 8; neither = 1
- Cluster 9: Neither in-group (n = 5); Clinton positive + Trump negative = 3;
Trump positive + Clinton negative = 0; neither = 2
- Cluster 10: Neither in-group (n = 2); Clinton positive + Trump negative = 1;
Trump positive + Clinton negative = 1; neither = 0

Table shows that of the 10 largest clusters about election on November 9 network, the day after election, three clusters recognized Clinton as in-group, three clusters Trump as in-group, and four clusters neither of them as in-group. In the three Clinton in-group clusters, 64 tweets identified Clinton as the in-group (the sum of Clinton positive + Trump negative in the three clusters). In these Clinton clusters, 38 tweets were not positive toward her (sum of Trump positive and Clinton negative in these clusters). There were 48 tweets that recognized neither candidate as the in-group.

Table 7.5: In-group Characteristics in the 10 Largest Clusters of November 9 Network

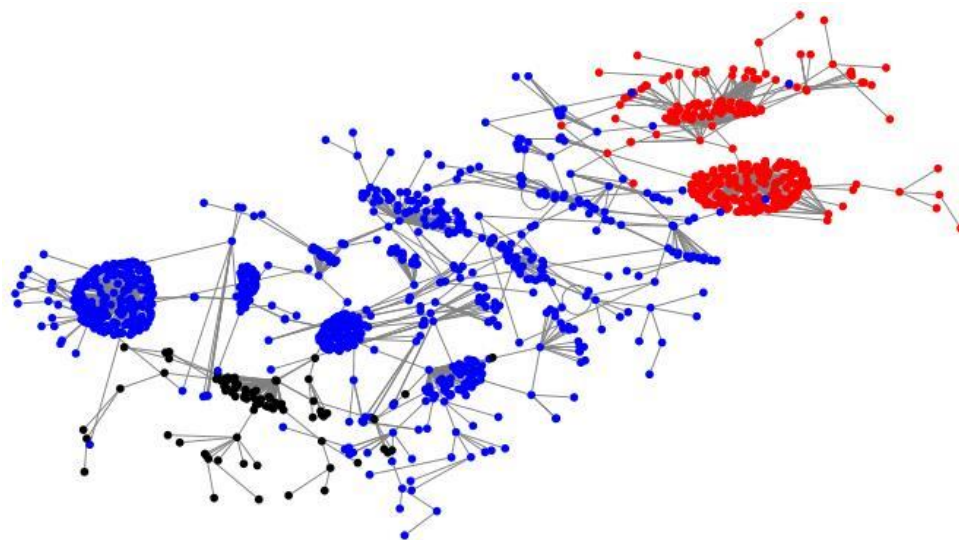
	Clinton positive + Trump negative	Trump positive + Clinton negative	Neither	Total
Clinton	22	19	26	67
	21	5	8	34
	21	14	14	49
	64	38	48	150
Trump	25	38	21	84
	1	8	1	10
	3	8	2	12
	29	54	24	106
Neither	3	0	0	3
	3	0	1	4
	3	0	2	5
	1	1	0	2
	10	1	3	14
Total	103	93	75	270

In the three Trump in-group clusters, 54 tweets were identified as Trump in-group (sum of Trump positive and Clinton negative in these clusters) and 25 tweets were not

positive toward him (the sum of Clinton positive + Trump negative in the three clusters). In these Trump clusters, 27 tweets identified neither of the candidates as in-group. The four neither clusters had a total of 14 tweets, 10 of which were positive toward Clinton (Clinton positive + Trump negative), one was positive toward Trump (Trump positive + Clinton negative), and 3 of them identified neither of the candidates as in-group.

RQ2d asked about in-group characteristics of the dominant clusters within the Twitter network four days after the U.S. 2016 presidential election. There were 198 original tweets in the 10 largest clusters on the November 12 network. Analyzing these tweets for positive, negative, and neither framed revealed 7 clusters as Clinton in-group, 2 as Trump in-group, and 1 as neither. Again, in Figure 7.8, the ten clusters are shown in three different colors according to their in-group characteristics – blue for Clinton in-group, red for Trump in-group, and black for neither clusters.

Figure 7.8: The 10 Largest Clusters Colored in November 12 Network



Created with NodeXL Pro (<http://nodexl.codeplex.com>) from the Social Media Research Foundation (<http://www.smrfoundation.org>)

The findings of the analysis for positive, negative, and neither frames in the 10 largest clusters on November 12 are briefly reported in the below bullet point, in which the total number of original tweets in each cluster is stated in parentheses.

- Cluster 1: Clinton in-group (n = 9); Clinton positive + Trump negative = 7;
Trump positive + Clinton negative = 0; neither = 2
- Cluster 2: Trump in-group (n = 9); Clinton positive + Trump negative = 0;
Trump positive + Clinton negative = 7; neither = 2
- Cluster 3: Clinton in-group (n = 18); Clinton positive + Trump negative = 6;
Trump positive + Clinton negative = 4; neither = 8
- Cluster 6: Trump in-group (n = 42); Clinton positive + Trump negative = 13;
Trump positive + Clinton negative = 25; neither = 4
- Cluster 5: Clinton in-group (n = 25); Clinton positive + Trump negative = 12;
Trump positive + Clinton negative = 8; neither = 5
- Cluster 6: Clinton in-group (n = 10); Clinton positive + Trump negative = 5;
Trump positive + Clinton negative = 2; neither = 3
- Cluster 7: Clinton in-group (n = 34); Clinton positive + Trump negative = 9;
Trump positive + Clinton negative = 7; neither = 18
- Cluster 8: Clinton in-group (n = 25); Clinton positive + Trump negative = 12;
Trump positive + Clinton negative = 8; neither = 4
- Cluster 9: Neither in-group (n = 17); Clinton positive + Trump negative = 6;
Trump positive + Clinton negative = 6; neither = 5
- Cluster 10: Clinton in-group (n = 9); Clinton positive + Trump negative = 6;
Trump positive + Clinton negative = 1; neither = 2

As shown on Table 7.6, from the 10 largest clusters about election on November 12, our days after the election day, six clusters were identified as Clinton in-group, two clusters as Trump in-group, and two clusters as neither of the candidate's in-group. In the six Clinton in-group clusters, 52 tweets identified her as the in-group (the sum of Clinton positive + Trump negative in the three clusters). In these six clusters, there were 26 tweets that were not positive toward Clinton (sum of Trump positive and Clinton negative in these clusters). Also, 43 tweets identified neither of the candidates as their in-group.

Table 7.6: In-group Characteristics in the 10 Largest Clusters of November 12 Network

	Clinton positive + Trump negative	Trump positive + Clinton negative	Neither	Total
Clinton	7	0	2	9
	6	4	8	18
	11	6	8	25
	5	2	3	10
	9	7	18	34
	12	8	5	25
	6	1	2	9
	56	28	46	130
Trump	0	7	2	9
	13	25	4	42
	13	32	6	51
Neither	6	6	5	17
Total	75	66	57	198

In the three Trump in-group clusters, in 33 tweets Trump was identified as in-group (sum of Trump positive and Clinton negative in these clusters) and 13 tweets were not positive toward him (the sum of Clinton positive + Trump negative in the three clusters). In these three Trump clusters, 5 tweets identified neither of the candidates as in-group. The two neither clusters had 27 tweets in total, 11 of which were positive toward Clinton (Clinton positive + Trump negative), 8 were positive toward Trump (Trump positive + Clinton negative), and 8 tweets had neither of the candidates as their in-group.

In sum, 17 clusters were recognized as Clinton's in-group clusters, 12 as Trump's in-group clusters and 11 as neither. From the total sample ($n = 1,114$), 29.8 percent of the tweets were positive about Clinton and Negative about Trump, 29.62 percent were positive about Trump and negative about Clinton, and 40.66 percent of them were neither positive nor negative toward the candidates.

Accordingly, from the 633 tweets in Clinton's clusters, 39.02 percent of them identified Clinton as in-group (Clinton positive + Trump negative), 21.16 percent identified Trump as in-group (Trump positive + Clinton negative), and 39.81 percent identified neither of the candidates as in-group. From the 378 tweets in Trump clusters, 49.20 percent of them recognized Trump as in-group (Trump positive + Clinton negative), 16.13 identified Clinton as in-group (Clinton positive + Trump negative) about Trump, and 34.92 percent identified neither of the candidates as in-group. Of the 103 tweets in the neither in-group clusters, 23.3 percent identified Clinton as in-group, 9.7 percent Trump as in-group, and 66.99 percent neither of the candidates as in-group.

As Table 7.7 shows, the Clinton clusters had softer support for Clinton, because there were more Trump positive + Clinton negative tweets in the Clinton clusters (134 tweets) than there were Trump negative + Clinton positive in the Trump clusters (61). Furthermore, there were more neither tweets in Clinton clusters (252) than in Trump clusters (132), which can indicate that there were non-partisan conversations in Clinton clusters compared to Trump clusters. In the neither clusters, there were more positive tweets for Clinton than Trump, because the Clinton positive + Trump negative tweets (24 tweets) were more than Trump positive + Clinton negative tweets.

Table 7.7: *Tweet Frames of Candidate In-group Clusters for Four Network*

Tweet Frames	Clinton In-group Clusters	Trump In-Group Clusters	Neither Cluster	Total
Clinton positive + Trump negative	247 39.02%	61 16.13%	24 23.30%	332 29.80%
Trump positive + Clinton negative	134 21.16%	186 49.20%	10 9.70%	330 29.62%
Neither	252 39.81%	131 34.92%	69 66.99%	452 40.66%
Total	633	378	103	1114

RQ3a-d were about the framing of tolerance and intolerance among the 10 largest clusters in each of the four networks. Each tweet in the sample (n = 1,114) was coded for tolerance, intolerance or neither. These research questions were answered by chi-square tests on the frequency of frames of tolerance, intolerance, and neither among Clinton, Trump, and neither clusters. Chi-square test calculates the significance of

relationships between two or more non-parametric variables (Wimmer & Dominick, 2011). First, the differences were explored for each day by running a chi square test, and then for all four days together.

RQ3a asked how the content was framed in terms of tolerance and intolerance in the 10 largest clusters the day before the U.S. 2016 presidential election. The results found no statistically significant differences in the expression of tolerance and intolerance between the candidates' in-group clusters on November 7 ($\chi^2 = 4.412$, $df = 4$, $p = .353$). Table 7.8 shows similar break down in the expression of tolerance and intolerance for both Clinton and Trump clusters.

Table 7.8: Frames of Tolerance and Intolerance by Candidate's In-group Cluster on Nov.7

	Cluster			Total
	Clinton	Trump	Neither	
Tolerance	8 (4.5%)	4 (5.6%)	1 (4.8%)	13 (4.8%)
Intolerance	69 (39.2%)	22 (30.6%)	4 (19.0%)	95 (35.3%)
Neither	99 (56.3%)	46 (63.9%)	16 (76.2%)	161 (59.9%)
Total	176	72	21	269

$\chi^2 = 4.412$
 $df = 4$
 $p = .353$

Note: Percentages are by columns (e.g., the 8 Clinton cluster tweets exhibiting tolerance are 4.5 percent of the 176 Clinton cluster tweets).

There was little difference in the expression of tolerance between Clinton (4.5 percent) and Trump (5.6 percent). Clinton's clusters had more intolerant tweets (39.2 percent) than Trump's clusters (30.6 percent), but the difference was not significant.

Trump cluster tweets had a higher percentage of tweets that expressed neither tolerance or intolerance (63.9 percent) than Clinton cluster tweets (56.3 percent). A key finding was that in both sets of clusters, about 60 percent of the tweets were neither tolerant nor intolerant. This means that for both candidate in-group clusters, a majority of the tweets did not include frames for tolerance or intolerance toward either candidate.

RQ3b asked how the content was framed in terms of tolerance and intolerance in the 10 largest clusters on the day of the U.S. 2016 presidential election. There were no significant differences in the framing of tolerance and intolerance between the two sets of clusters ($\chi^2 = 6.167$, $df = 4$, $p = .187$) (See Table 7.9).

