

Media Agenda-Setting and Gatekeeping: The Twitter Takeover of Traditional Mass
Media Practices Through the Use of Networked Journalism

Vandon Gene

Supervisor: Dr. Frauke Zeller

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Abstract

With a growing number of people moving away from traditional sources of information providers, towards new online sources, it has become evident that the agenda-setting and gatekeeping functions of the past have been altered. Due to such alteration, it can be said that the profession of information dissemination has all but evaporated into a cesspool of opinion that has been framed to uphold the viewpoints of a particular ideology. While most studies to date have been effective in highlighting the alteration of agenda-setting and gatekeeping, this paper attempts to focus on the shift in such practices, away from traditional mass media institutions, to a new form of media through the practices of networked journalism. In order to demonstrate the following, this paper uses the 2016 U.S. Presidential Election as a case study. Tweets from traditional mass media institutions, new media institutions (such as thought opinion leaders), and the public are collected and examined in relation to information dissemination, via topic coverage. An analysis of these tweets confirms such shift in agenda-setting and gatekeeping, where the powers of information dissemination move away from traditional mass media institutions, towards a model of information that is dependent upon the public and its engagement of such information. This study is part of a larger body of research on the twenty-first century phenomenon of publicly sourced information dissemination in the networked society. In focusing on the shift that is occurring within society, this study will contribute to future publications on a similar topic.

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Dr. Frauke Zeller
Supervisor

Dr. Robert Clapperton
Second reader

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1. Introduction

The topic of this paper revolves around the effectiveness of agenda-setting and gatekeeping in today's network society, where the new practice of networked journalism will be examined in terms of how it has shifted the agenda-setting and gatekeeping principles of traditional journalism. With the prominence of print and TV journalism, information dissemination has largely been dictated by the agenda-setting and gatekeeping powers of distinguished traditional mass media institutions. They have been viewed as the twentieth century's "public sphere", where political discourse takes place and public opinion is created (Livingstone & Lunt, 1994 p. 88). In the twenty-first century, however, there is an emerging use of networked communication products such as the social media platform of Twitter. People are moving en masse away from print and TV journalism, to a new "networked journalism", where information is received and consumed through cyberspace via the hyperlink (Meraz, 2009, p. 700-702). Early studies, which focus on this new information dissemination method of networked journalism, have concluded that the agenda-setting and gatekeeping functions of traditional mass media have been altered in some way. The goal of this paper is to further study how this new method of information dissemination has shifted the agenda-setting and gatekeeping framework for traditional mass media institutions. This paper hypothesizes that the use of Twitter as a method of information dissemination is one of the main causes for this shift in agenda-setting and gatekeeping functions away from traditional mass media institutions, to a more publicly sourced information pool, supported by the practices of networked journalism.

2. Literature Review

This research paper includes several important concepts pertaining to the field of journalism and public sphere theory, which must be further explained in detail in order to comprehend the relation between one another. While the connections between the concepts of gatekeeping and agenda-setting are understood in a general sense, such connection must be thoroughly explained, along with their connections to the concepts of networked journalism.

2.1 What is Gatekeeping and Agenda-Setting?

At its most basic level, the concept of gatekeeping comes from the field of communication that addresses the various decision-making processes that go into the dissemination of information (Lewin, 1947). While no formal definition of gatekeeping exists, it can be generally described as an information control process that includes the “selection, addition, withholding, display, channeling, shaping, manipulation, repetition, timing, localization, integration, disregard and deletion of information” (Barzilai-Nahon, 2008, p. 2). This concept has been applied more broadly in the field of journalism to represent a working theory on how media organizations operate among the public. The theoretical framework of gatekeeping postulates that news editors at a news organization are given the power to decide what stories should and should not be covered, based on the subjective grounds of what the ‘gate keeper’ deems to be important and representative of their culture (White, 1950). In this selection process, the ‘newsworthiness’ of a story is determined by the gatekeeper by estimating the level of interest the audience has in a particular story (Hirsch, 1977).

By selecting what stories to cover, the gatekeeper legitimizes some stories over

others, thus 'setting the agenda' for topics of discussion among the public. The agenda-setting concept goes hand-in-hand with the concept of gatekeeping, as it involves the elite selection of whether or not a story is newsworthy enough to be covered (McCombs, 2004). Following the similar trend of gatekeeping, agenda-setting can be generally defined as the gatekeeper's action in determining what the public thinks and worries about (McCombs & Shaw, 1972). In addition to elite selection, agenda-setting incorporates the elite framing a particular issue as reality, thus perpetuating the legitimization of the stories selected by media institutions (McCombs & Shaw, 1972).

2.2 Gatekeeping and Agenda-Setting: From Past to Present

Contemporary literature surrounding the theoretical frameworks of gatekeeping and agenda-setting largely study their application to the twentieth century model of traditional or 'legacy' media institutions. As Lewin (1947) puts it, the concept of gatekeeping is by in large the ways in which information is circulated, or not circulated, to the public. In the twentieth century's model of the unidirectional flow of communication, mass media institutions held a seismic role in the control of public information (Lewin, 1947). Due to the scarcity of resources and the difficulties surrounding the collection of information, traditional media institutions were given the task of compiling information, filtering through such information, selecting the most contextually relevant information, and disseminating it to the public through mass communication channels (White, 1950). This filtering and selection of information consisted of the 'gatekeepers'; elite newsroom producers and editors, selecting the stories that they deemed integral to their audience (White, 1950). The audience, constituted as a homogenous 'mass' audience, would receive such information and accept its validity on the basis of traditional media outlets

receiving confirmation of information as facts by verified sources (Meraz, 2009).

Since scarcity played a large role in the collection of news, traditional media outlets were effectively given the power to direct the agenda of topics discussed among society (Scheufele & Tewksbury, 2007). By selecting the information to disseminate and the order in which such information would be delivered, traditional mass media outlets would create a perceived hierarchy of importance to the stories presented, that mass audiences subliminally ascribe to world events (McCombs & Shaw, 1972). This established hierarchy would in turn apply “strong, long-term effects on [mass] audiences, based on the ubiquitous and consonant stream of messages” presented to the audiences (Scheufele & Tewksbury, 2007, p. 10). In other words, due to the scarce information made available to mass audiences through traditional media institutions, the public socio-political agenda became set through a manufacturing of consent.

The broad and vast effects of gatekeeping and agenda-setting applied not just to information, but also to the visible public opinion of such disseminated information (Barzilai-Nahon, 2008). Since the gatekeepers of society are in complete control of all information received by the public, they are therefore also in control of how the public perceives the rest of society’s reaction to news stories. Due to the unidirectional flow of information, the sole producers of all public knowledge are the gatekeepers of the traditional mass media institutions, where the public audience is not able to freely create information (Barzilai-Nahon, 2008, p. 3). Take, for example, the letters to the editor section of a newspaper, a section dedicated to voicing the views of the readers. All letters are submitted to the newspaper’s headquarters, where the gatekeepers are able to filter through submissions and select only those that benefit their objectives (Burns, 2008, p. 3-

5). Similarly, news articles published which discuss the public's opinion on the matter, such as a public opinion poll article covering the mood of an electorate, is produced entirely by the gatekeepers. Traditional mass media institutions are the ones which conduct the polls, and select which data, if any, they choose to disseminate to the public. Through framing, they are then able to analyze the disseminated data in an angle that benefits their objectives (Herman & Chomsky, 1988, p. 20-35). In a sense, traditional mass media institutions are not just a manufacture of consent, but also, a manufacturer of public opinion, as even the 'beliefs' of the populous are subject to the gatekeeper's agenda-setting practices.

While this unidirectional flow of information worked in establishing a gatekeeping and agenda-setting function for traditional mass media institutions in the twentieth-century, it is not a practical model to study in the present reality of the multidirectional flow of information in the networked society (Chin-Fook & Simmonds, 2011). Due to the rise of accessibility and availability of the internet, the scarcity of information pertaining to issues of interest to the public have largely been reversed. Instead, there is now an abundance of information readily available to members of the public, particularly those who have access to the internet (Singer, 2014). According to Meraz (2009), this abundance has turned the table on the gatekeeping and agenda-setting effects of mass media on the public. Given the readily available information scattered throughout cyberspace, the public is given more than a handful of options as to where they consume their news. Furthermore, with the creation of social media, user-generated content has empowered the public with the tools for becoming their own gatekeepers and agenda-setters of information (Meraz, 2009).

A review of the various pieces of literature pertaining to gatekeeping and agenda-setting in today's networked society shows that there has been much debate over the actual erosion of the gatekeeping and agenda-setting functions of traditional mass media. Heinderyckx and Vos (2016), for example, argue that while much of the information received and consumed by the public today is through online mechanisms, most of this information in fact originates from traditional mass media. Moreover, they argue that while today's digital communication services allow for user-ended creation of information, it is traditional mass media institutions that still dominate the production of news (Vos, 2016, p. 30-31).

On the other hand, Meraz (2009) argues that the elite hold of gatekeeping by traditional media outlets no longer exists universally, as the "independent blog platform is redistributing power between traditional media and citizen media" (p. 701). Instead, traditional mass media outlets are just one part of the greater ecosystem of information disseminators. Meraz studied the effects of blog networks on gatekeeping and ultimately concluded that the gatekeeping power of traditional mass media outlets are exerted in finite ways, when compared to the past (p. 701). Contrastingly, citizen media and opinion leaders are able to seismically shift the agenda to their liking, along the long tail of media choices in today's society (p. 686-701). In other words, the plethora and diversity of information disseminators allows for the gatekeeping powers of traditional mass media institutions to erode and ultimately be removed of its powers in setting the public agenda.

Finally, some scholars such as Singer (2014) portray more of a middle ground in the reformation of the gatekeeping and agenda-setting powers of traditional mass media. In her approach to defining the present state of information dissemination, Singer (2014)

states that the journalist from a mass media outlet still acts as the gatekeeper, but that members of the audience play a role as ‘secondary gatekeepers’; individuals with an online following that are able to distribute information to an even smaller audience of people with similar interests to the so-called ‘secondary gatekeeper’ (p. 58). In other words, a two-step gatekeeping process is created where traditional mass media institutions are the primary gatekeepers that set the agenda for consumers of information. The consumers of such information then become secondary gatekeepers, as they actively disseminate or suppress the information they consume to their audience.

With all of these depictions as to the current state of gatekeeping and agenda-setting among traditional media outlets, one must wonder which of the following scenarios presented holds the most amount of truth. Could it be that traditional media outlets do in fact still hold power over information dissemination in today’s networked society? If so, how much power do they hold? Furthermore, if traditional media outlets continue to set the agenda and act as gatekeepers of information, does it mean that social media sites like Twitter have no effect on information dissemination? These questions are enticing and in the peripheral of much of the contemporary literature surrounding this topic. As such, these questions largely remain unanswered by the plethora of scholarly work. It is the goal of this paper to delve deeper into this core complexity, to study which of the following ‘realities’ of the twenty-first century are accurate when it comes to the gatekeeping and agenda-setting powers of traditional mass media institutions.

2.3 Networked Journalism

Prior to solving the mystery of the traditional mass media’s actual control over the gatekeeping and agenda-setting of information, we must first understand

how such hypothetical control would be administered today, through the practice of networked journalism. The concept of networked journalism can be best understood as the “combination of critical and orientational storytelling, triggered by a demand from [members of] the public as well as a demand from the profession itself” (Bardoel & Deuze, 2001, p. 97). Where networked journalism incorporates the medium of the internet, it requires that producers of information orient their stories towards a specific audience, rather than a broad ‘created’ one (Bardoel & Deuze, 2001, p. 97). As digital media, the practice of networked journalism allows for technology to become the central tenant that controls the distribution of media messages (Bardoel & Deuze, 2001, p. 97) via blogs, new media websites, (Beckett & Mansell, 2008) and most importantly, through social media ‘microblogs’ such as Twitter (Hermida, 2010).

While networked journalism is a new phenomenon, current academic discourse summates that journalism as a whole becomes decentralized as consumers of news move away from traditional media outlets as their only source for information (Beckett & Mansell, 2008); democratized, in the sense that the format of information dissemination provides more opportunities for public debate (Beckett & Mansell, 2008); and disintermediated, by removing the ‘middleman’ journalist due to new technologies and an increase in individuals who actively seek information through such new technologies (Bardoel & Deuze, 2001). As a result, the so-called ‘old journalism’ of the past no longer owns the megaphone of discourse in society (Bardoel & Deuze, 2001). In a sense, the gatekeeping and agenda-setting practices of the past do not universally apply today, as average citizens have been given the power to circumvent traditional media outlets’ gatekeeping presence and set their own agenda with regards to the importance of news

stories (Bardoel & Deuze, 2001).

The power beholden to the citizen in information dissemination is a central tenant of networked journalism. The democratization that allows the citizen to produce and disseminate news is of major significance to the theoretical framework of networked journalism. The capability of an individual to create, contribute to, and share information to other individuals in a global setting is what threatens the very concept of a hierarchical system of information dissemination, driven by the gatekeeping and agenda-setting practices of traditional mass media institutions (Deuze, Burns, & Neuberger, 2007). As the former editor-in-chief of Reuters puts it, due to the democratization and economic scaling of media production, “the days of owning and controlling [information]... are over”, as anyone can obtain and produce news for an audience to consume (p. 323). Ultimately, this democratizing force is what unleashes networked journalism to become a threat to the concepts of gatekeeping and agenda-setting.

Yet while networked journalism leads to decentralization, democratization, and disintermediation of news, it also creates a hierarchal system through the use of hyperlinks and media metrics. In a digitized world where information is stored in the network, hyperlinks are used to disseminate information to audiences (Beckett & Mansell, 2008). Furthermore, the number of page clicks, retweets, and likes are what indicate the prominence of one’s status as an information provider in the age of networked journalism (Beckett & Mansell, 2008). In an era where an abundance of information exists, the competition for an audience becomes fierce. Many individuals use the metrics listed above as a way to appraise a digital ‘networked media’ institution, where the more retweets, page clicks, and hyperlinked mentions one gets, the more ‘legitimate’ they

become in the eyes of the average online information seeker (Hermida, 2010).

Based on contemporary literature, it can be said that while networked journalism in many ways collapses the gatekeeping and agenda-setting functions of traditional mass media outlets, it also re-establishes it, albeit in a digital format. Ultimately, the question with regards to the research interests of this paper becomes the following: In what way[s] does the implementation of networked journalism collude or collapse the old world gatekeeping and agenda-setting practices of traditional mass media outlets? In order to answer this, we must further study the strategies of traditional mass media outlets' execution of their networked journalism practices. For all intents and purposes of this paper, we shall only study their use of Twitter and hyperlinks on Twitter. Prior to studying this, however, we must also understand the importance of Twitter when it comes to information dissemination among political campaigns, as we will later attempt to study the 2016 U.S. Presidential Election in the context of networked journalism and the traditional mass media's power, or lack thereof, over gatekeeping and agenda-setting.

2.4 The Importance of Twitter in Political Campaigns

The literature examined thus far makes it clear that technology has radically altered the state of information dissemination. Due to the invention of the internet, there is an abundance of information, which was previously made scarce in the twentieth century (Singer, 2014). While the internet as a whole is important to this shift, no other technical component of the internet has been more important to the format of political campaigns than social media (Hong & Nadler, 2012). Specifically, the microblogging site of Twitter is the political sphere's favourite social media medium (Vergeer, Hermans & Sama, 2011). There are two main reasons for the popularity of Twitter as a political tool: [1]

politicians see Twitter as a tool to easily disseminate their message without going through the traditional mass media's gatekeeping and agenda-setting practices (Hong & Nadler, 2012) and; [2] the use of microblogging as a place where active citizens share their thoughts and beliefs about society, especially regarding politics (Metzgar & Maruggi, 2009).

Political campaigns see it beneficial that professional journalists have lost control over the agenda-setting and gatekeeping capabilities on Twitter, something which journalists attempt to hold onto in the traditional media dissemination methods of print and broadcast journalism (MacKinnon, 2005). More than ever, it is being argued that Twitter and other social media sites are becoming the so-called 'Fifth Estate'; in replace of the traditional mass media's 'Fourth Estate', where greater social accountability dominates due to the free-flowing discussions users have among one another and increasingly with politicians and governmental institutions (Dutton, 2007). Twitter effectively removes the need for traditional methods of information consumption, as both mass media and new media outlets disseminate information through the social media site, using hyperlinks to direct traffic to articles and text tweets to release condensed pieces of information (Saez-Trumper, Castillo & Lalmas, 2013). Such practice is networked journalism in action.

3. Research Questions

As the literature suggests, there appears to be a shift within the confines of information dissemination in today's connected world. According to Castells (2000), the gatekeeping and agenda-setting actions of traditional mass media institutions appear to be in question, as the threat of networked journalism takes a larger role in the day-to-day practices of information disseminators. As such, in order to compartmentalize such hypothesized shift, this paper will attempt to answer the following research questions:

RQ1: In what way has the social media tool of Twitter altered agenda-setting and gatekeeping principles through standard practices of networked journalism?

RQ2: Have traditional mass media institutions been effective in implementing their practice of networked journalism?

RQ3: Has networked journalism led to the decreased influence of traditional mass media institutions when it comes to major stories of significance?

While this paper will attempt to answer these questions, it is important to note that there are limitations in the conclusions that this paper will make. To begin, given the limited scope of this paper, it will be difficult to summate that the findings contained therein are exhaustive and all-encompassing of the field of journalism. The goal of this paper is to provide one specific example of how, if at all, the social media platform of Twitter has altered the agenda-setting and gatekeeping practices of traditional mass media institutions, through the modern framework of networked journalism. Furthermore, this paper will be studying a highly specified segment of journalism, that being political journalism. The changes that affect traditional mass media institutions, as observed in this paper, are not to be considered a *vade mecum* of the metamorphose in the twenty-first

century structure of journalism. Political journalism, while integral, is only one segment of the fourth estate and its role in disseminating information to the public.

