PROBLEM DEFINITION AND CAUSAL ATTRIBUTION DURING THE REPUBLICAN NATIONAL CONVENTION: HOW #MAGA DISCOURSE ON TWITTER FRAMED AMERICA'S PROBLEMS AND THE PEOPLE RESPONSIBLE

by

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A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Arts in Communication

Department of Communication

West Lafayette, Indiana

August 2017

THE PURDUE UNIVERSITY GRADUATE SCHOOL
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For Joe and Sheryl Potts, who continue to support me every step of the way. Thank you.

ACKNOWLEDGMENTS

Dr. Josh Scacco, for your guidance and encouragement throughout the thesis process. The best part of this M.A. program was being your advisee. Dr. Ralph Webb and Dr. Natalie Lambert, for your thoughtful feedback and investments of time and teaching. Grandpa and Grandma, for praying every day. Nathan, Sarah, Phuong, Ashleigh, Sheen, Liz, Holly, Elise, LBH, Hannah, Megan, Kelsey, and Ellie Bean, for keeping me sane.
I AM, for everything.

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ABSTRACT

Author: Potts, Lauren B. MA
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Degree Received: August 2017
Title: Problem Definition and Causal Attribution During the 2016 Republican National Convention: How #MAGA Discourse on Twitter Framed America's Problems and the People Responsible.
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This study is a descriptive textual analysis of the "Make America Great Again" slogan crafted by Donald Trump as it appeared in discourse on Twitter during the 2016 Republican National Convention. Approaching "Make America Great Again" as a problem definition and causal explanation frame (Entman, 1993), I analyzed the ways in which people tweeting with the phrase "Make America Great Again" or its derivative hashtag, "#MAGA," discussed politicians identified as enemies of making America great again: Barack Obama, Hillary Clinton, and Ted Cruz. Trump attempted to replace Obama, defeat Clinton, and subordinate Cruz, making these enemies integral to his platform and his political brand. In addition to investigating the ways in which the frame defined America's problems, scapegoated others, and positioned voting for Trump as the solution, I analyzed the dominant voices within the "#MAGA" discourse, the prevalence of incivility and "truthiness," and calls to "donate" or "vote" in support of the Trump campaign.

CHAPTER 1: INTRODUCTION

Following Barack Obama's model usage of social media to "embrace and listen to [his] supporters" in consecutive presidential campaign wins in 2008 and 2012 (Stromer-Galley, 2014, p. 1), the Donald J. Trump campaign took to social networking sites with fervor during Trump's 2016 presidential run. While Obama's Twitter audience, defined as users following "@barackobama," outstripped Trump's audience, "@realDonaldTrump," by nearly 60 million at the time of writing, Trump amassed a sizeable audience composed of roughly 27 million followers (Twitter, 2017). For context, this positions "@realDonaldTrump" as one of the 50 most-followed Twitter accounts, with an audience reach numerically comparable to that of celebrities like Adele and Kanye West and sports conglomerates like the NBA and ESPN (TwitterCounter, 2017). While the legitimacy of some of Trump's Twitter followers has been questioned in the press—with suggestions ranging from Trump "purchas[ing] fake followers" to Russian meddling with robot accounts in an attempt to disseminate fake news and influence public opinion—Twitter has been a key communication channel in American politics (Ingram, 2017).

One of the essential pieces of rhetoric pushed by Trump's campaign communications in the months leading up to the election was the slogan, "Make America Great Again," which was often shortened on Twitter to the hashtag, "#MAGA." The phrase demonstrated longevity such that the Trump team elected to carry it forward from the campaign to serve as his 2017 inauguration theme (Faulders, Mallin, Keneally, Fisher, & Stracqualursi, 2017). In fact, the *New Yorker* magazine recently ranked the now-iconic red cap bearing this now-iconic slogan as the single most definitive cultural object from 2016 (Walker, 2016).

Analysis of social media discourse during the 2016 presidential campaign has only recently appeared in the academic literature, with most studies choosing to focus on Trump's self-presentation and communication style as evidenced in the tweets he wrote prior to becoming president (e.g., Ahmadian, Azarshahi, & Paulhus, 2017; Ott, 2017). The content of Trump's tweets has also been of great interest to the popular press and has been much discussed in journalism outlets from the *New Yorker* to *The New York Times* (e.g., Cassidy, 2016; Grynbaum & Ember, 2016; Lee & Quealy, 2016; Marantz, 2016; Remnick, 2016). In addition, most other works address the content of Trump's tweets in aggregate, thereby attempting to understand Trump's activity on Twitter as one collective phenomenon (see Kollanyi, Howard, & Woolley, 2016, for an exception focused on the first presidential debate in 2016).

Even as the supply side (here, Trump and his campaign) of "Make America Great Again" information has been examined, lay journalists and communication scholars alike have yet to trace the content of the "#MAGA" discourse on Twitter from the demand side (defined here as Twitter users contributing to "Make America Great Again" discourse), or to examine at length the substantive or affective content of tweets posted by Twitter users other than Trump himself within a particular time frame. The 2016 Republican National Convention (RNC) was a key moment in the "Make America Great Again" discourse as Trump the candidate became Trump the Republican presidential nominee.

At this junction, the RNC fostered political rhetoric aimed at drumming up support for the Trump ticket by way of deriding Trump's predecessor, Barack Obama, his longest-standing Republican rival, Ted Cruz, and, of course, Hillary Clinton, the Trump campaign's most imminent enemy.

Moreover, the Republican National Convention intentionally provided a platform for like-minded people to hear from politicians whose rhetoric likely aligned with their predispositions. If, as the literature indicates, people tend to seek out information consistent with the views of the social groups with which they identify (Frey, 1986; Stroud, 2010; Tichenor, Donohue, & Olien, 1970), this proclivity reinforces the existence of political in-groups and out-groups and "opens [people] up for the flow of information through social networking sites from politicians who share their viewpoint" (Gainous & Wagner, 2014, p. 48). Sites like Twitter make it easier and cheaper for politicians to spread this information even as they make it easier and cheaper for audiences to consume it (Gainous & Wagner, 2014). On these sites, the frames politicians use to talk about problems and enemies on real-world stages are thus easier to disseminate and easier to encounter, possibly increasing the degree to which the frames can permeate political discourse online and offline.

Considering the potential implications of social networking sites for political content framing, I chose to examine the ways in which "Make America Great Again" may have operated as a content frame on Twitter during the Republican National Convention. Rather than exploring connections between specific frames and specific effects (e.g., Druckman, 2001b; Levin & Gaeth, 1988; Nelson, Clawson, & Oxley, 1997), I drew from literature demonstrating that framing in general possesses enormous power to influence people's awareness, attitudes, and actions (De Martino, Kumaran, Seymour, & Dolan, 2006; Druckman, 2001a; Scheufele & Tewksbury, 2007; Tversky & Kahneman, 1981; Tversky & Kahneman, 1986).

From a practical perspective, framing theory provided a vantage point from which to explore if and how political discourse on Twitter carried forward the in-group/out-group rhetoric of candidates and their campaigns. Though only 24 percent of online American adults used Twitter in 2016 (Pew Research Center, 2016), Twitter users represented more than a quarter of adult internet users (currently 86 percent of the population, again according to Pew). Even controlling for demographic skew among Twitter users, the proportion of the American electorate that used Twitter in 2016 more than met industry-accepted thresholds for meaningful political sampling (American Association for Public Opinion Research, 2017). Further, Entman's (1993) discussion of problem definition and causal attribution frames provided a basis for understanding how "Make America Great Again" discourse on Twitter talked about America's ills and those responsible. These two aspects of Trump's campaign were made especially pertinent by recent research suggesting that differentiation between in-groups and enemies was perhaps the most popular pillar of Trump's campaign communication: Within Trump's Twitter network, tweets attacking then-President Barack Obama and Hillary Clinton received more positive feedback, in terms of likes and retweets, than any of his other tweets (Wang, Luo, Niemi, Li, & Hu, 2016).

As such, I posited that "Make America Great Again" communication on Twitter during the Republican National Convention functioned as a problem definition and causal attribution frame (Entman, 1993). At face value, the enthymematic slogan supplied a deceptively abstract call to action, but the specific means of making America great again were implied (and easily understood): Vote for Trump. By extension, then, the implicit problem was America's present state of badness, and the implicit culprits were everyone not in alignment with Trump. If America could be cast as bad, Trump's call to action could be cast as the solution to the badness, thereby positioning divergent people, parties, and policies as the scapegoats for America's ills. In this way, "Make America Great Again" divided all the people, parties, and policies that entered the discourse surrounding the presidential campaign into two camps: those trying to make America great versus those trying to keep America bad. Accordingly, I investigated how in-groups and out-groups were talked about in the "Make America Great Again" discourse by analyzing references to Barack Obama, Hillary Clinton, and Ted Cruz within a random sampling of tweets containing the phrase "Make America Great Again" and/or the hashtag "#MAGA" that were posted during the dates of the Republican National Convention that took place Monday, July 18-Thursday, July 21, 2016.

To support the investigation of "Make America Great Again" as a problem definition and causal attribution frame (Entman, 1993), I first discussed aspects of framing literature pertinent to the definition of problems within political discourse, the casting of blame upon out-group entities, and the construction of political enemies. Specifically, I addressed the ways in which "Make America Great Again" positioned other politicians as the problem(s) to be solved and defined the solution to said problem(s) as voting for Trump. Next, I looked at how the characteristics of Twitter as a platform may have contributed to the divisiveness and reactivity of communication on it. I then discussed the unique ways in which social media may foment incivility and negative campaigning, as well as the opportunities for traditional calls to collective action ("vote," and "donate"). Subsequently, I illustrated the importance of the 2016 Republican National Convention as a context for framing research. I then provided an overview of the plan for the research followed by a brief discussion of the usefulness of text mining and textual analysis for exploring the research questions at hand. Following the methodology, I described my results and discussed the potential implications of this thesis.

CHAPTER 2: LITERATURE REVIEW

"Make America Great Again" as Problem Definition and Causal Explanation Frame

Political rhetoric often relies on the establishment of an exact solution, such as "Make America Great Again," before the establishment of an exact problem (Edelman, 1985). To present a solution and then define problems in such a way that the solution makes sense to potential voters, politicians rely on framing. As posited by Goffman (1974), framing suggests that information sources and public figures shape perceptions of problems by offering audiences a "schemata of interpretation" composed of suggestions about how to "locate, perceive, identify, and label" issues and events (p. 21). For Trump's campaign, locating the cause of problems within the ranks of the opposition was a key piece of the "Make America Great Again" message. "Make America Great Again" portrayed the problem as America being bad and, quite strategically, reflected back to potential voters the things they perceived to be bad or problematic while linking those bad and problematic things with particular political enemies. Trump had only to "diagnose the cause" of this badness by "identify[ing] the forces creating the problem" (Entman, 1993, p. 52): Barack Obama, Hillary Clinton, and Ted Cruz. Thus "Make America Great Again" offered up these enemies as scapegoats for whatever ills people were experiencing (see Pew, 2016, for a discussion of top issue concerns).

By using campaign rhetoric to articulate the composite problem of America's badness and indict the opposition as irresponsible, Trump's slogan "select[ed] some aspects of a perceived reality and [made] them more salient in communicating text[s], in such a way as to promote a particular problem definition [and] causal interpretation"

(Entman, 1993, p. 52). As "political elites and strategic communicators drive the mass communication process" (Matthes, 2012, p. 248), Trump's repeated use of his slogan had the potential to help focus coverage of and conversations about the presidential campaign around the idea that America was currently not great and that Barack Obama, Hillary Clinton, and Ted Cruz were to blame (Engel, 2017).

Researchers have suggested that more coverage of and conversations about politics are beneficial, because people who are more informed about politics are better able to make decisions to benefit themselves and society as a whole (Edelman, 1988; Gainous & Wagner, 2014). However, the "information" in question often consists not of unilaterally accepted facts but of malleable constructions that change according to point of view and can therefore be used to win supporters for a particular political point of view (e.g., Anderson, 2006; Jamieson, 1992; Papacharissi, 2015). This is especially true when the very nature of a fact is itself seemingly up for debate (Conway, 2017). When political behavior is based not on facts, per se, but on the constructions of political figures, candidates and their campaigns cannot galvanize social support if they do not define social problems in such a way as to position the candidate as the solution (Jamieson, 1992; Trent & Friedenburg, 2008).

For the people within Trump's in-group, "Make America Great Again" was portrayed as the solution to the specific problems people were experiencing or perceiving, Trump supporters' top concerns being the economy, terrorism, immigration, and foreign policy (Pew Research Center, 2016). The slogan spoke powerfully to the subjective realities of Trump supporters, constructing a problem definition and causal explanation that not only made sense but reinforced the rightness of Trump's frame and, in turn, their rightness in accepting it. The slogan further "provide[d] precise operational guidelines" (Matthes, 2009, p. 350) in urging people to vote for Trump, contributing to polarized discourse split along the lines of Trump's in-group, composed largely of Republicans and conservatives, and an out-group composed of Democrats, progressives, and Republican competitors.

In effect, Trump seized upon a cultural moment and points of view ripe for the propagation of his slogan. "Make America Great Again" resonated with many people because of its power to evoke those points of view "about the social and political world…and therefore of perceptions, anxieties, aspirations, and strategies" within the specific context of the 2016 election (Edelman, 1988, p. 10; Silver, 2016). As a symbol of people's actual experiences, "Make America Great Again" became the medium through which Trump's adherents interpreted their social, economic, and cultural frustrations as well as the explanations and solutions offered to them during the campaign. Even social problems with which most people did not have direct experience, such as terrorism and foreign policy (Pew Research Center, 2016), were made relevant by Trump—because it was politically advantageous to do so—thereby increasing their relevance to people within his communication networks. For example, though Trump's grasp of terrorism and foreign policy was dubious (Barbaro, 2015; Bierman & Wilkinson, 2016), his ambiguity and perpetual return to the theme of his dominance and others' failures let audiences fill in their desired details and meanings, lending the slogan greater longevity and significance in the minds of potential voters (see Papacharissi, 2015, for a partial review of ambiguity as political strategy). "Make America Great Again" became "a part of the culture" of the campaign and what it meant to be a Trump supporter, from its physical presence in media texts to its cognitive and affective presence among the Trump faithful (Matthes, 2012, p. 248-249; Tumulty, 2017; Twitter, 2016).

Causal Explanation and Construction of Enemies

As mentioned above, defining whose interpretations were wrong, and who was responsible for the problem of America not being great, was a prerequisite for the coalescence of potential voters around the problem definition and explanations proffered by "Make America Great Again." A political campaign must ensure that the opposition is scapegoated for the problems the campaign has identified, so that there is no ambiguity in presenting the candidate in question to voters as the obvious solution (Trent & Friedenburg, 2008). In demonizing Barack Obama and Hillary Clinton as well as Ted Cruz as his primary Republican challenger (Trump's speech to the RNC, 2016), Trump's "Make America Great Again" rhetoric suggested these politicians were responsible for the problems and frustrations citizens had experienced. In turn, these politicians became enemies, symbolic of threat and failure even as "Make America Great Again" and the man behind it became symbolic of protection and success (Edelman, 1988). Where before vague experiences of economic disenfranchisement or fear of terrorism may have bubbled beneath the conscious surface, the "Make America Great Again" frame essentially "reduce[d] ambiguity to certainty [and] multivalent people to egos with fixed ideologies" (p. 3).

Securing public attention and galvanizing the voting public requires hyperbolic exhortations and issue portrayals that pinpoint for potential voters which choices are good (compatible with one's political in-group) and which are bad (in line with a different "out-group"), such that the distinction becomes almost automatic, precluding careful evaluation of other people, issues, and events (Robins & Post, 1997; Volkan, 1988). Without enemies to demonize—not just disagree with—the amorphous, complex, and deeply entrenched nature of problems like economic insecurity and terrorism would be much harder to convey in an evocative way (Jackson, 2007; Jamieson, 1992). As Barack Obama and Hillary Clinton were often featured in "Make America Great Again" communication as enemies of Trump, I considered these politicians and their supporters to be members of the "out-group" in question. In addition, Ted Cruz, arguably the longest-running Republican threat to Trump's candidacy, was berated in the "Make America Great Again" discourse. For this reason, I also looked at mentions of Ted Cruz, who was vilified even more intensely after delivering a keynote address at the RNC that avoided endorsing Trump, to the shock and dismay of many Trump supporters.