Table 7.9: Frames of Tolerance and Intolerance by Candidate's In-group Cluster on Nov. 8

	Cluster			Total
	Clinton	Trump	Neither	
Tolerance	11 (6.2%)	9 (4.9%)	3 (17.6%)	23 (6.1%)
Intolerance	55 (31.1%)	55 (30.1%)	7 (41.2%)	117 (31.0%)
Neither	111 (62.7%)	119 (65.0%)	7 (41.2%)	237 (62.9%)
Total	177	183	17	377

$\chi^2 = 6.167$
 $df = 4$
 $p = .187$

Note: Percentages are by columns (e.g., the 11 Clinton cluster tweets exhibiting tolerance are 6.2 percent of the 177 Clinton cluster tweets).

Table 7.9 demonstrates similarities in the expression of tolerance and intolerance between Clinton and Trump clusters. Clinton clusters had slightly more tolerant (6.2 percent) and intolerant (31.1 percent) tweets than the tolerant (4.9 percent) and intolerant (30.1 percent) tweets in Trump clusters. The Trump clusters had slightly

more tweets (65 percent) that were neither tolerant nor intolerant than Clinton clusters (62.7 percent). Similar to the day before the election, in both sets of candidate in-group clusters, more than 60 percent of the tweets were neither tolerant nor intolerant.

RQ3c asked how the content was framed in terms of tolerance and intolerance in the 10 largest clusters the day after the U.S. 2016 presidential election. There was no significant difference in the expression of tolerance and intolerance between the three sets of clusters ($\chi^2 = 5.143$, $df = 4$, $p = .273$) (See Table 7.11). Table 7.10 shows differences between cluster groups in their expression of tolerance and intolerance.

Table 7.10: Frames of Tolerance and Intolerance by Candidate's In-group Cluster on Nov. 9

	Cluster			Total
	Clinton	Trump	Neither	
Tolerance	12 (8%)	4 (3.8%)	1 (7.1%)	17 (6.3%)
Intolerance	96 (64%)	61 (57.5%)	10 (71.4%)	167 (61.9%)
Neither	42 (28%)	41 (38.7%)	3 (21.4%)	86 (31.9%)
Total	150	106	14	270

$\chi^2 = 5.143$
 $df = 4$
 $p = .273$

Note: Percentages are by columns (e.g., the 12 Clinton cluster tweets exhibiting tolerance are 8 percent of the 150 Clinton cluster tweets).

Clinton clusters had more tolerant tweets (8 percent) than neither (7.1 percent) and Trump (3.8 percent) clusters. There were more intolerant tweets in neither (71.4 percent) clusters than Clinton (64 percent) and Trump clusters (57.5 percent). Trump Clusters had more tweets that were neither tolerant nor intolerant (38 percent) compared

to Clinton (28 percent) and neither (21.4 percent). On this day (the day after election), more than 60 percent of the tweets were intolerant. This suggests that, the day after the election, more than half of the tweets included intolerant frames toward the candidates.

RQ3d asked how the content was framed in terms of tolerance and intolerance in the 10 largest clusters four days after the U.S. 2016 presidential election. There was no significant difference in the expression of tolerance and intolerance among the candidate in-group clusters ($\chi^2 = 1.173$, $df = 4$, $p = .882$) (See Table 7.11).

Table 7.11: Frames of Tolerance and Intolerance by Candidate's In-group Cluster on Nov. 12

	Cluster			Total
	Clinton	Trump	Neither	
Tolerance	5 (3.8%)	3 (5.9%)	1 (5.9%)	9 (4.5%)
Intolerance	67 (51.5%)	24 (47.1%)	10 (58.8%)	101 (51.0%)
Neither	58 (44.6%)	24 (47.1%)	6 (21.4%)	88 (44.4%)
Total	130	51	17	198

$\chi^2 = 1.173$
 $df = 4$
 $p = .882$

Note: Percentages are by columns (e.g., the 5 Clinton cluster tweets exhibiting tolerance are 3.8 percent of the 130 Clinton cluster tweets).

Both Trump and neither clusters had the same level of tolerance (5.9 percent) while Clinton clusters had fewer tweets with expressions of tolerance (3.8 percent). Neither clusters had more intolerant tweets (58.8 percent) followed by Clinton clusters (51.5 percent) compared to Trump's clusters (47.1 percent). Trump clusters had more tweets that were neither tolerant nor intolerant (47.1 percent) in comparison to Clinton

(44.6 percent) and neither clusters (21.4 percent). Four days after the election, more than 50 percent of the tweets were intolerant. This indicates that after the election, more than half of the content contained intolerant frames toward the candidates.

Candidate In-Group Expressions of Tolerance and Intolerance Patterns for the Entire Sample

To explore the extent to which the candidates' in-group clusters reflect tolerance and intolerance in the discourse over the four-day election period, two analyses were conducted: 1) a chi-square test tested the aggregated data from all four days ($n = 1,114$), and 2) a descriptive analysis of the patterns that emerged from the four days.

The chi-square test found no significant differences in the expression of tolerance and intolerance between Clinton and Trump clusters ($\chi^2 = 6.398$, $df = 4$, $p = .171$). Table 7.12 shows that even though the differences between categories are not significant, there are some interesting patterns in the discourse, which are discussed in the following section.

Clinton in-group tweeters were slightly more tolerant and intolerant than Trump tweeters. Neither of the candidate's tweeters were as tolerant as the neither in-group tweeters. As shown on Table 7.12, the Neither candidate clusters had the highest percentage of tolerant tweets (8.7 percent) compared to Clinton (5.7) and Trump (4.9) in-group clusters. This also demonstrates that people who were in favor of neither of the candidates (those who were not clearly partisan) tweeted with more tolerant frames than those who supported one of the candidates.

In Clinton in-group clusters, 49 percent of the tweets were neither tolerant nor intolerant, more than 45 percent of the tweets were intolerant, and more than 5 percent

of them were tolerant. At the same time, more than 55 percent of tweets in Trump clusters were neither tolerant nor intolerant, more than 39 percent of them were intolerant and only 4.9 percent of them were tolerant. Comparing the tweets from Clinton and Trump clusters, nearly half of the Clinton in-group cluster tweets were intolerant over the four-day period (45.33 percent), which was slightly more than the four-day total for the Trump in-cluster (39.3 percent). The similarities in the expression of tolerance and intolerance between Clinton and Trump clusters indicate that both liberals and conservative were equally tolerant and intolerant toward each other. Moreover, Clinton clusters had slightly more intolerant tweets than Neither clusters (44.9 percent).

Table 7.12: Frames of Tolerance and Intolerance by Candidate's In-group Clusters in the four networks

	Cluster			Total
	Clinton	Trump	Neither	
Tolerance	36 (5.7%)	20 (4.9%)	6 (8.7%)	62 (5.6%)
Intolerance	287 (45.3%)	162 (39.3%)	31 (44.9%)	480 (43.1%)
Neither	310 (49%)	230 (55.8%)	32 (46.4%)	572 (51.3%)
Total	633	412	69	1,114

$\chi^2 = 6.398$
df= 4
p = .171

Note: Percentages are by columns (e.g., the 36 Clinton cluster tweets exhibiting tolerance are 5.7 percent of the 310 Clinton cluster tweets).

Overall, there was little tolerance (just 5.6 percent of tweets showed tolerance in their tweets). Also, more than 50 percent of the total 1,114 tweets were neither tolerant

nor intolerant toward any of the candidates or parties. More than 43 percent included expression of intolerance. The fact that about half of the candidate in-cluster tweets revealed neither tolerance or intolerance (Clinton, 49 percent; Trump, 55.8 percent) showed that about half of the discourse from those who clearly supported one candidate over the other revealed no apparent partisanship that reflected tolerance or a lack of it. About half of the discourse from partisans was neither tolerant or intolerant.

An important finding was that the discourse became less tolerant after the election. On the first two days, the majority of tweets were neither tolerant nor intolerant. However, both candidates' tweeters became more intolerant after the election, but the intolerance exhibited in the Clinton clusters was a bit higher than in Trump clusters. Clinton cluster tweeters became intolerant the day after the election, and remain a majority intolerant four days after the election. Correspondingly, the percentage of neither tolerant or intolerant tweets on the days after the election decreased. In other words, in the first two days, the majority of the tweets for both candidate in-group clusters were not partisan. In the days after the election, the tweets become more partisan (intolerant). This was really the case on the day after the election and four days after the election that less than half of the tweets for both candidates' in-group clusters had no expression of tolerance or intolerance.

RQ4 asked whether there were associations between tolerance and intolerance and measures of network centrality: in-degree and out-degree, betweenness, and closeness. Network centrality measures deal with the location of individual nodes or actors in the network (Wasserman & Faust, 2009). In-degree and out-degree centrality measures are about in-coming and out-going ties in a network (Freeman, 1979;

Kadushin, 2012). In a communication network, in-degree centrality is about popularity, which deals with the identification of the most active, important, and powerful actors based on the number of in-coming connections they receive in a network (Barnett & Sung, 2006; Freeman, 1979; Kadushin, 2012; Wasserman & Faust, 2009). In contrast, out-degree centrality (in a communication network) deals with less popularity and under-dominance (Freeman, 1979; Kadushin, 2012; Wasserman & Faust, 2009). People with highest out-degree centrality scores are the ones who nominate so many people as their friends but those people may not respond mutually (Wasserman & Faust, 2009). Betweenness centrality refers to the number of times a node or an actor acts as a bridge along the shortest path between two important but otherwise disconnected nodes (Krebs, 2016; Wasserman & Faust, 2009). Nodes with high betweenness centrality have great influence on the information flow in a network and without such node, the ties between important actors will be cut off (Hanneman & Riddle, 2005; Krebs, 2016). Closeness or distance is the average length of the shortest path between a node and all other nodes in a network (Wasserman & Faust, 2009). Actors with higher closeness centrality are closer to all nodes compared to other actors, they can reach everyone in a network faster than others (Hanneman & Riddle, 2005; Lieberman, 2014).

As shown in Table 7.14, like all social network data, the centrality scores were skewed and not normally distributed. The average in-degree centrality in among the 40 clusters is .34 ($SD = 5.127$), which means on average, nodes received less than one in-coming tie (being retweeted, replied to, or mentioned). The mode for in-degree centrality was zero, which means that the most frequent number of in-coming ties was zero. The median was in 0.00, which also means that the midpoint for the frequency of

in-coming ties was zero in the network even though in-degree centrality ranged from zero to 128. The mean score for out-degree ties was 1.76 ($SD = 1.179$) suggesting that on average, users were connecting with more than one other user (retweet, reply, mention). The mode for out-degree centrality was one, which means that the majority of nodes had connections to one other user in the network. The median was 1, which means that the midpoint for the frequency of out-going ties was one in the network even though in-degree centrality ranged from 1 to 10.

Table 7.13: Network Centrality across the Four Networks

	In-degree	Out-degree	Betweenness Centrality	Closeness Centrality
Mean	.34	1.76	28,247.922	.00005
Median	.00	1.00	.000	.00005
Mode	0	1	.000	.000059
Std. Deviation	5.127	1.179	128,885.241	.00006
Skewness	21.393	2.736	9.047	19.646
Std. Error of Skewness	.073	.073	.073	.073
Kurtosis	484.136	11.036	98.544	406.663
Std. Error of Kurtosis	.146	.146	.146	.146
Range	128	9	1,818,181.981	.0014
Minimum	0	1	.000	.00002
Maximum	128	10	1,818,181.981	.00141

The mean score for betweenness centrality was 28,247.922 ($SD = 128,885$), which means on average a node connected two important nodes more than 28,247 times. The mode score for betweenness centrality was zero (.000), which means that the

majority of nodes had zero betweenness centrality – indicating the majority of the users had no influence on others. The median score was also zero even though betweenness centrality ranged from .00 to 1,818,181.981.

The mean for closeness centrality was .00005 ($SD = .00006$), which means that on average users were not close to everyone within the clusters. The mode score for closeness centrality was nearly zero (.000059), which means that the majority of users had nearly zero closeness centrality and could not quickly interact with all other actors in the network. The median score was .00005, which shows that the middle point for reachability among users was almost zero.