4. Data Collection Approach

In order to study the extent to which Twitter has altered agenda-setting and gatekeeping principles, especially with regards to the effectiveness of traditional mass media outlets, this paper will examine tweets from both the public, new media institutions, and mainstream media institutions during the 2016 U.S. Presidential Election. Using Netlytic, a total of five datasets have been created; each with a specific term, date, and general type of audience. For two of the five datasets, the hashtag “#MAGA” [Donald Trump’s campaign slogan - Make America Great Again] is used as the specific term, in order to collect tweets from the public audience that is supportive, sympathetic, or highly interested in Donald Trump. The dates of the tweets in the datasets are November 7, 2016 and November 9, 2016 respectively; specific dates to allow for an examination of what this audience was discussing both one day before and one day after the election.

For another two of the five datasets, the hashtag “#ImWithHer” [Hillary Clinton’s campaign slogan] is used as the specific term, in order to collect tweets from the public audience that is supportive, sympathetic, or highly interested in Hillary Clinton. Again, the dates of the tweets in these datasets are the same as the dates of the tweets in the “#MAGA” datasets, for the same reasons mentioned above and to allow for an apples to apples comparison of tweets issued by each public audience.

By using these two political campaign hashtags, the data collected will provide a sense of the general themes, moods, and thoughts of the public, pertaining to Donald Trump and Hillary Clinton. Additionally, the tweets collected will also display the type of information and news stories that people are discussing and disseminating throughout the Twitterverse.

Finally, for the fifth dataset, the hashtag “#Election2016” is used as the specific term, as it became known as the standard hashtag among established journalists and media organizations to use when tweeting news about the campaign. The dates of the tweets collected range from November 7, 2016 to November 9, 2016, in order to best study the media’s reaction one day before the election, the day of the election, and one day after the election. This dataset only focused on the Twitter accounts of several traditional mass media outlets, in order to discern what stories they tweeted, how they worded their tweets, what rich content was included in the tweets, and most importantly, how many retweets and conversations did their tweets garner. The specific Twitter accounts included in this dataset are as follows: @cnn, @msnbc, @foxnews, @abcnews, @nbcnews, @cbsnews, @wsj, @huffingtonpost, @nytimes, @washingtonpost, @latimes, and @usatoday. These accounts were selected as they are recognized by the public as reputable legacy media institutions. These specific accounts are also considered to be the most viewed Twitter accounts among traditional mass media outlets (Pew Research Center, 2011).

A total of 4,392 tweets have been collected, among the five datasets. Ultimately, these datasets will assist in the attempt to answer the research questions listed above. By limiting the data collected to the social media tool of Twitter, this paper will be able to isolate the findings to specifically address the research questions contained within. By applying the theoretical concepts of gatekeeping, agenda-setting, and networked journalism, along with studying the usage of Twitter by both new and traditional mass media institutions, and the public, this paper will discern to what extent, if any, Twitter has had on information dissemination [albeit, within the limited context of information

pertaining to the 2016 U.S. Presidential election]. Furthermore, the data collected will allow this paper to deduce whether or not traditional mass media institutions have been able to successfully implement the practices of networked journalism, as the data will present quantifiable evidence depicting their relative reach to the masses on the microblogging platform, and whether or not the public at large refers to traditional mass media institutions for information on stories of significance, such as the 2016 U.S. Presidential election.

5. Methods of Analysis

Using the data collected, along with the nomenclature of theory pertaining to agenda-setting, gatekeeping, and networked journalism, this paper will take a mixed methods analysis approach to answering the questions listed above. Specifically, the qualitative method of textual analysis will be used in tandem with the method of quantitative content analysis.

5.1 Qualitative Analysis

Using a textual analysis approach, this paper will attempt to analyze what topics each of the audiences listed above are discussing with regards to the election, if either audience has a preference for news sources; and more importantly, the differences in topics being discussed between each of three main cohorts; Trump enthusiast, Clinton enthusiasts, and traditional mass media outlets. This will be done by using the Netlytic text analysis software, along with a manual coding of the tweets compiled (see Appendix D). The most used terms in each dataset will be studied further and put into context, to summate the general themes. These themes, when contextualized, will provide this paper with a window into the world of the public and their thoughts pertaining to the Presidential candidates and their campaigns. Furthermore, using the headlines from several traditional and new media sources to analyze the top headlines for the dates of November 7 and November 9, this paper will study what new stories of the day each cohort disseminated throughout the Twitterverse.

5.2 Quantitative Analysis

Similarly, using a quantitative content analysis approach, this paper will utilize the meta-analysis process of studying market penetration/reachability with regards to

traditional mass media and new media/opinion leaders, using retweet counts as a barometer. The information collected in the fifth dataset detailed above will be compared to the information collected in the four other datasets, in order to juxtapose the differences in how new media/opinion leaders/news consumers and traditional mass media outlets broadcast information, and how the public receives, interpolates and shares this information. Furthermore, the tweets of new media/opinion leaders/news consumers and traditional mass media organizations will be compared to one another and analyzed in terms of their reach. The metrics used to quantify reach will consist of retweets, responses to the tweet, and conversation starters. This will be done using information interpretation created by Netlytic’s network analysis software. Here, Netlytic counts all the usernames of Twitter accounts captured within a given dataset and visualizes the information in a network graph. Each username is assigned a dot on the graph, known as a node. The connections between nodes is then visualized with links drawn between each node-to-node interaction, where an interaction counts as either a retweet, mention [where one user mentions the username of another], or a reply/conversation starter. The greater the amount of interactions a user makes, the larger their node is represented within the graph. Nodes that are clustered together form a community, where a high amount of interaction takes place among each other. Nodes that are on the edges of the network graph are isolated ones, where little to no interaction takes place between them and other users. Ultimately, the greater the interaction of a node, the larger the impact and reach it has within the network.

5.3 Operationalizing the Research Questions

Research Question (RQ)	Tools	Qualitative Analysis	Quantitative Analysis
To what extent has the social media	Netlytic	Text analysis	

tool of Twitter altered agenda-setting and gatekeeping principles through standard practices of networked journalism?			
	Excel	Content analysis/Topic analysis	
Have traditional mass media institutions been effective in implementing their practice of networked journalism?	Excel	Content analysis/Topic analysis	
Has networked journalism led to the decreased influence of traditional mass media institutions when it comes to major stories of significance?	Netlytic		Network analysis
	Twitter/Excel		Meta-analysis

Table 1: Operationalizing research questions

The analysis of the data compiled for this paper will follow the deductive research approach. Focusing on the pre-existing theoretical concepts of gatekeeping and agenda-setting, this paper will analyze the effects that Twitter has on the power of traditional mass media outlets. The paper will also apply the theory of networked journalism to study whether or not traditional mass media outlets have instituted a successful mode of outreach in today’s technologically driven media landscape. Finally, through the deductive approach, this paper will compare the reach and effectiveness of traditional mass media outlets, in comparison to new media outlets/opinion leaders, in relation to the public penetration in the market of information dissemination, using the 2016 U.S. Presidential election as a case study. In order to study the following, this paper will attempt to answer the three research questions listed above using the following methods:

RQ1: *In what way has the social media tool of Twitter altered agenda-setting and gatekeeping principles through standard practices of networked journalism?*

Using Netlytic’s text analysis software, the qualitative method of text analysis will be used to discern the top themes that each dataset incorporates. By examining the top ten used terms among the tweets compiled in each dataset, this paper will be able to sketch a general picture of the conversations taking place among users within the network.

Similarly, using the Excel filter function, a qualitative content and topic analysis will be

administered. Upon reviewing the headlines from both traditional and new media sources on November 7, 2016 to November 9, 2016, along with manually combing through the tweets from each dataset, this paper will be able to comprehend the differences in news stories discussed and disseminated among each of the following cohorts. Codes will be applied to the collected tweets in each dataset that will comply with the key topics being discussed, in order to allow for the filtering of data to take place. Such filtering will allow this paper to identify which key topics are being significantly discussed by each of the following cohorts. Finally, in order to analyze how the social media tool of Twitter has altered agenda-setting and gatekeeping principles through the standard practice of networked journalism, this paper will highlight the key differences in key topics being discussed and disseminated among traditional mass media institutions and new media/opinion leaders.

RQ2: *Have traditional mass media institutions been effective in implementing their practice of networked journalism?*

Upon completing the coding of tweets for the purpose of attempting to answer RQ1, this paper will further analyze the results found. Specifically, this paper will examine how each dataset covers four crucial stories (1) the FBI clearing Clinton of criminal wrongdoing story; (2) the John Podesta email story; (3) the Russia connection story; (4) the polls/horserace story, and how they differ from what new media/opinion leaders/news consumers are disseminating, and most importantly, using the theoretical concepts of networked journalism, analyze if and how traditional mass media institutions have failed in transitioning to a twenty-first century method of news coverage. Additionally, this paper will delve further into the coded tweets among each dataset to analyze usage

patterns among Twitter users. Numerous studies regarding Twitter content have taken such an approach by examining the varying aspects of a user or users' behaviour on Twitter, such as Bagdouri's (2016), who looked at the key differences in usage among journalists on Twitter from different parts of the world. For the intents and purposes of this study, this paper will examine the differences, if any, in the engagement level between traditional mass media institutions and new media/opinion leaders/news consumers, in addition to identifying any dissimilarities in the implied practices of two core groups on Twitter.

RQ3: *Has networked journalism led to the decreased influence of traditional mass media institutions when it comes to major stories of significance?*

Using Netlytic's network analysis tool, a quantitative method of network analysis will be used to discern what interaction, if any, each of the following cohorts has among each other. By manipulating the information contained within Netlytic's network analysis displays, this paper will be able to understand the overall reach of tweets issued by individual accounts [nodes], along with how much interaction each user [node] has among other users [nodes] within a network. While the dataset pursuant to traditional mass media institutions only includes tweets sent out by the networks listed above, the mentioning of the networks in the four other datasets will shed light into how much interaction they receive among new media/opinion leaders/news consumers. Specific information as to how this identification and determination is made will be further explained in the pages below. Additionally, using the Excel filter function, this paper will be able to quickly find tweets of a similar nature from all datasets, in order to compare side-by-side their retweet count; a unit of measurement which provides a clear numerical value to a tweet's reach.

This retweet comparison will shed light into whether or not traditional mass media institutions are receiving an equal, greater than, or less than reach when compared to tweets originating from new media/opinion leaders/news consumers.

6. Findings

The aim of this MRP is to analyze if the gatekeeping and agenda-setting functions of mass media institutions are still applicable in today's connected society, where the advent of networked journalism, due in part by the creation of the networked communication tool of Twitter, has ushered in a new form of information dissemination. Results of the mixed-method analyses outlined above are revealed and discussed in the pages below, sorted by research question.

6.1 RQ1: The Altering of Agenda-Setting and Gatekeeping in the Twitterverse

This section discusses the analysis process and the key findings pursuant to the changes in the agenda-setting and gatekeeping powers of traditional mass media institutions, when it comes to information dissemination on Twitter. First, using Netlytic's text analysis software, the top ten keywords of each dataset will be identified. General points of interest will be noted in the differences among the top terms of each dataset. Second, the key news stories discussed among each dataset will be identified. The coding process implemented in the Excel filtering function administered to identify these key topics will be explained, along with the method by which top news headlines were determined. Finally, this section will then conclude with a summation of the general findings within the datasets. Similarities and differences in the top stories covered within each of the five datasets and three cohorts will be highlighted, along with the core differences in information dissemination between traditional mass media institutions and new media/opinion leaders/news consumers.

RQ1: Keywords and Top Themes

Figure 2: Top 10 words in dataset A

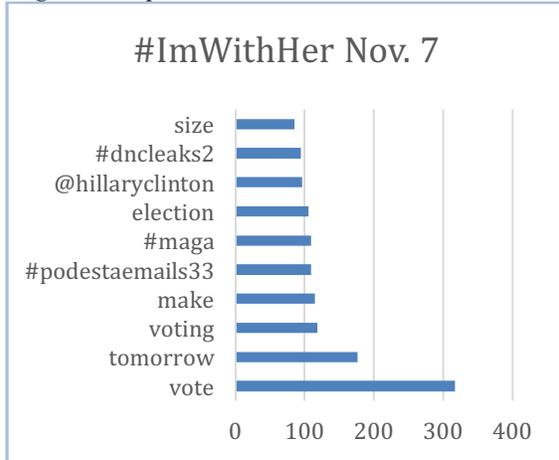


Figure 3: Top 10 words used in dataset B

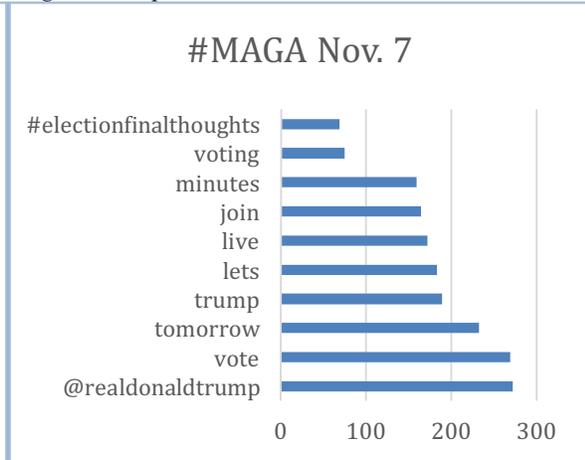


Figure 4: Top 10 words in dataset C

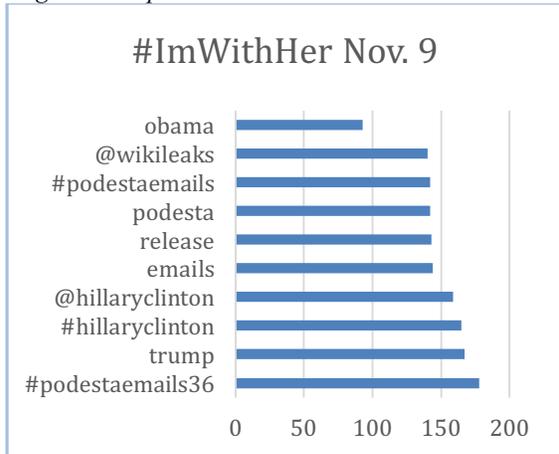


Figure 5: Top 10 words in dataset D

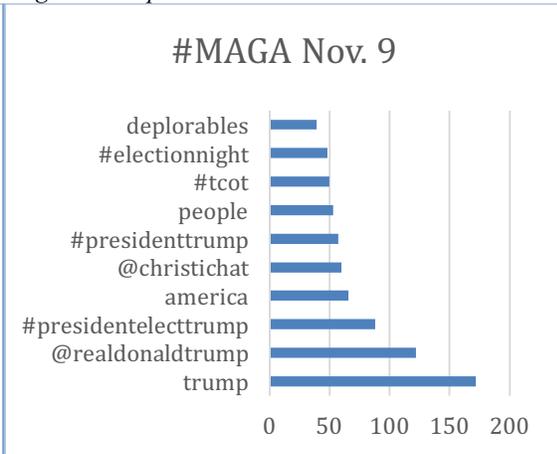
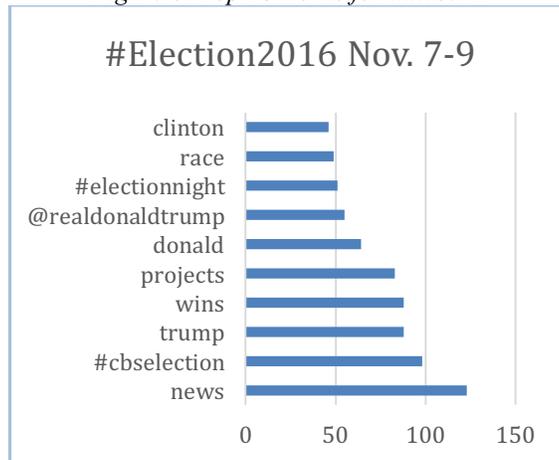


Figure 6: Top 10 words for dataset E



Upon studying the graphs above, it is evident that all five datasets include similar

themes, with differing levels of interest among these topics, yet are exclusive to one another in terms of their overall focus. For example, the term ‘trump’ appears as one of the top ten used terms in four out of the five datasets, with dataset A being the sole dataset to not have the term used such frequently. While dataset A does not include the term ‘trump’ among its top ten words used, it does include ‘#maga’ as the sixth most used word. The hashtag ‘#maga’, an acronym for Donald Trump’s campaign slogan “Make America Great Again”, is clearly linked with Donald Trump, much like the term ‘trump’ is. Therefore, it can be deduced that the campaign of Donald Trump is a similar theme that is present in all five datasets.

While it is clear that some themes are present across all five datasets, there are other themes that are exclusive to individual datasets and cohorts. Take the word ‘podesta’ for example. This word refers to John Podesta, chairman of the Hillary Clinton Presidential campaign. Due to the timing of the mentioning of his name, the term ‘podesta’ could be associated to the leaking of his emails by hackivist group Wikileaks. While the word ‘podesta’ itself is only present as a most commonly used word in dataset C, it is clear that the story pursuant to this term is commonly discussed among the Clinton cohort, as dataset A includes the word ‘#podestaemails33’ as the fifth most commonly used word among all tweets contained within its collection. While the ‘podesta’ theme is present among datasets A and C, both datasets pursuant to tweets involving Clinton [as the hashtag #ImWithHer was used to collect tweets for the datasets], the theme does not transcend past the Clinton cohort. None of the top ten words in datasets B, D, or E incorporate the use of, or allude to the ‘podesta’ theme. This discrepancy in topics being covered among the datasets will be analyzed further, through a coding of the collected

tweets among the five datasets.