If "division and consensus go hand in hand" (Edelman, 1988, p. 70), Trump's widening of the rift between his supporters and others simultaneously served to strengthen his supporters' identification with the ideology behind his slogan. "Make America Great Again" suggested that one could not desire the good of the country if one did not oppose, even hate, the enemies Trump had maligned. In fact, as discussed shortly in the context of Twitter, much of the discourse seemed to suggest that making America great again actually consisted in large part of opposing and hating these enemies. For example, when the news of Clinton's usage of a private email server broke, Trump capitalized on the furor by reminding audiences of the issue at every opportunity, speculating about the extent of Clinton's misdeeds, and even inviting Russia to hack Clinton's email and publicize its findings (Crowley & Pager, 2016). These communication choices helped disseminate Trump's interpretation of this highly publicized event as supposed proof that Clinton was indeed a dangerous enemy (Edelman, 1988). The identification of these enemies versus the in-group of Trump supporters gave rise to the following research questions:

1) *Which concepts were discursively connected to each other directly and indirectly within "Make America Great Again" tweets mentioning Barack Obama?*
2) *Which concepts were discursively connected to each other directly and indirectly within "Make America Great Again" tweets mentioning Hillary Clinton?*
3) *Which concepts were discursively connected to each other directly and indirectly within "Make America Great Again" tweets mentioning Ted Cruz?*

Political Discourse on Social Media

I explored "Make America Great Again" frames on Twitter with a conceptual background focused primarily within two areas of the literature. First, I examined how incivility and negative campaigning manifested in discursive frames in social media, such as the space of the "Make America Great Again" discourse on Twitter (e.g., discursive framing in Anderson, Brussard, Scheufele, Xenos & Ladwig, 2014; Borah, 2014; Papacharissi, 2004; Rowe, 2015). Second, I looked at how social media discourse may have helped candidates and their campaigns facilitate favorable collective action, such as calls to vote Trump or to donate to his campaign (e.g., collective action in Cheung & Lee, 2010; Choi & Park, 2013; Copeland, Hasell, & Bimber, 2016; Dolata & Schrape, 2015; Lim & Datta, 2013; Segerberg & Bennett, 2011). In this case, the calls to support Trump reflected how the "Make America Great Again" frame defined America's problems as other politicians and voting for Trump as the solution to America's problems (Entman, 1993). Incivility, negative campaigning, and collective action were of interest here because of their potential to reinforce in-group and out-group divisions (see Himelboim, Smith, & Shneiderman, 2013; Iyengar, Han, Krosnick, & Walker, 2008; Mutz, 2006), a phenomenon necessary for "Make America Great Again" to move people to elect Trump.

"Make America Great Again" may have gained discursive traction in part because certain groups of social media users were "more readily available to be targeted" by Trump's campaign (Gainous & Wagner, 2014, p. 48), both in terms of the longstanding frustrations that Trump addressed and the technological affordances of Twitter that made it possible to reach those users with the "Make America Great Again" message, connecting those with sympathetic views to one another. As a collective, these users may have been more "likely to avoid certain types of information that [was] generally and collectively inconsistent with the positions of [their group]" (Gainous & Wagner, 2014, p. 48). Though social networking sites seemed certain to expand people's participation in politics when use of the sites became widespread (Carpentier, 2011), the exponential increase in content in online environments further contributed to a consumerist approach to communication for many social media users rather than enhanced democratic engagement with civic information, which in turn may have increased user receptiveness to Trump's rhetoric (Dean, 2005; 2009). According to Dean, many users existed as infotainment consumers within perpetual cycles of what Siapera (2016) referred to as "content production and enjoyment." Further, social networking sites, beyond even the ability to algorithmically determine the visibility of content for users (Siapera, 2013), may have "condition[ed] users to the economy of likes and shares" by "[prioritizing] popularity (measured in likes and shares) over everything else" (Gillespie, Boczkowski, & Foot, 2014: Siapera, 2016, p. 102).

As such, the short, catchy, divisive rhetoric deployed by the Trump campaign, including and alongside "Make America Great Again," further increased the likelihood that Trump's rhetoric would take discursive hold, due to its being more appealing to social media users than nuanced, neutral evaluations of political issues, a preference compounded by Twitter's 140-character content limit and the characteristics of that platform. From a mechanical standpoint, the phrase was an archetypal example of political rhetoric engineered for social stickiness and discursive longevity. If "the more simply and plainly an idea is presented" renders it more likely to be "understandable…and therefore…credible" (Luntz, 2007, p. 5), Trump's catchphrase embodied the stark polarity of his platform, one that hinged upon scapegoating those not explicitly part of making America great again as responsible for keeping America bad (Reicher & Haslam, 2017). Put differently, "the simplicity of the slogan [matched] the candidate and the campaign" (Luntz, 2007, p. 7), allowing for only one sensible course of action—voting Trump—and highlighting the "capacity of language that is present and of language that is absent to structure" possible responses (Edelman, 1988, p. 47).

In accordance with the prevailing "preference for simple words and acronyms" in popular culture, "Make America Great Again" compressed an entire political platform into a memorable, emotionally charged phrase (Luntz, 2007, p. 6). The slogan, while short and deceptively straightforward, directed public dissatisfaction and hostility toward the other politicians scapegoated for America's ills, even as it supplied seeming proof of Trump's own leadership potential, fostering confidence in Trump's ability to fix these problems and endowing him with “personal authority and responsibility” (Edelman, 1988, p. 60). Central to the theme of Trump as solution was, of course, the casting of his opponents—again, Barack Obama, Hillary Clinton, and Ted Cruz —as the problems. Accordingly, rather than invite divergent viewpoints on relevant political issues, much of Trump’s rhetoric embodied the incivility and personal attacks characteristic of negative campaigning (see Jamieson, 1992, for definition and explanation of negative campaigning).

Incivility and Negative Campaigning

From vilifications of Hillary Clinton as the cause of America’s problems to chants of “Lock her up!” promoting Clinton’s incarceration, much of the “Make America Great Again” discourse did not reflect the democratic ideal of civility in political discussion (e.g., discussion of civil communication ideals in Herbst, 2010). Defined as “features of discussion that convey an unnecessarily disrespectful tone toward the discussion forum, its participants, or its topics” by Coe, Kenski, and Rains (2014, p. 660), incivility in political discourse is hardly new (see Herbst, 2010; Massaro & Stryker, 2012; Papcharissi, 2004; Sapiro, 1999; and Uslaner, 1993, for full review).

Nevertheless, Twitter as a platform had multiple implications for incivility and negative campaigning. Trump’s Twitter usage of the “Make America Great Again” rhetoric during the campaign often involved in-person and online disparagement of those he perceived to be responsible for keeping America bad, so much so that *Politico* dubbed him the “Twitter Cry-Bully” (Keohane, 2016). The immediacy and interactivity of Twitter enabled more people to participate in the incivility. Once instigated, unnecessarily disrespectful terms and catchphrases caught rhetorical fire, used thousands of times by thousands of Twitter users in a matter of moments (Sobieraj & Berry, 2011). Observing the popularity of Trump's disrespectful rhetoric as evidenced by the high number of retweets, favorites, mentions, and replies accrued by Trump's attack tweets, the *New York Times* acknowledged that Trump wielded Twitter in a way that was "pithy, mean, and powerful" (Barbaro, 2015(b)). This power derived in part from the degree to which other Twitter users adopted Trump's rhetoric, in such a way that the "political promotion, score-settling, and attack" characteristic of Trump's tweets became characteristic of the "Make America Great Again" Twitter discourse as well (Barbaro, 2015(b)).

Again, though negative campaigning through personal attacks on and disparagement of the opposition was not a novel strategy (see Jamieson, 1992, for a partial review), the intensity and frequency of negativity were compounded by the repetition of the invectives used by those tweeting with the "#MAGA" hashtag and/or the phrase "Make America Great Again," as well as the skew toward pro-Trump sentiment and rhetorical identification within the "in-group" of Trump supporters in that communication space (McCosker, 2016, p. 23). Even though most Americans self-reported that they viewed incivility in political discussion in a negative light and saw incivility as a problem (Public Religion Research Institute, 2010), incivility and negative campaigning were effective in rallying members of an in-group and further dividing said in-group from the opposition (Hopp & Vargo, 2017). Moreover, the entertainment and instigation capacities of incivility and negative campaigning in the age of the internet have been well documented (Berry & Sobieraj, 2013).

As a problem definition and causal explanation frame, “Make America Great Again” rhetorically targeted and contributed to the harassment of these enemies, Clinton in particular. The extent and longevity of the rhetorical venom directed at Clinton in the “Make America Great Again” discourse, in context, seemed to reflect the affordances and characteristics of Twitter as a platform. With “permissiveness and freedom of expression” as two of Twitter’s core values, “belligerent users” were able to communicate freely without much pushback from platform administrators (Quodling, 2016, p. 136). In the words of former Twitter CEO Dick Costolo, “we suck at dealing with abuse” (Tiku & Newton, 2015). Certainly, attacks are part of political campaigns. Yet the platform of the attacks here differentiated the “Make America Great Again” discourse, a content frame characterized by vitriolic opposition rather than measured criticism, much less respect for Barack Obama, Hillary Clinton, or Ted Cruz. Most crucially, increased negative campaigning has been linked to heightened Twitter activity, in turn linked to increased citizen incivility (Hopp & Vargo, 2017). Trump’s relentless use of disrespectful rhetoric in talking about his perceived enemies may well have contributed to the popularity of “Make America Great Again” on Twitter with all its attendant incivility.

In sum, Twitter provided space and offered people other than the candidate himself the opportunity to participate in the attacks within the echo chamber composed of other Twitter users sympathetic to their views (e.g., echo chambers in Colleoni, Rozza, & Arvidsson, 2014; Key, 1996). Social networking sites have been especially conducive to subversive rhetoric as a means of group identification as well as a means of response to large-scale events with collective implications, such as the Republican National

Convention or perceived attacks on one's in-group (Carlson & Frazer, 2016). This group identification on Twitter was still in place two months later, when Clinton called Trump supporters a "basket of deplorables" (Clinton, 2016, in Chozick, 2016). Rather than galvanizing Clinton's political in-group, the comment gained subversive traction with Trump supporters. Trump supporters appropriated this "demonizing discourse," inspiring "sympathetic tweeters" to incorporate Clinton's turn of phrase into tweets and usernames (Carlson & Frazer, 2016, p. 125) that then identified those Twitter users as members of the "Make America Great Again" movement and enemies of Clinton.

I examined incivility and negative campaigning during the Republican National Convention as revealed by textual analyses based upon Trump's self-proclaimed enemies. First, I investigated the ways in which the "Make America Great Again" discourse discussed Obama, Clinton, and Cruz by generating semantic network maps for the conversations around each of these three politicians based on semantic co-reference lists. In other words, I looked for the pairs of words that occurred together most frequently in the tweets mentioning each politician and then plotted those words on a network map to learn more about which words shaped the discourse around each politician. I calculated and analyzed network metrics for each of the three datasets. I then examined the presence of words targeted at the disparagement of the opposition. My goal was to investigate the kind of rhetoric used by participants in the MAGA discourse to talk about members of the opposition.

Collective Action

As "Make America Great Again" was picked up by Twitter users within Trump's Twitter network, the slogan may have been used to "mobilize and advance an online…movement that activated an offline movement," in this case, calls to vote on Twitter potentially connecting with voter decisions at the polls (Harlow, 2011, p. 226). While there was not a "clearly delineated dichotomy" between Trump's offline rallying cry and online usage of the hashtag "#MAGA" or the phrase "Make America Great Again" (Carlson & Frazer, 2016, p. 126), Twitter provided a space to respond to and perpetuate Trump's communications at the Republican National Convention. On social networking sites like Twitter, a user's network of connections within the site have been shown to influence not only the content to which that user was exposed (Himelboim, McCreery, & Smith, 2013), but also the likelihood that the user would "adopt" the content to which they were exposed. In fact, a user's network has been shown to "play a significant role in the adoption of content" (Bakshy, Karrer, & Adamic, 2009, p. 325). The "Make America Great Again" rhetoric on Twitter became a nexus of pro-Trump Twitter activity and provided a way for users to access and find content in line with Trump's views. In the context of this study, that content was tweets containing any rendition of the "Make America Great Again" frame ("#MAGA," "MAGA," "#MakeAmericaGreatAgain," or "Make America Great Again"), and "adoption" was defined as posting a tweet containing the frame or retweeting or liking a tweet containing the frame.

Even in the pre-internet era, when reaching group members and accessing political information was far more difficult than it was for Trump and "Make America Great Again" tweeters during the Republican National Convention, group membership organized around a strong leader served as a "catalyst of conformity" (per characteristics of framing identified by Edelman, 1988, p. 37). The content of tweets already tended to "coalesce around shared worldview(s)," indicating which groups users are "part of or apart from" (Vivienne, 2016, p. 149). As a phrase with the potential to "excite the imaginations of large numbers of people and…help to organize and discipline them" (Edelman, 1988, p. 37), "Make America Great Again" was made even more potent by the instantaneous exposure to and interaction with information that characterizes political discourse on Twitter. In facilitating this connection between users, social networking sites enabled the formation of in-groups across geographic distance and "vastly disparate social and cultural contexts" (Carlson & Frazer, 2016, p. 124). Regardless of location or specific frustration, then, people from many different walks of life could experience the social identification of aligning with Trump's rhetoric.

The pull of a leader with the perceived ability to connect people across divides, combined with the constant rhetorical reinforcement made possible by Twitter, may have contributed to the proliferation of calls to vote for and donate to Trump because of the "practical and affirming" nature of "social connectedness" that could be experienced via rhetorical identification with Trump (Vivienne, 2016, p. 149). Similarly, "Make America Great Again" discourse on Twitter lent itself to the formation of norms for identifying oneself as a member of the coalition for Trump or the opposition to Trump. The adoption and repetition of the "Make America Great Again" frame and its core ideas among Trump supporters reflected the Trump campaign's emphasis on "curated personal congruence" along supporter or enemy lines, as tweets fell clearly within Trump's in-group or within the out-group of the opposition (Vivienne, 2016, p. 148-149).

Specifically, I looked for two calls to action, all indicative of political advocacy. Calls to "vote" or "donate" were explored via textual analysis of those words within each of the three politician-centered datasets. Additionally, I looked for the words most commonly used in proximity to these calls to action, such as “#trumptrain” or “#crookedhillary.” Inquiry into these calls to action was directed by three additional research questions:

4) *What are the direct and indirect discursive connections involving the concepts, “vote” and “donate,” in tweets mentioning Barack Obama?*
5) *What are the direct and indirect discursive connections involving the concepts, “vote” and “donate,” in tweets mentioning Hillary Clinton?*
6) *What are the direct and indirect discursive connections involving the concepts, “vote” and “donate,” in tweets mentioning Ted Cruz?*

The Republican National Convention

Tweets during the Republican National Convention presented a unique body of data for looking at problem definition and causal explanation framing. Much of the literature using political national conventions as context(s) had focused on the speeches made by candidates (e.g., Buchanan, 1992; Campbell, 1972; Frank & McPhail, 2005; Gibson & Heyse, 2010; Ritter, 1980; Rowland & Jones, 2007), delegates to the conventions (e.g., Masket, Heaney, Miller, & Strolevitch, 2009; Roback, 1975; 1980; Soule & Clarke, 1970; Usher, 2000), policing and protest at the conventions (e.g., Earl, 2009; Janiszewski, 2002; Vitale, 2007), or the conventions’ cultural import for political parties and for society (e.g., Fiorina, Abrams, & Pope, 2005; Katz & Kolodny, 1994; Kirkpatrick, 1975; May, 1973; Rapoport, McGlennon, & Abramowitz, 2015). While Hughes & Palen (2009) looked at the use of Twitter during the Democratic National Convention and the Republican National Convention in 2008, they sought to understand

Twitter's "use during mass convergence and crisis events" (p. 249). In addition to the national conventions, they examined Twitter use during two Category 4 hurricanes in 2008 (Hughes & Palen, 2009). As such, their insights focused on the emergency management potential of Twitter and user behavior during these four events. By contrast with the literature mentioned, I focused not on candidate speeches, policing, cultural impacts of the convention, or user behavior, but rather on the content of tweets sent during the time frame of the 2016 Republican National Convention as it pertained to "Make America Great Again" as a content frame.