To answer **RQ4** about the association between tolerance and intolerance, the clusters and centrality measures (in-degree, out-degree, betweenness, and closeness centrality) a set of ANOVA analyses were conducted. ANOVA tests for differences among groups first by looking for main effects of each IV on the DV and then the effects of the interactions of the IVs on the DV (Tabachnick et al., 2001). The ANOVA tests in this study first looked for the main effect of each of the of the IVs (tolerance and cluster) on in-degree, out-degree, betweenness, and closeness centrality measures and then for the effects of the interaction of tolerance and cluster on these centrality measures. Tolerance and cluster were the IVs and in-degree, out-degree, betweenness, and closeness centrality measures were the DVs. Tolerance was measured in three categories of frames: tolerance, intolerance, neither. Cluster was measured by its candidate in-group affiliation, Clinton, Trump or neither.

Before the ANOVA tests could be run the centrality data was transformed from a power to normal distribution, and reverse transformation was the best fit for in-degree,

out-degree and closeness centrality measures. Inverse transformation creates an inversed set of data that impacts how the data are interpreted. For instance, the mean values for closeness centrality in relation to tolerance ($M = 22,456.4$) intolerance ($M = 21,713.6$), and neither ($M = 21,310.1$) were interpreted in the inversed manner. Accordingly, the examples above would be interpreted to mean those tweets that were neither tolerant nor intolerant had higher closeness centrality (reachability) than those with tolerant and intolerant tweets. Logarithmic transformation came out the best method for normalization of betweenness centrality.

Tolerance and In-degree Centrality

There were only 44 cases that had in-degree values more than 0. Therefore, these 44 cases were used in an ANOVA test for differences in tolerance and candidate in-group clusters. Because the number of cases in the dependent variable was very small, the results should be interpreted cautiously.

An ANOVA test found no significant differences between tolerance and in-degree centrality, $F(2, 36) = .068, p = .935$. Similarly, there were no significant differences between candidate in-group cluster in relation in-degree centrality, $F(2, 36) = .457, p = .637$. Also, there were no significant difference in the interaction of tolerance and cluster in to in-degree centrality, $F(3, 43) = .519, p = .672$.

Tolerance and Out-degree Centrality

An ANOVA test found significant differences between tolerant and intolerant content in relation to out-degree centrality, $F(2, 1,105) = 3.113, p = .045$ (See Table 7.14). The tweets with neither tolerant nor intolerant frames ($M = .714$) had higher out-degree centrality than tweets with intolerant ($M = .777$) and tolerant frames ($M = .802$).

This means that the users with tweets that were neither tolerant nor intolerant were significantly retweeting, mentioning and replying to others more than the users with intolerant and tolerant tweets. There were no significant differences between tolerant and intolerant tweets and out-degree centrality.

Table 7.14: Tolerance and Interaction of it with Cluster in Relation to Out-degree Centrality

Main Effects								
	Intolerance			Neither			Tolerance	
Out-degree	.777b			.714a*			.802b	
Interaction								
Intolerance Clinton	Intolerance Trump	Intolerance Neither	Neither Clinton	Neither Trump	Neither Neither	Tolerance Clinton	Tolerance Trump	Tolerance Neither
.703	.792	.834	.751	.706	.685	.724	.792	.889

*Note: *p < .05*

The values are inverse-coded and the different letters indicate significant differences alphabetically (e.g., “a” is larger than “b”).

There were no significant differences between candidate in-group clusters in relation to out-degree centrality, $F(2, 1,105) = 1.536, p = .216$. However, the interaction between tolerance and candidate in-group clusters was significantly associated with out-degree centrality, $F(4, 1,113) = 4.141, p = .002$. This means that there were significant differences between nodes with tolerant, intolerant, and neither tweets in Clinton, Trump, and neither clusters in relation to out-degree centrality. Clinton in-group clusters retweeted, replied or mentioned in both tolerant and intolerant tweets had higher out-degree centrality than Trump cluster nodes that retweeted, replied, or mentioned tolerant and intolerant tweets. People in Trump in-group clusters with neither tolerant nor intolerant tweets had higher out-degree centrality than those with tolerant and intolerant. Likewise, people in the clusters that did not identified as the candidate

in-group who retweeted, replied or mentioned in tweets had higher out-degree centrality than those with tolerant and intolerant tweets.

Tolerance and Betweenness Centrality

Tolerant and intolerant content had no significant differences on the basis of betweenness centrality, $F(2, 499) = .83, p = .920$. Likewise, there were no significant differences between Clinton, Trump, and Neither clusters in relation to betweenness centrality, $F(2, 499) = .560, p = .571$. The interaction between tolerance and cluster was not significantly associated with Twitter users' out-degree centrality $F(4, 507) = 1.121, p = .346$.

Tolerance and Closeness Centrality

Tolerant and intolerant tweets were not significantly different in relation to closeness centrality, $F(2, 1,105) = .990, p = .372$. But candidate in-group cluster was significantly associated with closeness centrality, $F(2, 1,105) = 23.269, p = .000$. Twitter users in Clinton clusters had significantly higher closeness centrality ($M = 19,537.2$) than those in Trump ($M = 22,612.8$) and neither ($M = 23,330.0$). This indicates that people in Clinton clusters were more reachable to each other within the clusters rather than outside the cluster compared to people in Trump clusters (See Table 7.15). At the same time, people in neither clusters were not so close to their in-group people. The difference between Trump and neither cluster was not significant ($p = .423$). The interaction between tolerance and cluster was not significantly associated with closeness centrality $F(4, 1,113) = 801, p = .525$.

Table 7.15: Framing of Tolerance and Intolerance in Relation to Closeness Centrality

	Main Effects		
	Clinton	Neither	Trump
Cluster	19,537.2a*	23,330.0b	22,612.8b

*Note: *p < .05*

The values are inverse-coded and the different letters indicate significant differences alphabetically (e.g., “a” is larger than “b”).

In sum, RQ4 found significant differences between tolerant and intolerant tweets in relation to out-degree. The study also found significant association between the interaction of tolerance and candidate in-group cluster in relation to out-degree centrality. Moreover, there were significant differences between candidate in-group clusters in relation to closeness centrality. However, in-degree, betweenness, and closeness centrality measures had no significant associations with tolerance.

Results Summary

The results to RQ1a-d found that the network structures did not differ from November 7 to November 12. There were similarities between the four networks in terms of size, centralization, modularity, geodesic, distance, reciprocity. RQ2a-b found that the proportion of Clinton and Trump in-group clusters were almost the same even though Clinton had more in-group clusters than Trump. More than 40 percent of the tweets identified neither of the candidates as in-group. RQ3a-d found no significant differences in the framing of tolerance and intolerance across clusters. RQ4 found significant differences between tolerant and intolerant tweets in relation to out-degree centrality. There were significant differences in users’ out-degree centrality based on the interaction of tolerance and intolerance in their tweets and in-group cluster. Also,

there were significant differences between candidate in-group clusters in relation to closeness centrality –people in Clinton in-group clusters had significantly higher closeness centrality than people in neither and Trump in-group clusters. But there were no associations between tolerance and cluster with in-degree centrality, betweenness centrality.

Chapter 8: Discussion

This dissertation seeks to understand the relationship between online social network structures and tolerance and intolerance in political discourse on Twitter during the U.S. 2016 presidential election. Online social networks, in particular social media, have enabled the public to not only directly take part in political discussions, but also to form political virtual communities and discussion groups (Ankerson, 2015; Kietzmann, Hermkens, McCarthy, & Silvestre, 2011; Schwartz, 2015; van Dijck & Poell, 2015). The virtual space is a new marketplace of ideas where people from all kinds backgrounds and distances can take part in discussions and information exchange, which is very fast, easy, accessible, and cheap (Papacharissi, 2002; Schmuhl & Picard, 2005). The revolution in digital communication technologies have resulted in the abundance of information sources accessible at anyplace, anytime, and in any format, which have empowered citizens to choose any media platforms and sources that gratify them (Arceneaux & Johnson, 2013; Castells, 2015; Gade & Lowrey, 2011). Studies have found that people often use digital media to communicate with individuals and groups who have similar backgrounds and ideologies as their own (Himmelboim et al., 2013; Kadushin, 2012; Lieberman, 2014; McPherson et al., 2001; Valenzuela et al., 2009). Studies of political discourse on Twitter have shown that political discussions are often polarized and that there is little interaction among clusters from opposing ideological groups (Himmelboim et al., 2013; Lieberman, 2014). If one believes that freedom of speech is essential to democracy, then one must accept that people will use their freedom in ways that others will not like or agree (Mill, 1861/1999; Sullivan et al., 1993). Thus, tolerance of views unlike one's own is embedded in freedom of expression

(Locke, 1713/1988; Sullivan et al., 1993). An ideal place for practice of tolerance can be a public sphere where everybody's exchange of thoughts and opinions are welcomed (Habermas, 1994). Social media are widely used as a space for free exchange of ideas and opinions, in particular political, where tolerance and intolerance are both present. The existence of intolerance in public discourse on social media brings into question the ideas that the Internet is flat and democratic in nature and that it is an ideal place for practice of tolerance among people.

In 2016, the U.S. presidential election was one of the biggest and most controversial political events in the world, in which Donald Trump and Hillary Clinton competed for the 45th U.S. president (Jackson, 2017). The election campaigns were full of controversial scandals and personal attacks between candidates (Killough, 2016; Niose, 2016). The candidates used social media, in particular Twitter, as tools to express partisan conversations and personal attacks, which were later shared and retweeted among the public (Killough, 2016; McCormick, 2016; Rubin, 2016). Both candidates had controversial backgrounds including scandals and accusations. For instance, Clinton was accused of betraying the American public by using personal email while dealing with Libya crisis over the death of the American ambassador there (Bradner, 2016; Farenthold, 2016). Trump was accused of several sexual assault incidents, which was exacerbated with the release of a tape of him with misogynistic words from Access Hollywood in 2005 (Farenthold, 2016; Graham, 2016). Despite the controversial issues, scandals, and personal attacks for the candidates, Trump won the election from Clinton by winning more than 30 states including nine swing states (Bradner, 2016; Berenson, 2016). The election results were unlike what polls predicted

–Clinton’s victory – and she only won the popular vote (Berenson, 2016; Bradner, 2016; Tumulty, Rucker, & Gearan, 2016). Soon after the election, there were surges of protests in reaction to the election results and the conversations on the election and the candidates continued on Twitter and other online media (Ali & Hassan, 2016; Gibbs, 2016).

To explore how public discourse was created and how people used social media to engage in this discourse, this study analyzed Twitter network structure in relation to the Twitter content or tweets during the U.S. 2016 presidential election. Thus, this study was a combination of social network analysis and content analysis of four days surrounding the election, including election day. The sample included networks of political discourse on Twitter before, during, and after the election, November 7, 8, 9, and 12. NodeXL software program was used for data collection and social network analysis, which included the analysis of network structure (both general graph metrics of the network and node-specific metrics) as well as identification of clusters within the network. A sample of 1,114 original tweets from 10 largest clusters of each network (n = 40 clusters) were content analyzed: 1) for positive and negative frames toward candidates (for identification of in-group cluster), and 2) for frames of tolerance and intolerance. Then, the tolerant and intolerant and in-group clusters were examined in four sets of two-way ANOVA analyses in relation to four node-specific measures of network –in-degree, out-degree, betweenness, and closeness centrality.

This chapter discusses the findings of this study in relation to the existing literature. First, the findings on the four networks’ structures are discussed based on the findings of previous studies. The second part of this chapter focuses on cluster

characteristics. The third section of this chapter talks about frames of tolerance and intolerance in the tweets. Part four of the chapter discusses the findings on the association between network structure and tolerance and intolerance. Part five talks about the shortcomings of this study and suggestions for future research, and the chapter ends with a brief conclusion on the overall dissertation.

Network Structure

The graphs for the four networks look very different from each other, but their descriptive structural scores are not so different. In other words, the scores for centralization, density, modularity, and reciprocity are similar even though the networks' graphs look different across the four days. The networks were similar in that they had low centralization and high modularity. Still, there were patterns of small differences and similarities in the scores for network structural measures. All of the four network structures had low centralization scores (ranging from .016 to .059). Considering that network centralization ranges between 0 and 1, the centralization scores in the four networks were slightly more than zero. A low centralization means that network is flat and non-hierarchical, not dominated by a few central nodes (Freeman, 1979; Himelboim et al., 2017; Wasserman & Faust, 2009). The low centralization scores in the four networks in this study suggest that these networks were not centralized; instead, they were decentralized, flat, and split into groups. This finding fits with the argument that online network structure is flat and decentralized, and that people communicate in fragmented groups in this environment (Bennett, 2012; Gade & Lowrey, 2011; Tewksbury, 2005; Turner, 2005).

