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Political Television Hosts on Twitter: Examining Patterns of Interconnectivity and Self-Exposure in Twitter Political Talk Networks

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This study takes a social networks approach to studying the Twitter talk evoked by politically oriented cable television hosts. Two aspects of user interactions are examined: the interconnectedness of users as an indication for users' networks of exchange of opinions and information, and exposure to a political diversity of information sources. Findings suggest that users prefer exposing themselves to politically like-minded information sources. Furthermore, television hosts failed to evoke an exchange of opinions and ideas among their followers. In contrast, other information sources that reported about these hosts evoked denser interaction among their followers.

Politically opinionated hosts on television are gaining popularity, in particular on cable television (The State of the News Media, 2010). The politically controversial content typically introduced by these show hosts is often picked up and discussed by other media. Twitter provides a social space where users can be simultaneously exposed to a range of information sources, potentially from a range of views, and discuss them. Exposure to cross-ideological opinions has long been considered beneficial to individuals and society at large (e.g., as early as Mill, 1859, and more recently in the context of online discussions by Delli Carpini, Cook, & Jacobs, 2004). From an institutional perspective, informed citizenry has long been an important role of news media (Picard, 1985; Siebert, Peterson, & Schramm, 1956).

This study examines the Twitter social environment triggered by television hosts, focusing on the diversity of information sources users draw from (e.g., media, bloggers, politicians) and users' interaction with one another. Because information

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seeking and exchange occurs within the network of follow relationships that users establish on Twitter, this study takes a social network approach. Specifically, this study examines patterns of interaction and information seeking among Twitter users who discussed four popular television show hosts: the right leaning Sean Hannity and Glenn Beck and the left leaning Rachel Maddow and Keith Olbermann. Patterns of relationships on Twitter (follow, mention, and reply) are mapped, identifying major subgroups of highly interconnected users (i.e., clusters) and the most followed users in each cluster (i.e., hubs). Density of relationships among users in clusters is first examined in order to evaluate the extent to which these traditional media hosts trigger Twitter talk that draws from more than one source. Identifying the major sources of information within these networks, this study then examines the question of exposure to cross-ideology information sources. Theoretical, methodological, and practical implications are discussed.

Literature Review

Facing an economic crisis, cable news networks often cut the more costly aspects of news, such as investigative reporting and foreign news, while increasing spending on the less expensive host-driven shows (The State of the News Media, 2010). The content provided by opinionated hosts such as Glenn Beck on the Fox News Channel or Rachel Maddow on MSNBC is compelling—designed to persuade or support the opinions of viewers on the right and the left, respectively. Such shows are characterized as one-sided and sarcastic (Quart, 2009) and criticized for their extreme views, inaccuracy, and divisive influence (Larson, 1997). Furthermore, earlier research suggests that Americans often respond to this range of channels by selecting news coverage congenial to their predispositions (Stroud, 2008). This selective exposure along ideological lines has provoked concerns that the fragmentation of news programs may fuel opinion polarization among viewers (Jamieson & Cappella, 2008; Sunstein, 2009). For the American democracy, such fragmentation can be problematic, as it may lead to two strongly ideological camps on the left and right of the political spectrum drawing upon entirely distinct bases of information, pursuing distinct political agendas, and talking past each other (Manjoo, 2008; Sunstein, 2009).

Television hosts are becoming popular Twitter users. For example, MSNBC's Rachel Maddow has over two million followers and Glenn Beck and Sean Hannity are followed by just under half a million users each. The growing popularity of these television hosts on social media, and on Twitter in particular, may have implications for the concerns about informed citizenry on two levels. First, social media overcomes one fundamental limitation of television: its one-way flow of information, allowing users to interact with one another and exchange opinions and information. Twitter allows audiences and media persona to break the traditional one-way communication and interact with one another about political issues brought up in the television shows. Second, these popular shows often attract attention from other news sources, including both traditional and user-generated media sources, such as popular bloggers. Via Twitter, users can choose to expose themselves to (i.e., follow) other information sources that address the show, possibly providing different points of view. At the interpersonal level, there is growing evidence that while the opportunity to converse with others across political differences exists, in practice, internet users prefer interacting with like-minded individuals (Adamic & Glance, 2005; Choi, Park, & Park, 2011; Himelboim, McCreery, & Smith, 2013). However, at the information sources level, the question of cross-ideological exposure remains understudied.

This study, then, poses two overarching questions. First, to what extent do television hosts trigger an interaction among users who talk about the show or the host on Twitter? Second, to what extent are users who talk about the shows or hosts exposed to cross-ideological information sources on Twitter? Next, literature about the role of news media and implications of interpersonal interactions on informed citizenry is reviewed. A discussion about Twitter as a social network of information exposure and political talk follows. Specific research questions and hypotheses are then introduced.

News Media and Online Political Talk

It is the role of the news media to provide the information and range of views that enables the public to make relatively informed decisions about candidates, politicians, and issues (Picard, 1985; Siebert et al., 1956). Evoking conversations about issues of societal importance is another way for news media to contribute to informed citizenry. Studies suggest that engaging in conversations about news and politics is associated with political knowledge (Scheufele, 2000) and issue salience (Holbert, Benoit, Hansen, & Wen, 2003). Furthermore, the interaction between interpersonal communication and news media consumption predicted understanding of political issues (Eveland & Scheufele, 2000) and political participation (Scheufele, 2002). Political talk may occur in person, such as around the water cooler at the office, or on social media spaces, such as Twitter. News media, then, can contribute to informed citizenry in two distinct, but related, ways: by making a range of views available to their audiences and by evoking an exchange of views and information.