While national conventions no longer supply the drama they once did when nominees were decided at the convention rather than by state primaries preceding the convention, the event was nonetheless a "highly staged television pep rally" (Barrow, 2016) that, in the case of the RNC, sought to engage potential voters in the spectacle of Trump. Trump used his time at the convention to attempt to make that spectacle more likeable and appealing to prospective voters. Trump was an anomaly in this regard. His existing fame and established celebrity persona enabled him to use the RNC not to garner new publicity but to continue selling "the primary product…his personal brand" (Barrow, 2016) and the campaign that came with it. "Make America Great Again" here moved beyond being a mere slogan to become an inseparable part of this personal brand, benefiting from the publicity and popularity grafted from its source. Senior campaign aide Paul Manafort explicitly stated that Trump would be "out on the stage" at the RNC, "projecting an image…for [the] purpose" of making his framing of the issues as pervasive and persuasive as possible (Manafort, meeting with members of the Republican

National Committee, 2016). Where Trump was most visible, so, too, was his slogan most visible, indicating that the Republican National Convention was a fruitful time to examine discourse on Twitter involving the "Make America Great Again" frame.

Research Overview

To investigate how "Make America Great Again" functioned as a problem definition and causal explanation frame on Twitter during the 2016 Republican National Convention, I utilized text mining and semantic network analysis. Textual analysis has been a technique used previously in political and mass communication scholarship (e.g., Bligh, Kohles, & Meindl, 2004; Namenwirth, 1969; Popping & Roberts, 2009; Roberts, 1997; Roberts, 2000; Roberts, Zuell, Landmann, & Wang, 2010; & Van Cuilenberg, Kleinnijenhuis, & De Ridder, 1986). The method has facilitated analysis of large amounts of social network data and enabled analysts to look at aspects of a text in relationship to many other texts and aspects of texts in visual ways that revealed new insights (e.g., Grimmer & Stewart, 2013; Tambayong & Carley, 2013). Specifically, examined the ways in which Trump's slogan identified the pertinent political problem as America not being great and cast strategic blame for this lack of greatness on his enemies. As discussed, I also looked at calls to action within these semantic networks, including calls to vote Trump and donate to his campaign.

To understand how "Make America Great Again" may have functioned as a problem and causal attribution frame, an exploration of how other Twitter users interacted with the slogan was necessary. With the goal of understanding how other Twitter users tweeting with the hashtag "#MAGA" or the phrase "Make America Great Again" during the Republican National Convention either replicated or diverged from the verbiage Trump used in talking about Obama, Clinton, and Cruz, I first collected all tweets containing that hashtag or phrase that were sent during the Republican National Convention. Then, I completed separate textual analyses of the sub-groups of tweets referring to Obama, Clinton, or Cruz, respectively. I generated a semantic network depicting the discourse around each of these politicians as well as a textual analysis of all tweets pulled to gain a composite picture. I then created and analyzed network maps highlighting important metrics for each politician's dataset and for the larger dataset containing all collected tweets.

CHAPTER 3: METHODOLOGY

Network Analysis: A Primer

Key Terms and Example Uses

Put simply, network analysis consists of examining a set of entities and analyzing the meaning that underlies relationships among those entities. Entities may be referred to as “nodes,” “entities,” or “objects,” and can represent people, companies, words, locations, and more. The relationships among the entities may be referred to as “links,” “ties,” or “edges” (Hansen, Shneiderman, & Smith, 2011). Network analysts generate a network “map,” or network graph, of all the entities (nodes) and the connections among them (edges). Because network analysis focuses on meaningful relationships, the methodology may be applied to any group of entities related to each other such that they are interdependent in some way. Thus the network approach to understanding data may yield benefits in disciplines ranging from medicine to management. Specific communication-related contexts for network analysis include work with information systems (e.g., Milo, Shen-Orr, Itzkovitz, Kashtan, Chklovskii, & Alon, 2002; Scott, 2012), marketing communication and reputation management (e.g., Hajer & Wagenaar, 2003; Resnick & Zeckhauser, 2002), and politics, from networks that help shape the identities of nations (Castells, 2003), to networks that influence political participation (Scheufele, Nisbet, Brossard, & Nisbet, 2004), to the implications of online spaces for political communication today (e.g., Grant, Moon, & Grant, 2010; Klinger & Svensson, 2015).

Network Mapping

Network analysts utilize a variety of visualization tools, ranging from mapping a small network by hand to inputting data into powerful computational network analysis programs that then map the data according to algorithms. One such program, and the one utilized for this study, is NodeXL Pro. Once NodeXL has generated a network map, visual properties like node size, shape, and color, or the opacity and width of an edge, can be set to reflect metrics of interest. For example, node size can be set to reflect how many connections a certain word has with other words in the dataset. The more connections the word has, the bigger its corresponding node is on the network map. Similarly, edge width can be set to reflect how many times two words occur in close proximity. In this instance, words often paired together would have a much thicker edge connecting them than would words that rarely appeared near each other.

Semantic Network Analysis

Importantly, while this study used “network analytic techniques,” it was a semantic network analysis and was, therefore, different from traditional network analyses. As opposed to traditional network analysis focused on “who communicates with whom,” semantic network analysis is concerned with “meaning networks” (Doerfel, 1998, p. 23) arising from “paired associations based on shared meaning,” specifically, an emergent meaning available only via data-driven discovery (Doerfel, 1998, p. 16). In this study, I explored the direct and indirect relationships among discursive concepts used within the “Make America Great Again” discourse in connection with Barack Obama, Hillary Clinton, and Ted Cruz, respectively. I was not concerned with paired associations between actors, nor “behavioral or perceived communication links” (Doerfel, 1998, p.

16). Further, semantic network analysis was a means toward minimizing researcher bias by not imposing a priori categories or questions on the data. Rather than divorce concepts from context through frequency counts or categorization, I instead sought to explore the "semantic content of message[s] in the actual, natural language in which they were originally expressed, resulting in greater external validity" (Danowski, 1993, p. 219).

In other words, the focus of my semantic network analysis was on "analyses of meaning networks, in which the nodes [were] words" (Doerfel, 1998, p. 18). Beyond the assumption that words share meaning, the method assumed that new meaning might arise from the very fact of the connections between words. At the simplest level, two pairs of words that would normally have nothing in common could, in a network, have taken on a new meaning because of the shared meaning of another word. For example, the words "black," "death," and "Chicago" each possess a range of meanings unto themselves. Taken together, however, a new meaning altogether is born of the connections between the words (Monge & Eisenberg, 1987).

Network Metrics

One of the challenges of working with network analysis was the lack of a widely accepted schematic for analysis. There was no systematic process of interpretation for network analysis studies that I could apply to my dataset (Doerfel, 1998). Rather, it was up to me to make use of the metrics that made sense for the study at hand. In this way, the semantic network analysis was both qualitative and quantitative. While network maps and metrics were based on mathematical calculations, qualitative immersion in the dataset was necessary to consider which metrics might be meaningful based on the kind of data under investigation and the contexts from whence they were collected. In the following paragraphs, I describe the specific measures that proved helpful in my investigation of relationships among concepts within the dataset of tweets that referenced "Make America Great Again."

Network-level density and centralization

Once the network had been mapped, many different types of metrics could provide insight about individual nodes, pairs or groups of nodes, and the network as a whole. As this section provides just a few examples of the metrics available via NodeXL, I describe the specific metrics recorded and utilized for my data later in the thesis, alongside my results. (For reference, I use "node" and "vertex" interchangeably.) First, "network density" assessed how highly connected the graph (entire network) was by dividing the number of actual connections in the network by the total number of possible connections. This was an example of a network-level metric that could point toward network characteristics along the lines of cohesion or solidarity (Hansen, Shneiderman, & Smith, 2011).

"Centralization" was another key network-level metric I used, because it can facilitate insights about the structure of the network. For example, a network with a high centralization value would be characterized by a few highly important (central) vertices. A network with a low centralization value would indicate that, for the most part, there were not two nodes/pairs that were substantially more prevalent than any other possible pairs. (Again, the specific network measures utilized in this study are discussed in detail later.) Because I assumed relationships between entities to be indicative of frames, network density and centralization metrics helped determine how prevalent certain frames were within the "Make America Great Again" discourse overall by showing whether the discourse was characterized by a few important entities (frames) and how the conversation followed or diverged from those frames.

Nodal-level centrality values and geodesic distance

To understand more about individual vertices, centrality measures (among other vertex-level metrics) were useful for understanding the relative importance and network positions of individual vertices. Vertex centrality metrics differed from the overall network centrality mentioned above. On the vertex level, centrality values helped me learn more about the relative importance of a vertex within the network as well as the role that entity may have played within a network. The basic metric of "degree centrality" represented the total number of edges connected to the vertex in question. Additional vertex-level centrality insights helped describe the structure of the network, complementary to the insights made possible by network-level structural analysis as touched on above.

For example, when a pair of nodes was not directly connected, but there was a third node connecting them, the third node could be thought of as a "broker" or "bridge" (Hansen, Shneiderman, & Smith, 2011, p. 40). There would be a "structural hole" in the network if that third node was not there, because without it the first two nodes would not be connected (Hansen, Shneiderman, & Smith, 2011, p. 40). In this vein, "geodesic distance" measured the length of the shortest possible path from one vertex to another. A node that was on many of the shortest possible paths between nodes—a broker node—was considered to have a high "betweenness centrality." As it reflected the extent to which an entity connected other entities, betweenness centrality was an important metric in this study because it helped reveal how concepts were connected to one another within the “Make America Great Again” discourse, as well as shed light on the new, shared meanings that arose out of the relationships among concepts.

Clusters and groups

The concept of “groups” or “clusters” was also important in my semantic network analysis. A group was a set of vertices that were connected to each other more than to the other vertices in the network. Sometimes, there was even a group of nodes within the network that was self-contained, connected only to nodes within its group and not to the larger network. When the network could be separated into distinct sub-networks composed of these groups, the sub-networks were called “components.” Far from always being formal or circumscribed, groups, clusters, and components were sometimes present in the data and based on social ties, only discoverable via data-driven discovery, specifically computerized community detection algorithms (Hansen, Shneiderman, & Smith, 2011). In other words, groups may have existed within the network even where they were not expressly identified or categorized. Once identified, clusters facilitated strategic insights and decisions and made the larger network more comprehensible, among other benefits. Because I was investigating frames within the “Make America Great Again” discourse, clusters and groups helped identify key concepts as well as the shared meanings arising from the conversation around those key concepts.

Semantic Network Analysis: This Thesis

Each node in the networks used for this thesis represented a word or hashtag that appeared in the “Make America Great Again” dataset. It is important to note that words and hashtags were qualitatively different. While hashtags were composed of words and were used as such in the discourse, they had meaning beyond the words themselves, a meaning arising from usage and purpose in context. Hashtags were a way of injecting oneself into a public conversation in such a way that one identified oneself as part of a discourse and followed a thread of ideas (Kwak, Lee, Park, & Moon, 2010). Just as connections between words contributed new meanings arising from the associations, so, too, did hashtags illuminate particular meanings of the concepts to which they were connected (see, for example, discourse attending the #BlackLivesMatter movement). When a hashtag was present in a tweet, the rest of the content in that tweet was placed in the conversational context that hashtag represented. In this case, MAGA tweets containing hashtags, such as “#NeverHillary,” indicated enemy framing and placed related concepts in the context of that frame.

Each edge signified that the nodes at either end appeared together in a tweet. Thus, this study was classified as a topic-centric “semantic network analysis,” because it was concerned with concepts and the relationships among them (Drieger, 2013). With regard to additional classification, the co-occurrence pairs examined in this study composed a “unimodal network,” because both vertices in each pair represented the same type of entity, words, as opposed to one vertex representing words and the other representing users, for example. While there is room within network analysis to acknowledge that the entities represented by vertices may in fact have been connected in many ways, network maps usually depict only one kind of connection at a time for the sake of clarity and meaningful analysis (Hansen, Shneiderman, & Smith, 2011), and I did the same. The specific metrics I chose to represent and analyze are discussed in detail in the results and analysis sections.

Based on Entman's definition of framing as the selection and salience of aspects of a perceived reality (1993), I conceptualized frames as webs of concepts both creating and representing the meanings of the concepts within them. If the relationships between concepts could help me learn the meaning(s) of the discourse, what I learned from the meaning(s) would then help identify frames (Doerfel, 1998). Thus semantic network analysis was a beneficial way to identify and analyze frames within the "Make America Great Again" discourse. The method facilitated exploration of how concepts were used and linked within the discourse; in other words, the method helped illustrate which frames and central themes shaped the "Make America Great Again" conversation.

Certainly, not all entities composing the semantic network represented a frame. Further, within the "Make America Great Again" frame, there were smaller, overlapping frames present in the discourse that are discussed in the results section of this thesis. Based on my assumption that meaning within this discourse arose not from concepts in isolation but from the connection of concepts taken together, it was this compound meaning I considered to be a frame. While individual concepts themselves could be considered mere topics of discourse, measurable by a frequency count, the relationships revealed by semantic network analysis went beyond identifying topics to represent the ways in which connections among topics created a framework for understanding the topics in question. Where nodes in the network graph represented aspects of the "Make America Great Again" frame, I used semantic network analysis to visually map the "aspects of a perceived reality" that Twitter users "[made]…more salient" in tweets containing the hashtag "#MAGA" or the phrase "Make America Great Again," drawing upon relationships of meaning to ascertain whether the discourse did indeed reflect the problem definition frames and scapegoating that were lynchpins of the "Make America Great Again" worldview (Entman, 1993, p. 52). Similarly, the presence of groups and clusters in the network map did not automatically indicate the presence of a frame. Rather, each cluster was evaluated qualitatively against the rest of the network to determine the meaning of the relationships within it. Each cluster was then located and examined within the original tweets, verifying in the original context the presence (or absence) of the meaning drawn from the network map.

Said insights were possible only via exploration of potential relationships of meaning in the data as could be revealed through network mapping and metrics. As with any network, getting from one node to another often involved tracing a "path" through intermediate nodes such that the beginning and endpoints of the trajectory now had these nodes in common. Far from existing within an environment shaped exclusively by the other nodes to which they were directly connected, key terms within the "Make America Great Again" discourse could therefore be examined for potential connections to seemingly unrelated entities elsewhere in the network (Hanneman & Riddle, 2005).

Likewise, network theory provided theoretical space for exploring the possible processes of rhetorical diffusion within the "Make America Great Again" discourse and for examining potential relationships within the Obama-centered, Clinton-centered, and Cruz-centered semantic networks. Because I aimed to describe relationships of meaning on the intensely relational platform of Twitter using datasets comprising thousands of tweets, semantic network analysis was a good theoretical and logistical fit.

As mentioned earlier, this semantic network analysis of the "Make America Great Again" discourse recognized that the discrete event used to demarcate the dataset, the

Republican National Convention, did not stand in isolation. Rather, the RNC came at the end of an embittered Republican primary campaign, culminating with Trump accepting the presidential nomination and kicking off his official presidential campaign at the top of the Republican ticket. Network theory was a strong choice for analysis of the discourse in context as it allowed me to differentiate between backcloth and traffic (see Atkin, 1977, for discussion of the backcloth and traffic model). Put another way, network-based textual analysis helped me explore both the "backcloth," or medium (here, Twitter), and the larger context (the campaign), in which the nodes and edges existed, while also exploring the "traffic," the nodes themselves and the relationships between them.