6.2 RQ1: Key News Stories Covered Among Datasets

As noted above, the key themes persistent among the five datasets, as per the top words used, were similar, although not the same. Some datasets and cohorts included exclusive themes present within. While at a macro level, it can be deduced that the information disseminated by traditional mass media institutions [dataset E] is mostly in sync with the information being disseminated by new media/opinion leaders/news consumers [datasets A to D], such a conclusion would be premature. Much of the data collected is a representation of the Twittersverse; there is a great amount clutter and noise persistent among Twitter. Thousands of tweets are sent out by users at any given moment, often filled with convoluted messages and meanings. Thus, in order to fully understand the similarities and differences among information that is being discussed and disseminated within each dataset, this paper will dive further into the data collected by highlighting quality information of significance. This will be done by filtering through each dataset with key terms and applying codes to them, in order to sort the collected data into topics of importance.

These topics of importance will consist of top news stories from November 7, 2016 and November 9, 2016 respectively, as these dates correspond to the dates pursuant to the datasets being studied. The top news stories that will be studied were chosen by scouring through the headlines of several major traditional and new media sources, along with a manual evaluation of content discussing top news stories that were consistent throughout tweets within the five datasets.¹ The top news stories are as follows: [1] The FBI

¹ In order to determine these top stories, a Google News search was conducted for the top news stories of the specified dates of November 7, 2016, November 8, 2016 and November 9, 2016. A filter

investigation into Hillary Clinton's private email server; [2] The John Podesta email leaks; [3] The Russian connection to the U.S. Presidential election, and; [4] The tightening of polls in the lead up to election day. The corresponding codes used for the news stories are as follows: [1] FBI; [2] Podesta; [3] Russia; [4] Polls. A total of 4,392 tweets were combed through, with 647 tweets, or 14.7% of all tweets collected, being coded.

Code 1: FBI

For the first code pertaining to the story surrounding the FBI's investigation into Hillary Clinton's private email server, it should be noted that while the story persisted throughout the campaign, it received additional attention on Monday, November 7, 2016, as the day preceding, FBI director James Comey announcing that Clinton was once again cleared of any criminal wrongdoing. (The Guardian, 2016). This reiteration of Clinton's innocence was broadcast by the FBI director as just days earlier, he announced that the bureau was re-opening the investigation to comb through newly found emails by Clinton, on the cellphone of former Congressman Anthony Weiner (The Guardian, 2016). As such, this re-opening and reiteration of Clinton's innocence made for an abundance of news on the campaign trail, with many on social media discussing the saga. While discussion and dissemination pertaining to this story began to fade on Monday, November 7, 2016, it did still make for significant headlines among some traditional mass media institutions (The Guardian, 2016) and many new media institutions (Breitbart, 2016). Thus, the author of this paper concluded that the story should be included within the greater context of this study. Specifically, the FBI story should be considered a story of significance contained

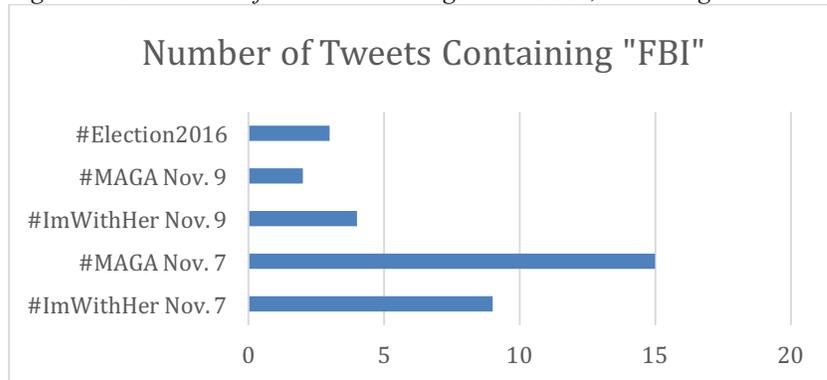
was applied to only show results from the traditional mass media outlets included in the #Election2016 dataset.

within the datasets collected for this study.

In order to understand the amount of coverage pertaining to the FBI story on Twitter, the tweets compiled among the five datasets must be coded for any and all language relevant to this story. As such, using the Excel filtering function, the following key terms were used to find tweets that discussed the FBI story: ‘FBI’; ‘Comey’; ‘Probe’; ‘Emails’; ‘Server’; ‘Private’; ‘Weiner’; ‘Investigation’. These key terms were selected as they convey a strong connection to the story in question.

An analysis of the tweets compiled within the five datasets shows that a total of 33 tweets were found to have at least one of the key terms mentioned above. Those tweets were then coded under ‘FBI’ and broken down according to the dataset with which they belonged to. The results are displayed in figure 7.

Figure 7: Breakdown of tweets containing code “FBI”, according to datasets



Dataset B included the largest number of tweets discussing the FBI story, with 15 tweets coded. Contrastingly, dataset D included the least number of tweets pursuant to the FBI story, with 2 tweets coded. It is interesting to note that both datasets B and D fall under the Trump cohort of tweets; a finding that will be discussed in greater detail below. Dataset E, however, includes the second lowest number of tweets coded ‘FBI’, with a total of 3.

Code 2: Podesta

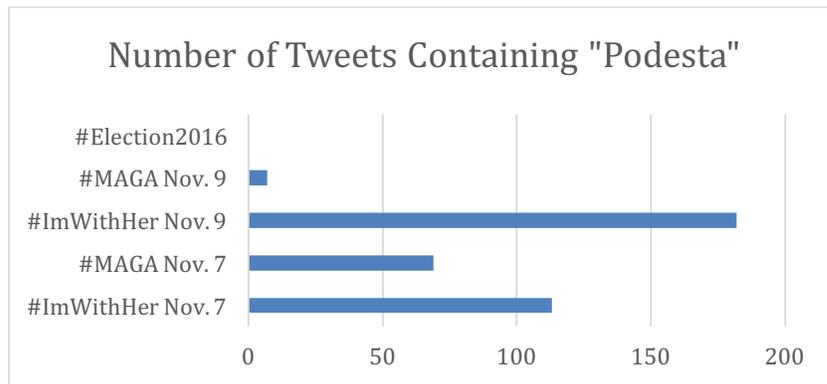
For the second code pertaining to the story surrounding the leaking of Clinton campaign manager John Podesta's emails, it should be noted that this story continued to unravel throughout the campaign. Wikileaks, a hacking group, continuously released damaging information about the Clinton campaign and its associates throughout the 2016 U.S. Presidential election. On Monday, November 7, 2016, Wikileaks released part 33 of their data compilation of John Podesta's personal emails (Wikileaks, 2016), many of which were controversial, as they revealed campaign strategies and personal positions of Clinton (Russia Today, 2017). Many new media sites, including Breitbart (2016), InfoWars (2016), and even Right Wing Watch (2016) produced headlines regarding the latest data dump. In addition to this, after combing through the tweets of all five datasets, it became evident that many members of the public began to discuss and disseminate information pursuant to the Podesta email leak. Hashtags such as '#podestaemails33' were commonly used in tweets to further disseminate the link containing the document of leaked emails. Given these two factors of consideration, it was decided to include the Podesta story as one of significance, contained within the datasets collected for this study.

In order to understand the amount of coverage pertaining to the Podesta story on Twitter, the tweets compiled among the five datasets must be coded for any and all language relevant to this story. As such, using the Excel filtering function, the following key terms were used to find tweets that discussed the FBI story: 'Podesta'; 'Spirit'; 'Cooking'; 'SpiritCooking'; 'Pizza'; 'Gate'; 'PizzaGate'. The term 'Wikileaks' was omitted, as the term is not mutually exclusive to the Podesta story, but instead, connected to several stories relating to the hacking website. These key terms were selected as they

convey a strong connection to the story in question.

Upon an analysis of the tweets compiled within the five datasets, a total of 371, or 8.48% tweets were found to have at least one of the key terms mentioned above. Those tweets were then coded under ‘Podesta’ and broken down according to the dataset they belonged to. The results are displayed in figure 8.

Figure 8: Breakdown of tweets containing code “Podesta”, according to datasets



Dataset C included the largest number of tweets discussing the Podesta story, with 182 tweets coded. Contrastingly, dataset E, the dataset which includes only tweets from traditional mass media institutions, included the least number of tweets pursuant to the Podesta story, with 0 tweets coded. This major discrepancy will be studied extensively in the pages below.

Code 3: Russia

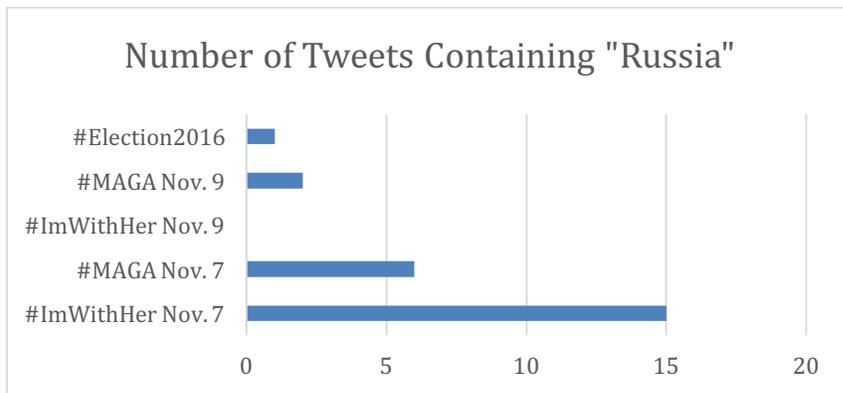
The third code relates to the story surrounding Russian interference in the 2016 U.S. Presidential election. It should be noted that this story was given life in the dead summer months of the campaign, after Trump insinuated that the Russian government should hack Clinton’s email server (Brenson, 2016). Towards the end of the campaign, Clinton accused Trump of potentially colluding with the Russian government to skew the results of the election in his favour, using the email leaking as proof of such collusion (The

Guardian, 2016). On Monday, November 7, Wikileaks, a hacking group, continuously released damaging information about the Clinton campaign and its associates throughout the 2016 U.S. Presidential election. On Monday, November 7, 2016, the New York Times ran an opinion piece claiming that the election was rigged in part by the Russian government (Krugman, 2016). On Wednesday, November 9, 2016, the day after the Presidential election, numerous traditional mass media and new media sites began to lay the blame of the result of the election on Russia. Due to the mounting amount of headlines relating to the Russia connection to the election, it was in the opinion of this paper to include this story as one of significance and to be examined further, within the context of this study.

In order to understand the volume of coverage pertaining to the Russia story on Twitter, the tweets compiled among the five datasets must be coded for any and all language relevant to this story. As such, using the Excel filtering function, the following key terms were used to find tweets that discussed the FBI story: ‘Russia’; ‘Russian’; ‘Putin’; ‘Vladimir’; ‘VladimirPutin’; ‘Hack’; ‘Hacking’ ‘Kremlin’; and ‘Moscow’. These key terms were selected as they convey a strong connection to the story in question.

Again, upon reviewing the tweets compiled within the five datasets, a total of 24 tweets, or 0.55%, were found to have at least one of the key terms mentioned above. Those tweets were then coded under ‘Russia’ and broken down according to the dataset with which they belonged to. The results are displayed in figure 9.

Figure 9: Breakdown of tweets containing code “Russia”, according to datasets



Dataset A included the largest number of tweets discussing the Russia story, with 15 tweets coded. Contrastingly, dataset C included the least number of tweets discussing the Russia story, with 0 tweets coded. It is interesting to note that both datasets A and C fall under the Clinton cohort of tweets; a finding that will be discussed in greater detail below. Dataset E, however, includes the second lowest number of tweets coded ‘Russia’, with a total of 1.

Code 4: Polls

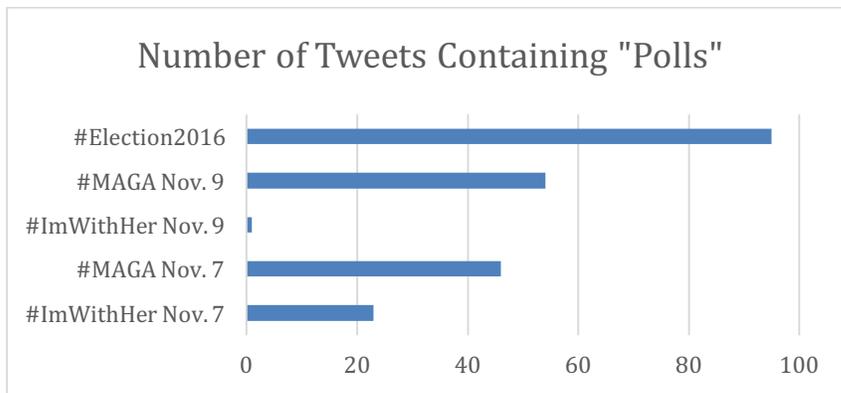
For the fourth and final code, which pertains to the story surrounding the tightening of the polls, it should be noted that this story began to receive popularity among traditional mass media outlets roughly one week before election day (Al Jazeera, 2016). Throughout much of the campaign, it was stated that polls highly favoured Clinton to win the Presidential election, with Trump trailing by a sizeable amount (Lauter, 2016). Towards the end of the campaign, the polls began to significantly tighten, and key battleground states were coined ‘too close to call’ (Zogby, 2016). With poll after poll being reported on, it became apparent that traditional mass media institutions may have become obsessed with the horserace storyline of the campaign; a complete reversal of their narrative that persisted throughout the majority of the campaign. On Monday, November 6, 2016, nearly every traditional mass media outlet ran a headline stating that

the election was in fact a horserace, with polls tightened and battleground states in a deadlock. This climax of a crescendo of an election coverage by traditional mass media institutions rendered this paper to believe that this must be further examined, in order to study the disconnect, if any, between what information mass media outlets were disseminating and new media/opinion leaders/news consumers were discussing.

In order to understand the amount of coverage this story received on Twitter by each cohort, the tweets compiled among the five datasets must be coded for any and all language relevant to this story. As such, using the Excel filtering function, the following key terms were used to find tweets that discussed the FBI story: ‘Ohio’; ‘Michigan’; ‘Carolina’; ‘Nevada’; ‘Pennsylvania’; ‘Hampshire’; ‘Wisconsin’ ‘Virginia’; ‘Florida’; ‘poll’; ‘polls’; ‘swing’; and ‘state’. The following states were listed as key terms due to the fact that they were each considered a swing state (Al Jazeera, 2016). Stories relating to the tightening of the polls almost always included at least one swing state in its reporting. As such, these key terms were selected for the filtering process as they convey a strong connection to the story in question.

Upon scouring through the tweets compiled within the five datasets, a total of 219 tweets were found to have at least one of the key terms mentioned above. Those tweets were then coded under ‘Polls’ and broken down according to the dataset with which they belonged to. The results are displayed in figure 10.

Figure 10: Breakdown of tweets containing code “Polls”, according to datasets



Dataset E included the largest number of tweets discussing the polls story, with 95 tweets coded. Contrastingly, dataset C included the least number of tweets discussing the polls story, with 1 tweet coded. It is interesting to note the vast discrepancy between dataset E and dataset A. On a similar note, it is interesting to see the great amount of interest placed on this story by traditional mass media institutions [reflected in dataset E], when compared to the other datasets. Datasets A, B, C, and D each included 1,000 compiled tweets, whereas dataset E compiled only 392 tweets. On a percentage basis, 24.2% of all tweets compiled in dataset E contained information pursuant to the ‘polls’ story. In contrast, a mere 0.1% of all tweets compiled in dataset C contained information pursuant to the ‘polls’ story. Similarly, datasets A, B, and D each contained miniscule amounts of tweets pertaining information to the ‘polls’ story, in comparison to dataset E, with 2.3%, 4.6%, and 5.4% respectively. This exaggerated variance between dataset E and datasets A, B, C, and D will be discussed in the pages below.

6.3 RQ2: Traditional Mass Media Outlets’ Twitter Troubles

This section will reveal the key findings pursuant to the effectiveness of traditional mass media institutions’ application of networked journalism principles. In order to study such effectiveness, this paper will further analyze the tweets coded to answer RQ1.

Instead of examining the tweets dataset by dataset, this paper will take a holistic approach

to the in-depth analysis of the coded tweets' content. It will categorize tweets as either tweets issued by traditional mass media outlets [which will henceforth be referred to as MMI], or tweets issued by new media/opinion leader/news consumers [which will henceforth be referred to as NPC]. The criteria by which user patterns will be identified are as follows: [1] engagement levels; [2] communication strategies; and [3] level of originality.

RQ2: Engagement Levels

As noted in the pages above, networked journalism incorporates the sharing of information by individuals in a global setting, where the public participates in a continuous conversation of news stories (Deuze, Burns, & Neuberger, 2007). This conversation and democratization of information dissemination is what removes the middleman journalist from the public sphere as an integral role (Bardoel & Deuze, 2001). In turn, this interconnectedness among the public is what begat the new era of journalism; one where engagement among the public is high and access to information is boundless. Thus, the public engagement levels of MMI and NPC data are significant units of measurement. The higher the level of engagement with the public, the stronger the application of a core principle of networked journalism, that is, audience captivity.