Cross-Ideological Exposure.

The ideal of exposure to cross-ideological opinions can be traced back to John Stuart Mill (1859), who pointed out that ''[I]f the opinion is right, they [people] are deprived of the opportunity of exchanging error for truth; if wrong, they lose what is almost as great a benefit, the clearer perception and livelier impression of truth produced by its collision with error'' (p. 21). Arendt (1968) asserted that exposure to conflicting political views plays a role in encouraging the capacity to form an opinion by considering a given issue from different viewpoints. Calhoun (1988) argued that democratic public discourse depends on the ability to create meaningful discussions across lines of difference. Furthermore, exposure to, and inclusion of, diverse opinions can also lead to more divergent thinking by better decision makers (Nemeth, 1986) and minority dissent stimulated a relatively unbiased search for more information (Nemeth & Rogers, 1996).

However, research indicates that that the American public is poorly informed about basic civics, current events, and political information (Bennett, 1989; Delli Carpini, & Keeter, 1996). This may be reinforced by the growing polarization and segmentation of American mass media. With a growing number of cable channels, Americans can limit their exposure to a small set of topics—news, sports, or entertainment, for example—they are interested in. The growing popularity of cable shows hosted by strongly politically opinionated television celebrities allows users to limit their exposure to like-mined news sources. Prior (2005) showed that increasing media choice widens gaps in political knowledge. An earlier explanation addresses the limitation of the medium: even with exposure the public learns relatively little from the news media (Neuman, 1976).

Twitter provides a social space where users can learn about current events from a variety of information sources, traditional and others. Many individual news media do not fulfill their social role of providing cross-ideological views. However, as a whole, the growing number of news sources available on the internet provides users with the desirable range of political views on issues of social importance. Early enthusiastic voices expected the internet would be used for the distribution of information and perspectives (McKenna & Bargh, 2000; Shapiro, 1999) and would increase exposure to marginalized viewpoints (Blader & Tyler, 2003; Mendelberg, 2002). In contrast, Sunstein (2006) warned that the availability of a growing number of sources leads to a narrowing of the scope of news and views to which people choose to expose themselves.

A growing literature suggests that at the individual level people prefer interacting with like-minded others. In a sense, birds of a feather flock together (McPherson, Smith-Lovin, & Cook, 2001). Van Alstyne and Brynjolfsson (1996) refer to this process as ''balkanization'': People spend more time on special interests and screen out less preferred content, leading to fragmented interactions and divided groups that are increasingly homogeneous. Earlier research showed that individuals selected face-to-face discussion partners that were similar to them (e.g., Laumann, 1973; Mutz, 2002) and avoided discussing politics when they believed others held opposing views (Noelle-Neumann, 1984). On the internet, literature suggests that users often show similar patterns of selective exposure. Adamic and Glance (2005), in an analysis of political blogs' hyperlinks, showed that conservative blogs preferred sending hyperlinks to other conservative blogs, and liberal blogs showed similar linking patterns, creating distinct liberal and conservative clusters. Additionally, Himelboim et al. (2013), found that Twitter users who discussed some of the controversial issues on the 2010 elections formed distinct clusters of users who shared political orientation (conservative or liberal) and distinct information sources (conservative and liberal pundits and news media).

Limited literature, however, has focused on major information sources, and news media in particular, that individuals choose to be exposed to. Krebs (2004), in a network analysis of Amazon's lists of books that were ''also bought'' by those who bought selected political titles, found that American book buyers were split into liberals and conservatives in terms of the books they consumed and recommended. A study by Adamic and Glance (2005), mentioned earlier, also indicated that conservative blogs were more likely to link to news media associated with the political right while liberal blogs tended to link to more liberal media. In social networking sites, Robertson, Vatrapu, and Medina (2009) analyzed content and links posted on the Facebook ''walls'' of Barack Obama, Hillary Clinton, and John McCain over two years prior to the 2008 U.S. Presidential election. These studies show that users tend to cite or refer, in a sense, to information sources they agree with. In contrast, on Twitter, users can respond to comments or use them to evoke a conversation. Political journalists, such as news media pundits, are sources of information. As such, they may evoke discussion across the political spectrum, but also may remain a source and topic of discussion within their like-minded audiences. The overarching research question is therefore: To what extent do Twitter users expose themselves to cross-ideological information sources when discussing controversial television hosts?

Interpersonal Interaction.

Studies examining political talk demonstrate that interpersonal interactions play a major role in political learning and attitude formation (Huckfeldt & Sprague, 1995; MacKuen & Brown, 1987) and were associated with increased local news consumption (McLeod et al., 1999). Examining online political discussion forums, Eveland (2004) identified a positive relationship between political discussions and political knowledge. Online interactions via other social media spaces were associated with other desirable political behaviors. Rojas and Puig-i-Abril (2009) showed that informational uses of the internet and mobile phones are significantly related to expressive participation in the online domain, which in turn results in a host of offline civic and political participatory behaviors. Zhang, Johnson, Seltzer, and Bichard (2010) found that interpersonal discussion on social networking sites fosters both civic participation and political activity.