Overview of Network Insights

I analyzed the "Make America Great Again" discourse using a combination of the three levels of network analysis identified by Borgatti, Everett, & Johnson (2013): nodal, dyadic, and network-level. First, nodal-level analysis spoke to the frequency and co-occurrence of key concepts within the discourse, illuminating which aspects of the frame were perceived as most important or most attractive by Twitter users participating in the discourse. Analysis at this level was conducive to exploration of associations between entities and outcomes (e.g., textual evidence that the key aspects of the "Make America Great Again" frame took hold among Twitter users participating in the discourse).

Second, analysis at the dyadic level focused on pairs of nodes. As the name suggests, this level of analysis was concerned with the pairwise relations between entities that, taken together, composed a network. Dyadic measures, such as the co-occurrence of terms like "#MAGA" and "#NeverHillary," formed the basis of many network-level insights. Dyadic analysis also enabled investigation of relationships among concepts while circumventing the limitations that would otherwise be imposed by analyzing a dyadic relationship in isolation, that is, outside the context of the network (see Kenny, Kashy, & Cook, 2006, for a partial review of the benefits of dyadic-level analysis).

Third, network-level insights permitted description of the “Make America Great Again” discourse by looking at the data in aggregate (see Provan, Fish, & Sydow, 2007, for a partial review of the benefits of network-level analysis). Attempting to explore framing theory via isolated communication phenomena might have undercut the complexities and implications of how framing theory could be applied to this context. By contrast, utilizing network-based textual analysis enabled in-depth exploration of the “Make America Great Again” discourse on Twitter through the lens of framing theory. Specifically, I operationalized problem definition and causal attribution frames (per Entman, 1993) as characterized by a focus on specific named entities. These entities were Barack Obama, Hillary Clinton, and Ted Cruz.

As such, the dataset incorporated all edges between all nodes in the network representing words that appeared in the “Make America Great Again” discourse on Twitter during the 2016 Republican National Convention (per the definition of a network dataset in Borgatti, Everett, & Johnson, 2013). Underlying assumptions about this dataset included political bias in the results and candidate-related themes. My analysis also considered the fact that the tweets composing the dataset were generated by individuals who had an awareness on some level that what they said would be publically available, who desired to participate in a public conversation. In the same vein, hashtags on Twitter reflected popular if partial public opinion, but did not necessarily reflect the views of everyone on Twitter. Accordingly, assuming that the demographic makeup of Twitter was or is representative of the entire U.S. electorate would be unwise. Similarly, the networks analyzed in this thesis should not be taken as representative of or generalizable to other political situations or the larger electorate.

Data Collection

Criteria for Data Collection

Three sampling criteria served to delimit which tweets met the criteria for sampling consideration. First, the Republican National Convention, which took place from July 18-21, 2016, set the time boundary for the data. Only tweets posted during this date range were eligible to be collected. Second, with the slogan-as-frame being the focus of this study, only tweets sent during the RNC that contained a direct reference to the frame (#MAGA OR MAGA OR Make America Great Again OR #MakeAmericaGreatAgain) met the criteria for inclusion in the dataset. Third, only English-language tweets were of interest here.

Using these entities allowed for determination of which tweets were relevant. As mentioned earlier, when tweets contained identifiable markers like these hashtags or phrases, the text of the tweets was "still public, but the intended flow of conversation [was] clearer" (Hansen, Shneiderman, & Smith, 2011, p. 46). Similarly, these "markers of addressivity" made it possible to "capture the attention" of a specific group or conversation stream (Hansen, Shneiderman, & Smith, 2011, p. 46). In other words, the hashtag was the tool that allowed Twitter users to attend to and/or participate in online discourse pertaining to Making America Great Again.

As all identifying information, such as Twitter handles and profile information, was stripped for private individualas, and analysis focused on the content of the tweets and not the identities of the individuals tweeting where the individuals were private citizens and not public figures, the study fell under the "non-human subjects/review not required" designation available from the Institutional Review Board for studies utilizing publicly available data. The completed Human Subjects Determination Worksheet was submitted to the IRB, and the formal documented designation of "IRB Review Not Required" was obtained in case of future publication. Once retrieved, data were securely deposited by Sifter into a DiscoverText account. All data were securely stored and encrypted in this private account in DiscoverText before being securely exported to my password-protected personal computer.

Collection of Tweets and Creation of Datasets

Collection of tweets was accomplished via Sifter and DiscoverText, linked applications used by academic researchers to pull for analysis all undeleted tweets meeting given criteria within given time constraints (Texifter, 2017). In accordance with Sifter syntax, the query used to collect these data was: *"Make America Great Again" OR #MakeAmericaGreatAgain OR MAGA OR #MAGA lang=en*. The query as submitted yielded a Sifter estimate of 433,337 tweets matching the sampling constraints for a total cost of $161. Once the data request had been processed and paid for, all tweets were loaded into DiscoverText and made available via the DiscoverText dashboard as a new "project."

DiscoverText capped project archives at 50,000 tweets, resulting in nine "archives" of tweets for this project. Legally, Twitter required that all data be converted from these archives and reformatted within the confines of DiscoverText before it could be exported for analysis outside of DiscoverText. Thus, I created nine buckets for each of the archives. Then I created queries for each bucket that would pull tweets mentioning Obama, Clinton, and Cruz, respectively. To collect tweets referencing Obama, I ran the query "Obama OR Barack OR BarackObama OR Barry OR Nobama OR ThanksObama" in each of the original nine buckets, and then added the resulting tweets to a new bucket. To collect tweets referencing Clinton, I ran the query "hillary OR hrc OR hillaryclinton OR clinton (each instance here examined after retrieval to determine mention of Hillary and not Bill) OR neverhillary OR hillaryforprison OR crookedhillary OR hillno OR hillyes OR imwithher OR lockherup OR lock OR killary OR lovetrumpshate OR scumhag" in each of the original nine buckets, and then added the resulting tweets to another new bucket. To collect tweets referencing Cruz, I ran the query "Ted OR Cruz OR TedCruz OR LyinTed" in each of the original nine buckets, and then added the resulting tweets to a third new bucket. The terms used in these search queries contained derivations of the politicians' names as well as terms drawn from existing research detailing the names that Trump had previously used to refer to these three politicians (Lee & Quealy, 2017).

Next, I created "datasets" from the Obama, Clinton, and Cruz buckets, respectively. (Within DiscoverText and with Twitter data, datasets were the only format permitted for export.) In total, the Obama dataset comprised 11,276 tweets. The Clinton dataset comprised 56,621 tweets, and the Cruz dataset comprised 24,764 tweets. With an export maximum of 50,000 tweets per day, downloading the datasets for analysis took two days. Once these datasets were saved as .csv files, I imported them into separate

Excel workbooks. I then randomized the rows in each workbook and pulled a randomized 10 percent of the tweets from each candidate. This resulted in final datasets containing 1,127 tweets mentioning Obama, 5,662 tweets mentioning Clinton, and 2,476 tweets mentioning Cruz.

Data Preparation

Plain Text

I copied the text of the tweets mentioning Obama into Notepad, creating a .txt file. This step was necessary for AutoMap to be able to analyze the text without getting mired in metadata or preexisting formatting. Then I did some text cleaning in Notepad, where the find and replace function was easier to use than setting specific filters in AutoMap. Then I found all instances of "&amp," a common html error in ampersand translation, and deleted them. As I was not interested in hyperlinks for the present study, I deleted all instances of hyperlink-related code, including "http," "https," "://t.co/," and "://t…" to remove partial URLs that seemed to have spliced in the initial download of the tweets.

AutoMap

Once I had completed these steps, I saved the text file as a new file so that the original would remain intact. I then imported the new file into AutoMap, selecting "let AutoMap detect text encoding," and selecting input text direction to be left to right and top to bottom. Then I was ready to begin AutoMap preprocessing to prepare the data for analysis. This entailed removing text that occurred often but did not have meaning, i.e., was not of conceptual value to the dataset. Namely, this included pronouns, prepositions, indefinite and definite articles, and verbs of negligible semantic import (e.g., "being," "go"). The three categories of preprocessing in the program included "Text Cleaning," "Text Preparation," and "Text Refinement." As I aimed to do the least amount of preprocessing necessary to generate a usable dataset, I did not complete all tasks in each category. Nor did I complete the tasks in a circumscribed order other than what was qualitatively useful in removing text that was not meaningful.

Under "Text Cleaning," I removed extra spaces and converted British to American spellings. Then, under "Text Preparation," I removed noise verbs, or verbs like "be" and "go" that did not contribute substantial meaning, and prepositions. Under "Text Refinement," I removed punctuation entirely and did not choose to replace the deleted punctuation with extra space. Under "Text Preparation" once more, I removed single letters (this did not impair the data as all MAGA stems and hashtags were processed as sequences and not standalone characters by the algorithm) and numbers as words. I further removed all pronouns because I was interested in actual named concepts, and the ambiguity of pronouns when isolated from context would not have been helpful. Back under "Text Refinement," I deleted all html symbols to remove the syntax errors that I had not manually deleted previously in Notepad. Under "Text Preparation" one last time, I removed all noise words (again, words like articles or prepositions that did not contribute substantial meaning).

Once these preprocessing steps were completed, I generated a preliminary concept list in AutoMap to drill down and discover which other text was creating noise in my data. This preliminary concept list quantified the frequency of entities within the dataset. The concept list helped determine whether additional preprocessing of the data was required before the generation of a semantic network that assessed co-occurrence of word pairs.

Accordingly, text fragments and strings of syntax errors from attempting to translate emojis were identified by hand and added to a new Excel sheet in order to create a custom delete list. I kept the default options suggested by Automap for this command. Once this concept list was open in Excel, I sorted all concepts from largest to smallest using the values in the frequency column. I then chose to examine only those concepts that had appeared five or more times in the dataset, as the entities appearing less often than that had clearly not been picked up within the overarching discourse. I therefore added all items mentioned four or fewer times to the custom delete list as well. Finally, I saved this custom delete list and closed out of the preliminary concept list I had generated. I then copied the Excel delete list entries into a .txt file to ensure compatibility with AutoMap.

Back in Automap, under "Text Refinement," I applied this custom delete list. I chose rhetorical delete processing. I then generated another concept list to check if my previous text-cleaning measures had indeed cleaned the data. Then I generated a named entities list, which was interesting but did not yield results relevant to the research questions. Finally, I generated a semantic network co-reference list wherein word pairs could be ranked according to frequency. The list recorded bidirectional co-occurrence of words, since word order in the tweets did not need to be preserved. This, then, was the data eventually imported to NodeXL.

Once the Obama tweets had been prepared for the next step of analysis, I followed the same steps with the dataset of tweets referencing Cruz, eventually generating a custom delete list to further clean the text in AutoMap. I again checked the second concept list to ensure that the text had been sufficiently cleaned before generating the semantic co-reference list. I saved the Clinton tweets for last because they composed the largest dataset. The same series of preprocessing steps was followed. Based on the repetition of concept list entries due to misspellings that I had seen with the Obama and Cruz sets, I also instructed AutoMap to fix common typos.

Though there has been concern around the involvement of bots and fake Twitter accounts among the ranks of Trump's followers and, by extension, these "fake" contributions to the MAGA discourse, systematic verification of the top usernames present in the datasets did not turn up a single bot. Even those usernames that struck me as suspicious were borne out as valid on investigation; I checked the connected Twitter account and then located a second source (other social media, directory data, etc.) of identity verification.

CHAPTER 4: RESULTS

Figures and Tables

Network Graph Metrics

Each graph was undirected as edges represented relationships between entities, and not a specific direction of interaction, such as “following” another user or tracing the trajectory of a particular entity through the network. Of all three networks, the Clinton network, which contained the most tweets, also contained more entities (as represented by vertices) and more connections between those entities (as represented by edges) than did the other two networks. Self-loop and component values further reflected the relative size of the datasets. Importantly, the Clinton graph had a much larger geodesic distance value than the other two networks, indicating that there were more disparate entities within the Clinton discourse (Table 1).

In other words, the MAGA discourse around Clinton included more topical entities and was, therefore, a wider-ranging discussion. Similarly, the higher average degree value for vertices within the Clinton network suggested that a given entity was connected to a greater number of other entities than was the case within the other two networks, or that the conversation was, for the most part, centrally located around a few nodes, which were used across tweets containing many different entities. The relatively large average betweenness centrality value of vertices within the Clinton graph provided additional evidence that certain entities were tweeted in conjunction with more and more diverse entities than were present in the other two datasets (Table 1).

According to Hansen, Shneiderman, and Smith (2011), when an entity had a high betweenness centrality value, it was an indication that “a lot of nonredundant information pass[ed] through [that entity]” (p. 150). While statistical significance does not apply in network analyses in the same way that it does in other quantitative methodologies, high betweenness centrality values indicate that particular entities are semantically and structurally significant within a network. Without these entities, the meaning and overarching theme(s) of a network would be fundamentally different. For example, my results showed that a few nodes within the Clinton network anchored most of the discourse, tying otherwise disparate topics together. High betweenness centrality values revealed the entities that anchored the conversation. Conversely, vertices with low betweenness centrality values “provide[d] largely redundant information” (Hansen, Shneiderman, & Smith, 2011, p. 151).

Table 1. Metrics describing the network of entities within MAGA tweets.

Graph Metric	**Obama**	**Clinton**	**Cruz**
Graph type	Undirected	Undirected	Undirected
Vertices	210	929	299
Total edges	539	2409	954
Self-loops	1	7	0
Connected components	28	69	18
Single-vertex connected components	0	3	0
Maximum vertices in a connected component	147	766	260
Maximum edges in a connected component	467	2216	910
Maximum geodesic distance	9	16	9
Average geodesic distance	3.348737	4.55177	3.28805
Graph density	0.012303486	.002786181	0.01070683
Minimum degree	1	1	1
Maximum degree	55	137	34
Average degree	2.581	2.601	2.68
Minimum betweenness centrality	0	0	0
Maximum betweenness centrality	6607.915	112953.411	5652.327
Average betweenness centrality	122.243	1123.028	161.784

Top 10-15 Most Frequently Co-Occurring Entities

Top entities within the “Make America Great Again” discourse included “tcot,” the hashtag abbreviation for “top conservatives on Twitter,” and “ccot,” the hashtag abbreviation for “Christian conservatives on Twitter.”

Table 2. Obama network.

Entity 1	Entity 2	# Pairs
Tcot	Ccot	277
GOP	Ccot	228
Obama	Copied	97
Johnkstahlusa	Barry	96
Trumppence16	Af9 (link to Obama plagiarism article)	94
Tcot	Exempt	54
Rhetoric	Overheated	54
Michelle	Obama	50
Obama	Gabbyinca	48
Nra	Ccot	47
Stormbeware	Obamaclinton	46
Stormbeware	Progressive	46
Stopislam	Nra	46
Racism	Police	46
Progressive	Deception	46

Table 3. Clinton network.

Entity 1	Entity 2	# Pairs
Tcot	Ccot	1427
Maga	gop	1363
GOP	Ccot	1355
America	Great	730
Donald	Trump	602
Making	Things	542
Hrc	johnkstahlusa	326
Maga	neverhillary	307
Hillary	Clinton	289
Johnkstahlusa	maga	255
Maga	trumptrain	246
Post	Analysis	226
Crooked	hillary	216
Maga	Tcot	189
Maga	Trump2016	184

Table 4. Cruz network.

Entity 1	Entity 2	# Pairs
Maga	Gop	352
Tcot	Maga	163
Tcot	Meat	110
Politically	Dead	110
Dead	Meat	110
Endorse	Trump	79
Donald	Trump	77
Benedict	Arnold	49
Tcot	Cruz	44
Trump	Maga	43
Romney	Lose	43

Table 5. Whole network.

Entity 1	Entity 2	# Pairs
Maga	Gop	1715
Ccot	tcot	1704
Ccot	Gop	1583
America	Great	730
Donald	Trump	602
Making	Things	542
Maga	Tcot	541
Hrc	johnkstahlusa	326
Maga	neverhillary	307
Hillary	Clinton	289
Johnkstahlusa	maga	255
Maga	trumptrain	246
Analysis	Post	226
Crooked	Hillary	216
maga	Trump2016	184

Top 10-15 Entities with Highest Betweenness Centrality Values

Table 6. Obama network.