The day before election, users were more split (lowest centralization score and highest geodesic distance) and strongly engaged in in-group conversations (highest modularity score), but disconnected from out-groups. On the election day, people were closer to each other (highest centralization and lowest geodesic distance), more connected to a few central actors such as candidates, news media, and high profile politicians (centralized), and more connected across groups. The clusters were more interconnected in this network (higher density), which led to a lower modularity score. The day after the election, people were fragmented across the network (lower centralization and higher geodesic distance), more connected at the group level (high modularity) and disconnected from other groups. Four days after the election, people were more densely connected in the network, more centralized/hierarchical than November 9, more interactive, but less interconnected at the group level.

The differences in the networks' structures across the four days might be due to the relative sensitivity of the American public toward the election (Ali & Hassan, 2016; Gibbs, 2016). In other words, the Twitter network from November 7, the day before election, was divided with high modularity, and the discussions varied across clusters on the basis of political ideology, news coverage, polls, personal predictions about the elections, and campaigning for a certain candidate. The network from November 8, the day of election, was more centralized compared to other networks with lower modularity, in which the clusters overlap on each other and the discussions were generally about voting and encouraging people to take part in the election. In the election day network, some of the fragmentation apparent from the day before was less apparent, as people across in-group clusters focused more on the election and traditional

democratic processes of voting. The election day network was more highly centralized and lower modularity compared to others, which indicate that the users were looking for a smaller number of twitter sources (the media and candidates) for news and information more on this day. This was unlike the finding of previous studies that polarization reaches its peak in mediated political discourse on the day of election (Adamic & Glance, 2005; Himelboim et al., 2013; Himelboim et al., 2017). In other words, there was not much echo chamber (Lieberman, 2014; Smith et al., 2014). Instead, there were ech chambers –several groups of people talking about different topics.

The network after the election day, November 9, looked more divided than the election day. The centralization score for this network was lower than November 8 network, which suggests this network was less hierarchical than the network on election day. However, this network was denser with higher modularity score than the election day network, which indicates that the people were more interconnected across the network as well as within their own in-groups the day after election compared to the day before the election. This also means that after the election day, people went back to their clusters and the networks became less hierarchical and more partisan. November 9 was the day after the election in which people were divided over the election results and social media were inundated with reactions of the public toward or against the election (Ali & Hassan, 2016; Berenson, 2016; Bradner, 2016a; Gibbs, 2016; Tumulty et al., 2016).

Even though the November 12 network looked more divided and flat compared to the November 9 network, it had a higher centralization score, which means the

network was more hierarchical and less flat than the day after election. The reason for more hierarchy in this network is that there were many protests across the country on this day, and some groups even called for national day of protests. Therefore, people were looking at a few sources (probably news media) to orient themselves to what was going on. This network had the highest levels of density and reciprocity among the four networks, which stand for higher interconnectivity and interaction among nodes across the network. Also, this network was fragmented (high modularity) because people were interacting more about the protests with others like them to hear what their in-groups were saying.

The reciprocity scores were very low across the clusters indicating that there was little interactivity among users in all four networks. This also means that even though social media provide the opportunity for people to be very interactive in the communication process (Castells 2003; Shaffee & Metzger, 2001; Singer, 2011), they seldom reply to other people's posts. Despite the fact that Twitter is an easy medium for interactivity, because people can respond to others in 140 characters or less (Arceneaux & Weiss, 2010; Duggan et al., 2015; Smith et al., 2014), the percentage of replying in all four Twitter networks ranged from 0.001 to 0.005. The means that the highest number of replies in the four network was not more than 5 out of 1,000 tweets.

Power law distribution. In all of the four networks, high profile politicians, mainstream media, and some organizations and popular supporters of candidates (including their children) had the highest in-degree ties. As shown in Figures 8.1 - 8.4, in all of these four Twitter networks, people like Trump, Clinton, Bernie Sanders, news media such as *The New York Times*, ABC, CNN, FOXNEWS, Donald Trump Jr.,

WikiLeaks, etc. were among the most popular nodes in the four networks. The people shown in the graphs were the 10 most important nodes who received the highest number of retweets, mentions, and replies, but all of them had zero out-degree scores. In other words, these popular nodes, did not retweet, mention, or reply to others.

As predicted by the power law distribution, a small number of people receive the most connections and the majority receives a small number of connections – the rich get richer in terms of power and popularity in the network (Adamic et al., 2001; Barabasi, 2002; Castells, 2009). The dominance of candidates, high profile politicians, and news media in the four networks confirmed the logic of power law distribution that central nodes received the most connections, because they were used as bridge between disconnected nodes and clusters (See Table 8.1).

The graphs also show that some of the key nodes were not among the candidates, politicians or news organizations (e.g., Christopher Hayes, Red Retract, Nathan Zed, Good looking loser and GirlPost). These users were the citizens who became opinion leaders on social media by advocating for certain ideologies or people. The presence of these people provide examples of what the Internet and social media do – they allow non-institutional actors, even average citizens, the opportunity to express themselves and sometimes develop large audiences (Castells, 2003; 2015).

Figure 8.1: The 10 most Central Nodes in November 7 Network

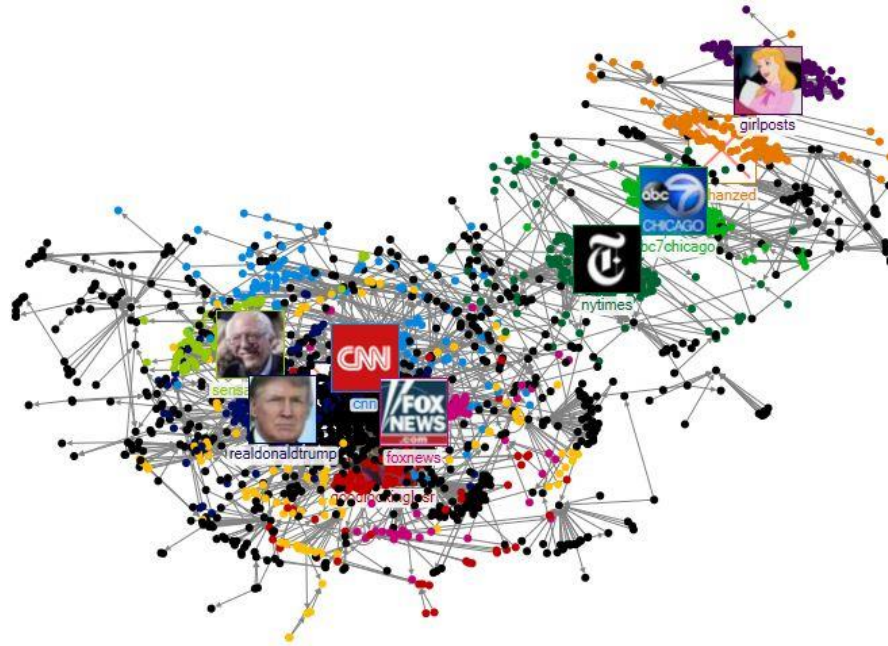


Figure 8.2: The 10 most Central Nodes in November 8 Network

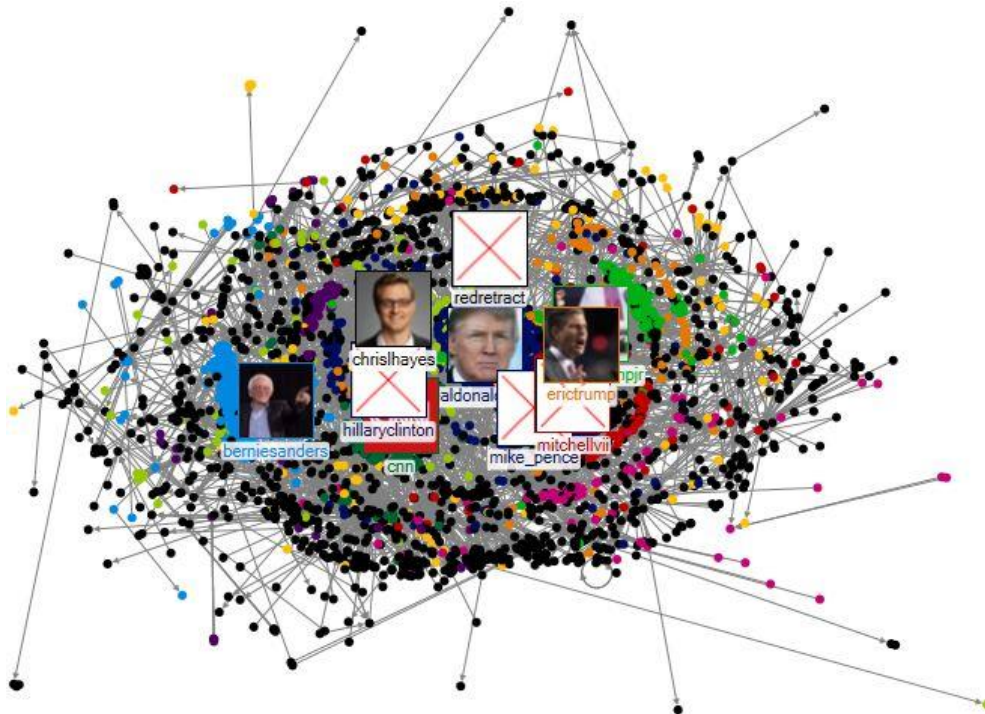


Figure 8.3: The 10 most Central Nodes in November 9 Network

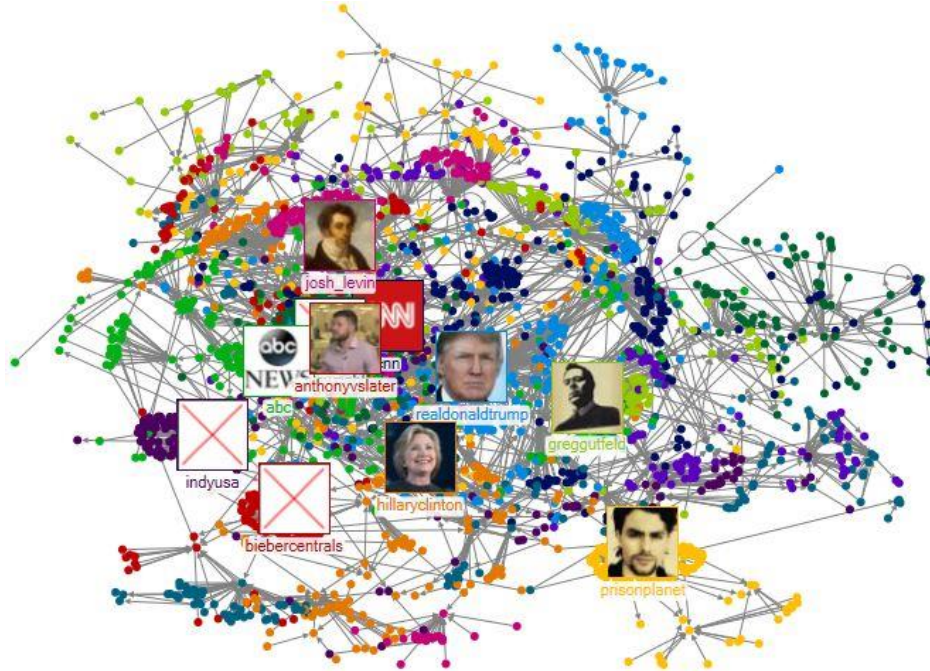


Figure 8.4: The 10 most Central Nodes in November 12 Network



Table 8. 1: Nodes with the Highest In-degree Centrality in four Networks

	November 7	November 8	November 9	November 12
1	Nytimes (128)	Realdonaldtrump (810)	Cnn (185)	Usatoday (212)
2	abc7chicago (108)	Cnn (191)	Jfreewright (185)	Wikileaks (185)
3	Nathanzed (103)	Berniesanders (177)	Biebercentrals (125)	Joyannreid (101)
4	Hillaryclinton (98)	Donaljdtrumpjr (172)	Prisonplanet (115)	Realdonaldtrump (68)
5	Goodlookinglosr (92)	mike_pence (143)	Realdonaldtrump (115)	Prisonplanet (67)
6	Sensanders (90)	Mitchellvii (117)	Greggutfeld (107)	Buzzfeednews (61)
7	Girlposts (83)	Hillaryclinton (96)	Abc (104)	Time (61)
8	Cnn (80)	Redretract (84)	josh_levin (100)	Williamjordann (58)
9	Realdonaldtrump (74)	Erictrump (71)	Indyusa (94)	Kurteichenwald (57)
10	Foxnews (62)	Chrislhayes (70)	Anthonyvslater (67)	Orgynextdoor (46)

Network Clusters

Characteristics. Of the 40 largest clusters, 16 of them were recognized as Clinton’s in-group, 13 as Trump’s in-group and 10 as neither of the candidates’ in-group. While the number of in-group cluster for each candidate was similar on November 7 and 9, it differed on November 8 and 12. The day before election, there

were equal number of clusters for Clinton and Trump (3 clusters for each) and 4 clusters as neither candidate in-group. But on the election day, there were 5 clusters for Trump, 3 for Clinton, and 2 as neither candidate in-group. The day after the election, there were equal number of clusters for Clinton and Trump (3 clusters for each) and 4 as neither candidate in-group, which was similar to the number of clusters for candidates on November 7. Four days after the election day, there were 7 clusters for Clinton, 2 for Trump, and one as neither candidate in-group.