For the explicit application of Twitter, level of engagement can be measured in terms of replies conversations. A Twitter reply is a tweet that responds to a subsequent tweet. The reply is linked to the original tweet that is being responded to. For example, tweet B is a response to tweet A. Tweet B is therefore linked to tweet A in the Twitter API. Similarly, a Twitter conversation is a compilation of reply tweets, constituted as a thread. For example, if tweet A was issued by Twitter user 1 and tweet B was issued by

Twitter user 2, tweet C, issued by Twitter user 1 would be connected to tweet A and B in the form of a thread. Figures 11 and 12 display examples of a reply and conversation, as visualized through the Twitter API. In terms of the display of a reply and a conversation

Figure 11: Example of a reply tweet as displayed on Twitter



Figure 12: Example of a conversation as displayed on Twitter



tweet within the CSV export files created by Netlytic, an at [@] sign is indicative of such a specimen. Typically, when responding to a tweet on Twitter, the at [@] sign is present at the beginning of the tweet, as the Twitter handle of the recipient of the reply is included as the preamble of the tweet. This is however not always the case, as Twitter recently changed its API to allow replies and conversations to take place without the need for such preamble, as figures 11 and 12 showcase.

It is important to note the limitation in the data collected, pursuant to the collection protocols enrolled for the purposes of this paper. The Netlytic software application allows users to collect tweets using hashtags. Each of the five datasets were given a specific hashtag as a requirement for a tweet to be included within the dataset. As such, replies and conversations relating to a tweet collected within a dataset may have been excluded, as it did not incorporate the specified hashtag within the body text of the tweet. Therefore, the results contained within this subsection of this paper are not exhaustive in relation to the total amount of replies and conversations relating to the tweets collected.

With a total of 99 tweets, or 25.3% of all MMI collected tweets coded, 0 tweets, or 0.0% of all tweets collected were replies, or tweets that were a part of a conversation. In contrast, with a total of 548 tweets, or 13.7% of all NPC collected tweets coded, 8 tweets, or 1.46% of all tweets collected were replies, or tweets that were part of a conversation. While these numbers are not large, it does highlight one point; of the 99 MMI tweets coded, not one single tweet incorporated a reply or was part of a conversation. Although only 8 coded NPC tweets incorporated a reply or was part of a conversation, the discrepancy in comparison to the nonexistent MMI tweets is significant. In fact, a difference between 0 and 1; even with the large variance surrounding the total amount of tweets collected and coded among MMI and NPC groupings, is considered to be statistically significant as a result.² This result will be discussed further, in the pages below.

RQ2: Communication Strategies

One standard practice that has established itself as a cornerstone practice of

² A statistical relevance calculator was used to determine true relevance. For more information, visit: <http://getdatadriven.com/ab-significance-test>.

networked journalism is targeted, segmented communication. Recall that networked journalism revolves around the building of core consistencies, or oriented publics, where producers of information disseminate their stories to a specific audience (Bardoel & Deuze, 2001). This targeted method of communication is a practice which significantly increases the impact and overall reach of an information producer's content. Rather than attempting to appeal to an imaginary broad audience, a successful information producer would target a group of information consumers who are sympathetic to their story or viewpoint, with the ultimate goal of further building and solidifying their viewership. Ultimately, this standard practice is a key identifier of networked journalism in action. As such, this paper will attempt to identify whether or not traditional mass media institutions have been successful in implementing networked journalism practices, by further examining the data collected.

For the explicit application of Twitter, communication strategies can be measured by studying the use of hashtags in a tweet's body of text. Specific and direct hashtags indicate the use of strategic targeted communication, while general hashtags are indicative of broad, mass communication. For example, a specific hashtag would be #MAGA, as it is user-generated, targeted towards a specific entity [that being the Donald Trump campaign]. In contrast, an example of a general hashtag would be #ElectionNight, as it is not user-generated, but instead, a universal term for an entity [that being the night of the election] that is being transcribed into a hashtag format. For the intents and purposes of this study, one is able to decipher between a specific and general hashtag by examining the words contained within a hashtag. Generic words or terms used as a hashtag are considered to be general hashtags, while detailed word and character combinations are

considered to be specific hashtags, geared towards one particular community, or subset of communities.

It is important to note that the data collected, pursuant to the collection protocols enrolled for the purposes of this paper, ensures that every tweet will have at least one specific hashtag. The Netlytic software application allows users to collect tweets using hashtags. Each of the five datasets were given a specific hashtag as a requirement for a tweet to be included within the dataset. As such, this paper will exclude the hashtags #ImWithHer, #MAGA, and #Election2016 from counting as specific hashtags, in order to remove interferences with the interpretation of the data.

With a total of 99 tweets, or 25.3% of all MMI collected tweets coded, only 28 tweets, or 28.3% of all tweets collected were considered to be of a targeted communication nature. The remaining 71 tweets, or 71.7% of tweets were considered to be of a mass communication nature. In contrast, with a total of 548 tweets, or 13.7% of all NPC collected tweets coded, 483 tweets, or 88.1% of all tweets collected were considered to be of a targeted communication nature. The remaining 65 tweets, or 11.9% of tweets were considered to be of a mass communication nature. The discrepancy between the overall communication nature of MMI and NPC tweets are astounding. Based on these results, it can be said that, in general, traditional mass media institutions do not in fact issue tweets of a targeted nature, whereas tweets issued by new media/opinion leaders/the public do. Thus, it would be reasonable to conclude that traditional mass media institutions, as a whole, do not apply the networked journalism practice of is targeted communication.

RQ2: Level of Originality

The final metric by which this paper will assess the usage patterns of users on Twitter, in order to determine how successful traditional mass media institutions have been in implementing practices of networked journalism is through gaging the level of originality contained within their information. Contrary to traditional journalism practices, networked journalism encourages a reduction in the originality of the information being disseminated (Beckett, 2010, p.15). Rather than fostering an importance and intrinsic value in providing new information, networked journalism structures its practice by creating clusters of information transmission, where networked journalism entities thrive off of recycling information (p.15). This is due in part to the fact that networked journalism is dependent upon easily accessible information, where members of the public can attain such information in an effortless fashion (p.15-18).

As such, the practice of retweeting a story is akin to recycling public information to one's targeted audience. By retweeting a tweet, the network journalism entity is reaffirming the practice of instilling a cluster of information dissemination, where such cluster becomes an echo chamber of already existing information. Thus, for the intents and purposes of this study, this paper will examine the retweet metrics between all coded MMI and NPC tweets, in order to decipher which, if any, of the two groups follow the networked journalism practice of information recycling.

With a total of 99 tweets, or 25.3% of all MMI collected tweets coded, only 11 tweets, or 11.1% of all tweets collected were retweets. The remaining 88 tweets, or 88.9% of tweets consisted of original content. In contrast, with a total of 548 tweets, or 13.7% of all NPC collected tweets coded, 512 tweets, or 93.4% of all tweets collected were retweets. The remaining 65 tweets, or 11.9% of tweets consisted of original content.

Based on these results, it can be said that, in general, traditional mass media institutions do not in fact follow the networked journalism practice of information recycling, whereas tweets issued by new media/opinion leaders/the public do.

6.4 RQ3: The Altering of Agenda-Setting and Gatekeeping in the Twitterverse

This section will reveal the key findings pursuant to the level of influence traditional mass media institutions hold, in comparison to new media/opinion leaders/the public, on the networked journalism microblogging tool of Twitter. Using Netlytic's network analysis software, this paper will be able to analyze the overall reach of individual tweets collected within a given database. In accordance with programming instructions, Netlytic's network analysis software uses the metrics of retweets, replies, mentions, and organic impressions to visualize a connection. The visualization is presented with nodes, where each user is represented as a node. The connections made between users [nodes] is represented with an 'edge', where edges link between nodes, to display a connection. The more 'node-to-node' connections made between a node and other nodes within a dataset, the greater their connectedness, and therefore, the higher their influence. Similarly, the greater the size of a node, the higher their overall reach, and therefore influence, as the node's size represents the number of interactions the user either initiated or received. Finally, isolated nodes, as displayed through Netlytic's network analysis software as those teetering on the outskirts of a dataset's cluster, represent content without a connection to the larger network at play. These network analysis modules will be further broken down in the pages below.

RQ3: Dataset Network Modules

Figure 13: Network analysis module of dataset A

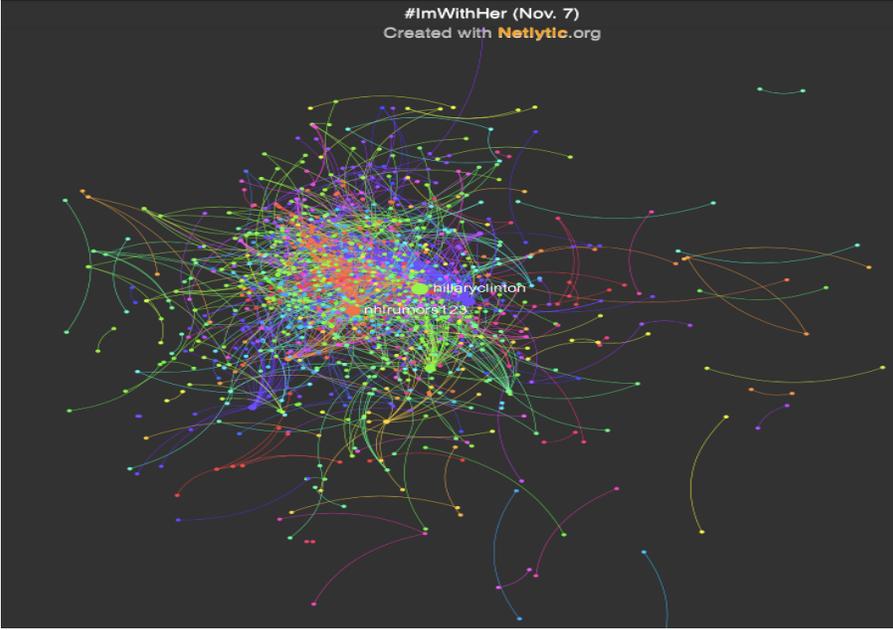


Figure 14: Network analysis module of dataset B

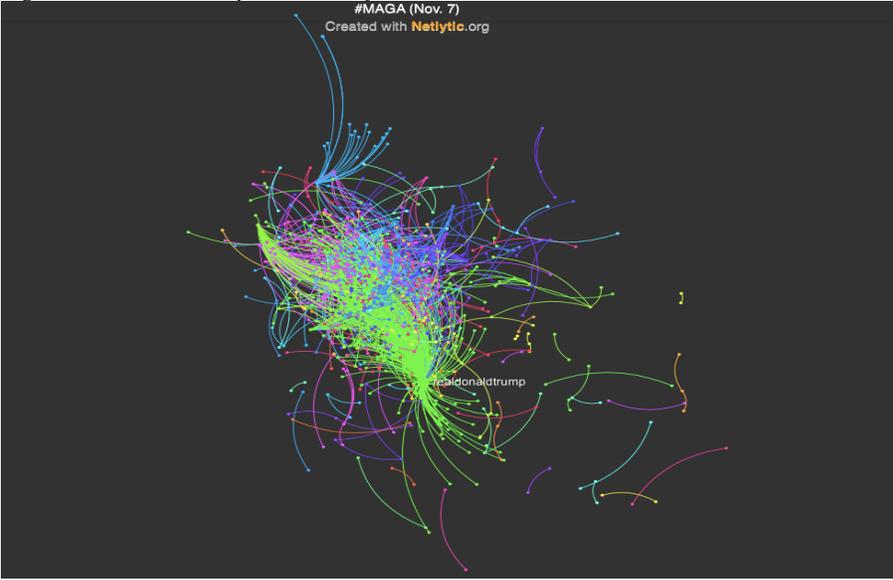


Figure 15: Network analysis module of dataset C

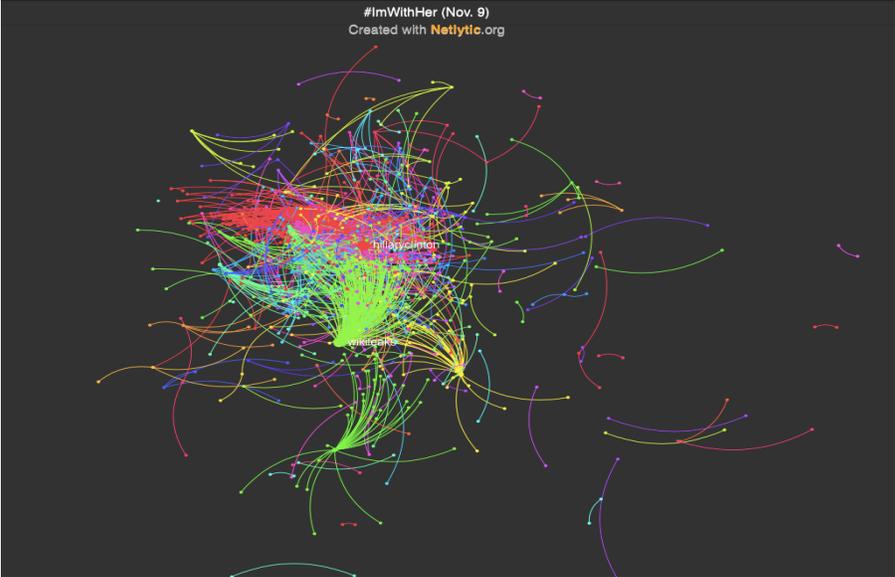


Figure 16: Network analysis module of dataset D

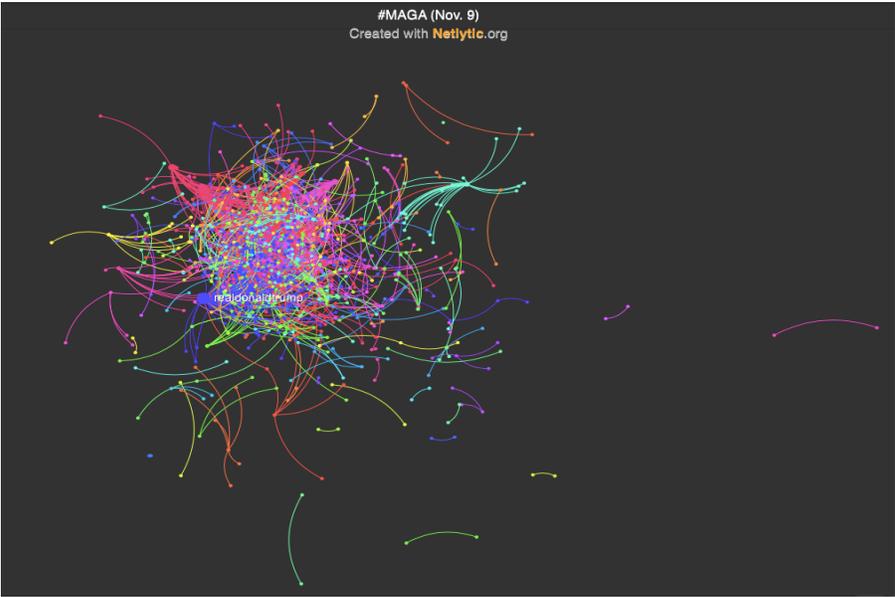
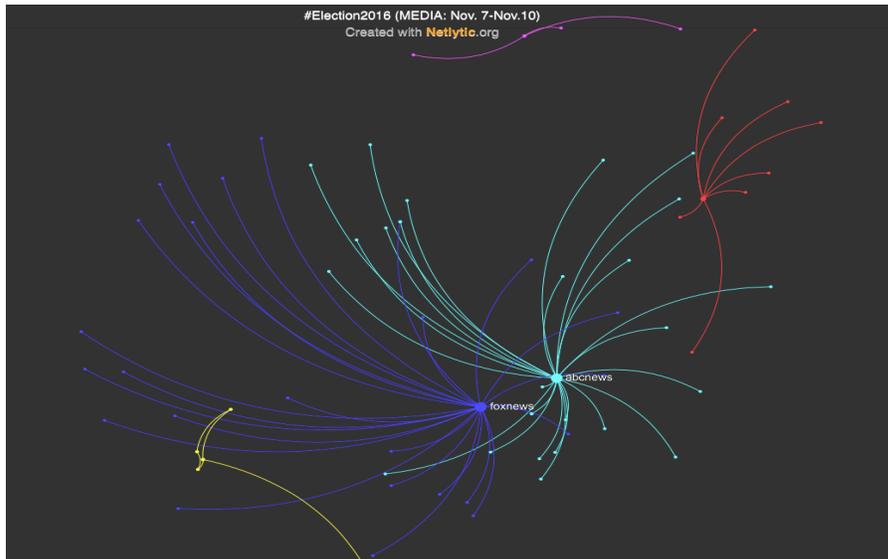


Figure 17: Network analysis module of dataset E

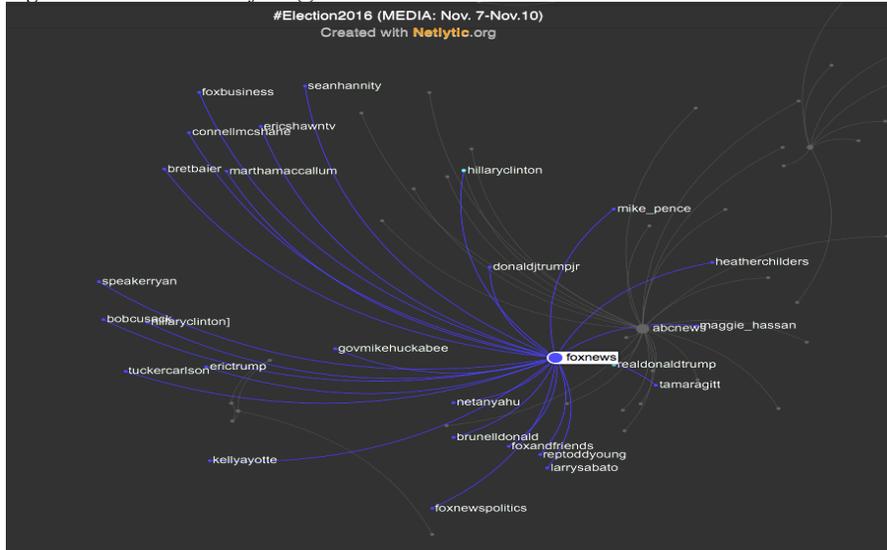


Upon examining the five dataset network analyses modules, it is evident that there are some key differences among dataset E, when compared to datasets A, B, C, and D. To begin, it is clear that in datasets A through D, users converse with one another. Each of the four dataset modules incorporates a core cluster, where connections are being made among nodes. Hundreds of node-to-node connections are established, with only a fraction of isolated nodes hanging on the outskirts or ends of the modules' clusters. In contrast, dataset E highlights a segmentation of nodes within the module. There is no cluster, where the interconnectedness of nodes commences. Instead, individual nodes become semi-clusters, where fragmented node-to-node connections are established. This fragmentation signifies that in the case of traditional mass media institutions, their connectedness is limited and isolated. A disconnected and isolated network analysis renders a result which stipulates that nodes within the dataset possess a limited or negligible amount of influence on Twitter. Datasets A to D however possess nodes with an abundance of influence on Twitter, as clusters are formed, which signify the bountiful quantity of node-to-node connections.