Vertex	Betweenness Centrality Value
Obama	10
Tcot	5.7
Johnkstahlusa	3.5
Af9 (link to Obama plagiarism article)	3.0
Trumppence16	2.9
Gop	2.5
Carminezozzora	2.2
Networksmanager	2.1
Cruz	2.1
Police	2.1

Table 7. Clinton network.

Vertex	Betweenness Centrality Value
Maga	10
Tcot	6.7
Trump	6.0
Hillary	5.6
Johnkstahlusa	3.9
Hrc	3.6
Neverhillary	3.5
Post	3.2
Analysis	3.1
Hillaryclinton	3.0
Trump2016	2.8
Clinton	2.7
Trumptrain	2.7
America	2.5
Crookedhillary	2.4

Table 8. Cruz network.

Vertex	Betweenness Centrality Value
Trump	10
Trumppence	5.8
Carminezozzora	4.2
Johnkstahlusa	4.1
Knp2bp	3.5
Suthen_boy	3.3
Tcot	3.1
Political	3.1
Rnc	3.1
Good	3.0
Americafirst	2.8
Vote	2.8
Best	2.7
Imagine	2.7
Endorse	2.7

Table 9. Whole network.

Vertex	Betweenness Centrality Value
Maga	10
Tcot	6.7
Trump	6.0
Hillary	5.6
Johnkstahlusa	3.9
Hrc	3.6
Neverhillary	3.5
Post	3.2
Analysis	3.1
Hillaryclinton	3.0
Trump2016	2.8
Clinton	2.7
Trumptrain	2.7
America	2.5
Crookedhillary	2.4
Rncincle	2.4

Table 10. Semantic pairs referencing Clinton that appeared within the top 500 most frequent co-occurring pairs of entities within the MAGA discourse, listed from greatest to least frequency. The table suggests that the webs of meaning around Clinton-related entities served largely to disparage the enemy and rally around Trump far more than discuss Clinton's attributes or positions on issues or compare the candidates.

Neverhillary	Maga
Hillary	clinton
Crooked	Hillary
Hillaryclinton	Maga
Clinton	Foundation
Hillary	Obama
Voting	Hillary
Lockherup	Lockherup
Beat	Crooked
Magalink	Hillary
Hillary	Racism
Hillarymy	Analysis
Crookedhillary	Maga
Hillary	Lifetime
Beat	Hillary
Obamaclinton	Stormbeware
Neverhillary	Crookedhillary
Hrc	Reason
Defeat	Hrc
Scumhag	tcot
Americafirst	neverhillary
Beat	Hrc
Hrc	Groups
Pro	Hrc
Trump2016	Neverhillary
Trumppence	Hillaryclinton
Maga	lockherup
Neverhillary	trump
Clinton	Breaking
Dems	Clinton
Maga	Hillary
Son	Hrc
Scumhag	Buy
Clintons	Johnkstahlusa
Clintons	Promised
Hrc	Continues
Hrc	Huge
Crookedhillary	Makeamericagreatagain
Neverhillary	Makeamericagreatagain
Hrc	hear

Network Graphs

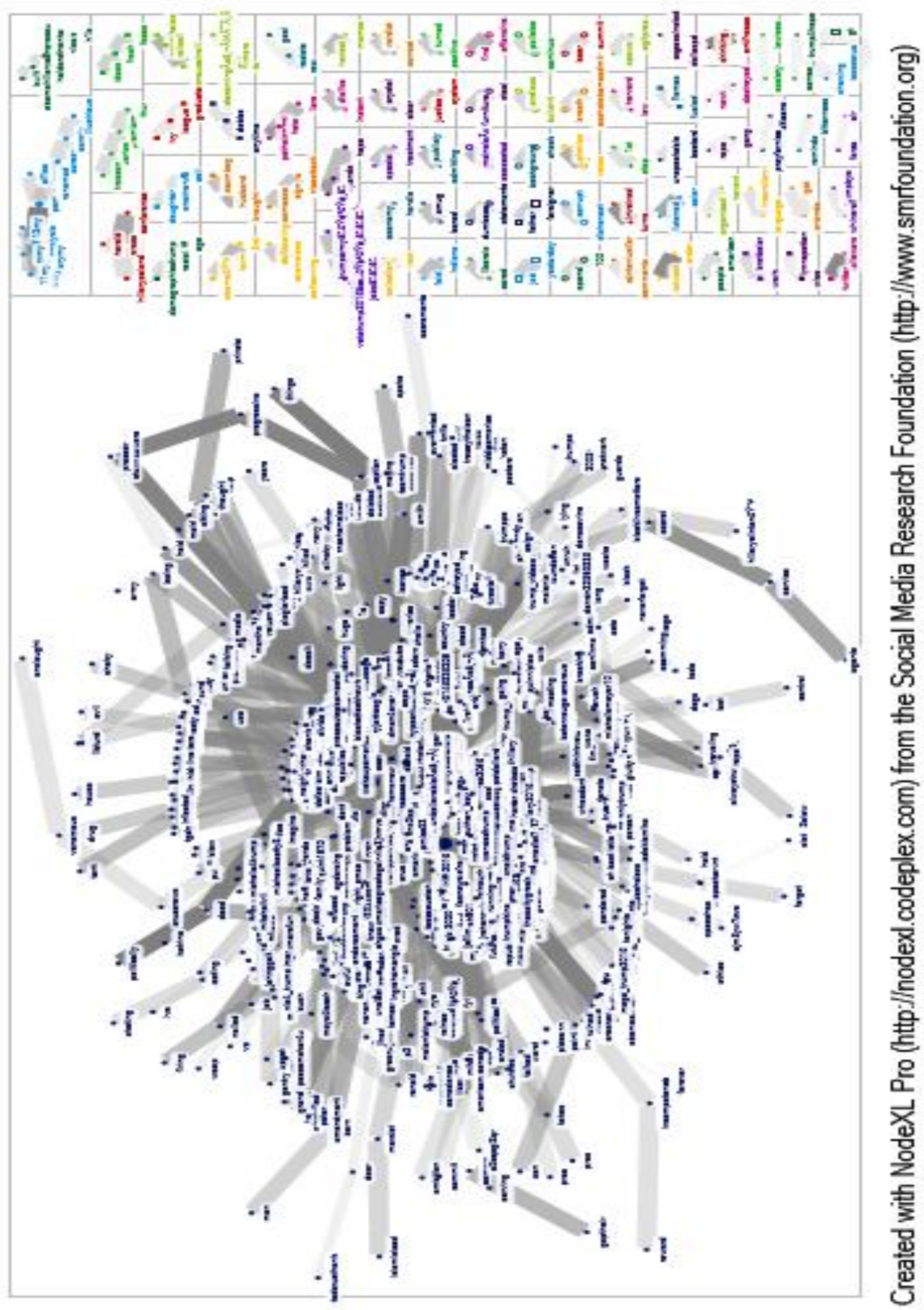
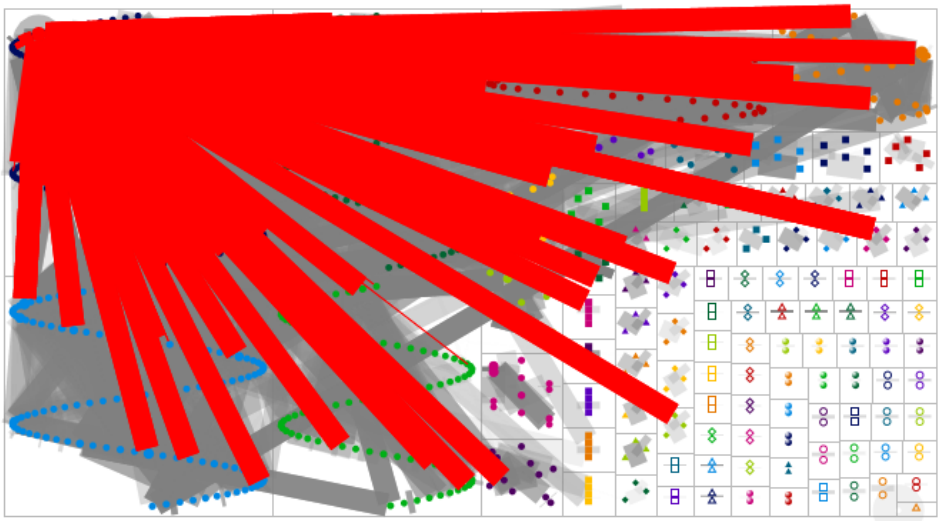
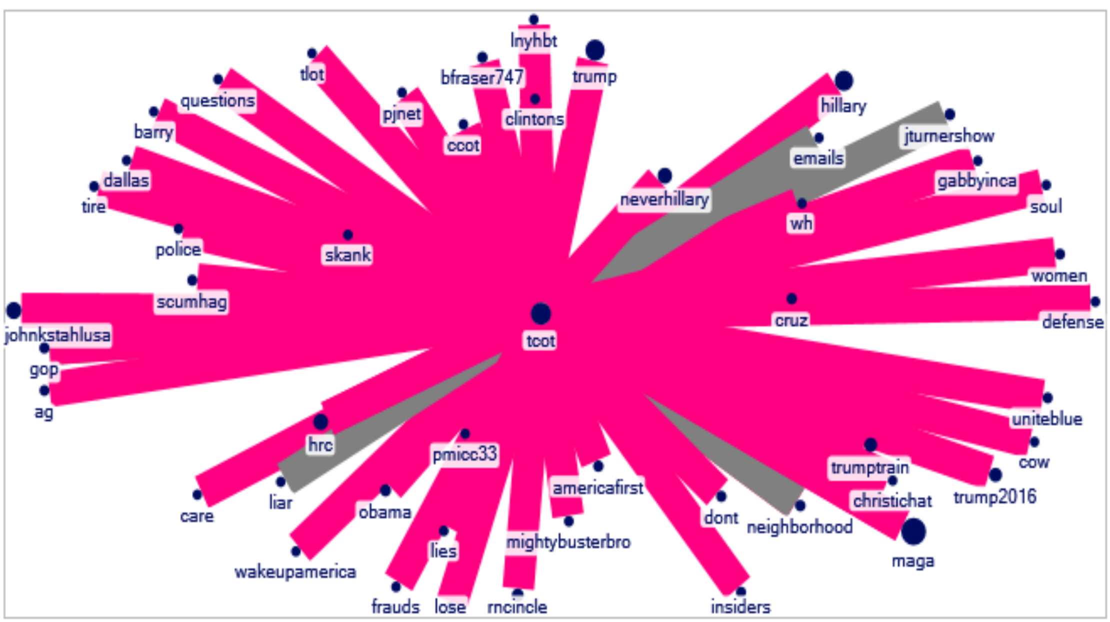


Figure 1. A bird's-eye view of the whole network reveals one major connected component and many smaller disconnected components. In other words, the graph shows that the bulk of the "Make America Great Again" discourse was thematically consistent, and most participants contributed discourse focused around key ideas.



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

Figure 2. The graph reveals that the hashtag, “#tcot,” meaning “top conservatives on Twitter, dominated the “Make America Great Again” discourse. Across the different conversational clusters within the discourse, the entity, “tcot,” is here highlighted red to show its prevalence.



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

Figure 3. The graph reveals that “top conservatives on Twitter” served as a structural center of the “Make America Great Again” discourse, anchoring mentions of other entities.

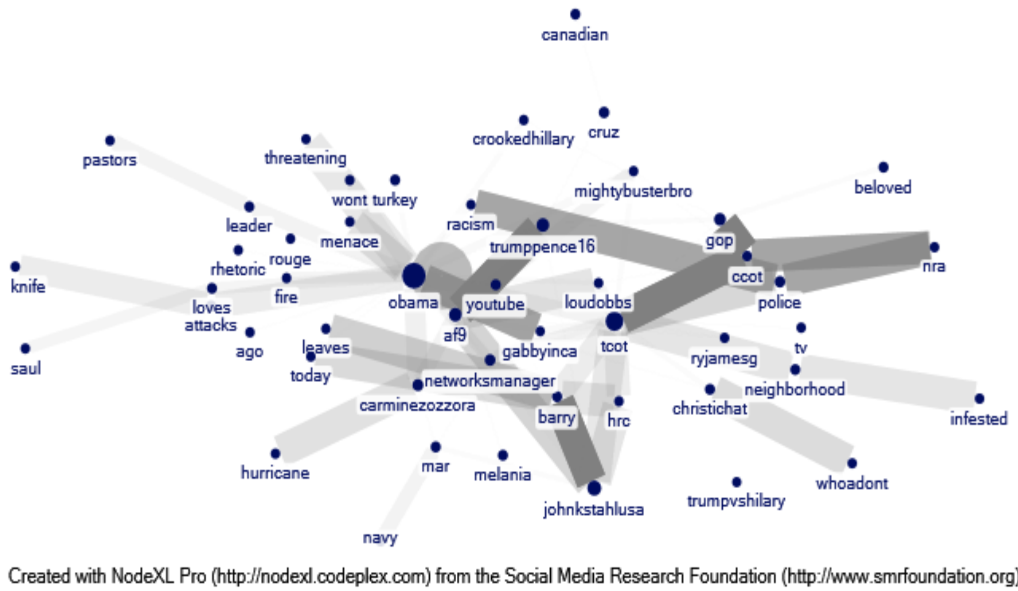


Figure 4. This graph of the entities within the Obama network that had the highest betweenness centrality values demonstrates dominant themes. The reaction to Obama's alleged past plagiarism after Melania's speech gaffe (entity "af9") was prevalent, as were key conservative voices and issues of religion ("ccot," or "Christian conservatives on Twitter") and race ("police, "racism").