Even though the number of in-group candidate clusters over the four days for Clinton (16) was more than Trump (13), the sum of all positive and negative tweets for both candidates reveal that they had similar number of in-group tweets (Clinton = 332 and Trump = 330). In other words, Clinton and Trump had similar percentage of positive and negative tweets (positive Clinton + negative Trump and positive Trump + negative Clinton) over the four days (more than 29 percent each). More than 40 percent of the total tweets were neither positive nor negative toward the candidates.

In Clinton in-group clusters, more than 39 percent of the tweets were positive toward Clinton and negative toward Trump, and more than 21 percent of the tweets were positive toward Trump and negative toward Clinton. Conversely, in Trump in-group clusters, more than 49 percent of tweets were positive toward Trump and negative toward Clinton, and more than 16 percent of the tweets were positive about Clinton and negative about Trump. The high percentage of pro-Trump tweets in Clinton clusters indicate that she had softer support from her in-group clusters compared to Trump. In other words, only 16 percent of the tweets in Trump in-group clusters were pro Clinton. Also, the pro-Trump people were posting in the Clinton clusters. These

people know where the opponents: reside online and post on their networks using the using the tags and hashtags.

Although the total number of positive and negative tweets for Clinton (332) and Trump (330) were nearly identical, there were patterns in the number of positive and negative tweets for candidates across the four days. On November 7, Clinton had more positive tweets (75) than Trump (66). On November 8, Trump had more positive tweets (105) than Clinton (79). On November 9, Clinton had more positive tweets (103) than Trump (93). On November 12, again, Clinton had more positive tweets (75) than Trump (66). These patterns suggest that there were more pro Trump and anti-Clinton tweets on the day of election than the other three days before and after election. Also, there were more pro-Clinton and anti-Trump tweets before and after the election.

Fragmentation more than polarization among clusters. One of the key findings of this study is the existence of non-partisan clusters in the election network on social media. Previous studies ignored the clusters in the network structures that did not reflect polarization (Adamic & Glance, 2005; Himelboim et al., 2013; Himelboim et al., 2017). However, this study had two main findings regarding online network clusters: First, the clusters were not simply polarized around the candidates, and second, those clusters not identified as candidate in-group clusters tended to be organized around topics, issues and themes that were related to the election but the content was not clearly supportive of one candidate over another.

Many Trump people were posting on Clinton in-group clusters and vice versa. Most of the postings on the out-group clusters occurred when people expressed intolerance toward the opposing group and used tagging and mentioning to let the

opposing group see those tweets. For instance, in negative tweets in Clinton's clusters against Trump, there were many tags and hashtags on Trump and Trump-related people and issues. At the same time, there were negative tweets about the candidates in their own in-group clusters. In particular, there were more negative tweets about Clinton in her own in-group clusters than the negative tweets about Trump in his own in-group clusters. This not only shows that the clusters were not simply polarized, but also there were clusters that did not identify as candidate in-group (neither clusters) and their content were organized around topics, issues and themes related to the election but were not clearly supportive of one candidate over another. In short, the findings show that the networks were not divided primarily around two candidates. But there was considerable election-related discourse that was not pro-con toward one candidate.

Dominance of duplicate content. More than 50 percent of the entire data was retweeted content and more than 25 percent was mentions. This means that only more than 22 percent of the data was unique (Tweets and replies) – written by the users themselves. This means there was little original content and many more people shared the content created by a few others than create original content of their own. Much of the discourse on Twitter consists of information that is shared, retweeted and duplicated without adding any additional content (Himmelboim et al., 2017). The low percentage of replies in the network (3.58 percent) shows that people seldom reply to others' tweets in comparison to retweeting, mentioning, and tweeting.

The low percentage of original tweets in the networks demonstrates that people seldom write their tweets, and most of the time, they retweet other people's or organization's tweets. In other words, even though online media have enabled citizens

to create their own content (Arceneaux & Johnson, 2013; Castells, 2015; Gade & Lowrey, 2011; Kietzmann et al., 2011), they often rely on duplicate content in their social media activities. They often share news and information from news media that they like or interest them. This is one of the reasons that traditional news media still remain important in the digital age, despite so many media choices (Albrecht, 2006, 2007; Baum & Groeling, 2008; Gurevitch et al., 2009; Himelboim et al., 2013; Meraz, 2009; Tumasjan et al., 2010). The news media are still agenda setters (signaling to citizens what is important), and social media users often redistribute news media stories through their social networks (Albrecht, 2006, 2007; Baum & Groeling, 2008; Gurevitch et al., 2009; Himelboim et al., 2009, Himelboim et al., 2013; Meraz, 2009; Tumasjan et al., 2010). Accordingly, the news media use social media, in particular Twitter, as platforms to share news stories with the public and receive more viewership (Lasorsa, Lewis, & Holton, 2012).

The creators of social media also play an important role in the structure of social media networks, because they have designed these platforms in ways that people can easily access and share duplicate information they see in their news feeds on their very close friends' social media walls (Sunstein, 2017). Those tweets – the types of content that people pass through social media, and the people from whom that content comes – are recorded for each individual user by owners of social media platforms (Agichtein et al., 2008; Aggarwal & Zhai, 2012; Castells, 2003; Romero et al., 2011; Sunstein, 2017). The data are used to create algorithms that display information to social media users based on the level of circulation and number of viewership (Romero et al., 2011; Sunstein, 2017). Thus, these algorithms expose people to the kind of

information that are shared or circulated the most among the friends and friends of friends (Romero et al., 2011). In other words, people often see the information on their social media walls that is analogous with what they often click on and from friends and sources they often communicate with (Agichtein et al., 2008; Aggarwal & Zhai, 2012). This puts people in the bubbles of like-minded others and keeps them far from those different from them (Romero et al., 2011; Xiang & Gretzel, 2010).

Equally intolerant clusters. Some scholars also argue that the online/virtual space can create the environment for expression of hate speech that facilitates discriminatory conversations among people (Arthur, 2011; Fisher, 2001). Accordingly, based on the findings of this study, the Internet creates the environment for expression of intolerance more than tolerance. Only 5.6 percent of the tweets were tolerant and more than 43 percent of the tweets were intolerant. Clinton and Trump in-group clusters were similar in their expression of tolerance and intolerance. But these differences were not statistically significant. These similarities indicate that both liberals and conservatives are equally tolerant and intolerant toward each other. This supports the findings of previous studies that liberals and conservatives show similar levels of biases toward each other (Adamic & Glance, 2005; Brandt et al., 2014; Himelboim et al., 2013).

Although more than half of the total tweets were neither tolerant nor intolerant, the percentage of intolerant tweets increased to 60 percent in the samples from days after the election. First, the clusters that were not aligned with either candidate (neither clusters) were about different issues related to election and promoting candidates rather than expression of acceptance of groups of people or attacks on opposing candidate or

party. Second, there were differences in the percentage of intolerant and neither content across the four days. On the day before election and the day of election, 60 percent of the tweets were neither tolerant nor intolerant and more than 30 percent of the tweets were intolerant. However, more than 60 percent of the tweets were intolerant the day after election and more than 50 percent four days after election. Second, one of the main reasons for the difference in the percentage of intolerant tweets between the first two days and the last two days is that on November 7 and 8, the majority of the conversations were about the election coverage and voting issues and predictions. However, the discourse dramatically changed after the election as a result of the reactions of people toward and against the outcome of the elections. For instance, there were so many protests across the country against and in support of the election of Trump as the 45th president (Ali & Hassan, 2016; Gibbs, 2016).

Tolerance and In-Group Cluster and Network Centrality

The frames of tolerance and candidate in-group cluster were examined in relation to four measures of network centrality: in-degree and out-degree, betweenness centrality, and closeness. These centrality measures deal with the locations of the nodes in a social network and their importance as receivers of ties, connectors, bridges and so forth (Freeman, 1979; Kadushin, 2012; Wasserman & Faust, 2009).

The findings show a significant association between tolerance and intolerance and out-degree centrality. The users with tweets that were neither tolerant nor intolerant had significantly higher out-degree centrality than those with tolerant and intolerant tweets. These users were significantly retweeting, mentioning and replying to others more than the users with tolerant and intolerant tweets. This also means that nodes with

tolerant and intolerant tweets were less likely to retweet, mention, and reply to others compared to those with tweets that were neither tolerant nor intolerant. But the difference between nodes with tolerant tweets and nodes with intolerant tweets in relation to their out-degree was not significant. Also, there were no significant differences between candidate in-group clusters in relation to out-degree centrality. The interaction between tolerance and candidate in-group clusters associated with out-degree centrality was significant.

The significant association between out-degree centrality and frames of tolerance and intolerance makes sense, because out-degree ties are established active decisions of the Twitter users. In other words, the users actively decide who to retweet, mention, and reply to. People with high out-degree centrality are not the powerful and popular people in the network such as candidates, news media, and celebrities who often have very high in-degree and betweenness centrality scores (incoming ties and bridges). Instead, people with high out-degree centrality scores are the common users who often spread the posts of popular/central nodes by reposting, retweeting and replying (Wasserman & Faust, 2009).

The difference between candidate in-group clusters were statistically significant in relation to closeness centrality. People in Clinton clusters had significantly higher closeness centrality than people in Trump and neither clusters. This suggests that Clinton in-group tweeters were closer and more reachable to each other than to people outside their groups compared to Trump in-group and those from neither clusters. Previous studies have also found that the tendency for engagement in polarized communication processes can increase the chances for people's involvement in

interactions with in-group people (Gurevitch et al., 2009; Himelboim et al., 2013; Lieberman, 2014; Meraz, 2009; Tumasjan et al., 2010). The findings of this study is somewhat mixed, especially, for Clinton.

The study found no significant differences between tolerant and intolerant content and cluster in relation to in-degree centrality and betweenness centrality. In-degree centrality is about the number of in-coming ties to a node, which is not in the control of the node itself (Wasserman & Faust, 2009). In other words, if Trump has the highest in-degree centrality in November 8 network, it does not mean that he chose to be retweeted, mentioned, and replied to by other Twitter users. Instead, people choose to retweets, mention, and reply to him.

This study found no significant differences between the content frames (tolerance or intolerance) and betweenness centrality. Betweenness centrality measures the extent to which a node becomes the connecting point (bridge) between two otherwise disconnected nodes (Hanneman & Riddle, 2005; Wasserman & Faust, 2009). People use popular actors in their networks to communicate across different groups, not vice versa (Hanneman & Riddle, 2005; Wasserman & Faust, 2009). In other words, betweenness centrality is related to in-degree centrality, in particular, mentions and retweets on Twitter, which is not controlled by the central node itself. Other people choose whom to mention and retweet on Twitter and the central nodes do not have any control of that.

Overall, the main implications of this study is that Twitter networks can be used for fostering both tolerance and intolerance among people. But the key point is that those who initiate conversations (users with high out-going ties) play more important

roles in fostering tolerance and intolerance than those with central and powerful locations (users with high incoming ties) in the network. It is also noteworthy that users with content that is neither tolerant nor intolerant are more willing to retweet, mention, and reply to others compared to the users with tolerant and intolerant content.