It is important to note the limitation in the data collected, pursuant to the collection protocols enrolled for the purposes of this paper. In order to differentiate traditional mass media outlets from all other accounts, dataset E was given specific data collection protocols. As per Netlytic's collection methods, data collected for datasets E excluded #Election2016 tweets from all Twitter accounts, except for the ones omitted, as mentioned in the pages above. As such, the network analysis module for dataset E will only display interaction between different traditional mass media institutions, while excluding interactions that all other users make which involves the specified traditional mass media institutions. This exclusion only applies to tweets, replies, mentions, and conversations initiated by outside accounts not included in the dataset's collection protocols. Tweets initiated by the accounts included within the dataset's collection protocols that includes #Election2016 however, is included in the dataset and will therefore be visualized in the dataset's network analysis module. In other words, for the intents and purposes of this study, the information collection method for dataset E was manipulated to limited specifications. Interpretation of dataset E's network analysis module is therefore still relevant, but not indicative of the overall significance of traditional mass media institutions' decline in influence.

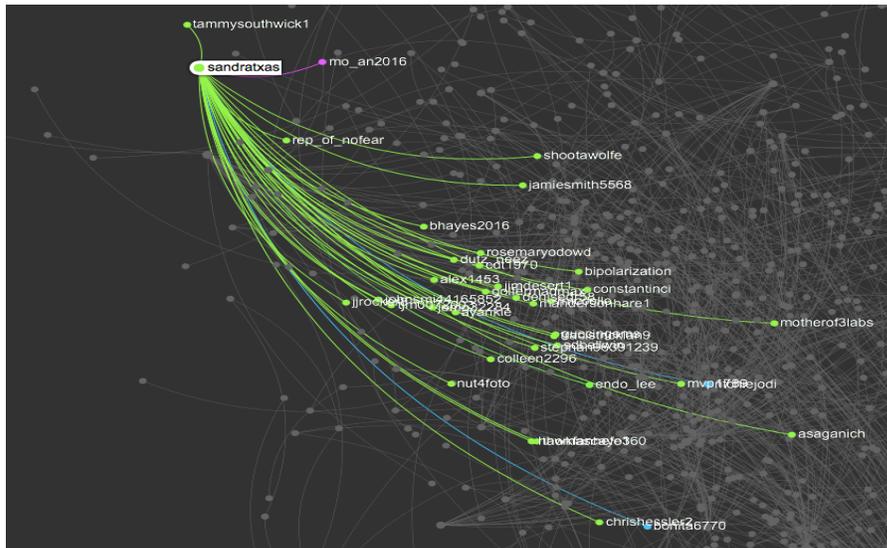
In order to better understand the disconnectedness in dataset E, this paper will study a specific example. The Fox News micro-cluster will be looked at. In this example, it is clear the node/user '@FoxNews' is a central hub for connectivity, as it is made node-to-node connections with 26 other nodes/users [see figure 18].

Figure 18: Micro-cluster for '@FoxNews' in dataset E



These connections are still largely fragmented, as they all expand outward from the micro-cluster. Zero of the node-to-node connections made with @FoxNews made connections with other nodes in the micro-cluster, or with other nodes not connected with @FoxNews, but contained within the same module. Additionally, all node-to-node connections made within the micro-cluster stayed within its own echochamber. In other words, there was no crossover between micro-clusters with nodes connected to @FoxNews. Contrastingly, the micro-cluster relating to the node/user '@sandratxas' in the network analysis module for dataset B [Figure 19]. Note that the node-to-node connections made within this micro-cluster contains two connections that are outside of the main micro-cluster. The connections from the separate micro-clusters

Figure 19: Micro-cluster for '@Sandratxas' in dataset B



are displayed by the different colours of the edges connecting the nodes. Here, the connections made between @sandratxas and '@mo_an2016' (Figure 20), '@ritchiejodi' (Figure 21), and '@bonita6770' (Figure 22) are differentiated with purple and blue edges respectively. The connections made between @sandratxas and the aforementioned accounts highlights the relative influence users within this dataset have. The connections made among different micro-clusters is what accelerates the reach of a user and the information that they disseminate. This point is emphasized in the network analysis module by visualizing the connection made between one micro-cluster and another. It can therefore be said that, when compared to traditional mass media institution accounts in dataset E, users of Twitter who belong to new media/opinion leaders/the public have a much higher level of influence. On a similar note, it is therefore evident that traditional mass media institutions are in fact losing influence on information dissemination on Twitter, a tool powered by networked journalism in action.

Figure 20: Micro-cluster link between '@sandratxas' and '@mo_an2016' in dataset B

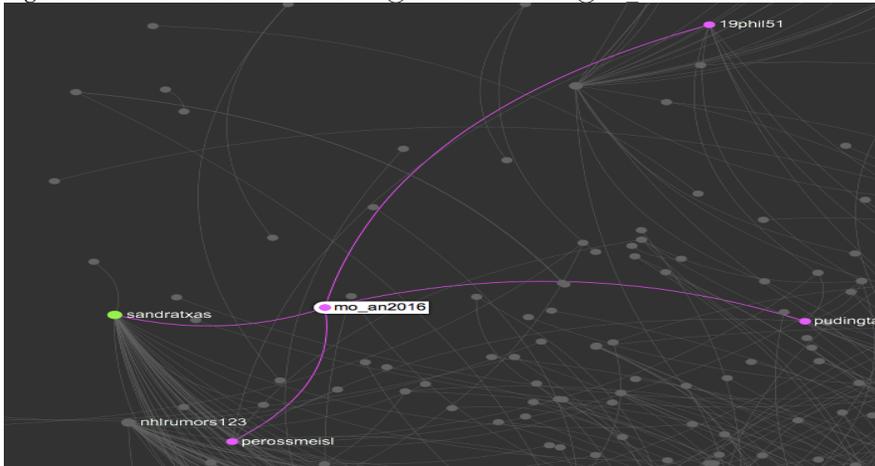


Figure 21: Micro-cluster link between '@sandratxas' and '@ritchiejodi' in dataset B

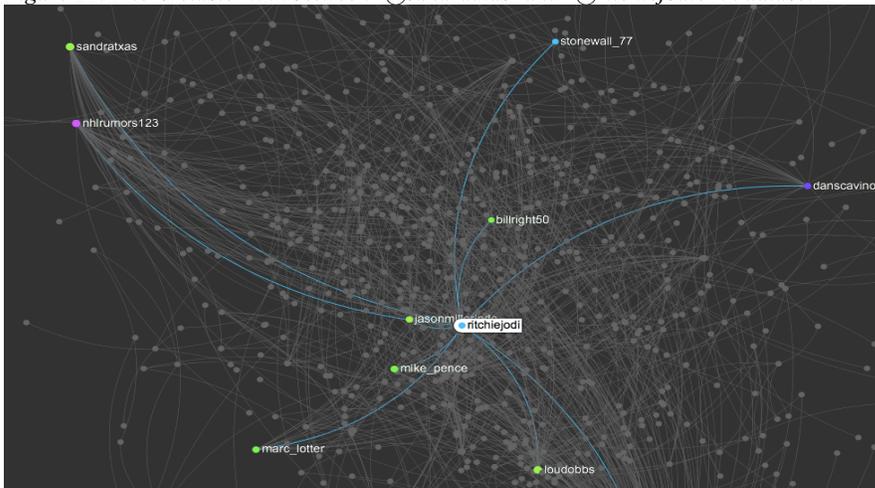
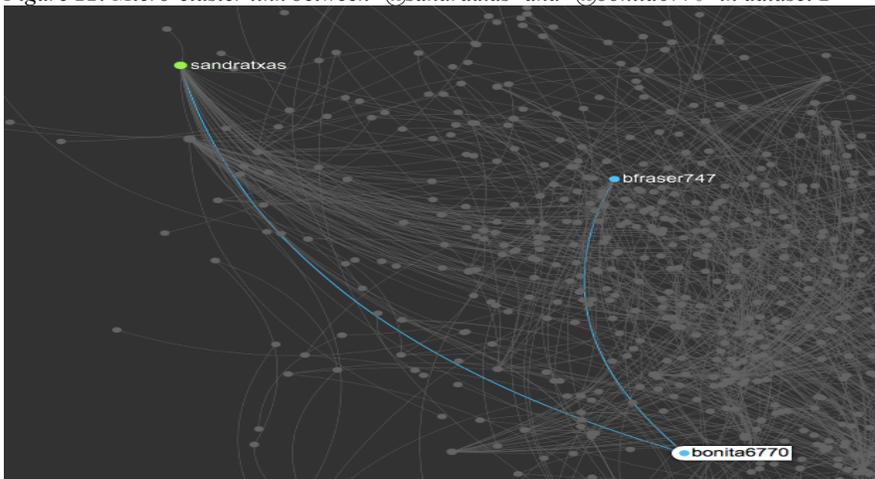


Figure 22: Micro-cluster link between '@sandratxas' and '@bonita6770' in dataset B



7. Discussion of Results

7.1 RQ1: The Altering of Gatekeeping and Agenda-Setting Functions Through Twitter

The results presented in this study clearly highlight the fact that the social media tool of Twitter has altered the agenda-setting and gatekeeping roles of traditional mass media institutions in a noticeable way, through standard practices of networked journalism. Recall that the agenda-setting and gatekeeping functions of traditional mass media institutions have historically been to select, add, withhold, shape, manipulate, disregard, and even delete information as they see fit, for the greater good of the public (Barzilai-Nahon, 2008), while also selecting the level of importance or significance placed on each story covered (McCombs & Shaw, 1972). The social media tool of Twitter has disrupted this model. The data collected and interpreted rendered a result signifying that there is a significant disconnect between traditional mass media institutions and the public, when it comes to information dissemination.

One example is the media's complete ignorance of the John Podesta email leak story; one of the most talked about news stories on Twitter. Datasets A to D had a significant portion of collected tweets dedicated to this story. A total of 371 tweets between these datasets were coded to have included some relevance or mention of this story. In contrast, dataset E; that is, the dataset which includes only tweets from traditional mass media institutions, included 0 coded tweets that included some relevance or mention of this story.

On a similar note, traditional mass media institutions appeared to have attempted to control the agenda of the 2016 U.S. Presidential election by covering the typical 'horserace' of an election campaign. A sizable amount of tweets issued in dataset E

focused squarely on the polls in the run-up to election day, along with state-by-state results, 95 out of 392 tweets collected coded. Only 4 tweets from dataset E were coded among the three other stories that were examined in the pages above. While traditional mass media institutions were narrowly focused on this story, with 24.2% of all tweets compiled in dataset E containing information about polls, new media/opinion leaders/the public were not as interested, with 3.1% of all tweets compiled among datasets A to D containing information about polls.

The disparaging disconnect between stories covered and information being disseminated reveals the fact that traditional mass media institutions have lost control of the public information dissemination model they once monopolized, at least in some form. While new media/opinion leaders/the public on Twitter have constituted themselves into targeted, segmented groups for information dissemination and consumption; indicative of the hashtags pursuant to stories, such as #podestaemails33 for the Podesta story, traditional mass media intuitions have been focusing on a broad, non-existent audience to control. By refusing to accept the networked journalism practices of orientational storytelling and target audience segmentation (Bardoel & Deuze, 2001) that new media/opinion leaders/the public have been utilizing, it can be confidently said that the social media tool of Twitter has in fact altered the gatekeeping and agenda-setting functions of traditional mass media intuitions.

7.2 RQ2: Traditional Mass Media Institutions' Impasse of Networked Journalism

While the social media tool of Twitter has altered the gatekeeping and agenda-setting functions of traditional mass media institutions, it is fair to conclude that these institutions have not attempted to reverse the situation, as to the date of the publication of

this study, such institutions have failed to implement practices of networked journalism. Recall that networked journalism is the new standard method by which information is disseminated in today's network society (Castells, 2000). With an abundance of information made available to all members within this network society, information dissemination is best received through strategic methods. These methods, which include targeted communication (Baroel & Deuze, 2001), community engagement (Duffy, 2012), and information recycling (Beckett, 2010), were measured and examined in the pages above. As noted before, this study found that traditional mass media institutions have not implemented such practices, at least in the context of Twitter.

Upon further examining the levels of engagement for example, it is reasonable to draw the conclusion that traditional mass media institutions somewhat neglect the public and therefore, neglect the functioning of networked journalism. Due to the abundance of access to information, engaged citizens participates in a continuous conversation of news stories (Deuze, Burns, & Neuberger, 2007), where information is disseminated and consumed at an infinite level. Within the network society, where many of the existing advantages in the physical world cease to exist, producers and consumers of news are on an equal-level playing field. The transmission of information is passed on and through users, where no elite status innately exists (Beckett, 2010). This information transmission requires a level of engagement among users within the network society. Traditional mass media institutions have largely omitted themselves from such engagement, as they take an elitist approach towards information dissemination. In the context of this study, traditional mass media institutions outright ignored the public, with 0 tweets, or 0.0% of all tweets collected within dataset E included replies, or tweets that were a part of a conversation.

Contrastingly, 8 tweets, or 1.46% of all NPC tweets collected in datasets A to D included replies, or tweets that were part of a conversation. As stated before, although the percentages are not large, the sheer fact that traditional mass media institutions did not engage with the public at all, while new media/opinion leaders/other members of the public did; albeit, in limited terms, solidifies the fact that traditional mass media institutions have failed to implement practices of networked journalism.

Similarly, by actively attempting to communicate to a broad audience, traditional mass media institutions are outright ignoring or discounting the power of the practices of networked journalism. Orientational storytelling, with a focus on appealing to a target audience(s), is a cornerstone practice of networked journalism (Bardoel & Deuze, 2001). Yet, as identified in the pages above, traditional mass media institutions largely ignored this practice, opting for generic storytelling, with a focus on appealing to a broad audience, or a vast majority of already existing audiences. With only 28 tweets, or 28.3% of all tweets collected in dataset E, traditional mass media institutions failed to incorporate a targeted communication strategy. Contrastingly, 483 tweets, or 88.1% of all tweets collected in datasets A to D were considered to be of a targeted communication nature. The discrepancy between the overall communication nature of traditional mass media institutions and new media/opinion leaders/the public, puts traditional mass media institutions at odds with all others in the network society.

Ultimately, it is reasonable to conclude that traditional mass media institutions have been ineffective in implementing practices of networked journalism. In fact, it is fair to state that, from the data provided, traditional mass media institutions have been largely ignoring not only the practices of networked journalism, but the entire notion of

networked journalism itself. Further research should be conducted to study how and why traditional mass media institutions are ignoring networked journalism.

7.3 RQ3: Traditional Mass Media Institutions' Impasse of Networked Journalism

As traditional mass media institutions lose gatekeeping and agenda-setting domination through the altering of such principles, while also losing traction through their failure to implement practices of networked journalism, it would be understandable if one began to draw the conclusion that traditional mass media institutions have lost their influence. This paper does not outright draw conclusions predicated on general assumptions. Instead, this paper attempts to qualify and quantify verifiable conclusions. Ultimately however, this paper does deduce from the examining of collected data that traditional mass media institutions have indeed lost their influence, at least within the confines of this study. The data interpreted within this study finds that traditional mass media institutions are largely fragmented in today's network society, where users are typically intertwined.

Referring back to the example noted above, traditional mass media institutions' tweets do not transcend their own network. Node-to-node connections in the micro-cluster of @FoxNews do not reach out and engage with other micro-clusters, unlike the micro-clusters of new media/opinion leaders/the public, such as @sandratxas'. The containment of @FoxNews' tweets onto itself and its main network/audience [micro-cluser] is what creates an echo chamber of its own information. In contrast, @sandratxas' network/audience branches off into other networks/audiences and therefore gains influence, as a new set of users is now engaging with and potentially consuming @sandratxas' information. This crossover between audiences is a powerful characteristic

that works as a multiplier effect for the audience, in terms of reach and influence.

Similarly, upon looking at the macro level of interconnectedness among datasets A to D, and the lack of interconnectedness of dataset E, it is fair to state that traditional mass media institutions have lost some influence over the public. The degree to which this is so cannot be measured due to the limitations of this study, however, the overarching theme is identified in this paper. The clusterization of node-to-node connections in datasets A to D are indicative of the interconnectedness among micro-clusters, where many micro-clusters have at least one interaction with at least one other micro-cluster. Juxtaposed to this summation is dataset E, where it is clear that there is a great amount of fragmentation among traditional mass media institutions. Only one of the micro-clusters make contact with another micro-cluster; that being '@msnbc' and '@nbc', via '@nbcout'. This connection should be viewed as a mere technical and not meaningful one, as the connection made consists of accounts belonging to the NBC family.