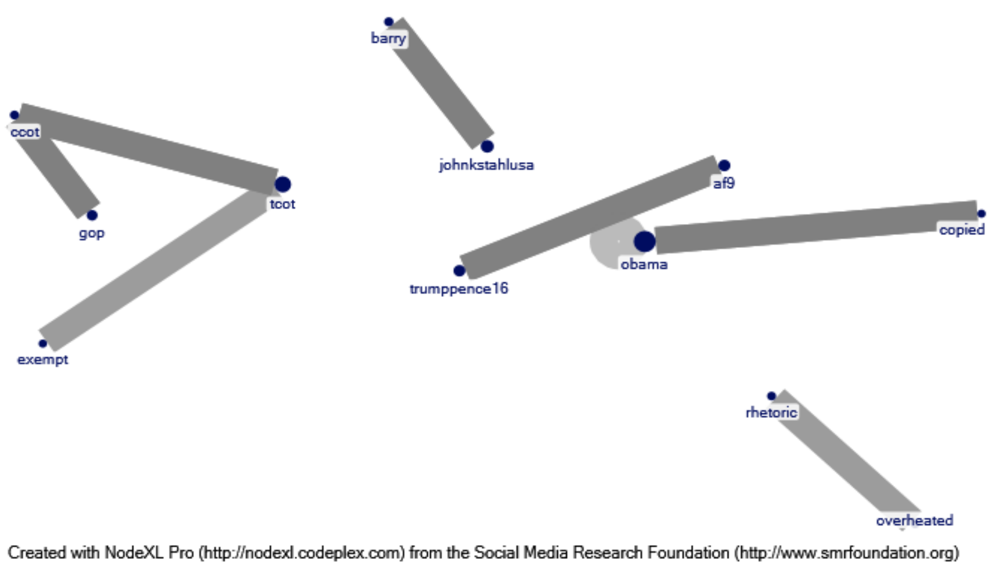
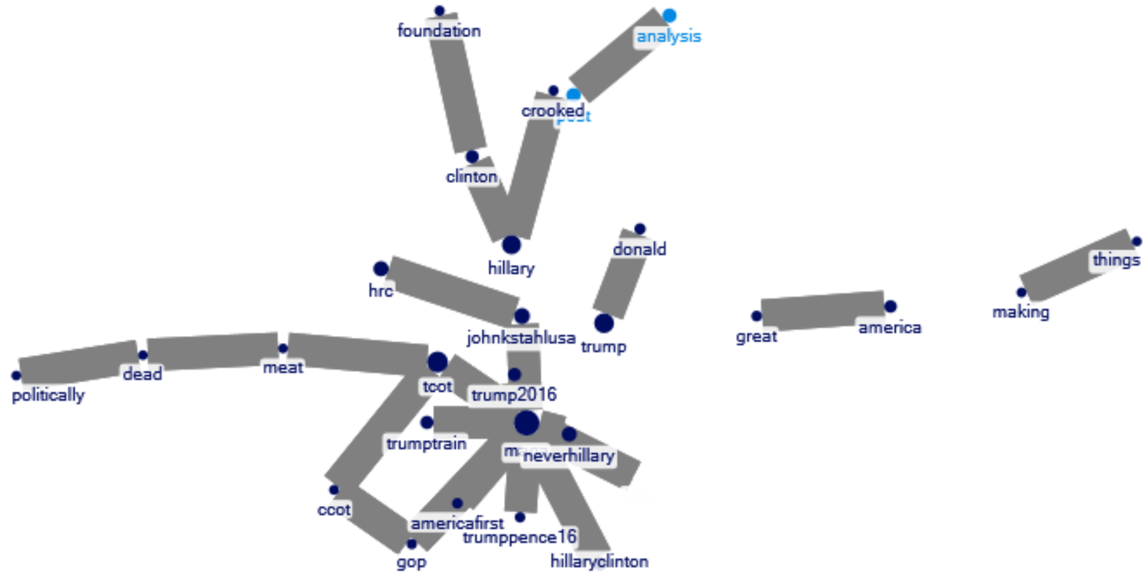
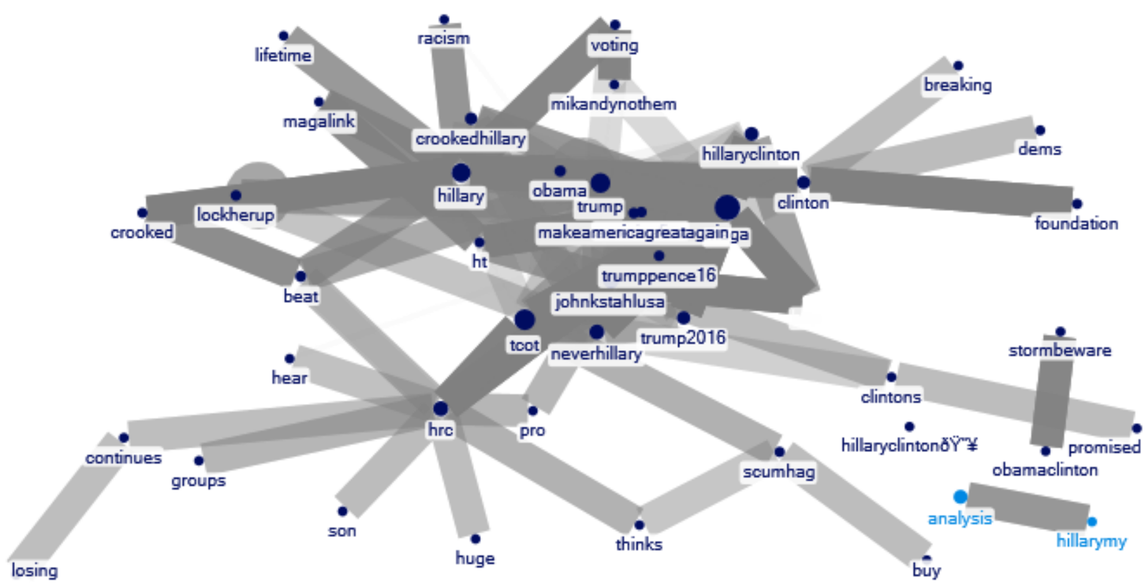


Figure 5. The graph of the strongest associations between entities in the Obama network shows that the conversation was narrowly focused. A few key voices ("ccot," "tcot," "johnkstahlusa") and themes (allegations that Obama "copied" and rallying cries for "trumppence16") were dominant.



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

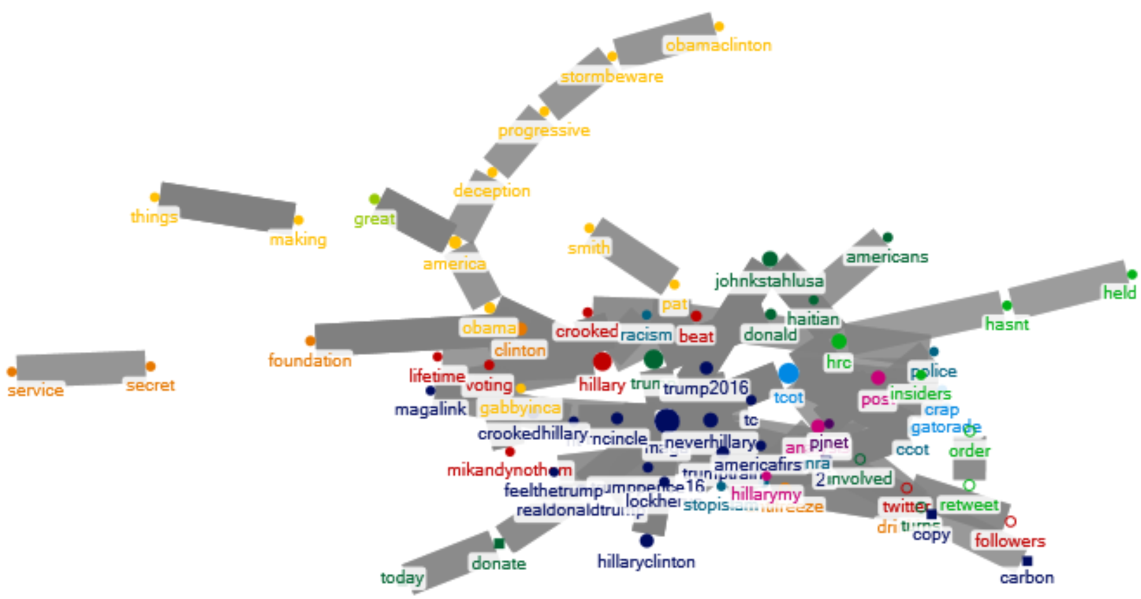


Created with NodeXL Pro (http://nodexl.codeplex.com) from the Social Media Research Foundation (http://www.smrfoundation.org)

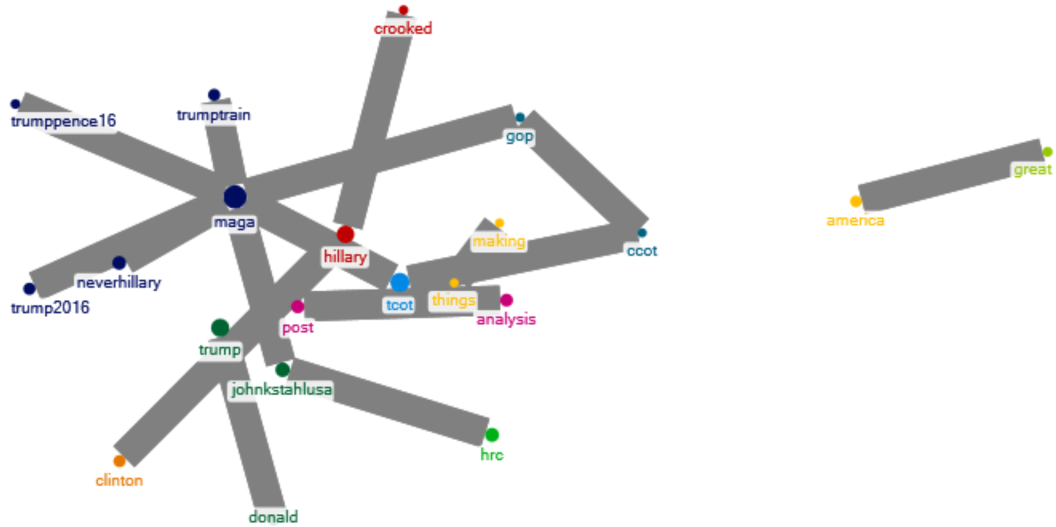
Figure 6. The most frequently co-occurring pairs and the entities with the highest betweenness centrality values in the "Make America Great Again" network illustrate discursive foci. The "Make America Great Again" discourse privileged messages from conservative communication elites and social identification and denigrating enemies.

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

Figure 7. References to Clinton anchored the discourse. References that ranked within the top 500 entities in terms of betweenness centrality value for the whole network appeared dominant, as reflected by high betweenness centrality values indicating the presence of Clinton-related entities among new strands of meaning and high rates of co-occurrence between Clinton-related entities and other entities within the discourse.

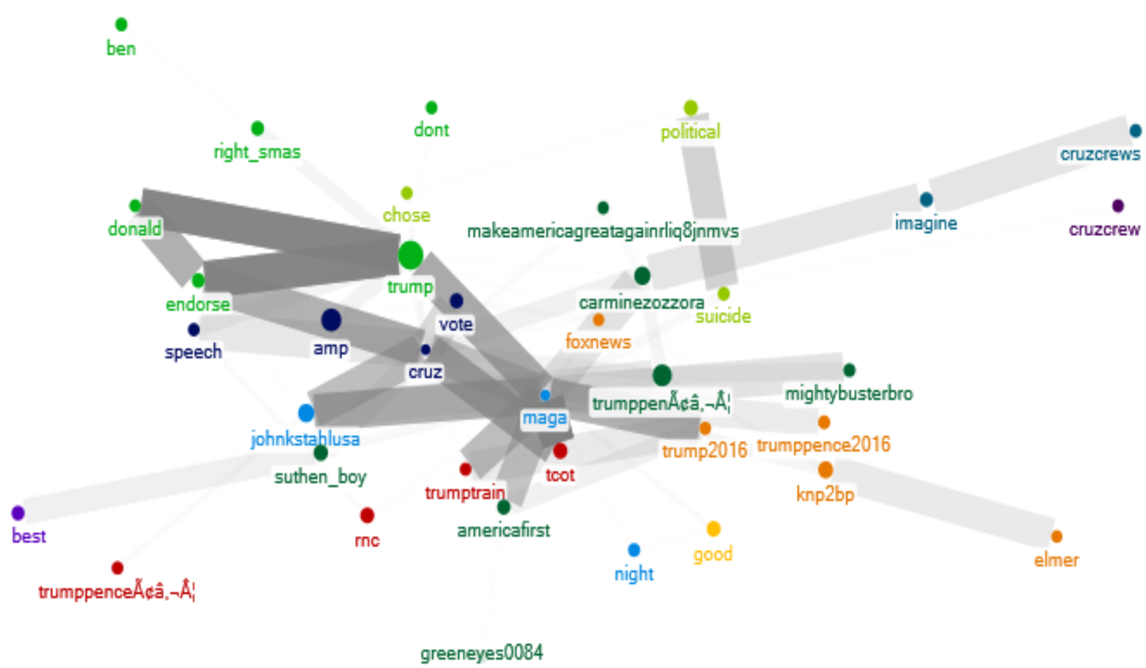


Created with NodeXL Pro (http://nodexl.codeplex.com) from the Social Media Research Foundation (http://www.smrfoundation.org)

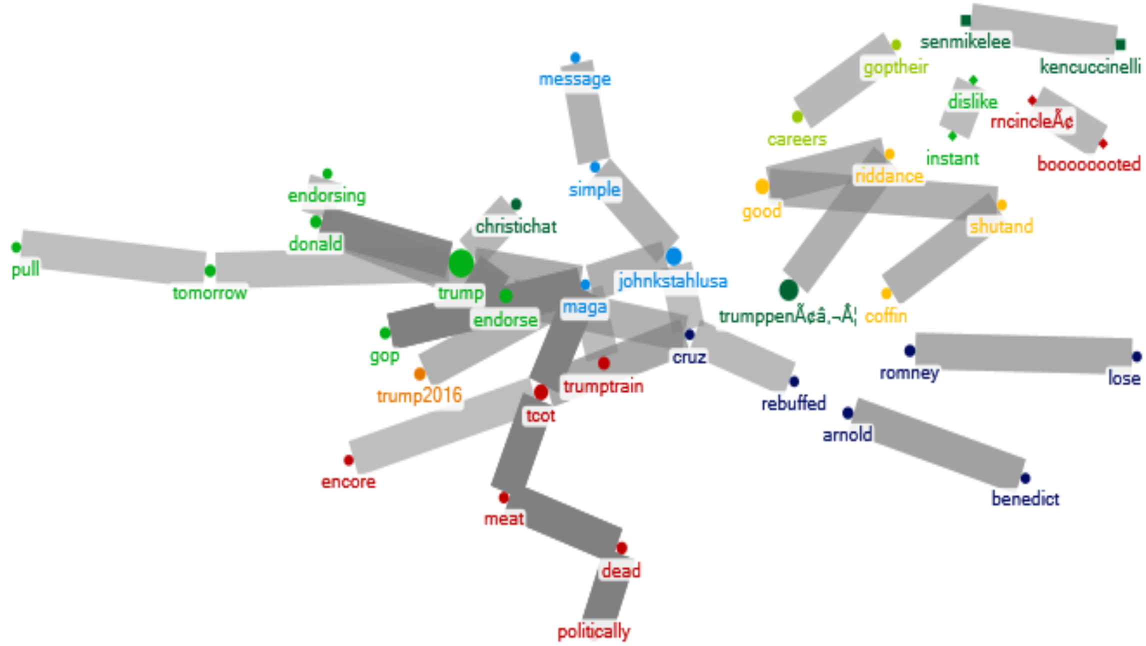


Created with NodeXL Pro (http://nodexl.codeplex.com) from the Social Media Research Foundation (http://www.smrfoundation.org)

Figure 8. The Clinton conversation consisted primarily of catchphrases denigrating Clinton and promoting Trump (e.g., "crooked Hillary" and "feelthetrump") and was again driven by the voices of conservative elites. The above graphs illustrate the most frequently co-occurring pairs of entities and entities with the highest betweenness centrality values in the discourse.

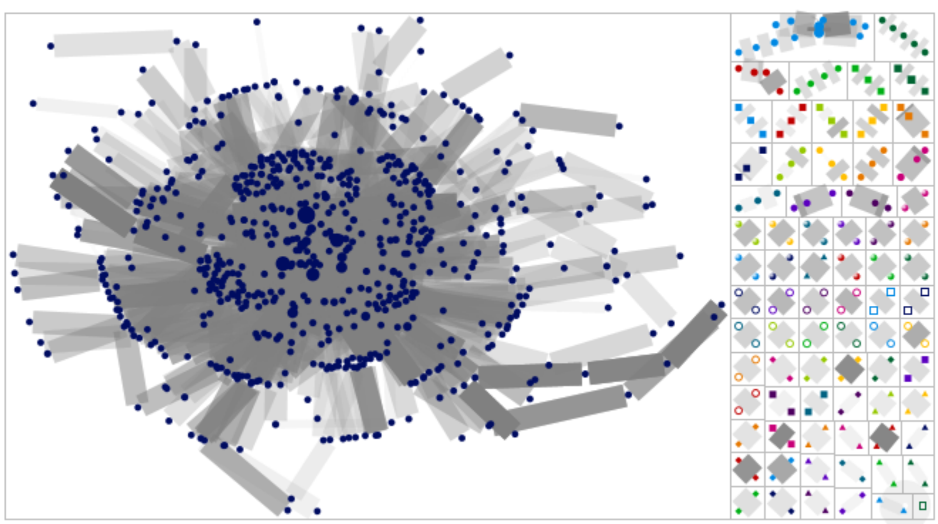


Created with NodeXL Pro (http://nodexl.codeplex.com) from the Social Media Research Foundation (http://www.smrfoundation.org)



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

Figure 9. The graphs show that conversation around Cruz centered on his failure to endorse Trump formally during the RNC and reveal the continued prevalence of Twitter handles belonging to conservative elites.



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

Figure 10. This graph of all "Make America Great Again" tweets mentioning Obama, Clinton, or Cruz reflects the conversational structure of one dominant connected component and many smaller, peripheral components.