Political show hosts have become active on social media sites, and Twitter in particular. Twitter has become a venue for these shows and their hosts not only to disseminate news and views to the public, but also to interact with their audiences. Furthermore, Twitter users can now talk about and respond to statements made on the shows without watching the show or following the show or its hosts on Twitter. In other words, Twitter users can either talk directly to the hosts or talk about them without directly interacting with the hosts. By opening the traditional one-way communication channel that characterizes the relationships between television persona and their audiences to a two or multi-way communication channel, Twitter allows users to interact with one another and with major information sources.

Such interaction, as discussed earlier, can have desirable implications for informed citizenry. The second overarching research question for this study is therefore: To what extent do television hosts trigger an interaction among users who talk about a politically opinionated television host on Twitter?

Twitter provides a social space that can bring together the advantages of social interactions with the wide variety of information sources from which users are free to draw. On Twitter, social interactions among users and patterns of information seeking take the form of a social network. This study, therefore, proposes taking a network approach to examining user interaction and the information sources those users draw from. Next, Twitter activity in general and the overarching research questions for this study are conceptualized in terms of social networks.

Twitter as a Social Network

Broadly speaking, a social network is a structure created by social actors, such as individuals and organizations, when links are formed among them. Social network theories suggest focusing on relational ties among social entities and on the patterns and implications of these relationships (Wasserman & Faust, 1999). On social media, users form social networks by articulating a list of other users with whom they share a connection. To interact on Twitter, users may choose to follow other users, mention them, or reply to their messages. This activity creates a social network (Hansen, Shneiderman, & Smith, 2011). These relationships are indications for the flow of information and opinions among users, including the flow of information from major information sources, such as news media and blogs.

Understanding patterns of social interactions on Twitter can inform the two potential contributors for informed citizenship discussed earlier. The social networks in question include users who posted messages about the opinionated television hosts. These include the hosts themselves, other media and bloggers, and individual users. Density, the extent to which a group of users are interconnected in a network, is an indication of the interaction among these users. Hubs, the few Twitter users that attract a large and disproportionate number of followers, are the information sources that users choose to expose themselves to.

In social networks, smaller sub-groups of interconnected users—clusters—often arise. Clusters, also referred to as "communities," refer to subgroups in a network in which nodes are substantially more connected to one another than to nodes outside that subgroup (Carrington, Scott, & Wasserman, 2005; Newman, 2004). On Twitter political networks, users' major exposure to political tweets derives from the users they follow. Twitter users, then, are more likely to read content posted by their cluster-mates than by users in other clusters. Likewise, users in a given cluster have chosen to expose themselves to the same set of hubs, which serve as popular information sources among these users. Clusters are therefore the relevant social context for examining density as an indication for user interaction, with hubs representing the major information sources.

Twitter Hubs.

A few participants in online interactions are likely to attract a large and disproportionate number of social ties (for example: Huberman & Adamic, 1999; Raban & Rabin, 2007). On Twitter, then, a small number of users—hubs—are likely to attract a large number of followers. The more followers a user has, the more users are potentially exposed to that user's posts. A few hubs, then, are responsible for much of the information and opinions that flow in a network or a sub-network (e.g., cluster). As discussed earlier, while there is limited research specific to the exposure to cross-ideological information sources on social media, studies suggest that at the individual level, users prefer interacting with like-minded individuals (e.g., Himelboim et al., 2013). That said, selective exposure at the individual level on television (Stroud, 2008) and the use of hyperlinks on blogs (Adamic & Glance, 2005) and Facebook (Robertson et al., 2009) show similar patterns of self-exposures. These earlier findings, therefore, lead us to propose the following hypotheses, addressing the first overarching question regarding exposure to cross-ideological information sources on Twitter:

H_1: Hubs in a given cluster will be associated with one side of the political spectrum (i.e., conservative or liberal).
H_2: More links will be found across similar ideology clusters—liberal or conservative—than across conservative and liberal clusters.

Density of Twitter Interactions.

The second overarching question proposed for this study was related to the extent to which politically opinionated television hosts evoke interaction among Twitter users. The extent to which users in clusters are interconnected is an indication of the interaction among these users. Some clusters of Twitter users may take advantage of the technology and create densely interconnected sub-networks by following, mentioning, and replying to others who discuss the same topic. Others may replicate the traditional one-way relationship they have as television audiences by following key sources and engaging in little or no interaction with one another or with the host. Considering that political interaction is associated with political knowledge and behavior, the density of interaction among users who discuss a given topic is an important indicator for the realization of this democratic potential of Twitter. Do political television hosts evoke dense interaction among users? On the one hand, such television hosts often make controversial comments, which may trigger lively interaction. On the other hand, studies show that media professionals tend to keep old practices when using new technologies (Boczkowski, 2004, 2010; Himelboim & McCreery, 2012). On Twitter, this means continuing to broadcast their content with less concern about audience response or interactions.

Not all sub-groups of users (or clusters), however, revolve around television hosts' accounts. As controversial comments are often reported and discussed by other news media personnel and bloggers, these may also become hubs for clusters of users on Twitter discussing television hosts. Less traditional information sources, such as bloggers, tend to be more conversational (Herring, Scheidt, Bonus, & Wright, 2005). As such, they may evoke more interaction among users. The first research question is therefore:

R_1: Are clusters that include a television host Twitter account (i.e., host clusters) different in terms of their density values?