Ultimately, it is reasonable to conclude that traditional mass media institutions are losing their influence over the public, at least in the network society. In fact, it is fair to state that, from the data provided, traditional mass media institutions have been largely been fragmented and insignificant to the information dissemination and consumption process. Further research should be conducted to study this trend, in a more in-depth manner.

8. Limitation of Results

Although this study consisted of quantifiable evidence pursuant to the questions it sought out to answer, it should be noted that this paper's results and interpretation of results is by no means exhaustive. As noted throughout this paper, the limitations pertaining to the data collection method in Netlytic, allow for this paper to interpret only data within the set confines of the collection protocols. In turn, these confines may set biases or may manipulate and skew data to a degree that may overestimate or underestimate reality. In essence, this study's data, findings, and foregone conclusions are only a sliver in the overall literature pursuant to the academic research of traditional mass media institutions' gatekeeping and agenda-setting principles in the new age of networked journalism, as administered explicitly by the social media tool of Twitter. This study is by no means the ultimate work in relation to the following topic. Instead, this study should act as one of many which attempt to better understand the new phenomenon of networked journalism existing through social media. Finally, while the data collected does meet ethical standards, it must be once again noted that due to the nature of data collection and interpretation, implicit biases may be present, which can lead to an overestimation or underestimation of the actualities in existence.

9. Conclusion

The ultimate goal of this paper was to examine the effectiveness of agenda-setting and gatekeeping in today's network society, where the new practice of networked journalism has shifted the agenda-setting and gatekeeping principles of traditional journalism. As this paper only examined one highly specified segment of journalism, that being political journalism, its conclusions must be contained to only this specific genre of journalism. That being said, it is in this paper's view that the role of traditional mass media institutions being agenda setters and gatekeepers of information is highly outdated in today's network society.

It has been made clear by the data and the analysis of such data that the social media tool of Twitter has fundamentally altered agenda-setting and gatekeeping to the point of it becoming significantly weakened and, to some degree, irrelevant. This alteration of agenda-setting and gatekeeping has taken place due to the practices of networked journalism being implemented through Twitter by new media, opinion leaders, and the larger public, who have become producers, in addition to consumers of news.

Furthermore, it has been made clear that traditional mass media institutions have been ineffective in implementing their practices of networked journalism. From the lack of engagement by traditional mass media institutions with the public due to their elite ways, to the refusal of their producers to implement an orientational way of storytelling in order to focus their information dissemination on target audiences, it must be noted that the practices of networked journalism are largely missing in the world of traditional mass media institutions.

Finally, with a supposed refusal or failure to implement the practices of networked journalism, in tandem with the alteration of agenda-setting and gatekeeping through the

social media tool of Twitter, it is clear that traditional mass media institutions have in fact lost a great deal of influence over the dissemination of information that the public receives.

While the ultimate hypothesis pursuant to this paper has been proven, it should be noted that this is not the end of the research surrounding this topic. As stated before, further research should be conducted in order to understand the wider effects that networked journalism is having on the agenda-setting and gatekeeping functions of traditional mass media institutions.

Nevertheless, this paper has provided a launch pad for future research of the following topic. In summation, it can be said that, within the confines of this paper, traditional mass media institutions are at a crossroads in today's network society. Not only is their influence and relevance been reduced, but their future pertaining to the outright control of public information dissemination is in question.

10. Appendix I: Code Book

Coding the Presidential Election: Codes, Themes, and Patterns Persistent Within the Twitterverse

Objectives

The ultimate goal of coding the data collected is to extract a sufficient amount of information from the tweets compiled. This information will then be used to assist in answering the following key research questions:

- 1) To what extent has the social media tool of Twitter altered agenda-setting and gatekeeping principles through standard practices of networked journalism?
- 2) Have traditional mass media institutions been effective in implementing their practice of networked journalism?
- 3) Has networked journalism led to the decreased influence of traditional mass media institutions when it comes to major stories of significance?

Interpreting the information relayed from the coding of data will provide the researcher with trends, themes, and specific patterns present among the datasets.

In answering the following questions above, the researcher must look for specific topics that tweets within the following datasets discuss. There are three main constituencies pursuant to the datasets, that being Trump-specific tweets, Clinton-specific tweets, and tweets issued by traditional mass media institutions regarding the 2016 U.S. Presidential election.

The researcher must keep an eye out for differences in the topics discussed by each constituency. Due to the specific dates of November 7th, November 8th, and November 9th of 2016, the following topics expected to be discussed are as follows:

- 1) FBI/Comey investigation into Hillary Clinton
- 2) Podesta email leaks
- 3) Russian connection to Donald Trump
- 4) Swing state horseraces

These topics were chosen in tandem with the top headlines for the corresponding dates, according to both traditional and new media institutions (SOURCE CNN, CBS, DEMOCRACY NOW, BREITBART, and OCCUPY DEMOCRATS).

Theme #1 – FBI/Comey Investigation into Hillary Clinton (CODE: “FBI”)

Using the excel filtering function, the following keywords were used in finding tweets pertaining to the headline story of the FBI investigating Hillary Clinton. On Sunday, November 6, 2016, FBI Director James Comey issued a letter to the Senate Intelligence Committee, stating that the Bureau had cleared newly found emails from Clinton’s private server of any criminal wrongdoing.

The keywords (codes) used in the filtering process are as follows:

- “FBI”
- “Comey”

	A	B	C
1	id	author	description
2		431 DorianGreg2 @PRPOnline	we're everywhere. Pizza guy, tax guy, FBI guy, car guy. They'll be found. #maga #draintheswamp #spiritcooking #hillaryforprison
3		937 sparkyNadini RT @gerfingerpoken:	Trump warned of Clinton-Abedin-Weiner security risks - American Thinker https://t.co/cRP7p68Xku #MAGA #PJNET 999 - http%0_

#Election2016 (Nov. 7-9)

	A	B	C
1	id	author	description
2		130 USATODAY	On today's #frontpage: @FBI clears #Clinton on emails - again; #Election2016 candidates make their closing arguments https://t.co/W8NuX3CMTw
3		23 FoxNews	#ExitPoll Results on Economy, Hillary's Emails, Trump's Treatment of Women #ElectionNight #Election2016 #FoxNews2016 https://t.co/9rcXs3Tm7k
4		39 FoxNews	.@marthamacallum on new exit polls: "6 in 10 say the Clinton email issue bothered them." #FoxNews2016 #ElectionDayâ€¡ https://t.co/MS8CQAhckt

Theme #2 – Podesta Email Leaks (CODE: “Podesta”)

Using the excel filtering function, the following keywords were used in finding tweets pertaining to the headline story of Hillary Clinton Presidential campaign chairman John Podesta’s emails being leaked by hacktivist website Wikileaks. On Monday, November 7, 2016, Wikileaks released the 33rd data dump of compiled emails from John Podesta’s account.

The keywords (codes) used in the filtering process are as follows:

- “Podesta”
- “Spirit”
- “Cooking”
- “Spirit Cooking”
- “Pizza”
- “Gate”
- “Pizzagate”

The search terms used in the filtrations process incorporated human intelligence to decipher between tweets of significance and tweets of insignificance. By studying the word preceding and following the keyword/code within the tweet, the researcher is able to understand the context of the tweet. By then expanding the examination of the tweet by studying the entirety of the message, the researcher is able to identify whether or not the tweet in question is related to the theme of “Podesta”, as described above.

Additionally, human intelligence was used to ensure that tweets were not duplicated in the coding, as some tweets include more than one keyword/code.

The tables below showcase the compilation of information pursuant to the theme “Podesta”, among the five datasets.

#ImWithHer (Nov. 7)

	A	B	C
1	id	author	description
2	4	politicalredc	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
3	9	Ldicassiolorr	RT @kr3at: Hillary Buying Votes With äöIFREEäö Concert Tickets https://t.co/7zwYtimq2T via kr3at #PodestaEmails31 #PodestaEmails32 #ImWithHeräö
4	10	TexDotOrg	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
5	14	magates68	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
6	20	hawkinscarte	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
7	26	CastleTownP	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #ImWithHer https://t.co/wzxeh70oUm httpsäö
8	41	iamronaldpa	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
9	60	GinnySpears	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
10	67	podella_v	RT @perfectsliders: #ElectionFinalThoughts #Poll Who ru voting 4 president? #ImWithHer #ElectionFinalThoughts #DNCLeaks2 #podestaemails32 #äö
11	78	MerienneL	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
12	128	tyrelle123	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
13	129	bboneusa	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #ImWithHer https://t.co/wzxeh70oUm httpsäö
14	162	mattweaver	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
15	194	Gr8fulam63	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
16	199	robertd5150	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #ImWithHer https://t.co/wzxeh70oUm httpsäö
17	206	vlynn2016	RT @kr3at: Hillary Buying Votes With äöIFREEäö Concert Tickets https://t.co/7zwYtimq2T via kr3at #PodestaEmails31 #PodestaEmails32 #ImWithHeräö
18	210	ChristiD724	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
19	246	RitchieJodi	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
20	250	GunDecal	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
21	291	TimothyCowi	RT @kr3at: Hillary Buying Votes With äöIFREEäö Concert Tickets https://t.co/7zwYtimq2T via kr3at #PodestaEmails31 #PodestaEmails32 #ImWithHeräö
22	292	TheyCallMeB	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
23	347	MskatieChap	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
24	360	JasonCh1991	RT @perfectsliders: #ElectionFinalThoughts #Poll Who ru voting 4 president? #ImWithHer #ElectionFinalThoughts #DNCLeaks2 #podestaemails32 #äö
25	389	DFoxx13	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
26	397	joeppepersa	RT @kr3at: Hillary Buying Votes With äöIFREEäö Concert Tickets https://t.co/7zwYtimq2T via kr3at #PodestaEmails31 #PodestaEmails32 #ImWithHeräö
27	398	TamiStLouis	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
28	402	Blindsquirrel	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #ImWithHer https://t.co/wzxeh70oUm httpsäö
29	404	Cassiel_Ange	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
30	417	Darrinbillings	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
31	436	JimBurdsv	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
32	438	DaizyChains	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
33	445	MarkJShuler	RT @wikileaks: RELEASE: The Podesta Emails Part 32 #PodestaEmails #PodestaEmails32 #HillaryClinton #ImWithHer https://t.co/wzxeh70oUm httpsäö
34	473	KarenKyla	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
35	477	GreenBelind	RT @realDonaldTrump: RETWEET IF YOU'RE VOTING FOR #TrumpPence16 #electionfinalthoughts #PodestaEmails33 #imwithher DNC CNN #election2016CEæTruäö
36	484	PDQACCESS	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
37	486	ermolenkota	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #ImWithHer https://t.co/wzxeh70oUm httpsäö
38	489	Tomatjax	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
39	495	dpleader172	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
40	498	_sean_casey	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
41	510	Geddy009	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
42	511	FreedomFro	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
43	523	tanishaBgirl	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
44	561	tambinjulia	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö
45	570	mishshell196	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeaks2 #MAGA #ElectionFinaaö

Running Head: MEDIA AGENDA-SETTING AND GATEKEEPING

	A	B	C
46	573	PRforCanada	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
47	578	12aptor	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
48	582	Gingie133	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
49	594	ctsew377	RT @JennieAllannah: #JohnPodesta #TonyPodesta #PizzaParty #imWithHer #MadeleineMcCann https://t.co/CX0tfsX9QO
50	595	BethThomps	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
51	623	snOwba111	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
52	630	benelongtim	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
53	637	karenhondur	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
54	655	stephan9639	RT @PamelaStar23: #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinalThoughts @SpeakerRyan #JillNotHill #FeelTheBern https://t.co/3ö
55	666	tinalewis150	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
56	670	norvilgirl	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
57	674	qwerty91231	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
58	676	PiratesLife4A	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
59	687	MSGrits1155	RT @kr3at: Hillary Buying Votes With äöIFREÄäö Concert Tickets https://t.co/7zwYtimq2T via kr3at #PodestaEmails31 #PodestaEmails32 #imWithHeräö
60	689	rmoore0625	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
61	692	LizCawleyFee	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
62	694	ngrgrvdr99	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
63	696	poodeb1	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
64	697	rick2forestvil	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
65	699	LindaLouwal	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
66	716	Tinywillis3	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
67	736	homer3ja	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
68	738	FredStaples3	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
69	741	cathyevatty	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
70	744	RealDemocr	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
71	749	Cristian1606	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
72	750	SaintBruin	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
73	753	lynn_gie	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
74	766	Jmillion8Johr	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
75	774	killarotts	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
76	777	ernierawlins	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
77	780	Renee60832	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
78	788	salted3	RT @RoadWarriors360: I VOTE 2 MAKE AMERICA GREAT AGAIN! JR #ElectionFinalThoughts #wikileaks #podesta #clinton #imwithher #DNCLeak2 #BombShäö
79	794	KickinBrass1	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
80	797	ZeroDarkDor	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
81	803	mex_man20	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
82	811	GreenEmera	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
83	813	drmyraponcl	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
84	815	lululexie	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
85	816	Rikrj61	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
86	823	TinaOrt7959	RT @kr3at: Hillary Buying Votes With äöIFREÄäö Concert Tickets https://t.co/7zwYtimq2T via kr3at #PodestaEmails31 #PodestaEmails32 #imWithHeräö
87	832	cbmontpetit	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
88	834	everydayisbil	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
89	835	Jennydog2	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
90	851	AVIVKLN	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
91	857	JesusWithMe	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
92	859	LindaGarriss	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
93	871	AnniElocin	RT @perfectionsliders: #ElectionFinalThoughts #Poll Who ru voting 4 president? #imWithHer #ElectionFinalThoughts #DNCLeak2 #podestaemails32 #äö
94	873	gretel_ander	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
95	883	siesienna	RT @perfectionsliders: #ElectionFinalThoughts #Poll Who ru voting 4 president? #imWithHer #ElectionFinalThoughts #DNCLeak2 #podestaemails32 #äö
96	891	Suntan48	RT @RoadWarriors360: TRUMP\’S GOING 2 CLEANOUT THE WH! JR #ElectionFinalThoughts #ImVotingBecause #wikileaks #Podesta #imwithher #DNCLeak2 #äö
97	904	indianHackr	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
98	905	GlennManev	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
99	912	cranes5	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
100	917	PollyAnnNon	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
101	930	cfoldgovt	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
102	932	WorldPeacef	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
103	933	GatesRobin	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzkeh70oUm httpsaö
104	940	prietoj	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
105	949	em0223	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
106	950	Rwolf19448c	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
107	951	texmexranch	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
108	952	brsquared	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
109	967	BPPope	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #imWithHer #DNCLeak2 #MAGA #ElectionFinaö
110	183	DiscoverTrut	#imWithHer masses try #SpiritCooking their way into the cabal. https://t.co/4ETeN0uB0v
111	324	suthernboy1	@killerbee805 @HillaryClinton @realDonaldTrump #strongerTogether #imWithHer #SpiritCooking #SatanicHillaryäö https://t.co/OGWncPrPvj
112	426	Teria423	I can\’t take anymore of this shit. SHE\’S A GD CRIMINAL! #ElectionFinalThoughts #DNCLeak2 #MAGA3X#SpiritCookingäö https://t.co/GgSMwXwCyV
113	672	PeskyVarmt	@FredG299 @SheWhoVotes O.M.G! You mean, you had a Spirit Cooking and didn\’t invite me? I\’m offended! ;) #FlushYouTrump #imwithher
114		beastrider70	RT @NahBabyNah: Martha Stewart, Amateur#imWithHer #Hillary#HillaryForPrison2016 #hillaryindictment#spiritcooking https://t.co/upl0rW4äö

#ImWithHer (Nov. 9)

	A	B	C
1	id	author	description
2	10	mcesar1970	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
3	15	runninman2	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
4	25	Oatcake196	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
5	26	LaurenHaller	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
6	31	Makanani00	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
7	35	Drancosta	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
8	40	Sammie_Sni	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
9	44	SillyPutty78	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
10	58	votewithlogi	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
11	64	alabamafan2	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
12	65	MarieOakes	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
13	73	steffie_steff	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
14	74	Mandi_M_C	RT @halsteadg048: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/QG6V9YeYdS â€¦
15	80	jaazee1	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
16	84	CheddarRob	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
17	93	SirJamesGra	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
18	98	JohnTrumpC	RT @halsteadg048: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/QG6V9YeYdS â€¦
19	107	Chlanandria	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
20	110	halsteadg04	RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHerâ€¦ https://t.co/k0ZEbVH5xj
21	115	scottomalley	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
22	128	nezy_esfand	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
23	147	americasbas	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
24	149	prosefarrell	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
25	150	Marsides	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARDjrFqq
26	152	giles_ash	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
27	153	nana5greatg	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
28	161	lynnarobe	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
29	163	sekalalazowi	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
30	168	winbabywin	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
31	170	Thomaspayr	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
32	177	HawaiiPeopl	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
33	184	The_Canadi	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
34	190	Snikk	RT @wikileaks: RELEASE: The Podesta Emails Part 35 #PodestaEmails #PodestaEmails35 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
35	191	JaneTalbot1	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
36	210	brad_studio	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
37	217	SeekWisdon	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
38	224	mccrow_bir	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARDjrFqq
39	229	floridayys	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARDjrFqq
40	231	doccigar	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
41	235	WwwCpclan	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARDjrFqq
42	240	FunnyAnima	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
43	243	woodywood	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
44	248	LeighLe3551	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦
45	260	thevisualran	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #ImWithHer https://t.co/wzxeH7hZLU httpsâ€¦