CHAPTER 5: DISCUSSION

Overview

Consistent with the view of "Make America Great Again" as a content frame privileging particular aspects of reality (as per Entman's definition of framing, 1993), each of the three networks, themed around Obama, Clinton, and Cruz, respectively, contained a dominant cluster of entities representing the bulk of the discourse around mentions of that politician, occasional mentions of an issue, and an assortment of much smaller—and often disconnected—conversations around highly specific issues or topics. Several significant findings came to light. First, the "Make America Great Again" conversation was not driven by ordinary citizens. The discourse heavily skewed toward messages created by members of the conservative establishment. Second, social identification against enemies anchored the discourse in the Obama, Clinton, and Cruz networks, with network graphs revealing that the main discursive clusters comprised mentions of Donald Trump or Trump and Mike Pence together, generally within a few nodes of mentions of the enemy politician in question. Third, incivility characterized references to enemies and was often linked with factually dubious claims and, ironically, vilifications of the opposition's untrustworthiness. Fourth, calls to action were closely tied to social identification against and denigration of enemies, and appeared relatively rarely alongside discussion of issues or policy positions.

Conservative Elites and the Religious Right

While Twitter has often been viewed as an inherently autonomous and egalitarian communication platform (Kaplan & Haenlein, 2010), the "Make America Great Again" discourse did not reflect a groundswell of content originating from everyday Twitter users. Rather, the entities with the highest betweenness centrality values in the network were consistently sourced from tweets initially written by conservative leaders and members of the conservative establishment (Figures 2, 3). Again, though Twitter has been hailed as a democratic space and a place where everyday people could contribute to the country's political conversations (Kaplan & Haenlein, 2010), my network graphs indicated otherwise. I found information cascades stemming from retweets and favorites of tweets sourced from political pundits and power groups. Certainly, the democratic potential of social media remains as novel communication channels open and anyone may, in theory, contribute and communicate with whomever they wish (Kaplan & Haenlein, 2010). However, my data suggested a communication pattern more closely aligned with the traditional two-step flow theory of media content dissemination (Katz & Lazersfeld, 1966), with elites driving the conversation and filtering the information available to the rest of the population.

Perhaps the most striking example of elites structuring the "Make America Great Again" discourse was the near-ubiquity of the "tcot" and "ccot" hashtags (Figures 2, 3). In every dataset, these were the nodes with the highest betweenness centralities, the nodes anchoring the conversation, and the nodes with the thickest edges between them, indicating the highest rates of co-occurrence. Further, while "tcot" and "ccot" shaped the bulk of the conversation, "gop" was the second most highly correlated entity with mentions of "ccot," but "tcot" was not highly associated with "gop." In fact, "tcot" only co-occurred with the entity, "gop," one time. Though beyond the scope of this study, this anomaly alone provides reason enough for additional investigation. The entities most frequently co-occurring with "ccot" were "nra," "tcot," "gop," "loudobbs," and "mightybusterbro," a user whose "Make America Great Again" tweets mentioning Obama all included the hashtag, "#deusvelt," meaning "God wills it," a battle cry used during the Crusades against Muslims in A.D. 1095 and a rallying cry for members of today's alt-right (see Morwood, 1998, for the history of "deus velt" and Tharoor, 2016, for modern usage).

Webs of meaning were organized around the "#tcot" hashtag, or "top conservatives on Twitter," and centered the "Make America Great Again" conversation around those top conservative voices, propagating their views instead of engaging Twitter users in meaningful discussion or evaluation of policy alternatives (Figure 6). As a result, the reactions of and conclusions drawn by top conservatives permeated the discourse, overshadowing discussion of the actual precipitating event. Rather than engage with the event itself, most of the discourse reflected likes and retweets of messages originating with the "top conservatives on Twitter." In fact, even though tweets sent by Democrats have been found to exhibit more homophily in general, Republican Twitter users who followed official Republican or conservative accounts demonstrated "higher levels of homophily than Democrats" (Colleoni, Rozza, & Arvidsson, 2014, p. 317). As a result, the conservative media establishment could construct powerful echo chambers reinforced by messaging within and across platforms (such as Twitter and Fox News). According to Key (1966), the output of a given echo chamber would be inextricably dependent upon its input. Ergo, the louder or more pervasive those initial echoes (say, coming from famous conservative voices), the more they would repeat and resonate. In this way, the "Make America Great Again" discourse on Twitter embodied an environment wherein the perceived social gain of aligning oneself to a particular set of views was heightened as the validity and rightness of these views was echoed over and over again (Jamieson & Cappella, 2008).

For example, fully 768 of the 11,276 tweets that mentioned Obama during the 2016 RNC were retweets of Lou Dobbs' tweet linking Obama's "plagiarism" with the hashtag "trumppence2016." Put differently, nearly 7 percent of "Make America Great Again" conversation around Barack Obama during the RNC was sourced directly from one person, Lou Dobbs, reacting to news coverage of Melania Trump's speech copying Michelle Obama, and attempting to focus attention on alleged plagiarism by Barack Obama that would have occurred nearly a decade prior. In fact, within the Obama network, it was Obama's alleged copying of a speech in 2008 that most often co-occurred with the advocacy/rallying cry/support hashtag, "#trumppence16." Only "johnkstahlusa" referring to Obama as "barry" alongside other patronizing and/or derogatory entities, mentions of how "Obama" allegedly "copied," and tweets containing "ccot" and "gop" or "ccot" and "tcot," co-occurred more often (Figures 4, 5).

The prevalence of "#tcot" and "#ccot" hashtags across the dataset suggested that previous explanations of Trump's victory as deriving largely from working-class support may have been incomplete (Cohn, 2016). The religious angle and targeting as well as the elite nature of these top conservative voices complicated the too-simple attribution of Trump's victory to working-class concerns, a question now being discussed in the popular press (Carnes & Lupu, 2017). My network graphs indicated that even the communications around this populist politician supposedly running a "people's campaign" were, in fact, still structured by official conservative communication elites.

Interestingly, the “#ccot” hashtag was noticeably absent from the “Make America Great Again” discourse where Cruz was concerned (Figure 9). While evangelical rhetoric provided a useful vantage point from which to condemn Obama as a supposed Muslim foreigner and gave rise to popular hashtags like “#stopislam,” Cruz was, himself, a longtime darling of the religious right and the evangelical establishment favorite prior to his defeat in the Republican primary (Martin, 2015). “#Ccot” also appeared frequently within the Clinton discourse as one of the primary entities used in tweets denigrating her (based on her alleged lies and positions on social issues) and advocating for Trump, but the hashtag was not deployed within the Cruz network, perhaps because it could have backfired and ended up rallying support for Cruz rather than rebuking him for his lack of endorsement (Fea, 2016).

As mentioned earlier, though Trump ran on a rogue platform and emphasized independence/outsider status as not being part of the Washington swamp, “Make America Great Again” discourse did not bear this out. The entities “maga” and “gop” co-occurred more together than any other pair of entities in the dataset and yielded high betweenness centrality values, seeming to anchor webs of meaning that were largely positive/adulatory/rallying in nature. Though further research would be needed to explore and test this idea, the “Make America Great Again” discourse promises insight into the transmutation that Trump underwent during the RNC from fringe alt-right celebrity to the Republican establishment candidate.

Enemies and Social Identification

Copious pro-Trump entities dominated the “Make America Great Again” network. Hashtags, such as “#trumptrain” or “#trumppence16,” and their counterparts, such as “#neverhillary” or “#crookedhillary,” indicated not only that Twitter users were taking to the platform to express their views but that Twitter users intentionally identified their contributions as part of the discourse by using these hashtags (Figures 7, 8). As discussed in the literature review, hashtags here were not just words, but tactics that people deployed to “self-brand” as “Make America Great Again” supporters, wielding the visibility conferred by hashtags as a tool to align themselves with the in-group and thereby “[increase] social…gain” (Page, 2012, p. 181).

Only a small number of tweets mentioning enemy politicians also contained references to social issues. Instead, the discourse around each politician tended to be used as incitement to support Trump or to focus on one particular (and generally reactive) entity, which ended up shaping the discourse (Figure 9). As such, much of the discourse was reactive in nature, suggesting strong ties between what was covered in traditional news media platforms and the “Make America Great Again” Twitter discourse. (I considered entities reactive if they centered around incidents occurring during the RNC that had been discussed in the media and/or contained aspects of the frames used by traditional media to discuss an incident.) Public reactions on Twitter have been found to favor messages from known names and recognizable sources (Szomszor, Kostkova, & St. Louis (2011), which my data supported. Moreover, research has demonstrated that hashtags often stemmed from existing information influencers in a way that “reflect[ed] and reinforc[ed]” their dominance in offline contexts, again supporting my finding that the discourse seemed largely to reflect (and retweet) the themes propagated by and typical of “mainstream media forms of broadcast talk” (Page, 2012, p. 181).

For example, following the uproar in media outlets after Melania Trump gave a speech that borrowed heavily from a speech previously given by Michelle Obama (CNN, 2016), “Make America Great Again” conversation on Twitter around “Obama” focused the conversation not on Melania Trump or Michelle Obama, but instead on allegations that Barack Obama had earlier committed plagiarism when he “copied” part of a speech given in 2008 from a 2006 speech given by then-governor of Massachusetts Deval Patrick (Snopes, 2016). Strikingly, though Michelle Obama did feature peripherally within the larger Obama network cluster, only a miniscule portion of the Obama discourse was concerned with her or Melania Trump, despite their roles as the two main players in the precipitating plagiarism scenario.

The bulk of mentions of Obama, Clinton, and Cruz across the “Make America Great Again” network were invoked as foils to making America great again and attempted to establish these politicians as motivation, of sorts, to support the Trump ticket (Figure 7). In other words, the definition and blaming of enemies within the “Make America Great Again” frame seemed to serve the purpose of differentiating the in-group of Trump supporters from the out-group of his detractors, reinforcing the divisive function of the frame as discussed previously in the literature review. This was evidenced by the structure of the network graphs around these entities, where the politicians’ names were connected to strings of discourse evidencing pro-Trump rhetoric (e.g., “trumppence16”), and not discussion of issues. When mapped in aggregate, the entire dataset combining references to Obama, Clinton, and Cruz was similarly structured, which supported the validity of these visualizations. One notable exception to this pattern was the centrality of “racism” within the Obama network as it was connected to the entities “police,” “nra,” and “tcot.” Similarly, a discussion propagated by user johnkstahlusa tied “drug” “infested” “neighborhoods” to Obama’s lack of respect for “police.” While beyond the scope of this study, the interplay between “Make America Great Again” as a content frame and social issues in the spotlight at the time, such as race, deserves much additional research.

Incivility and Truthiness

Any discussion of Trump’s popularity and rise to the presidency would be remiss not to address the flexibility of and even disregard for the concept of truth that came to characterize this election and the subsequent administration. While Stephen Colbert coined the term “truthiness” on *The Colbert Report* in 2005 to describe political manipulations of fact during the George W. Bush administration (see Alfano, 2006), the voters composing Trump’s base of hard-core supporters have displayed, in 2016 and thus far in 2017, a remarkable ability to swallow whatever Trump told them, to disregard established facts (see *Fox News, The Daily Caller,* or *Breitbart* on climate change, for example), and to continue viewing Trump as trustworthy in the face of blatant falsehoods. At the same time, lying, untrustworthiness, and immorality were favorite complaints lodged against political opponents in order to disparage their suitability for office (Figure 7). This phenomenon seemed to indicate that alliance with one’s in-group in solidarity against perceived out-groups superseded all other concerns for Trump voters. In this way, rightness became whatever rhetoric was espoused by Trump and his leading supporters. Put differently, many supporters no longer felt the need for (or were actively against) unbiased, independently verified evaluation of important issues and politicians, instead upholding the interpretations and views of "tcot" and "ccot" as the accepted moral arbiters of American politics during and after the 2016 campaign.

Existing research has examined the "fatal attraction of truthiness" in political discourse from the perspective of normativity, that is, which information sources and "reasoning skills [were] fostered" by "environmental and educational influence" (Narvaez, 2010, p. 163). For many Trump supporters, the "alternative facts" promoted by media influencers such as Fox News and leading conservatives on Twitter became the norm for evaluation of politicians and issues alike (Kellyanne Conway, speaking in a broadcast news interview, 2017). Some (e.g., Gardner, 2012) have gone so far as to posit that, in some ways, truth may be naught but "an expression of power" in the age of Twitter (p. 20). If people believe that truth "cannot be established with any [measure of] validity" or perceive truth to be an inherently "vacuous concept," then criteria for evaluation of anything would necessarily originate with the those in positions of power whose messaging aligned most closely with one's political predilections (Gardner, 2012, p. 20).

As evidenced by the degree to which "Make America Great Again" framed America's problems and the enemies of America's greatness and the extent to which that frame was adopted and propagated by other Twitter users, truth may, in the most extreme cases, have been "nothing more than a majority vote on a webpage" (Gardner, 2012, p. 20). Indeed, much of the discourse was characterized by a "deep-seated epistemological relativism" wherein opinion, not reason, ruled the day, and volume largely trumped logic (Baym, 2013, p. 492). In addition, my data supported Jones' (2009) findings regarding the popularity and prevalence of "believable fictions" in American political media (p.

127). Similarly, the lack of issue discussion within the discourse in general and the token mentions of party lines on different topics suggested that scientific evidence had indeed been jettisoned in favor of "politicized truthiness" (Walton-Roberts, Beaujot, Hiebert, McDaniel, Rose, & Wright, 2014, p. 34).

Where truth mattered little, civility mattered even less. The name-calling and perpetuation of lies intended to damage the character of politicians who opposed Trump ran unchecked through much of the "Make America Great Again" discourse. From hysterical assertions that Obama was a "terrorist" intent on "destroying" America and imposing "Islam" on the country, to vilifications of Cruz as "dead meat" for not fervently endorsing Trump during his speech, to the ugliness of the rhetoric used around Clinton, the conversation was composed in large part of "claims that [were] inflammatory and superfluous" (Brooks & Geer, 2007, p. 2). Among some of the references to Clinton were the hashtags "#crookedhillary," referring to the over-hyped and (arguably) immaterial case of the Clinton emails and her work while Secretary of State, "#lockherup," the ever-popular cry to incarcerate Clinton for said offenses, and names like "scumhag," a spinoff of the colloquially viable "scumbag," that served to scorn Clinton for her gender as well as her character (Figure 8).

While Obama was certainly insulted and vilified, the power aspect was not as evident, perhaps reflecting the fact that he was already considered to be a neutralized threat: His replacement was inevitable, regardless of what happened during the primaries and the presidential campaign. Further support for this conjecture stemmed from my finding that the strongest conceptual association within the Obama network involved Obama and Clinton together. As a frame for interpreting information and events, "Make

America Great Again" rhetoric neatly transferred credibility issues from Obama to Clinton, associating her with guaranteed perpetuation of any problems Americans had been experiencing.

Collective Action

Though mentions (much less discussion) of actual issues (e.g., the economy, security, or jobs) were peripheral at best and often disconnected from the dominant connected components within the Clinton and Cruz datasets, calls to vote for or donate to Trump were highly and closely related to mentions of Clinton and Cruz, often tied to their equal and opposite rhetorical equivalents (e.g., "beat" "Hillary"). Perhaps reflecting the fact that Obama no longer represented a direct threat to Trump's ascent to the presidency, as mentioned earlier, these calls to action were absent from the Obama conversation. Calls to "unity" or to "unite" behind Trump appeared within the Clinton network in addition to calls to vote or donate, perhaps reflecting the necessity of in-group solidarity and extremity to defining Clinton as an enemy, with rhetoric reminiscent of the cries of a hero and his backers rallying to defeat an enemy invader.

Across the Cruz network, the geodesic distances between entities representing calls to "vote" Trump and damning entities representing Cruz and his failure to "endorse" Trump were quite short. Calls to "support" or "donate" were absent from the Cruz conversation, suggesting that, while Cruz was derided for his failure to "endorse" Trump, the conversation around Cruz was less focused on calls to action that would directly affect the Trump campaign, reflecting the much higher instances of chastisement toward Cruz for not endorsing Trump and calls to vote Trump. Clinton, as Trump's archenemy, may have been understood to invoke a more impassioned negative response and therefore be more effective in drumming up rhetorical support, reflected in the prevalence of calls to action within the Clinton network. As such, the network maps reflected the function of "Make America Great Again" as a frame for defining problems as other politicians rather than actual social issues, and proffering the treatment solution of supporting Trump (per the functions of frames identified by Entman, 1993).