Method

NodeXL

The network analysis and visualization Excel add-on NodeXL was used to collect the Twitter data and for network analysis. The free and open NodeXL can be downloaded from http://nodexl.codeplex.com. The tool is documented in the book *Analyzing Social Media Networks With NodeXL: Insights From a Connected World* (Hansen et al., 2011).

Data

Twitter usernames, user statistics (e.g., profile description and URL, # of followers), user images, and follow relationships were captured for four of the leading political television hosts (two conservatives, Sean Hannity and Glenn Beck, and two liberals, Rachel Maddow and Keith Olbermann). Television hosts were classified as liberal and conservative. Sean Hannity is described as "one of the most prominent and influential conservative voices in the country" on the Fox News Personalities page ("Online Personalities," n.d.). In a profile, *Forbes* magazine describes Glenn Beck as a "conservative host" ("Glenn Beck," 2012). Ben Wallace-Wells from *Rolling Stone* magazine describes Keith Olbermann as a "contemporary liberal television pundit" and quotes Rachel Maddow, who stated "I'm a liberal" (Wallace-Wells, 2007).

Data were collected using NodeXL's Twitter Search importer (Hansen et al., 2011), which identifies the most recent 1,000 Twitter users who included a candidate's full name in their Tweet (e.g., "Glenn Beck"), and the Twitter account of that host (e.g., glennbeck). These create topic-networks with the television host as the topic. This approach gave us high precision and standardization across datasets, but not perfect recall because users who tweeted hosts' nicknames or initials were missed. The Twitter Application Programming Interface (API) limits the amount of content that can be downloaded to about 1,000 users per dataset. Four data draws for each candidate were performed. For purposes of standardization, data were collected every Wednesday for five consecutive weeks—October 19, 2011 to November 16, 2011. One dataset, Sean Hannity at 10/19, was corrupted and therefore could not be used. Most of the television programs are broadcast on weekdays only, so by Wednesday one would expect that enough interaction on Twitter is created that can be captured for analysis.

Measurements

Network Analysis 1: Identifying Twitter Hubs.

Each of the twenty networks consists of Twitter users (nodes) and following relationships (directed ties). This study operationalized Twitter hubs as the most followed users in each cluster. Links are distributed unequally among users (a few users are followed, mentioned, and replied to by many, while others by very few), creating a slope in the distribution, separating the most connected users (i.e., hubs) from the rest, less connected users. The top hubs per cluster were identified by ordering users in each hub in descending order based on the number of users who followed, mentioned, or replied to them (for further methodological procedures, see Himelboim et al., 2013). When no clear curve in slope was found, the top five users in each cluster were selected. This procedure allows for selecting the top hubs in relation to other users in the cluster, notwithstanding hubs sizes in other clusters (some clusters may have more popular hubs than others).

Network Analysis 2: Identifying Clusters.

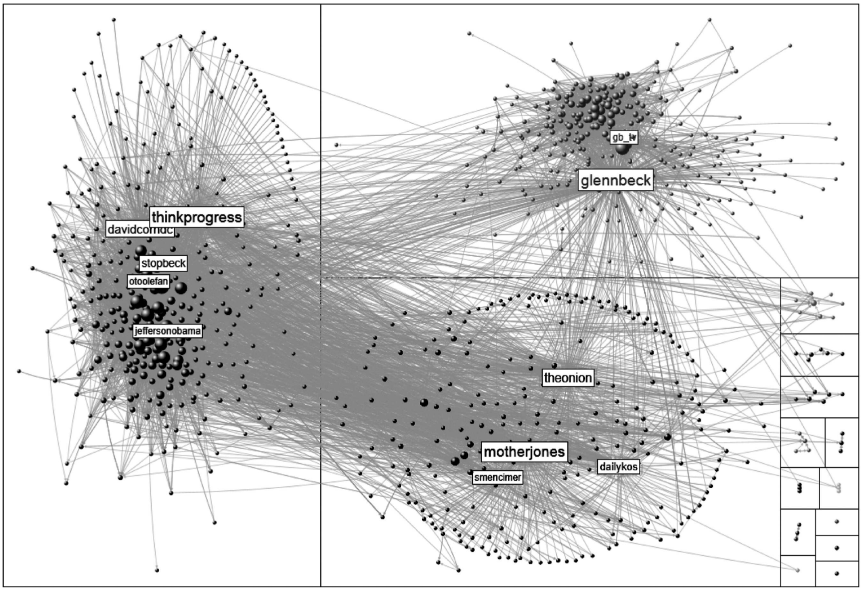
Clusters, as discussed earlier, are the social boundaries in which Twitter users are exposed to information. We identified clusters of relatively more connected groups of users in the topic-networks using the Clauset-Newman-Moore algorithm (Clauset et al., 2004), which is included in the NodeXL software. We selected this algorithm for its ability to analyze large network datasets and efficiently find subgroups. This algorithm uses edge betweenness as a metric to identify the boundaries of communities. Each user, then, is classified into the best fit group (cluster), in terms of the interconnectivity among users. The density of each cluster, a measurement of interconnectivity, was calculated as the number of existing following relationships among nodes within a given cluster divided by the total possible number of relationships among those same nodes. NodeXL also was used to determine the number of links between clusters and their direction.