Running Head: MEDIA AGENDA-SETTING AND GATEKEEPING

	A	B	C
46	263	danharw	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
47	265	stewart757	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
48	266	arcangel127	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
49	275	EzellHenry	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
50	279	loveschrist	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
51	280	achariw	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
52	294	d_cheriepie	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
53	304	rottiefreek	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
54	310	theillusivael	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
55	314	fiapmooz1	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
56	316	tate_schmal	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
57	320	ConsrvOutflr	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
58	325	IamVerySilk	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
59	342	ToasterBoxx	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
60	348	GarysHouse	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
61	352	CarmenCam	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
62	353	MarieMa49	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
63	375	Leebee331	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
64	377	DecisionZer	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
65	386	LedaNeilson	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
66	391	dsshep1959	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
67	400	sportsvenue	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
68	417	knkstumpy	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
69	426	EnkiTheFace	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
70	428	DoubleEagle	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
71	429	FergusLFerg	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
72	447	bitsy423	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
73	451	glensngm	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
74	454	CyberDeath	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
75	456	NancyKnittle	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
76	471	SheilaT9913	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
77	478	deplorablah	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
78	482	TonyArm2	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
79	488	speedprayer	RT @wikileaks: RELEASE: The Podesta Emails Part 35 #PodestaEmails #PodestaEmails35 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
80	491	_North_Carc	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
81	496	jssar	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
82	497	Markperugir	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
83	503	compurigtcc	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
84	509	votingtrump	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
85	514	Freechoice1	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
86	515	ROYALMRB	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
87	524	amovenezue	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
88	532	RickAndKim	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
89	533	zvrnghrsm	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfq
90	539	givethatsucc	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦

Running Head: MEDIA AGENDA-SETTING AND GATEKEEPING

	A	B	C
91	541	eclectelectri	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
92	542	Bernnaginstr	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
93	544	Magilla7	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
94	547	BanRomular	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
95	551	compandsqu	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
96	561	brenda_harr	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
97	562	DamnationN	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
98	563	Gran_Crackz	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
99	576	Grammy8	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
100	579	DReaDPiRaT	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
101	582	PetePetretic	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
102	587	Holly25Mari	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
103	589	mcarsonaos	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
104	590	trump_floric	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
105	602	EyeGloArts	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
106	604	Terryisawalk	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
107	617	SylviaAntoni	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
108	623	LuMcleanLiv	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
109	634	southpaw81	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
110	642	Go_Conserv	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
111	643	No_More_P	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
112	645	makhno8	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
113	649	Wenmay316	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
114	658	GovnForThe	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
115	659	kittyhunda	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
116	661	kazoolist	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
117	672	BcmrescueB	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
118	678	Godrix87	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
119	680	theelfthead	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
120	682	kaygrivas49	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
121	684	smmarrujo	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
122	694	iondc	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
123	696	redpilledchi	RT @backwaterdogs: Here #imstillwithher #ImWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrfqq
124	702	ironjrod	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
125	704	GiantofShire	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
126	706	manoskappa	RT @wikileaks: RELEASE: The Podesta Emails Part 32 #PodestaEmails #PodestaEmails32 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
127	716	ItzGeralyn	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
128	721	beachbaby7	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
129	722	grege1953	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
130	725	beckyblissr	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
131	727	Suspended_	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
132	730	pattyshephe	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
133	742	Moni538252	RT @KrankiT: #Podesta already knew that paid speeches were unethical in 2008. #PodestaEmails36 #WikiLeaks #imWithHer #FeelTheBernhttps://â€¦
134	758	pmanzo70	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
135	766	Thor_Waller	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦

Running Head: MEDIA AGENDA-SETTING AND GATEKEEPING

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136	767	EarthFreedo	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
137	771	NOH8ER	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
138	773	smillr	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
139	776	Veive257	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
140	781	TraplineMar	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
141	788	JrcheneyJoh	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
142	789	susann211	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
143	790	CavalcanteC	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
144	800	LiliaMorrax	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
145	801	GungHo2	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
146	807	LStevensonS	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
147	808	Pringle4Prin	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
148	817	BRIANHUGH	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
149	819	EdDonnahoe	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
150	821	Rudedog655	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
151	825	Lou_ise	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
152	841	citizenanny	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
153	848	GrumblyMui	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
154	849	Jillerforever	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
155	859	banks_joel	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
156	861	pdxfirecrack	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
157	862	chichignotea	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
158	863	Moni538252	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
159	865	Jsea989	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
160	875	azrocks1111	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
161	878	Lorie03979	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
162	893	Cheri_Kentu	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
163	897	jahmansting	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
164	898	SarahLovesT	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
165	905	VirtualWatc	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
166	912	MarthaWha	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
167	916	luvsthesun2	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
168	919	AntiAmnest	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
169	920	sharru4	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
170	925	Bravens105	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
171	930	Conniegall5	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
172	937	rkode79	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
173	940	pendleywife	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
174	941	duncanmacr	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
175	952	banrick	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
176	959	manoskapp	RT @wikileaks: RELEASE: The Podesta Emails Part 33 #PodestaEmails #PodestaEmails33 #HillaryClinton #imWithHer https://t.co/wzxe70oUm httpsâ€¦
177	967	JohnJohn55	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
178	973	Joseph_Gree	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
179	980	RiveraSunAu	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
180	988	iphonetecht	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
	A	B	C
181	990	HartForTrun	RT @backwaterdogs: Here #imstillwithher #imWithHer is why you think trump is a racist #Podestaemails36 https://t.co/jfARdjrFqq
182	997	BoomBoom	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦
183	998	GGG_says	RT @wikileaks: RELEASE: The Podesta Emails Part 36 #PodestaEmails #PodestaEmails36 #HillaryClinton #imWithHer https://t.co/wzxe7hZLU httpsâ€¦

#MAGA (Nov. 7)

	A	B	C
1	id	author	description
2	7	NeedA2ndJc	RT @hillrod4prison: Because he is a true patriot not owned by special interests and Wall Street #ImVotingTrump #MAGA #VoteTrump #PodestaEmaâ€¦
3	9	politicalredc	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
4	19	TextDotOrg	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
5	26	magates68	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
6	30	bobnfn1	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
7	31	divegawolf	RT @KarrieFleetwood: Yes! Please...end her rein of terror! #DrainTheSwamp #PayToPlay #MAGA #SpiritCooking #DNCLeak2 #PodestaEmails #WikiLeaâ€¦
8	42	hawkinscart	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
9	47	KYLEBUDAG	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
10	86	lamronaldp	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
11	100	bonita6770	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
12	106	GinnySpears	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
13	131	LPMMMontag	RT @bfraser747: ðŸ™ˆðŸ™ˆ #ElectionFinalThoughts #VoteTrump #MAGA say no to the #CorruptionHere is the release of #PodestaEmails33https://t.câ€¦
14	133	MerienneL	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
15	168	savellifrance	RT @bfraser747: ðŸ™ˆðŸ™ˆ #ElectionFinalThoughts #VoteTrump #MAGA say no to the #CorruptionHere is the release of #PodestaEmails33https://t.câ€¦
16	191	nanavotes	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
17	200	birthdaypall	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
18	204	Nut4Foto	RT @SandraTXAS: Scalia body wasnt even cold&Soros suggests SCOTUS Really want Soros &Hillary choosing our court?#MAGA Trump! #PodestaEmâ€¦
19	208	tyrelle123	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
20	253	mattweaver	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
21	273	LarryvilleLav	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
22	277	Nabi201611	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
23	299	Gr8flum63	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
24	315	ChristID724	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
25	337	mandersonh	RT @SandraTXAS: Scalia body wasnt even cold&Soros suggests SCOTUS Really want Soros &Hillary choosing our court?#MAGA Trump! #PodestaEmâ€¦
26	370	RitchieJodi	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
27	376	GunDecal	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
28	422	TheCallMeI	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
29	431	BrendaSue2	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
30	494	MsKatieCha	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
31	529	Mo_An2016	RT @SandraTXAS: Scalia body wasnt even cold&Soros suggests SCOTUS Really want Soros &Hillary choosing our court?#MAGA Trump! #PodestaEmâ€¦
32	544	Dfoxx13	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
33	567	Tamislouis	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
34	579	Cassiel_Ang	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
35	604	Darrinbiling	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
36	609	Rep_Of_NoI	RT @SandraTXAS: Scalia body wasnt even cold&Soros suggests SCOTUS Really want Soros &Hillary choosing our court?#MAGA Trump! #PodestaEmâ€¦
37	644	JimBurdasv	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
38	646	DaizyChains	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
39	652	ConstantinC	RT @SandraTXAS: Scalia body wasnt even cold&Soros suggests SCOTUS Really want Soros &Hillary choosing our court?#MAGA Trump! #PodestaEmâ€¦
40	666	mithroyalti	RT @RaptorRAF: The Clintons are rotten to the core.They have betrayed us all.#MAGA #SpiritCooking #Benghazi #PayForPlay #PodestasPizaâ€¦
41	691	KarenKyla	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
42	710	PDQACCESS	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
43	711	JAlexGSATX	RT @bfraser747: ðŸ™ˆðŸ™ˆ #NeverHillaryThis election isn't about Rep vs. Dem. It's about #Corruption vs #MAGA#PodestaEmails33 #DNC2Leak #Hilâ€¦
44	721	Tomatjax	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
45	725	KarrieFleatw	Yes! Please...end her rein of terror! #DrainTheSwamp #PayToPlay #MAGA #SpiritCooking #DNCLeak2 #PodestaEmailsâ€¦ https://t.co/BWperc20B7
	A	B	C
46	731	dpleader17	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
47	735	_sean_casey	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
48	750	GeddyY09	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
49	752	FreedomFro	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
50	766	tanishaBgirl	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
51	799	KWaters10	AAAND SEEMS PODESTA INTO DAHMER ART APPRECIATION+NAKED TEENS!! VIA REDDIT https://t.co/Ho8MEBtLJb @FBHâ€¦ https://t.co/2r5dyWncPJ
52	814	tambinijulia	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
53	822	misshell19	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
54	839	Gingie133	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
55	876	TnRina	RT @bfraser747: ðŸ™ˆðŸ™ˆ #ElectionFinalThoughts #VoteTrump #MAGA say no to the #CorruptionHere is the release of #PodestaEmails33https://t.câ€¦
56	916	benelongtin	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
57	923	karenhondur	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
58	960	shytowncha	RT @BSVLMJ: Please share.â€”#PodestaEmails33#MAGA #FeelTheBern#NBA #NFL https://t.co/AH9rYzPvWu
59	981	tinalewis15	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
60	985	norvilgirl	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
61	986	qwerty9123	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
62	987	shootawolfe	RT @SandraTXAS: Scalia body wasnt even cold&Soros suggests SCOTUS Really want Soros &Hillary choosing our court?#MAGA Trump! #PodestaEmâ€¦
63	989	PiratesLife4	RT @NHLRumors123: Who are you voting for? Please RT to get a large sample size! #PodestaEmails33 #ImWithHer #DNCLeak2 #MAGA #ElectionFinaâ€¦
64	79	ChrisGaryl	RT @TheMPHayze: #SpiritCooking #MAGA @mcbuban is a racist Hillary Shill who alienated 17M voters & no one gives 2 SHITS about mavs https://â€¦
65	184	pdj1	RT @Billright50: DO NOT BELIEVE MEDIA OR POLLS. ESPECIALY FOX! WE ARE GONNA WIN! VOTE! #maga #cubs #spiritcooking #dncleak2 #gotv #monstervâ€¦
66	235	Klyunch26	RT @Mindfayer1969: George #Soros linked to Comet Ping Pong #Pedophile #PizzaGate #SpiritCooking #WikiLeaks #DNCLeak2 #MAGA https://t.co/Eyâ€¦
67	282	PW45P	RT @GotToGoSoon: #PINKTHEVOTE because we don't do satanic #SPIRITCOOKING like -> @ladygaga does .#MAGA #neverhillary #GoTRUMP #DNCLeak2â€¦
68	391	RitchieJodi	RT @Billright50: DO NOT BELIEVE MEDIA OR POLLS. ESPECIALY FOX! WE ARE GONNA WIN! VOTE! #maga #cubs #spiritcooking #dncleak2 #gotv #monstervâ€¦
69	478	bhayes2016	RT @SandraTXAS: \Hillary Clinton & Isis funded by same money\ - Assange #WikiLeaks#SpiritCooking#Hillary #ImWithHer not! #MAGA #Trumpâ€¦
70	779	dutz_neez	RT @SandraTXAS: Black Trump Supporter Destroys Clinton Supporter: Mentions Satanic Ritual Spirit Cooking#DrainTheSwamp#MAGA #Trump#Hilâ€¦

#MAGA (Nov. 9)

	A	B	C
1	id	author	description
2	117	sparkyNadine	RT @ThomasBernpaine: Conspiring to trick Bernie Supporters to "Independent" PACs to siphon our \$#PodestaEmails36 #FeelTheBern #MAGA https%0_
3	218	tamargaye	RT @ThomasBernpaine: Conspiring to trick Bernie Supporters to "Independent" PACs to siphon our \$#PodestaEmails36 #FeelTheBern #MAGA https%0_
4	231	Kadrews1964	@NeilTurner_@trumpology @HillaryClinton I think if everyone read @wikileaks Podesta emails they wud have blinders lifted. #MAGA
5	332	CathyLanier3	RT @ThomasBernpaine: Conspiring to trick Bernie Supporters to "Independent" PACs to siphon our \$#PodestaEmails36 #FeelTheBern #MAGA https%0_
6	498	Devarim6v4	RT @jeller46: Our work isn't done!! We HAVE to make sure #HillaryForPrison happens!! #PodestaEmails36 #DrainTheSwamp #PresidentTrump #MAGA
7	513	ninanu11	RT @BishopsB2B: Damn, wish #WikiLeaks had access to @JohnPodesta's email this morning... #PodestaEmails36 #MAGA #DrainTheSwamp #ElectionNig%0_
8	431	DorianGreg2	@PRPOnline we're everywhere. Pizza guy, tax guy, FBI guy, car guy. They'll be found. #maga #draintheswamp #spiritcooking #hillaryforprison

#Election2016 (Nov. 7-9)

	A	B	C
1	id	author	description
2			
3			
4			
5			

Theme #3 – Russia Connection to U.S. Election (CODE: “Russia”)

Using the excel filtering function, the following keywords were used in finding tweets pertaining to the headline story of Hillary Clinton accusing Donald Trump of colluding with Russia to influence the U.S. Presidential election.

The keywords (codes) used in the filtering process are as follows:

- “Russia”
- “Russian”
- “Hack”
- “Hacking”
- “Vladimir”
- “Putin”
- “Kremlin”
- “Moscow”

The search terms used in the filtrations process incorporated human intelligence to decipher between tweets of significance and tweets of insignificance. By studying the word preceding and following the keyword/code within the tweet, the researcher is able to understand the context of the tweet. By then expanding the examination of the tweet by studying the entirety of the message, the researcher is able to identify whether or not the tweet in question is related to the theme of “Russia”, as described above.

Additionally, human intelligence was used to ensure that tweets were not duplicated in the coding, as some tweets include more than one keyword/code.

The tables below showcase the compilation of information pursuant to the theme “Russia”, among the five datasets.