Shortcomings and Areas of Future Research

Tolerance and intolerance are concepts that exist in almost all areas of social life. Democracies are thought to be the best place of existence of tolerance, which provides the environment for free exercise of rights, equality, and social justice among diverse groups of people (Locke, 1690/1963; Mill, 1861/1999; Sullivan et al., 1979). Intolerance, on the other hand, exists anywhere that tolerance norms are undervalued (Coward, 1986; Locke, 1690/1963; Mill, 1861/1999; Yang & Self, 2015). Despite the importance of tolerance in democracies, there were no established ways of measuring it in discourse. So, this study had to develop ways to operationalize it within the context of the political discourse. The measures could be refined in different contexts, and they would likely be operationally measured differently. Also, this study used framing in content analysis, and since this was the first study on framing of tolerance and intolerance, no thematic frames were found for expression of tolerance and intolerance. Future studies can focus on finding thematic frames for tolerance and intolerant in mediated content.

Another limitation of this study was the sampling of data, which was a combination of four snapshots from four days during and around the election time. There were hundreds of millions of tweets during the election week and 38,000 of tweets cannot represent the overall Twitter network during this time. In addition, the

limitation of NodeXL as the software program used for retrieval of the data from Twitter is another limitation of this study. The current version of NodeXL Pro retrieves 20,000 tweets at a time (from the last 15 minutes maximum) depending on the speed of computer and Internet and cyber traffic (<http://NodeXLcodeplex.com>, 2017). None of the samples in the four networks had 20,000 tweets, because most of them collected tweets from the last 1-5 minutes. Because the sampling involved four snapshots of data during just a few minutes over the four-day period, the extent to which the study's findings may represent the entire election discourse on Twitter is limited.

This study mainly used NodeXL for data collection and social network analysis, which was limited to calculation of certain network structural measures, not all of them. For instance, the current version of NodeXL Pro cannot compare different networks to show the significance of difference among them. Future researchers can expand their use of social network analysis software beyond NodeXL and explore the significance of differences in network structures across different points of time.

Future research can explore this problem in the following ways. First, this study was limited to a small sample size of four Twitter networks from four days surrounding the U.S. 2016 election, and only analyzed 1,114 tweets from a total of 16, 841 tweets from 40 largest clusters. Future research can further explore this problem by increasing the sample size and scope of the networks. Also, future research can examine this research problem using other social media networks such as Facebook. Furthermore, this idea can be examined in other problems in relation to online and offline social networks and other measures of network structure. Second, this dissertation was the first study examining tolerance and intolerance in content frames. Hence, almost all of the

measures for this content analysis were developed for the first time. Future research can build up on the measures developed in study and operationalize them in other ways. The types of questions that can extend this research would be: Is tolerance the same for all controversial issues? Should we pay more attention to the non-polarized groups? Should we explore for important non-institutional actors and consider their influence and how it develops and works? Should we consider more than two sides to discourse?

Conclusion

This dissertation explored tolerance and intolerance in political discourse on Twitter during 2016 the U.S. presidential election. The purpose of this research was to examine the discourse in relation to structure of online social networks, and the extent to which the structure of networks contributes to diverse and inclusive discourse. The study posed four sets of research questions about network structure and tolerance and intolerance and the relationship between the two. The findings showed that Twitter networks on the four days surrounding the election were non-centralized, flat, and fragmented –not polarized. There were a lot of cross-group communications in the candidate in-group clusters, in which the out-group people were talking positively about their own candidate or negatively about the in-group candidate. The tweets (content) exchanged within the candidate in-group cluster were more diverse than expected, especially for Clinton. In addition to positive tweets for Clinton in the Clinton in-group clusters, there were also more negative tweets toward her. Even though Trump in-group clusters also had negative tweets toward him, the number was smaller than those of Clinton's.

There was more intolerance than tolerance on social media discourse. One of the key findings was that the those who express or publish intolerant views tend to be the ones whose content is passed through the network. Intolerant content was more retweeted, shared and mentioned than tolerant content. But more than 50 percent of the 1,114 tweets were neither tolerant nor intolerant. Even though the day before and on the day of election, more than half of the Tweets were neither tolerant nor intolerant, the day after and four days after election more than half of the tweets were intolerant. The dramatic change in the days after the election was a result of the reactions, particularly, protests in support and against the outcome of the election (Ali & Hassan, 2016; Gibbs, 2016). Clinton and Trump in-group clusters were equally intolerant toward each other. But there were no significant differences in the framing of tolerance and intolerance among Clinton and Trump in-group clusters.

In sum, the main contribution of this study is that there are significant associations between online social network structure and tolerance and intolerance. Such a relationship is mainly established by non-central nodes who often choose to connect themselves with other nodes (in particular central/powerful or popular nodes) by tagging, sharing/reposting, and replying to them. Even though there was more intolerance than tolerance in political discourse on social media, Twitter users from different groups were equally tolerant and intolerant toward each other. Also, more than half of the conversations included neither tolerant nor intolerant frames, which contributed to diversity of thoughts in online discourse and reduced the possibilities for extreme polarizations among groups. The findings suggest that in the four days surrounding the

U.S. 2016 presidential election, people got more intolerant in their interactions on the days after the election compared to the election day and the day before the election.

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Appendix A: Tweets, Replies, and Retweets

Table 1: Tweets, Replies, and Retweets in the 10 Largest Clusters on November 7

Clusters	Tweets	Replies	Retweets	Total Tweets + Replies+ Retweets	Unique RTs	Duplicate RTs	Total (Tweets + Replies + Unique RTs)
1	18	9	117	144	50	66	77
2	14	5	129	148	47	82	66
3	5	3	147	155	25	122	33
4	1	0	123	124	7	116	8
5	1	1	104	105	12	92	14
6	0	0	117	117	6	112	6
7	0	3	88	91	33	55	36
8	3	0	90	93	4	86	7
9	4	1	79	84	16	63	21
10	0	0	83	83	1	82	1
Total	46	22	1,079	1,149	202	876	269
Percentage	4.00%	1.91%	93.90%	100.00%	17.58%	76.51%	23.49%

Table 2: Tweets, Replies, and Retweets in the 10 Largest Clusters on November 8

Clusters	Tweets	Replies	Retweets	Total Tweets + Replies + Retweets	Unique RTs	Duplicate RTs	Total (Tweets + Replies + Unique RTs)
1	22	19	821	862	58	763	99
2	3	2	184	189	12	172	17
3	9	7	151	167	29	122	45
4	0	1	165	166	24	141	25
5	0	4	118	122	30	88	34
6	5	3	114	122	23	90	31
7	1	1	91	93	26	65	28
8	3	3	74	80	28	46	34
9	2	2	79	83	26	53	30
10	8	1	71	80	24	47	33
Total	53	43	1,868	1,964	281	1,587	377
Percentage	2.69%	2.18%	95.11%	100.00%	14.30%	80.86%	19.14%

Table 3: Tweets, Replies, and Retweets in the 10 Largest Clusters on November 9

Clusters	Tweets	Replies	Retweets	Total Tweets + Replies + Retweets	Unique RTs	Duplicate RTs	Total (Tweets + Replies + Unique RTs)
1	6	22	193	221	39	154	67
2	18	13	107	138	53	54	84
3	0	0	184	184	3	181	3
4	2	3	145	150	29	116	34
5	0	0	138	138	4	134	4
6	4	11	88	103	34	54	49
7	0	1	127	128	9	118	10
8	1	0	113	114	11	102	12
9	0	0	107	107	5	102	5
10	0	0	94	94	2	92	2
Total Percentage	31 2.25%	50 3.63%	1,296 94.12%	1,377 100.00%	189 13.73%	1,107 80.39%	270 19.61%

Table 4: Tweets, Replies, and Retweets in the 10 Largest Clusters on November 12

Clusters	Tweets	Replies	Retweets	Total Tweets + Replies + Retweets	Unique RTs	Duplicate RTs	Total (Tweets + Replies + Unique RTs)
1	2	2	201	205	5	196	9
2	0	2	176	178	7	169	9
3	4	5	107	116	9	98	18
4	7	13	53	73	22	31	42
5	7	5	74	86	13	61	25
6	2	0	77	79	8	69	10
7	7	7	37	51	20	17	34
8	4	1	62	67	20	42	25
9	0	5	65	70	12	53	17
10	0	0	75	75	9	66	9
Total Percentage	33 3.30%	40 4.00%	927 92.70%	1,000 100.00%	125 12.50%	802 80.20%	198 19.80%

Appendix B: Clusters Characteristics

Table 5: November 7: Most repeated words, word pairs and retweets

Cluster	Category	Words	Word Pairs	Retweets
1	Clinton election	Hillaryclinton (86 times) Realdonaldtrump (66 times) Ohio (31 times)	election.day (32 times) election.eve (27 times) rt,hillaryclinton (21 times) hillaryclinton,realdonaldtrump (20 times) rt,shannonrwatts (18 times)	Ohio Dems breaking law (11 time) #NASTYWOMAN NOW BLOCKING #Deplorables (9 times) Latino voters will have powerful impact (8times) Who are you voting for (13 times) None of the five living First Ladies support Trump (6 times)
2	Clinton Wins	Clinton (61 times) President (58 times) Obama (40 times) Polls (35 times) Win (29 times)	president,Obama (33 times) rt,fivethirtyeight (29 times) hillary,Clinton (28 times) latest,polls (27 times) win,presidency (27 times)	Clinton has 71% chance to win (23 times) Obama gave his final speech as president (19 times) Obama: "I am betting ... you will reject fear and choose (9 times) It's all up to you now. No matter who you're voting for (7 times) This NASA astronaut voted from space (6 times)
3	Polls_Media	nytimes (124 times) know (96 times) polls (93 times) close (93 times) latimes (15 times)	nytimes,time (93 times) time,polls (93 times) polls,close (93 times) close,election (93 times) election,night (93 times)	What time will polls close on election night? (91 times) @nytimes @washingtonpost @latimes removing paywall (11 times) Thank you, @nytimes, for making your news available (6 times) Nytimes: We're giving all readers unlimited access (5 times) L.A.'s chances of winning the 2024 Olympic bid (4 times)
4	Young Voters	abc7chicago (106 times) chance (106 times) rapper (106 times) voting (106 times) voters (105 times)	chance,rapper (106 times) early,voting (106 times) abc7chicago,chance (105 times) rapper,leads(105 times) young,voters (105 times)	Rapper leads hundreds of young voters (102 times) Election night starter kit (8 times) The election results are in (6 times) Daddy, why did Donald Trump win the election? (3 times) What time will polls close on election night (1 time)
5	Make America great again	2016 (87 times) Imvotingbecause (86 times) back (98 times) Guide (85 times) Undecided (85 times) Votetrumpics (8 times)	guide,election (85 times) election,2016 (85 times) undecided,voter (85 times) voter,imvotingbecause (85 times) votetrumpics,hopefully (5 times)	A Guide to Election 2016 For the ""Undecided"" Voter! (81 times) Opportunity to make America great again (4 times) AMISH COULD SAVE AMERICA WITH THEIR VOTES! (3 times) Don't sit out this election – Protect your rights! #2A us #MAGA (3 times) #PodestaEmails33 #PodestaEmails34 Ok best campaign ad of 2016 (2 times)
6	When election was fun	election (124 times) remember (98 times) back (98 times) fun (98 times) candidate (98 times)	remember,back (98 times) election,fun (98 times) fun,games (98 times) accused,candidate (98 times) candidate,being (98 times)	When this election was all fun and games like (93 times) Don't let this election distract you (15 times) Only 1 more day till we have to hear about a ""rigged election"" (5 times) My friend ...worried about me ... post election (2 times) Enjoying life for a minute then realizing the election is tomorrow (2 times)
7	Clinton's scandal/ Pray for Trump	Clinton (23 times) Comey (22 times) Day (21 times) Tomorrow (19 times) Obama (16 times)	election.day (14 times) rt,seanhannity (12 times) election,night (10 times) state,dept (10 times) dept, 5 (10 times)	State Dept wants 5 years to review emails, Comey did it in eight days (10 times) Chelsea Clinton used foundation money for her lavish 2010 wedding (7 times) Trump needs all the prayers he can get! Retwee..." (6 times) We'll be updating our presidential odds LIVE over the course of Election (6 times) Obama say Illegal Aliens can vote in our election truly disturbs me (6 times)
8	Election should be holiday	election (94 times) vote (92 times) day (90 times) sensanders (89 times) national (88 times)	election.day (90 times) sensanders,election (88 times) national,holiday (88 times) everyone,time (88 times) opportunity,vote (88 times)	Election Day should be a national holiday (87 times) No, you cannot vote in the US presidential election by text message (2 times) If u dont vote dont complain about the outcome (1 time) This person from Chicago should have been First Female US President (1 time)
9	beating Clinton	election (100 times) Trump (37 times) 2016 (35 times) Clinton (33 times) Searches (32 times)	election,2016 (34 times) trump,beating (32 times) beating,Clinton (32 times) clinton,google (32 times) google,searches (32 times)	We'll have teams everywhere tomorrow (49 times) Trump beating Clinton in Google searches (26 times) Hillary Clinton barely able to walk off plane caught on camera (24 times) Hoping Amish voters will make election day a GOP barn raiser (21 times) A Guide to Election 2016 For the ""Undecided"" Voter! (4 times)
10	N Election	election (85 times) twitter (83 times) day (83 times)	girlposts,twitter (83 times) twitter,election (83 times) election.day (83 times)	Twitter on Election Day (83 times)