Clustering algorithms often divide a network into a few major clusters and several small ones. We ranked clusters by the number of users assigned to each. This creates a "Scree Plot," where a few clusters contain most of the users in the network. These clusters accounted for the majority of connected users and relationships, as detailed in the Findings section.

Network Analysis 3: Visualization.

Figure 1 visualizes one network (Glenn Beck, November 2, 2012). A researcher's decisions affect these presentations. NodeXL allows filtering nodes or links based on

Figure 1
The Twitter Social Network for Glenn Beck (11/2/2012)



Each node in the network represents a user who posted a message on Twitter mentioning Glenn Beck. A link connects two nodes if they have a Twitter relationship (i.e., follow, mention, or reply). The highly connected nodes (i.e., hubs) are represented with their names. Three major clusters of interconnected users were identified. In one (top-right), hubs are associated with the conservative host, and the other two with progressive or liberal information sources.

values associated with them (e.g., in-degree for nodes or weight for links). Because the majority of links were weighted 1 (e.g., two users followed each other, but did not mention or reply to each other), filtering for edge weight would dramatically reduce the network and its connectivity and therefore was not done. In order to capture clusters, data were not reduced by filtering nodes based on their level of connectivity (e.g., in-degree centrality). However, when visualizing the network, NodeXL was instructed to present each cluster in a box, helping to illustrate the differences between interconnectivity within and across clusters.

Content Analysis.

Each hub was first classified into one of the following categories: hosts' official Twitter accounts, traditional news media and affiliates, online only news media (as categorized by the mondotimes.com) and affiliates, political organization (such as political parties or politicians), advocacy organizations, grassroots organizations, and users who are not affiliated with any organization. Coders first examined the description of the user on Twitter, then, if needed, any posted hyperlink. If needed, coders also conducted a Google search for the full name of the user as indicated on her or his account. Second, each hub's political orientation or leaning was determined. Users who described themselves as conservatives or liberals/progressives were coded as such. Where needed, coders consulted the websites associated with users to determine their self-declared political leanings. Each hub, therefore, was coded as Conservative, Liberal, or No clear political leaning. Two coders were trained for purposes of content analysis. Coding 10% for reliability, Cohen's Kappa was .93.

K-Means Cluster Analysis.

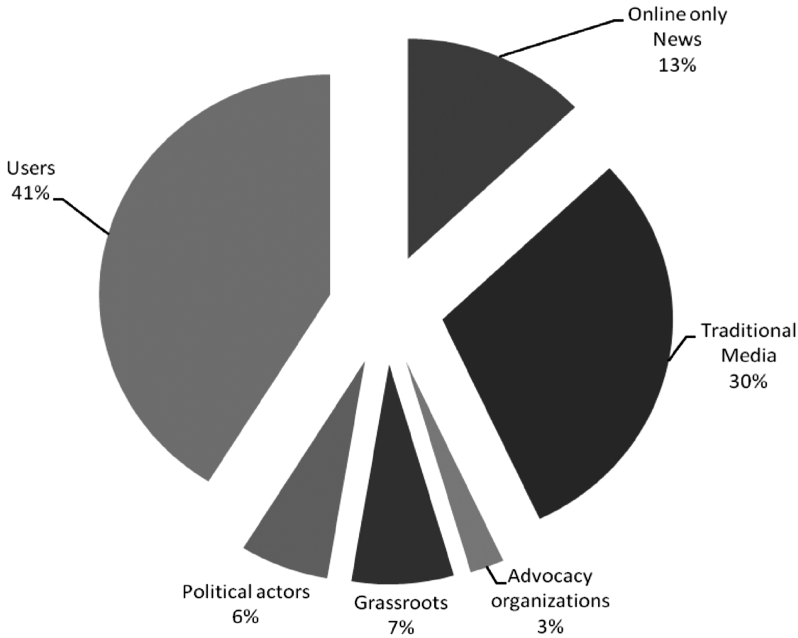
To address the first research hypothesis, a network cluster was used as a unit of analysis. For each network cluster, the portion of each of the following hubs was calculated: liberal, conservative, and neutral/unidentified. Using the initial set of network clusters as units of analysis, a nonhierarchicial cluster analysis (K-Means Analysis, using SPSS), examined both a two- and three-cluster solution. Following an examination of the effective separation of the clusters and an interpretation of their meaning, a multiple discriminant analysis was conducted to predict the overall goodness of fit of the three-cluster solution. It should be noted that the term ''cluster'' in this statistical procedure is different from the network cluster that was used elsewhere in this manuscript. Both network analysis and the K-Means cluster analysis use the term ''cluster'' differently.

Findings

Nineteen datasets were analyzed in this study, which included 5 points of time for each of the 4 politically opinionated television hosts (the dataset for Sean Hannity on 10/19 was corrupted). For each dataset, 1,000 users were included (datasets size limitation is determined by Twitter's API). The number of connections among users ranged between 3,027 and 7,482 (M = 5,575.11, SD = 1,420.45). A total of 58 major clusters were identified, which included 210 hubs. The majority of hubs had a clear political orientation: 107 (50.95%) of the hubs were classified as liberal and 66 (31.43%) as conservative. Thirty-seven (17.62%) had no clear political orientation. One hub was inactive by the time data were analyzed and therefore could not be coded. The vast majority of hubs who were coded as liberal or conservative (159 of 173) self-described themselves as such in their Twitter profile (text of a website they linked to). Five were coded as liberals and 7 as conservative, based on other websites associated with these hubs.