#MAGA (Nov. 7)

	A	B	C	D
1	id	author	description	
2	304	TRUMPWINN	RT @DonaldTrumpjr: Thank you Grove City, Ohio your energy is amazing. Now get out there grab some friends and go vote so we can #MAGA http://t.co/...	
3	718	shellametry	RT @DonaldTrumpjr: Thank you Grove City, Ohio your energy is amazing. Now get out there grab some friends and go vote so we can #MAGA http://t.co/...	
4	821	soniaerasmu	RT @me_shell70: Ty!!!!!! That's what I've been screaming! @ItsRickOhio @realDonaldTrump @mplay0000 #MAGA #VoteTrump https://t.co/2TcpfKZt4E	
5	715	VivianBunga	RT @Tnsud1: Mr Trump Gives Us Strength, Wisdom. And Joy \2016. Most Beautiful Year #MAGA #GoVote @BillPeriman @North_Carolina @3E	
6	52	powertrip51	Im in Michigan & we are goin red with @realDonaldTrump to #MAGA https://t.co/1BKSvXz36l	
7	67	ThePepperDi	RT @perfectsliders: #Poll Who r u voting 4 president? #GaryJohnson #JillStein #StrongerTogether #Maga #Iowa #Minnesota #Michigan #Colorado3E	
8	260	sapmcdowell	RT @perfectsliders: #Poll Who r u voting 4 president? #GaryJohnson #JillStein #StrongerTogether #Maga #Iowa #Minnesota #Michigan #Colorado3E	
9	524	Pamelaplante	RT @debsellslc: In #GrandRapids for #TRUMPS0Y2final Rally0Y2% 2 bring #Michigan0Y2 home0Y2 Time for #AutoIndustry0Y2—comeback #Cleanwater0Y2& #JOBS0Y2 #MAGA4E	
10	541	BarryMyokoi	Who likes money ? #Trump #Trump #ElectionFinalThoughts #MAGA #MichiganForTrump	
11	878	CyclistDad	RT @debsellslc: In #GrandRapids for #TRUMPS0Y2final Rally0Y2% 2 bring #Michigan0Y2 home0Y2 Time for #AutoIndustry0Y2—comeback #Cleanwater0Y2& #JOBS0Y2 #MAGA4E	
12	170	mwtittig	Come on Nevada we need your votes. Lets all #MAGA for the whole country not just Clinton's Cronies https://t.co/8QKbJzaJCR	
13	326	TRUMPWINN	RT @vivelafra: PENNSYLVANIA FOR TRUMP: \The war on coal is killing American jobs and making us dependent on our enemies.\ #MAGA #PAForTrum4E	
14	328	Trumpwoma	RT @HouseCracka: Trump is on fire in Scranton PA tonight and the energy of the crowd is electric! #PennsylvaniaForTrump #MAGA @GOP @RNC3E	
15	552	kardyer	RT @HouseCracka: Trump is on fire in Scranton PA tonight and the energy of the crowd is electric! #PennsylvaniaForTrump #MAGA @GOP @RNC3E	
16	973	CFluharty	RT @HouseCracka: Trump is on fire in Scranton PA tonight and the energy of the crowd is electric! #PennsylvaniaForTrump #MAGA @GOP @RNC3E	
17	82	a912m430o	RT @bbrettonwindham: FYI The largest @realDonaldTrump sign in New Hampshire is in @Clewandowski_hometown Windham #MAGA #nhpolitics @DanSca4E	
18	474	CannonballR	RT @wesearchr: If you live in #Wisconsin, MAKE SURE to #VoteTrump tomorrow! #WI is now a SWING STATE! #TrumpPence16 #tcot #MAGA3X #MAGA	
19	137	DarkTriadMa	RT @wesearchr: If you live in #Florida, MAKE SURE to #VoteTrump TOMORROW! #FL is a LEAN TRUMP STATE NOW! #TrumpPence16 #tcot #MAGA3X #MAGA	
20	161	DaBiggestGu	RT @wesearchr: If you live in #Florida, MAKE SURE to #VoteTrump TOMORROW! #FL is a LEAN TRUMP STATE NOW! #TrumpPence16 #tcot #MAGA3X #MAGA	
21	194	bossgrady	RT @wesearchr: If you live in #Florida, MAKE SURE to #VoteTrump TOMORROW! #FL is a LEAN TRUMP STATE NOW! #TrumpPence16 #tcot #MAGA3X #MAGA	
22	222	AmericanRec	RT @wesearchr: If you live in #Florida, MAKE SURE to #VoteTrump TOMORROW! #FL is a LEAN TRUMP STATE NOW! #TrumpPence16 #tcot #MAGA3X #MAGA	
23	285	mlong42947	RT @TeamTrump: Florida crowd stops @realDonaldTrump speech with booming chant: "PRESIDENT TRUMP! PRESIDENT TRUMP!" #MAGA!	
24	482	acastle96	RT @CarlHigbie: Thank you #Tampa #Florida #MAGA Vote Trump on tuesday https://t.co/Zz2a9Z7TR0	
25	770	Mamadoxie	RT @AgentSergeevna: ALL POLLS NOW "CORRECTING"... FLORIDA JUST FLIPPED. We've had FL entire time, lol. #ElectionFinalThoughts #MAGA https://t.co/...	
26	846	TNrina	RT @wesearchr: If you live in #Florida, MAKE SURE to #VoteTrump TOMORROW! #FL is a LEAN TRUMP STATE NOW! #TrumpPence16 #tcot #MAGA3X #MAGA	
27	855	Cardsfan101	RT @wesearchr: If you live in #Florida, MAKE SURE to #VoteTrump TOMORROW! #FL is a LEAN TRUMP STATE NOW! #TrumpPence16 #tcot #MAGA3X #MAGA	
28	898	irisflower33	RT @FreedomChild3: Florida's I-4 corridor is where the election could be won - AP News #VoteAgainstCorruption #VoteTrump #MAGA https://t.co/c3E	
29	474	CannonballR	RT @wesearchr: If you live in #Wisconsin, MAKE SURE to #VoteTrump tomorrow! #WI is now a SWING STATE! #TrumpPence16 #tcot #MAGA3X #MAGA	
30	918	erneststewar	RT @UndaSuhler: @LynnePatton: African-Americans Will Finally Vote Republican & Swing Election to Trump #ElectionFinalThoughts #MAGAhttps://t.co/...	
31	6	KaIV194	RT @TeamTrump: \Trump makes huge gains with women voters in new poll\ #MAGAhttps://t.co/3dgnR6jBrM	
32	67	ThePepperDi	RT @perfectsliders: #Poll Who r u voting 4 president? #GaryJohnson #JillStein #StrongerTogether #Maga #Iowa #Minnesota #Michigan #Colorado3E	
33	147	NoodleChom	@surftthespectrum @realDonaldTrump \I'll be at my polling location 7 am sharp #TRUMP #MAGA don't let Her bring us dow4E https://t.co/S7N1Y6XJKNS	
34	162	magentagree	RT @mbk595: Go out and vote! Do not trust the polls and media! #ElectionFinalThoughts #MAGA #TrumpPence16 https://t.co/k120bJZx9v	
35	184	pdjfl	RT @Billright50: DO NOT BELIEVE MEDIA OR POLLS. ESPECIALLY FOX! WE ARE GONNA WIN! VOTE! #maga #cubs #spiritcooking #dncleak2 #gotv #monsterv4E	
36	238	GiveMeLiber	RT @LouDobbs: Biggest Lead Yet for @realDonaldTrump: Trump 48.2%, Clinton 42.6% LATimes/USC poll https://t.co/wbndZ7mqxU #MAGA #TrumpPence4E	
37	260	sapmcdowell	RT @perfectsliders: #Poll Who r u voting 4 president? #GaryJohnson #JillStein #StrongerTogether #Maga #Iowa #Minnesota #Michigan #Colorado3E	
38	338	StclairBranC	RT @realDonaldTrump: Thank you America! #MAGARasmussen National Poll Donald Trump 43% Hillary Clinton 40% https://t.co/n4eZ3qpcjg	
39	350	slane9699	RT @TNdad35: Don't listen to any MSM they will lie their ass off with exit polling. Just stay strong and get out the vote. #MAGA #NeverHill4E	
40	358	Istayinforme	RT @TeamTrump: \Trump makes huge gains with women voters in new poll\ #MAGAhttps://t.co/3dgnR6jBrM	
41	369	garrett_runy	RT @JohnKStahlUSA: Today's polls have Trump up 7 in OH, up 4 in FL, up 1 in PA and up 1 in NV. Keep working. #tcot #ccot #gotv #maga https://t.co/...	
42	391	RitchieJodi	RT @Billright50: DO NOT BELIEVE MEDIA OR POLLS. ESPECIALLY FOX! WE ARE GONNA WIN! VOTE! #maga #cubs #spiritcooking #dncleak2 #gotv #monsterv4E	
43	433	BenB388	RT @JohnKStahlUSA: Today's polls have Trump up 7 in OH, up 4 in FL, up 1 in PA and up 1 in NV. Keep working. #tcot #ccot #gotv #maga https://t.co/...	
44	583	mavrick803	RT @LouDobbs: Biggest Lead Yet for @realDonaldTrump: Trump 48.2%, Clinton 42.6% LATimes/USC poll https://t.co/wbndZ7mqxU #MAGA #TrumpPence4E	
45	634	DJT4Prez	.Poll says it is the press that is most dangerous, not Russia #TeamTrump #DrainTheSwamp #TrumpTrain #TrumpPence164E https://t.co/wkKvtJJE4k	
46	770	Mamadoxie	RT @AgentSergeevna: ALL POLLS NOW "CORRECTING"... FLORIDA JUST FLIPPED. We've had FL entire time, lol. #ElectionFinalThoughts #MAGA https://t.co/...	
47	994	Rc84384636	RT @marc_lotter: Good AM from Duluth, MN. Gov @mike_pence will hit 6 states in 24 hours talking about @realDonaldTrump plan to #MAGA. https://t.co/...	

#MAGA (Nov. 9)

	A	B	C
1	id	author	description
2	227	MSREDMAM	RT @nathanielbumpo: IT%0*5 CONFIRMED! MICHIGAN GOES RED! #MAGA https://t.co/uTNTHOJWoh
3	27	Tweet2Youu	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
4	30	stony599	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
5	73	AKIzbeth	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
6	85	Vulpidentri	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
7	107	artmen	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
8	113	gutiemary	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
9	139	kmiles2907	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
10	164	SamanthaVa	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
11	170	jddesilva196	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
12	175	4jeansladyb	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
13	224	monogamism	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
14	253	grannycoc	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
15	256	Newsbeat1	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
16	279	Sammie_Snic	RT @StefanMolyneux: AP calls Pennsylvania for Trump. Congratulations President Donald J. Trump. #MAGA
17	286	billy357magr	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
18	312	lajasTweets	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
19	324	sean_waring	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
20	327	TampaloeJ	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
21	396	pmswolffy	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
22	438	juneebuge	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
23	464	sam0274	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
24	476	ver_vey	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
25	510	lanbrealet1	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
26	525	WrendyKulic	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
27	526	TMB3000	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
28	552	manny8	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
29	576	MAMASLAVN	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
30	579	Tmkerry204	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
31	599	albanese_sor	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
32	611	infidel_News	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
33	615	dale_je	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
34	617	Misty_Bella	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
35	636	cindy775200	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
36	649	JamesSandif	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
37	663	clantro	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
38	725	_TeamFlores	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
39	730	AgnesClaire	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
40	757	idubindubc	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
41	819	grammapecc	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
42	829	Bioben78	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
43	846	karenholewa	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
44	852	AddieGschw	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
45	856	rodmk74	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
46	863	BettyLuscio	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
47	919	KlosowskiLav	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
48	924	ka2wey	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
49	935	AZNSB	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
50	942	g_66mpco	RT @The_NewRight: They'll never see this, but let's thank our Pennsylvania Amish friends for helping us #MAGA! #PresidentElectTrump #TheDay%0
51	953	Ginlefebvre	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
52	996	LindaSuhler	RT @ChristiChat: On 10-28 I believed #Pennsylvania would vote for TRUMP. And WE DID! Thank you #PA we will #MAGA with#PresidentTrump#Elec%0
53	747	deb6090	RT @carrieksada: @SpeakerRyan make sure you thank @realDonaldTrump for the state of Wisconsin going red this #Election2016 #MAGA #Morning%0
54	99	HENSONmiki	RT @ezralevent: The rallies were real, the polls were fake. #MAGA
55	523	AlanBeasley4	4 yrs from now remember-DEMS claimed they'd win Senate-Polls had Hillary winning-Press said Trump COULDN'T win#LibsAreLiars #MAGA

#Election2016 (Nov. 7-9)

	A	B	C
1	id	author	description
2	33	CBSNews	Exit poll shows that most important quality in a President to Ohio voters is "can bring change"â€¦ https://t.co/2YVTWn1y1q
3	261	abcnews	.@realDonaldTrump defeats @HillaryClinton in #Ohio https://t.co/1f0jYzQK6D #Election2016 #ElectionNight
4	267	CBSNews	JUST IN: Donald Trump wins Ohio, CBS News projects #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/skjgmslztg
5	297	FoxNews	RT @FoxBusiness: Presidential race: #Ohio with 48 percent in. #ElectionNight #Election2016 https://t.co/H1fndPBpP6
6	369	CBSNews	NEW: Ohio is a toss-up between Donald Trump and Hillary Clinton, CBS News estimates https://t.co/H9n7JKbYS7â€¦ https://t.co/pNnbZKjF7
7	371	CBSNews	JUST IN: Rob Portman wins Ohio U.S. Senate race, CBS News projects #CBSElection #Election2016â€¦ https://t.co/gae06MMc6T
8	32	CBSNews	First exit poll of Election 2016 shows that the most important issue to North Carolina is the economy #Election2016â€¦ https://t.co/tbyURmav8e
9	50	FoxNews	.@connellmcshane: "One of the places to watch in North Carolina is going to be Mecklenburg County." #FoxNews2016â€¦ https://t.co/VDXQbOBSCL
10	256	CBSNews	JUST IN: Donald Trump wins North Carolina, CBS News projects #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/cmMGAcAZbh
11	286	CBSNews	Charlie Rose on Trump's new lead in North Carolina: "These are my people... and I am not sure what is happening"â€¦ https://t.co/bPULDhWFOQ
12	368	CBSNews	NEW: Hillary Clinton has an edge over Donald Trump in North Carolina https://t.co/H9n7JKbYS7 #CBSElectionâ€¦ https://t.co/M04NyrJEH0
13	224	FoxNews	RT @FoxBusiness: Presidential Race: #Michigan with 75 percent in. #ElectionNight #Election2016 https://t.co/19ck9Mo54D
14	273	FoxNews	RT @FoxBusiness: Presidential race: #Michigan with 28 percent in. #ElectionNight #Election2016 https://t.co/8KcFkleDxb
15	290	CBSNews	CBS News Decision Desk maps out the two key reasons why Trump could be on the road to winning Michigan tonightâ€¦ https://t.co/6Rp2NNeRH1
16	360	WSJ	Michigan and Pennsylvania headline 8 p.m. closings. Live #Election2016 results: https://t.co/TfjtRobZEq ðŸ™™ https://t.co/22md5tluZb
17	225	CBSNews	JUST IN: Hillary Clinton wins Nevada, CBS News projects #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/4jcnHPaujO
18	281	CBSNews	NEW: Nevada is toss-up between Donald Trump & Hillary Clinton, CBS News estimates https://t.co/H9n7JKbYS7â€¦ https://t.co/sV0AZ6fBBu
19	204	CBSNews	JUST IN: Pat Toomey wins Pennsylvania U.S. Senate race, CBS News projects #CBSElection #Election2016â€¦ https://t.co/JRrcuDxVrT
20	206	CBSNews	JUST IN: Donald Trump wins Pennsylvania, CBS News projects #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/eRdApOZgzT
21	216	WSJ	Trump wins Pennsylvania, AP says, all but vanquishing Clinton's hopes of gaining the presidencyâ€¦ https://t.co/CgiNm0mBQc
22	223	FoxNews	Pennsylvania results with 95% in - @realDonaldTrump leads @HillaryClinton 48.5% to 47.9%. #Election2016 #FoxNews2016 https://t.co/msdKe7YUS
23	226	WSJ	With 95.6% precincts reporting, Pennsylvania is tied -- live updates: https://t.co/Ryel57jZyB ðŸ™™ #Election2016 https://t.co/TTILESoFsy
24	231	FoxNews	RT @FoxBusiness: Presidential race: #Pennsylvania with 92 percent in. #ElectionNight #Election2016 https://t.co/dj8OUXBjfw
25	207	CBSNews	JUST IN: Donald Trump wins Wisconsin, CBS News projects #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/Ew4qYoED4s
26	229	CBSNews	UPDATE: Wisconsin leans toward Donald Trump, CBS News estimates #Election2016 #CBSElection https://t.co/H9n7JKbYS7 https://t.co/W1MhMUJWtb
27	234	CBSNews	UPDATE: Donald Trump has an edge over Hillary Clinton in Wisconsin https://t.co/H9n7JKbYS7 #CBSElectionâ€¦ https://t.co/bvi4Q0PHYG
28	136	abcnews	RT @zdaniele: People leaving @realDonaldTrump event in Virginia as he's 2 hrs late, massive queue to replace them #Election2016 https://t.co/aâ€¦
29	252	abcnews	.@HillaryClinton triumphs in #Virginia https://t.co/5gymLKPS9T #ElectionNight #Election2016
30	268	CBSNews	JUST IN: Hillary Clinton wins Virginia, CBS News projects #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/CTq4j708Rr
31	370	CBSNews	JUST IN: Donald Trump wins West Virginia, CBS News projects #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/11u1quwlaR
32	392	CBSNews	UPDATE: Hillary Clinton has an edge over Donald Trump in Virginia https://t.co/H9n7JKbYS7 #CBSElection #Election2016 https://t.co/v87ugblmLi
33	30	CBSNews	The first exit poll of #Election2016 shows that over a quarter of Florida voters are angry with the governmentâ€¦ https://t.co/vVK6k3VsQB
34	242	CBSNews	JUST IN: Donald Trump wins Florida, CBS News projects #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/gVUnuvqY82
35	243	CBSNews	Donald Trump will likely win Florida, CBS News estimates. #CBSElection #Election2016 https://t.co/H9n7JKbYS7 https://t.co/dP5qwCkwwT
36	251	abcnews	.@realDonaldTrump triumphs in #Florida, gives White House hopes big boost https://t.co/hWWD60UPMJ (Pic:Reuters)â€¦ https://t.co/mfpxRQcntu
37	260	WSJ	With Florida, Trump has turned the tables on Clinton. The race is extremely close -- live analysis: https://t.co/DmwuGM4Hs9 ðŸ™™ #Election2016
38	272	CBSNews	UPDATE: Donald Trump has an edge over Hillary Clinton in Florida https://t.co/H9n7JKbYS7 #CBSElection #Election2016 https://t.co/w2cPpYR0dE
39	296	WSJ	In Florida, Trump currently has a lead of less than 2 percentage points over Clinton. Live results:â€¦ https://t.co/MDuef6ccua
40	323	CBSNews	Polls are closed in half the country and Florida is a toss-up, with each candidate at 48% #CBSElectionâ€¦ https://t.co/09owjEPBAL
41	327	FoxNews	RT @FoxBusiness: Presidential race: #Florida with 88 percent in. #ElectionNight #Election2016 https://t.co/NcA44969o1
42	329	CBSNews	JUST IN: Marco Rubio wins Florida U.S. Senate race, CBS News projects #CBSElection #Election2016â€¦ https://t.co/UBA4jVLXjl
43	359	FoxNews	RT @FoxBusiness: Presidential race: #Florida with 71 percent in. #ElectionNight #Election2016 https://t.co/0pKHROjibH
44	363	FoxNews	RT @FoxBusiness: Presidential race: #Florida with 55 percent in. #ElectionNight #Election2016 https://t.co/hQ9tPlmIAQ
45	365	FoxNews	RT @FoxBusiness: Presidential race: #Florida with 53 percent in. #ElectionNight #Election2016 https://t.co/OBGolG43NE

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