Table 6: November 8: Most repeated words, word pairs and retweets

Cluster	Category	Words	Word Pairs	Retweets
1	Vote for Trump	Election (957 times) Realdonaldtrump (803 times) Vote (568 times) Keep (453 times) Up (452 times)	up,keep (451 times) vote,election (450 times) realdonaldtrump,up (449 times) keep,getting (449 times) getting,out (449 times)	Don't let up, keep getting out to vote - election is FAR FROM OVER! (386 times) I will be watching the election results from Trump Tower (197 times) If you stand for a stronger America, cast your vote for #TrumpPe... (78 times) Remember our bravest men & women who sacrificed everything (53 times) Election will come down to evening voters. Republicans with actual jobs (2 times)
2	Election day should be a national holiday	election (196 times) berniesanders (175 times) day (107 times) national (107 times) holiday (107 times)	today,election (163 times) election,day (108 times) berniesanders,fill (107 times) national,holiday (107 times) everyone,opportunity (107 times)	Election Day should be a national holiday (103 times) I hope everybody gets out to vote (55 times) Hillary Clinton news that could cost her the election (8 times) If Trump wins by a few votes, people are going to deal with reality (5 times) Don't be a jerry this election! #exerciseyourright (3 times)
3	Support for Clinton	voting (113 times) Hillary (87 times) Election (73 times) Trump (54 times) Clinton (52 times)	hillary,Clinton (44 times) married,37 (43 times) voting,Hillary (43 times) hillary,voting (43 times) voting,trump (43 times)	He's voting for Hillary. She's voting for Trump (40 times) Hillary Clinton leaves home in Chappaqua (24 times) No matter who you're voting for, see your vote counted (20 times) Women wearing pantsuits on #ElectionDay in support of Clinton (11 times) Please join me throughout the night for all the historic results (10 times)
4	MAGA	donaldjrumpjr (152 times) maga (94 times) vote (89 times) time (83 times) go (43 times)	go,vote (41 times) donaldjrumpjr,still (39 times) time,send (39 times) dc,biggest (39 times) biggest,message (39 times)	If you voted to drain the swamp! #MAGA #ElectionDay #Election (32 times) Send DC the biggest message in the past 60 years (28 times) Sporting MAGA hat, she has only asked 300 times if she can vote (18 times) Judge pushed poll watcher (18 times) My dad did not spend time raising \$ (14 times)
5	Republicans with actual jobs	Election (144 times) trump (62 times) voters (62 times) evening (59 times) republicans (58 times)	evening,voters (59 times) saying,election (56 times) election,come (56 times) voters,means (56 times) means,republicans (56 times)	Election will come down to evening voters. Republicans with actual jobs (44 times) The Trump Democrats (19 times) I will be watching the election results from Trump Tower (8 times) Trump is winning (7 times) If you stand for a stronger America, cast your vote for #TrumpPe (2 times)
6	Choosing Trump	erictrump (63 times) eve (60 times) always (60 times) remember (60 times) bravest (60 times)	erictrump,eve (60 times) eve,election (60 times) let's,always (60 times) remember,bravest (60 times) men, women (60 times)	Remember our bravest men & women who sacrificed (51 times) Red for the first time since 88 (30 times) I will be watching the election results from Trump Tower (3 times) Bernie voters and blacks voted for Trump (3 times) If you stand for a stronger America, cast your vote for #TrumpPe (1 time)
7	Voter Fraud caught & MAGA	election (79 times) trump (41 times) vote (40 times) fraud (33 times) Hillary (21 times)	voter,fraud (21 times) fraud,caught (11 times) video,voter (10 times) caught,camera (10 times) pennsylvania,election (10 times)	Exit poll favors Trump! #Trumplandslide #MAGA #HillaryForPrison2016 (9 times) This is how they will steal the election! commit fraud! Calvary Pentecostal (8 times) Don't vote for someone who enriches herself (7 times) Why Don't We Ever See #Democrat Votes Switched To #Republican (7 times) It's Not #Democrat VS #GOP It's The #Globalist #UniParty Vs The People (6 times)
8	When the polls close? _media	polls (38 times) know (26 times) look (22 times) live (22 times) exit (21 times)	exit,polls (21 times) wsj,first (20 times) first,look (20 times) look,exit (20 times) polls,5 (20 times)	We will get our first look at exit polls at 5 p.m. EST. (17 times) What time will polls close on election night? (14 times) When will we know we have a winner? (5 times) How the 50 million early voters may shape the election's outcome (4 times) Facebook "I Voted!" button seems to move +300k people to the polls (1 time)
9	Wikileaks release documents about Clinton	wikileaks (97 times) Clinton (35 times) Hillary (23 times) Campaign (22 times) assange's (21 times)	clinton,campaign (22 times) julian,assange's (21 times) wikileaks,wikileaks (17 times) statement,today (17 times) today,election (17 times)	Election Judge ""pushed"" Pollwatcher out of the polling place (17 times) What are the reasons behind WikiLeaks exposures of the DNC and the Clinton (15 times) Julian Assange's statement today on the US election (16 times) George W Bush and his wife Laura have voted for Hillary Clinton (10 times) Hillary not knowing where the heck she is going (4 times)
10	Clinton leaves Chappaqua	election2016 (23 times) trump (22 times) results (19 times) electionday (19 times) Clinton (19 times)	clinton,motorcade (14 times) leaves,Chappaqua (14 times) chappaqua,new (14 times) york,new (14 times) york,city (14 times)	The Clinton motorcade leaves Chappaqua, New York (14 times) When do polls close across the US? #ElectionDay (9 times) A couple is split on #Election2016: Do you guys actually love each other? (9 times) The most important election of our lifetime! Every vote makes a difference! (6 times) Michelle Obama: ""We deserve a leader who will ensure that our daughters (4 times)

Table 7: November 9: Most repeated words, word pairs and retweets

Cluster	Category	Words	Word Pairs	Retweets
1	Protestors come to streets after Trump's win	Protesters (69 times) Donald (68 times) trump's (58 times) win (53 times) take (52 times)	donald,trump's (52 times) protesters,take (50 times) streets,several (50 times) several,cities (50 times) presidential,win (50 times)	Protesters take to the streets in several cities after Trump's win (38 times) If enough upset-looking people block traffic the election is a do-ov... (31 times) As a woman and as a Latina, I feel very upset and oppressed (25 times) Election didn't shatter the glass ceiling, Senate's women of color quadrupled (23 times) Protesters gather near Trump Tower in New York over election results (16 times)
2	Best election	realdonaldtrump (92 times) president (20 times) bernieanders(19 times) people (19 times) proud (16times)	without,question (15 times) best,election (15 times) election,nite (15 times) reagan,80 (15 times) proud,realdonaldtrump (15 times)	Best election nite I've had since Reagan '80. So proud (13 times) Why care if people protest an real election? (10 times) PM spoke just now to @realDonaldTrump to congratulate him (9 times) Dems forgotten the people who cared about them (5 times) Why protesting against a fair election (4 times)
3	May Trump's election bring tough women to power	election (187 times) women (185 times) trump (185 times) bring (182 times) toughest(182 times)	trump,bring (182 times) bring,forth (182 times) fiercest,smartest (182 times) toughest,generation (182 times) generation,ass (182 times)	May the election of Trump bring fiercest, smartest, toughest women (181 times) White women won the election for Trump. Call it like it fucking is (2 times) Wakin up tmrw wishin this election just a bad dream🤪 (1 time)
4	March to Trump Towers	trump (129 times) protesters (82 times) cities (82 times) anger (71 times) hundreds (70 times)	hundreds,protesters (70 times) march,trump (70 times) trump,towers (70 times) towers,cities(70 times) cities,express(70 times)	Protesters in NYC and Chicago march to Trump Towers (68 times) Protesters take to the streets in several cities (39 times) Trump won't be free from civil fraud trial (13 times) California Legislative Leaders ""We will lead the resistance"" (7 times) Protesters take to the streets in several cities after Trump's win (7 times)
5	Crying with fear after election	look (123 times) white (123 times) black (123 times) races (123 times) crying (123 times)	look,white (123 times) black,different (123 times) different,races (123 times) crying,fear (123 times) fear,right (123 times)	White, black, all different races are crying with fear (122 times) Election showed us how prevalent hatred still is (14 times) The suicide prevention line is fucking busy. People want to die (1 time) So excited I was able to exercise my vote for the first time (1 time)
6	Reactions to election results	election (95 times) hillaryclinton (66 times) win (26 times) whitehouse (20 times) want (19 times)	win,election (20 times) hillaryclinton,want (19 times) hillaryclinton,outcome (17 times) outcome,wanted 17 sorry,win (17 times)	Not accepting election results: Protesters burn flags, block traffic (15 times) This is not the outcome we wanted. I'm sorry we did not win (15 times) Our campaign was about the country (11 times) Young people, don't think you can't make a difference (7 times) Everything old is new again. Revisit Dems' 2004 post-election trauma (7 times)
7	Your behavior is why Trump won	trump (106 times) protest (101 times) against (96 times) rioting (92 times) democratic (91 times)	against,democratic (91 times) democratic,election (91 times) rioting,protest (88 times) know,behavior (88 times) trump,won (88 times)	Your behavior is why Trump won in the first place (86 times) Putin advisor: Election of Clinton would have led to world war 3 (16 times) Crowds have gathered outside Trump Tower in Chicago (11 times) They're literally protesting AGAINST a democratic election (3 times) If election had gone other way, Trump supporters will not protest (2 times)
8	Do not protest against a democratic election	protest (65 times) against (56 times) middle (56 times) east (56 times) countries (56 times)	protest,against (56 times) middle,east (56 times) countries,killing (56 times) killing,gays (56 times) gays,democratically (56 times)	Cool if this was a protest against middle east countries killing gays? (52 times) Protesting after a fair, documented democratic election? (21 times) Every immigrant driver scoffs at your outrage over a legal election (10 times) Why care if people protest a real election? (8 times) I am willing to bet an overwhelming majority of protestors didn't vote (7 times)
9	The guy who said the election was rigged won the election	guy (97 times) rigged (97 times) won (97 times) presidency (97 times) votes (97 times)	guy,election (97 times) election,rigged (97 times) rigged,won (97 times) won,presidency (97 times) second,votes (97 times)	The guy who said the election was rigged won the presidency (96 times) The election results have shaken millions. (6 times) Been planning a post-election twitter break for a while. (2 times) The federal law enforcement agents who intervned in election (2 times) Trump's election marks the end of hope of limiting climate change (1 time)
10	The Muslim Ban plan removed from Trump's website	trump's (94 times) plan (94 times) ban (94 times) muslims (94 times) removed (94 times)	donald,trump's (94 times) trump's,plan (94 times) ban,muslims (94 times) america,removed (94 times) removed,website (94 times)	Trump's plan to ban Muslims from America removed from his website (93 times) Hundreds of protesters in NYC and Chicago march to Trump Towers (1 time)