Examining the types of hubs, 63 (30.0%) were associated with traditional media and their affiliates (including Twitter accounts of the television hosts themselves), 27 (12.9%) were online only news sources (including major blogs), 86 (41.0%) were users not affiliated with a specific organization or movement, 15 (7.1%) were

Figure 2
Hubs by Type of User



affiliated with grassroots organizations, 13 (6.2%) were accounts of politicians, and 5 (2.18%) were advocacy organizations. See Figure 2. In-degree centrality of hubs ranged between 12 and 898, with an average of 160.2 ($SD = 182.30$). The variation of values is a result of the different size of clusters. Smaller clusters will host hubs with lower in-degree centrality values, and vice versa. Also, the mean value is for illustration only and should be read with caution, as the distribution of in-degree centrality values is skewed. Out-degree centrality values of hubs (number of users hubs followed) were distributed normally, ranging between 0 and 52 ($M = 14.83$, $SD = 11.89$). The low values of hubs' out-degree centrality indicate that these popular users, while followed by many, follow many fewer users.

H_1: Hubs in a given cluster will be associated with one side of the political spectrum (i.e., conservative or liberal).

Using a network cluster as the unit of analysis, a cluster analysis resulted in a parsimonious cluster solution consisting of two- and three-cluster solutions. The results of both solutions indicate that the clusters' centers differ from one another significantly ($p < .001$). For the two-cluster solution, the descriptive statistics also give clear insight into the meaning of each cluster. That is, Cluster 1 consists of

Table 1
Network Cluster Taxonomy Based on Hubs' Political Orientation

Table 1a
Interpretation of Two-Cluster Solution

	Cluster			
Hubs' Political Orientation	Mean Square	*df*	*F*	Sig.
Right	71.316	1	54.276	.000
Left	143.922	1	86.033	.000
Neutral/Unclear	11.423	1	13.334	.001

Table 1b
Interpretation of Three-Cluster Solution

	Cluster			
	Mean Square	*df*	*F*	Sig.
Right	52.857	2	74.197	.000
Left	102.474	2	172.590	.000
Neutral/Unclear	11.883	2	18.344	.000

Twitter cluster networks of predominantly liberal or neutral hubs while Cluster 2 consists of network clusters with liberal-leaning hubs. For the three-cluster solution, the descriptive statistics also give clear insight into the meaning of each cluster. That is, Cluster 1 consists of Twitter network clusters of predominantly neutral hubs; Clusters 2 and 3 consist of network clusters with primarily liberal-leaning hubs. See Table 1 for the distribution of hubs by type. The two cluster solution supports H_1, as liberal- and conservative-dominated hubs were separated from one another.

> H_2: More links will be found across similar ideology clusters—liberal or conservative—than across conservative and liberal clusters.

Of the 19 data sets collected, only 7 (35%) included both liberal and conservative clusters. Most of the clusters in these datasets (85.71%) were associated with conservative pundits (Hannity and Beck). Only one dataset (associated with the liberal pundit Keith Olbermann) included clusters from both ends of the political spectrum. Of the datasets associated with conservative pundits, 60% included liberal and conservative clusters while only 10% of datasets associated with liberal pundits included such variety of clusters. The 7 cross-ideological datasets included 24 major clusters, 12 conservative and 9 liberal.

Table 2
Regression Analysis—Hypothesis 2

	Model 1[a]			Model 2[b]		
Variable	B	SE	β	B	SE	β
Number of links	−.011	.253	−.009	−.123	.164	−.103
Cross political dyad				−528.795	93.692	−.782*
Adjusted R^2		−0.045			0.565	
SE of estimate		341.918			220.593	

Notes. *$p < .001$.
[a]Model 1: total number of link was used as a control variable.
[b]Model 2: the independent variable, whether the two connected clusters are similar or different in terms of their political ideologies, was included.

A regression analysis was applied to examine the second hypothesis. The unit of analysis was a dyad of clusters, that is, two connected clusters ($N = 24$). The independent variable was categorical, measuring whether the two clusters in the dyad are *similar* (0) or *different* (1) in their political orientation. The dependent variable was the number of links across the two clusters (links in both directions were included). The total number of cross cluster links in each dataset was used as a control variable, as numbers of links across cluster may vary depending on the level of activity within each dataset. Findings supported the hypothesis ($F = 15.9$, $p < .001$) with an adjusted R^2 of .57. The contribution of the control variable to the model was not significant (Table 2).

In order to address concerns regarding a possible lack of independence between the units of observations (i.e., dyads of clusters), the GENLIN procedure for generalized linear models was used as it offers robust standard errors (the original Huber-White estimators for linear models), which adjusts the significance tests to account for non-independence. Results were very similar to the original analysis: the model was significant ($p < .001$) with an R square of .60, supporting the hypotheses (while the total number of links remains insignificant in the model).

RQ_1: Are clusters that include the television host Twitter account (i.e., host clusters) different in terms of their density values?

A two-step regression analysis was applied to examine the first question, using a network cluster as the unit of analysis ($N = 59$). A cluster's density value was the dependent variable. A variable indicating whether the host's Twitter account was included in that cluster was the independent variable. The television host associated with each dataset and the date of data collection were the control variables. At the first step of the regression analysis, the control variables were included. Their contribution was not significant or meaningful. Including the independent variable at the second step, the model supported the hypothesis. Host account clusters showed significantly ($p < .01$) lower density ($M = .013$, $SD = .013$) than other clusters ($M = .047$, $SD = .036$), with adjusted R^2 of .21. (See Table 3.)