Calls to action within the webs of meaning around Clinton and Cruz were most strongly characterized by power-oriented invectives and insults, e.g., Trump as strong and victorious and Clinton and Cruz as weak and failing, as well as invocation of power dynamics favoring Trump (e.g., "Lock her up!" dominant around Clinton mentions, and "dead" "meat" "politically" as the most central semantic string in the Cruz dataset). The perception of Cruz as "dead meat" as a reaction to how he had acted or not acted during the RNC was far more prevalent and structurally far more crucial to the social identification of Trump supporters and the framing of Cruz as an enemy than discussion of Cruz as a politician or rehashing of why, exactly, he was "dead meat" politically. The top five pairs of co-occurring entities in the Cruz dataset were "maga" and "gop," "tcot" and "maga," "tcot" and "meat," "dead" and "politically," and, of course, "dead" and "meat." He was clearly identified as the enemy, and that was enough.

Structural Findings

The Obama network revealed a conversation centered around a few entities closely connected to one another, while the Clinton and Cruz network graphs and the network as a whole revealed several prevailing thematic clusters (Figure 1, 10). The "Make America Great Again" network graph suggested one dominant connected component (Figure 1, 10). Unlike Obama, who would soon be out of office, Clinton and

Cruz remained threats during the RNC and therefore necessitated (in the minds of conservative elites) more complex and issue-inclusive conversation to be convincingly framed as the reasons for America's problems.

While the smaller, disconnected clusters within each network sometimes addressed specific complaints around a politician, such as Cruz being "Canadian" "born" and therefore anti-American (again, a concern regarding race and national allegiance), or discussed specific issues, such as Obama's problematic stance on "h1b" "visa" "holders"), these disconnected clusters did not, for the most part, contain calls to collective action in support of the Trump ticket. Further, far from hinting at the major themes in the discourse around each politician, the disconnected clusters generally contained mere fractions of the "Make America Great Again" conversation and were not generally linked to the larger body of conversation around each enemy politician. In other words, almost no one tweeting about Obama, Clinton, or Cruz within the context of "Make America Great Again" tweeted about these politicians in a way that combined the themes within the overarching cluster with the themes of the smaller, disconnected conversations. There was a clear separation between the bulk of the discourse and the smaller ancillary conversations taking place on the sidelines between smaller groups of Twitter users.

Interestingly, though the larger Clinton network contained a larger variety of entities and a greater number of connections between them, these smaller conversations did not appear to have much of an impact on the "Make America Great Again" frame overall. Even where a discursive "branch" was connected at some point to a central entity, such as "Clinton" or "crookedhillary," the branches tended to be somewhat isolated with regard to how many times the entities were used within the network as well as the low rates of co-occurrence that effectually stranded these entities within one discrete topic/area of conversation. These disconnected components diverged from the overarching themes undergirding the “Make America Great Again” frame in the discourse.

Limitations

Though highly detailed and meticulously executed, this study did have some important limitations. One, as mentioned earlier, was the absence of an existing schematic for the exact order of steps to be executed in semantic network analysis, particularly as pertained to the preprocessing commands carried out in AutoMap. Second, text cleaning prior to the mapping of entities in NodeXL was far from perfect, and leftover fragments and/or duplicates representing the same conceptual meaning could possibly have been organized differently and/or integrated in the dataset in such a way as to represent the webs of meaning within a given discourse even more accurately. By the same token, the possibility of multiple interpretations of meanings within a dataset constituted a strength of the descriptive nature of this type of study.

Next, while the RNC was useful in delimiting a subset of the discourse for scholastic examination, the event was four days long and served as but a partial window into the ways in which the “Make America Great Again” frame became such a huge part of American political discourse during the Trump campaign. Further, due to the timing of this thesis, much of what is now known or suspected about Russian involvement in U.S. politics in 2016 and many of the think pieces now being published on Twitter’s role in the presidential election could not be incorporated fully. Though these aspects were discussed following the study's results, I may have structured the study a bit differently had that knowledge been in play earlier.

Further limitations largely involved the amount of data and what was possible within existing time constraints. First, the data contained thousands of concepts and concept pairs, and I did not examine every single one within this study. In order to strengthen the theoretical grounding of the study and ensure that data-driven discovery adhered to the study's original intent, I focused specifically on Trump's three key political enemies: Barack Obama, Hillary Clinton, and Ted Cruz. Similarly, because I utilized the semantic co-occurrence lists function in AutoMap, the concepts identified were grouped as pairs and did not automatically work to graph strings of meanings in NodeXL that extended beyond two concepts. Rather, these extended meanings were attended to manually after the network graphs were generated. From a semantic standpoint, though the function and significance of hashtags versus regular words was acknowledged in the study, connections between hashtags may have been more useful and/or meaningful had they been illustrated separately and treated as frames in their own right.

CHAPTER 6: CONCLUSION

In conclusion, I explored the ways in which the “Make America Great Again” discourse on Twitter reflected “Make America Great Again” as a frame for understanding America’s problems, the people responsible, and the solution to said problems. Within three separate subsets of the data, I conducted semantic network analyses of entities used in conjunction with mentions of Barack Obama, Hillary Clinton, and Ted Cruz, respectively. The blaming of politicians other than Trump for America’s problems enabled many different people with many different concerns to insert their personal grievances into the blame and solution blanks allotted by the frame. As borne out by the general lack of discussion of specific issues within the discourse, the nature of one’s grievances and individual prioritization of problems were subsumed within the larger explanatory structure of the “Make America Great Again” frame.

Within the network, the prevalence of messages originating with communication elites, such as “tcot,” or “top conservatives on Twitter,” supported previous findings that Twitter was often used by the conservative political machine to reach out to constituents and campaign audiences (Golbeck, Grimes, & Rogers, 2009). Further, the prevalence of these entities and their preferred messages extended findings around Twitter’s ability to focus awareness and heighten prominence of specific aspects of an issue or event (Hughes & Palen, 2009). Based on Entman’s (1993) definition of framing, the “Make America Great Again” rhetoric served as a frame in that it selected and made salient specific aspects of the 2016 Republican National Convention and the 2016 presidential election.

Beyond mere discussion of ideas about America's problems and the people responsible, the prevalence of hashtags within the dataset indicated that Twitter users not only wanted to participate in the discourse but to be recognized as participants and to make their group identifications and political views known (see Honeycutt & Herring, 2009, for more on hashtags). Where thousands of voices were communicating messages related to "Make America Great Again" in the same communication space, hashtags and user mentions helped to continually capture the threads of conversation influencers (such as "tcot," "ccot," "loudobbs," and "johnkstahlusa," among others) and organize discursive contributions (see Hansen, Shneiderman, & Smith, 2011, for even more on hashtags). Moreover, the extent to which communication elites shaped the conversation was compounded by the tendency for social media users to "quickly converge on a consensus choice" for hashtags and keywords around an event (Hansen, Shneiderman, & Smith, 2011, p. 147). Of course, text changed as it traveled through the retweet process, with people revising to keep main ideas and remove extraneous characters in order to keep messages below the 140-character limit (not least because an endless string of retweets and usernames would leave no room for other content). As such, the entities that remained and retained value within network graphs provided a useful and accurate picture of the shape of the conversation. Network graphs revealed the entities that most strongly represented the core concepts and the users most strongly associated with those concepts in a given conversation.

Moreover, this thesis identified pro-Trump webs of meaning surrounding mentions of Obama, Clinton, and Cruz that could have provided valuable insights into how America would vote come Election Day 2026. As Mitchell & Hitlin (2013) found, people's reactions to political events on Twitter often "[differed] a great deal from public opinion as measured by surveys." Media outlets, professional journalists, and lay voters discounted Trump's presence on Twitter and the possibility that the positive reinforcement he received from many other Twitter users could have been meaningful or representative of the electorate (Hirschborn, 2016). Yet, taken together, "tweets [could have provided] an opportunity to understand [people's] overall sentiment" as they reacted to events (Diakopoulos & Shamma, 2010, p. 1195), and my data showed that the ideas driving "Make America Great Again" as espoused by top conservatives in agreement with Trump were perpetuated largely intact on Twitter. Had the "Make America Great Again" discourse on Twitter been considered in conjectures regarding election results, as were traditional methods of public opinion polling, the outcome of the presidential election would have been less surprising.

Future Research

First and foremost, future research would do well to explore which voices were most present in the discourse as represented by Twitter usernames and handles. Though in-depth investigation of the most ubiquitous voices was beyond the scope of this study, the presence of usernames belonging to Lou Dobbs or John K. Stahl near the top of betweenness centrality and co-occurrence frequency lists, for example, begged the question of who or what was driving the "Make America Great Again" conversation. Similarly, the fact that the hashtag "#tcot" was in the top three associated pairs for the Obama, Clinton, and Cruz datasets could be the basis of future investigation into whether and to what extent discourse on Twitter was shaped by pundits and conservative organizations versus ordinary citizens. The question of whether the discourse largely reflected a dominant narrative proffered by political communication professionals or whether it arose organically from the original reactions of everyday folks using Twitter is an interesting one, perhaps providing opportunities for the extension of Katz & Lazarsfeld's (1966) explication of two-step flow theory to modern media platforms and communication contexts.

In addition, the prevalence of "Christian conservatives on Twitter" in the discourse presents a moral quandary around the idea of moral superiority or the moral majority. Conservatives and religious groups were targeted by politicians promising to advocate for their interests (Mayer, 2016) and became key fonts of "Make America Great Again" rhetoric and points of dissemination for framing communication. As mentioned earlier, there seemed to be other values superseding that of "truth," and a redefinition of truth in ways more amenable to the need to preserve the status quo and existing seats of power. Whether critical in nature, examining, perhaps, the potential hypocrisy of the religious right, or descriptive or interpretive, future research would do well to examine the "Make America Great Again" frame from a religious angle. The progression of secular values placed in religious contexts could also be an interesting focal point for study, such as possible correlations between the values and past actions of politically influential top wage earners and the prosperity gospel, or the controversial theology that "God rewards faith with financial blessings" (*Christianity Today*, 2017). Building on Gardner's (2012) problematization of the concept of truth, there is further support here for the notion that many evangelicals perceived—or were content to perceive—wealth and power as evidence of truth. Additionally, future scholarship might explore the ways in which conservative political rhetoric exploited the perceived divide between science and Christianity and hardened conservative resistance to empirical evidence, rather than seeking to mend a gap that need not have existed in the first place.

The issues identified by Pew as being of top concern to voters (Pew, 2016) also merit future investigation as the foci of semantic network analyses (as opposed to the politicians used as focal points for this study). The sheer lack of issue-oriented discussion within the "Make America Great Again" conversation was striking, as revealed through the network graphs heavily focused around us vs. them-themed rallying cries and disparagement of political opponents. Studies questioning whether, how, and to what extent alternative viewpoints and solutions to issues facing voters were present in the discourse would contribute valuable insight into the ways in which the frame may have depended far more on scapegoating enemies for a broad swath of problems than on offering reasoned, viable alternatives to existing policy.

Further, the context of the Republican National Convention yields fertile ground for future research. For example, the RNC in 2016 marked some of the first instances of Trump staffers communicating with Sergei Kislyak, the Russian ambassador who would later appear frequently in the press as the Trump White House became embroiled in legal investigations over its dealings with Russia (Reilly, 2017; Smith, 2017). Current concerns about the presence of Russia-sponsored Twitter bots attempting to disseminate fake news and shape American political discourse further increase the relevance of the 2016 RNC to today's political milieu (O'Connor, 2017; Roth, 2017).

There would be material for an entire separate study focused on comparison points between the speeches given at the RNC and the simultaneous discourse pertaining to those speeches that took place on Twitter. One possibility would be a content analysis comparing repetition of concepts and words used in the speeches given by Donald Trump, Mike Pence, Paul Ryan, and Ted Cruz, respectively. Should time constraints and funding allow, future research might also be able to trace webs of meaning around identified political communication categories (such as collective action) over a much broader time span, sampling a significantly larger body of tweets.

By the same token, research examining the conversations on Twitter on the days of major breaking news stories could contribute valuable insight into how social media interacts with the ways in which news is framed by professional journalists, such as whether journalistic frames are propagated, questioned, disregarded, or subsumed within the original reactions of everyday Twitter users. In the present study, I identified the top 100 most frequently occurring entities in the Obama, Clinton, and Cruz datasets, and then went back to Twitter to determine the validity of these entities. I ascertained that the usernames in the most frequently occurring entities lists were indeed real people, and then verified their identities through a second source, be it a news article, directory listing, or additional social media site. Future research might seek to identify frames in the social media discourse surrounding major news events (such as the testimony of James Comey [Comey, 2017, as broadcast on *CSPAN*]) and verify key entities with an eye toward revealing the presence and reach of bots (Russian-backed or otherwise), as well as the degree to which these voices contributed to the webs of meaning present in related conversations on Twitter.

Similarly, I chose to remove hyperlinks from the dataset for this study because of the semantic and logistical complexity they would have presented. However, the extremely high frequencies of hyperlinks in correlation with mentions of Trump's political opponents necessitate additional investigation. Analyzing the original sources of the links and the nature of the hyperlinked content, whether journalistic/mainstream media content or heavily biased fake news sites, etc., would contribute valuable insight into the information that undergirded the webs of meaning in the discourse and possibly shaped people's views.

While Twitter was incredibly important in the 2016 election and continues to be a communication channel of great interest during the early months of Trump's presidency for people ranging from business ethics professors (Holt, 2017) to news organizations (Schectman & Kenning, 2017) and popular culture press (*Atlantic*, 2017), the site still trails behind Facebook and Instagram in terms of monthly unique users and user activity (Pew, 2017). Semantic network analyses of comments on the official RNC Facebook page, for example, might be able to make sense of even greater quantities of data representing a broader swath of online American adults. In addition, Instagram has yet to receive the same depth of academic attention as have its social media competitors. Investigation of how (if at all) Instagram users make sense of political events and issues on the platform would be valuable. Research into the semantic differences between primarily text-based media, like Twitter, and primarily image-based media, like Instagram, would further contribute to scholarly understanding of the ways in which political discourse operates on social networking sites.

From a theoretical perspective, there are also promising avenues for diverse future inquiry. Framing proved a natural and useful fit for the research questions I posed in this thesis, but approaching the data with research questions stemming from aspects of agenda-setting theory or the media systems dependency paradigm—just to name a few—

would certainly be worthwhile work. Similarly, while the dataset was and is endlessly fascinating from a media theory standpoint, organizational communication inquiries into the structure of the discourse networks would be valuable and intriguing as well. This perspective hearkens back to the ideas mentioned at the start of this section pertaining to which voices, individuals, and organizations were shaping conversations on social media. The question of whether a given social media discourse is largely organic (composed primarily of original contributions arising naturally from users participating in the conversation) or composed of largely managed communication (wherein the official messaging of politicians and pundits permeates the conversation) merits investigation as well.

Last but not least, the 2016 election brought gender issues further into the national spotlight as the nation had its first ever major-party female presidential candidate in Hillary Clinton (Nicholas & Tau, 2016). Scholars and journalists alike have just begun exploring the campaign and the election through the prism of critical theory and gender (Huber, 2016; Katz, 2016; Lee & Lim, 2016; Lepore, 2016). Semantic network analyses could provide unique opportunities for identifying and understanding the webs of meaning arising around female candidates compared with the webs of meaning that may be gleaned from webs of meaning centered on male candidates. These webs could also yield insight into the ways in which people comprehend and talk about candidates for political office, illuminating potential means to combat the gender gap in political power and, just maybe, help deliver a different Congress come 2018—and a different White House come 2020 (Campbell, 2016; Price, 2017; Schneider, Holman, Diekman, & McAndrew, 2016; & World Economic Forum, 2016).

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