Table 8: November 12: Most repeated words, word pairs and retweets

Clusters	Category	Words	Word Pairs	Retweets
1	Hate incidents after Trump's win	Hate (194 times) 200 (190 times) Incidents (190 times) Reported (190 times) Donald (190 times)	more,200 (190 times) hate,incidents (190 times) reported,country (190 times) donald,trump's (190 times) trump's,election (190 times)	More than 200 hate incidents since Donald Trump's election. (190 times) Trump should call whoever he insulted and apologize (5 times) Trump's election has emboldened white supremacists to target Clinton supporters (4 times) Hate crime spike larger than post-9/11, experts say #TRUMP #Fascism" (1 time) Post-election spate of hate crimes worse than post-9/11, experts say (1 time)
2	Wikileaks: Newsweek recalls thousands of with Clinton in the cover	wikileaks (191 times) newsweek (162 times) recalls (162 times) 125000 (162 times) Copies (162 times)	wikileaks,newsweek (162 times) recalls,125000 (162 times) copies,magazine (162 times) whose,cover (162 times) shows,Clinton (162 times)	Newsweek recalls 125000 copies of its magazine with Clinton in the cover (160 times) The greatest thing happened is the information we got from #WikiLeaks (11 times) Wikileaks mocks Dems after Election (1 time) Prepare for Resistance. Protect our Constitution. Autocracy: Rules for Survival (1 time) Republicans will never win another general election if they don't...oh wait (1 time)
3	Trump's giant Populism	realized (86 times) trump's (86 times) populism (86 times) giant (86 times) con (86 times)	realized,trump's (86 times) trump's,populism (86 times) populism,giant (86 times) con,stood (86 times) election,night (86 times)	Trump's populism was all a giant con on Election Night (83 times) My favorite bit of Coen's takedownof Comey... 2016 Election Thank You Notes (9 times) Voter suppression laws likely tipped the scales for Trump, civil rights groups say (7 times) This election pointed out that civics is not taught in our education system (2 times) Hundreds of hate crimes, zero words from Trump (1 time)
4	Trump's election	realdonaldtrump (60 times) dineshsouza (15 times) help (14 times) white (13 times) house (13 times)	donald,trump (16 times) dineshsouza,white (13 times) white,house (13 times) counselors,hand (13 times) bereaved,groupies (13 times)	Will the White House have counselors to cope with Trump's election? (12 times) Donald Trump supporter laughing about election outcome. (10 times) Just had a very open and successful presidential election. Professional protesters (7 times) Mrs. Clinton had a black vote deficiency dilemma, they would not come out for (3 times) Congratulations to Donald Trump on winning the #US presidential election (2 times)
5	Reaction to the Election	trump (80 times) supporters (38 times) against (30 times) media (28 times) now (28 times)	lots,media (27 times) now,ripping (27 times) pre,election (27 times) election,trump (27 times) trump,articles (27 times)	Lots of media are now ripping off my pre-election Trump articles (23 times) 2 all Trump supporters: threats against me or my family will be reported to FBI (23 times) Mr. Trump: You have the power to start to heal our divides (13 times) Campuses Confront Hostile Acts Against Minorities After Election (4 times) Sick of Dems claiming voter suppression (2 times)
6	Disgusting election	trump's (61 times) coach (58 times) Calls (58 times) Donald (58 times) Disgusting (58 times)	coach,Gregg (58 times) calls,Donald (58 times) donald,trump's (58 times) trump's,election (58 times) election,disgusting (58 times)	Spurs coach Gregg Popovich calls Donald Trump's election ""disgusting"" (53 times) Zuckerberg will regret saying that fake news on Facebook influenced the election (16 times) The books, music, movies, and TV shows soothed my election-damaged soul (2 times) Ten of thousands in U.S. cities to protest Trump's presidency (2 times) Don't know what happened other than rigged election (1 time)
7	Reactions to election Result	trump (26 times) won (15 times) celebrities (13 times) gop (8 times) Donald (8 times)	trump,won (15 times) won,election (9 times) donald,trump (8 times) post,election (7 times) celebrities,leave (7 times)	Top 25 Celebrities On Leaving If Trump Won; Should We Force Them Out? (6 times) Celebrities Who Said Would Leave Country If Trump Won Turned Into Bullies (6 times) North Carolina GOP condemns KKK parade honoring President-elect (3 times) Even LA and NYC are getting hit with waves of racism post-election? (3 times) @CNN @msnbc pundits were DEAD WRONG all campaign are predicting (2 times)
8	Clinton blames FBI	election (53 times) vote (31 times) Comey (30 times) Clinton (27times) trump 20 times)	clinton,blames (18 times) blames,fbi's (18 times) comey,defeat (18 times) call,donors (18 times) fbi's,comey (17 times)	100 million people didn't vote. We told them it was important (13 times) Clinton blames FBI's Comey for her defeat in call with donors (10 times) Tens of thousands in U.S. cities to protest Trump's presidency (8 times) Trump looking at fast ways to quit global climate change (6 times) Comey's letter shakes election (6 times)
9	Electoral college	irony (44 times) hamilton's (44 times) federalist (44 times) Electoral (44 times) College (44 times)	irony,hamilton's (44 times) federalist,68 (44 times) electoral,college (44 times) created,reverse (44 times) reverse,election (44 times)	Irony... electoral college was created to reverse the election of an unfit candidate (41 times) Dear Liberals I don't believe that violent protesters represent you (5 times) For those saying Trump's selection has nothing to do with White nationalism (5 times) The server is her fault (4 times) We were writing about Trump's huge and troubling conflicts before the election (1 time)
10	Proud about election outcome	outcome (56 times) gallup (56 times) 2008 (56 times) 2012 (56 times) 2016 (56 times)	election,outcome (56 times) gallup,2008 (56 times) proud,election (51 times) 2008,67 (51 times) 67,2012 (51 times)	% of Americans "proud" about election outcome, per Gallup 2008 (47 times) Don't tell me that I am overreacting from this election again (13 times) % of Americans "afraid" about election outcome, per Gallup (4 times) If election of man endorsed by white supremacists isn't enough to wakes you up (4 times) Election of a KKK endorsed person (2 times)

Appendix C: Codebook for Tolerance and Intolerance

Definitions of Tolerance

- Tolerance refers to accepting other people's "inward beliefs" (e.g. religion) and not interfering in other people's lives rather than prosecuting or punishing them (Locke, 1690/1963).
- People need to be equally tolerant of others' freedoms as they themselves expect those other individuals to be tolerant of theirs (Mill, 1861/1999).
- Tolerance is about "a willingness to 'put up with' those things that one rejects" (Sullivan et al., 1979, p. 785).
- Tolerance is about rejection of prejudice at the cognitive level and acceptance of differences at the social level (Habermas, 2004).
- "Tolerance is a person's willingness to support the civic and political rights of fellow citizens with whom [he or] she disagrees" (Hiskey, 2013, p. 1).

Definitions of Intolerance

- Intolerance refers to unwillingness to accept (rejecting) those who have different beliefs and values from one's self (Locke, 1690/1963; Sullivan et al., 1979).
- It is about interfering in other people's lives willingness to prosecuting or punishing them (Locke, 1690/1963).
- It deals with discrimination and prejudice against other people on the basis of personal opinion, values, and beliefs (Coward, 1986; Yang & Self, 2015).
- It includes defamation, hate speech, name calling, attempt to attack violently, attempt to provoke outrage, cursing and swearing at someone, discriminating

against one's demographics or beliefs and values, and the use of fighting words (Smith, N.A; Chaplinsky v. New Hampshire, 1942; Snyder v. Phelps, 2011; Teeter & Loving, 2008; Texas v. Johnson, 1989).

- It also includes alarm or resentment, invasion of privacy, infliction of emotional distress, accuse someone of a crime, and attack their personal business and reputation (Snyder v. Phelps, 2011; Smith, N.A; Teeter & Loving, 2008; Texas v. Johnson, 1989).
- Tolerance is when there is expectation of in-group to accept out-group
- Intolerance can be when in-group is telling any groups to think or act differently in accordance to specific norms, values, and ideas of in-group. Or it refers to the rejection of views/acts of either in-group or out-group and resorts to language that expects or demands the group to think or act differently.

How to Look at the Content

To code for tolerance and intolerance:

- 1) Read the entire tweet
- 2) Look for hashtags (#words) and mentions (@words) to identify promotion or persuasion.
 - If there are such hashtags or mentions, then code as neither or intolerant.
 - If one tweet has hashtags or mentions about both candidates or groups, consider the whole text and code accordingly.
- 3) Identify the subject and the object of the tweet
- 4) If there is an object in the tweet, consider traits associated with the object

- 5) If the subject has no direct/indirect objects (any person or group), then consider the traits associated with the subject
- 6) If the tweet has more than one sentences (complete or clause), then a) code for the first one for tolerance and intolerance and b) if no tolerance or intolerance in the first clause, consider the second clause, etc.
- 7) Tweets with questions
 - a) If the whole tweet is a question, code as neither. Except if subject of the tweet is called names or accused of prejudice, corruption, or deceiving. Exemple, “The FBI now saying again nothing wrong with @HillaryClinton emails? All that drama before the election! ? ?Racist Trump close?”
 - b) If the whole tweet ends with a question, code it as neutral. But if there is a question with an answer in the tweet, code for the answer. Exemple, ““Daddy, why did Donald Trump win the election?’ Well son, our country had a hard time taking things seriously <https://t.co/?>”
- 8) If you **cannot understand** the tweet, code it as neither. Example: “While ur following @wikileaks & election duality 24/7 -7th gen prophecy happenin- Elders smoked from Crazy horse,Geroni?”

Coding

1. Intolerance: It can be identified in relation to any group, person, or set of ideas.
 - Creating the **us**” vs. **“them**” sense of competition: E.g., this is an election of Good vs. Evil
 - **Name calling:** Hitler, Crooked Hillary, stupid, Drump, ghost, corrupt, hipster, criminal, liar, bereaved, ass hole, afraid, evil, zodiac killer,

deplorable, immoral, whine, Nazi misogynist president, a bunch of fat-bags;
sore losers,

- **Rejecting:** Denying a person, group, ideology, etc. Examples: Let's drain the swamp, not my president, never Hillary, I don't want to hear your opinion, vote NO in gun control, forcing people out, I won't accept this election, take someone down, distrust, gross,
- **Punishing:** Go to jail, imprison, impeach, assassinate, block, Trump was dropped,
- **Attacking:** Threatening, warning, display of symbols that arouses anger, use of fighting words, abolish
- **Accusing for:** Corruption, rigging, deceiving, lying, suspicion, attempting to fix/manipulate, blowing the election, Dems posing as Republicans, cheating, stealing, slight of hand, gutting the voting rights
- **Cursing/swearing:** F*** Donald Trump, shame on the candidate/party, the bitch nigga trump,
- **Discriminating:** Expressing prejudice on the basis of race, ethnicity, sex, sexual orientation, religion, political ideology –e.g. people of this group are stupid; go to Middle East, attack the Middle Eastern countries, expressing **disgust** and **hate** toward other people or groups, sick of Dems
- **Humiliating:** Democrats, people scoff at you; Dems sat on their butts and lost; misled pigs; Trump will turn into pumpkin, slander, irony, laughing stock

- **Using hashtags:** Hashtags that contain intolerant words. Examples:
#nastywoman, #neverhillary, #Drump
- **Using negative Emojis:** Crying face, angry face, thumbs down or dislike, middle finger
- If protests are **clearly directed toward a specific person or group**, code it as **intolerant** (e.g., Hundreds of people took part in a protests/riots to express anger against Trump or Lady Gaga protest against Trump in front of Trump Tower).
- If protests are reported with **no clear subject and object**, code it as **neither** (e.g., Hundreds of protestors took streets after election).

2. Neither tolerance nor intolerance

3. Tolerance:

- **Acceptance of broad concepts:** Democracy, social justice, equality, diversity, etc.
- **Acceptance of America as a whole:** Let's vote to better sever our civic duty.
- It is **not coded tolerant** when there is **acceptance of in-group** or group of which one is expected to agree with. Example: Trump cluster –I support Trump
- If attempt at **promotion or persuasion** toward in-group (campaign slogans) is expressed as a broad appeal, then code as **neither**. Examples: Let's all

support Trump to same the 2nd Amendment, Make America Great Again
(MAGA), Strong together

- **Acceptance of those who disagree or reject the communicator's views:**

Example, I am a Democrat voting for Trump.