While not drawn directly from the research questions, examining the ratio of the number of users following a hub in the network (in-degree) over the number of users he or she followed (out-degree) may help explain the finding above. While all hubs were followed more than they followed others, television hosts showed the lowest ratio ($M = .025$, $SD = .018$). In comparison, user-hubs (i.e., not associated with an organization) showed the highest ratio ($M = .37$, $SD = .22$). Ratio values for the other types of hubs included traditional news media and their affiliates, not including the hosts ($M = .091$, $SD = .07$), online only news sources and affiliates ($M = .051$, $SD = .053$), advocacy organizations ($M = .16$, $SD = .14$), and grassroots organizations ($M = .15$, $SD = 12$). Differences are significant ($F = 30.60$, $p < .001$).

Figure 1 provides a visual representation of the findings. This figure depicts the Twitter social network of users who tweeted about Glenn Beck on November 2, 2011. In one cluster (top-right) the main sources were associated with Glenn Beck, the conservative television host. In the cluster on the left and the cluster on the bottom-right, hubs were associated primarily with left-leaning information sources (e.g., the progressive Daily Kos, the bloggers StopGlennBeck and ThinkProgress, and the magazine Mother Jones). The social network illustrates the tight interconnectedness among users across the two clusters with liberal hubs (left and bottom right clusters) and the looser connections with the hubs associated with the conservative host (top right).

Discussion

This study proposed two dimensions of political talk on Twitter to evaluating its contribution to democracy and society. The first is related to the exposure of users to diverse information sources. Findings suggest that despite the availability of cross-ideological information online, in the datasets examined, users preferred following politically like-minded information sources. The second dimension is related to interaction among users about content related to the television hosts. Here, findings indicate that such interactions appeared primarily among users who follow information sources other than the television host itself. Clusters of users who primarily followed the Twitter account of a television host exhibited a traditional broadcast structure in which users follow the hosts and have little interaction with one another.

As discussed earlier, interaction among individuals talking about political issues long has been associated with desirable consequences, such as understanding of discussed matters and political knowledge. This study identified two types of Twitter network clusters that differed in their users' interactions: host-clusters, where television hosts were the primary or only hubs, and non-host clusters, where users draw

Table 3
Hubs by Cluster and Political Orientation

Candidate	Date	Density	Hubs (Total)	Conservative Orientation	Liberal Orientation	No Orientation
Glenn Beck	26-Oct	0.00448	4	3	0	1
Glenn Beck	26-Oct	0.02542	5	1	3	1
Glenn Beck	26-Oct	0.05904	5	5	0	0
Glenn Beck	2-Nov	0.00967	4	0	3	1
Glenn Beck	2-Nov	0.02806	2	2	0	0
Glenn Beck	2-Nov	0.03666	5	0	5	0
Glenn Beck	9-Nov	0.00518	3	3	0	0
Glenn Beck	9-Nov	0.0367	2	2	0	0
Glenn Beck	9-Nov	0.09667	5	4	1	0
Glenn Beck	16-Nov	0.022	3	0	1	2
Glenn Beck	16-Nov	0.042	3	3	0	0
Keith Olbermann	19-Oct	0.00322	3	0	3	0
Keith Olbermann	19-Oct	0.01543	3	2	0	1
Keith Olbermann	19-Oct	0.0421	8	0	6	2
Keith Olbermann	26-Oct	0.00682	5	0	3	2
Keith Olbermann	26-Oct	0.0081	5	0	1	4
Keith Olbermann	26-Oct	0.05016	3	0	3	0
Keith Olbermann	2-Nov	0.00365	1	0	1	0
Keith Olbermann	2-Nov	0.03688	6	0	6	0
Keith Olbermann	2-Nov	0.04056	5	0	1	4
Keith Olbermann	9-Nov	0.00277	1	0	1	0
Keith Olbermann	9-Nov	0.02062	1	0	1	0
Keith Olbermann	9-Nov	0.02953	2	0	1	1
Keith Olbermann	9-Nov	0.06304	5	0	5	0
Keith Olbermann	16-Nov	0.0043	2	0	1	1
Keith Olbermann	16-Nov	0.02561	2	0	0	2
Keith Olbermann	16-Nov	0.02903	5	0	4	1
Rachel Maddow	19-Oct	0.01783	3	0	2	1
Rachel Maddow	19-Oct	0.08506	6	0	6	0
Rachel Maddow	26-Oct	0.00504	5	1	2	2
Rachel Maddow	26-Oct	0.03258	6	0	6	0
Rachel Maddow	26-Oct	0.08391	5	0	5	0
Rachel Maddow	2-Nov	0.00644	5	0	3	2
Rachel Maddow	2-Nov	0.01383	2	0	2	0
Rachel Maddow	2-Nov	0.10148	5	0	5	0
Rachel Maddow	9-Nov	0.00709	2	0	1	1
Rachel Maddow	9-Nov	0.02312	5	0	5	0
Rachel Maddow	9-Nov	0.10241	5	0	5	0
Rachel Maddow	16-Nov	0.00409	1	0	1	0
Rachel Maddow	16-Nov	0.0159	5	0	2	3
Rachel Maddow	16-Nov	0.07138	5	0	5	0

(*continued*)

Table 3
Hubs by Cluster and Political Orientation (*Continued*)

Candidate	Date	Density	Hubs (Total)	Conservative Orientation	Liberal Orientation	No Orientation
Sean Hannity	19-Oct	0.004	1	1	0	0
Sean Hannity	19-Oct	0.015	4	4	0	0
Sean Hannity	19-Oct	0.037	1	1	0	0
Sean Hannity	19-Oct	0.062	4	4	0	0
Sean Hannity	26-Oct	0.00544	3	3	0	0
Sean Hannity	26-Oct	0.02713	4	4	0	0
Sean Hannity	26-Oct	0.04497	5	5	0	0
Sean Hannity	2-Nov	0.00395	3	3	0	0
Sean Hannity	2-Nov	0.01709	5	0	3	2
Sean Hannity	2-Nov	0.04853	5	5	0	0
Sean Hannity	9-Nov	0.01624	2	2	0	0
Sean Hannity	9-Nov	0.02056	3	1	1	1
Sean Hannity	9-Nov	0.19295	3	3	0	0
Sean Hannity	16-Nov	0.0214	1	1	0	0
Sean Hannity	16-Nov	0.02643	5	0	3	2
Sean Hannity	16-Nov	0.03082	1	1	0	0
Sean Hannity	16-Nov	0.06807	2	2	0	0

Note. Each cluster is described here in terms of the television political host it is associated with, its density and the number of hubs with conservative, liberal, or neutral political orientation it includes.

from several hubs, such as blogs and news media who talked about the hosts or their show. Users in host-clusters followed hosts' Twitter accounts and posted messages mentioning these hosts. However, they showed little or no interaction among one another about the topic. As individuals, these users took advantage of the technology by spreading content related to these shows to their social networks, either by re-tweeting or by posting their own response. However, they did not create a group of interconnected users who interact with one another about the topic. In other words, the opinionated television hosts examined here failed to create an active exchange of ideas among their followers, which can add another layer of communication, beyond broadcast. In contrast, groups of users who draw primarily from other information sources that covered issues associated with the hosts formed more interconnected clusters. These users engaged in a richer informational environment, where they drew from multiple major sources and from one another.

Further examination of the types of hubs appearing in these clusters may provide an explanation. Television hosts had the lowest ratio of number of followers to number of users they follow in their respective networks. One explanation for the lower level of user-interaction in host-clusters, then, is the low level of interaction between host-hubs and other users in their clusters. Other hubs, such as users and grassroots organizations, interacted more with other users, and may have encouraged further interaction among users.

The exposure to cross-ideological content has also been widely discussed as desirable to democratic societies (e.g., Arendt, 1968; Mill, 1859). Literature suggests that while users can interact with unlike-minded individuals, they typically prefer connecting to individuals with whom they agree (e.g., Adamic & Glance, 2005; Himelboim et al., 2011). This study adds an institutional level to the discussion of cross-ideological content on the internet. Regardless of the types of clusters discussed previously, users prefer drawing from hubs with similar political leaning.

Theoretical and Methodological Contributions

Taking a social network approach to examining online political talk, this study proposed integrating two bodies of literature—one about cross-ideological exposure and another about online political interactions—to inform us about the democratic contribution of political talk on Twitter. Selecting a cluster as a unit of analysis adds a social component for understanding information exposure. On Twitter, subgroups of interconnected users (i.e., clusters) can be exposed to content either by directly following its source, or from their peers who re-tweet, mention or reply to the source. Mapping the relationships among users, this study presents a more comprehensive understanding of information flow and exposure on Twitter. This study also addresses a gap in the existing body of knowledge about cross-ideological exposure on the internet. While a growing body of literature indicates that individuals prefer interacting with like-minded others, this study provides support that such self-exposure patterns also characterize the selection of information sources on Twitter.

From a methodological standpoint, this study proposes capturing a subset of the Twitter network based on keywords of interest. This approach allows researchers to examine only the users who actively participated in a political talk about a given topic or persona, identifying hubs and clusters of users. Last, for the television industry, including the hosts themselves, this study provides evidence that the often controversial content associated with the television hosts can evoke an exchange of opinions and information among their Twitter audiences.

Limitations and Future Research

This study focused on the network of Twitter users, its structure, and popular information sources on Twitter. It did not examine the content of tweets users posted and examined the talk about only a handful of television hosts, which poses limitations on the cross-ideological exposure-related conclusions this study makes. One limitation is therefore that this study cannot speak to the possibility that the groups of liberal users, for example, follow conservative hubs, including television hosts. Such scenario will indicate cross-ideology exposure, weakening the conclusions of this study. Furthermore, because content of tweets was not analyzed, this study cannot identify a case where a cluster of liberal users, for instance, follow conservative hubs. That said, based on research about selective exposure suggesting that users tend to follow information sources that correspond with their political opinions (e.g., Himelboim et al., 2013), these scenarios, while possible, are likely to be rare. A related limitation is that this study does not report about users' responses to the content they are exposed to. They may agree with or criticize information sources they follow. Important future work may examine the reaction to exposure to opposing views. Furthermore, by applying content analysis of Tweets, future studies can provide insight into the issues, attitudes, and emotions these and other television hosts evoke.

Limitations also are related to the data collection decisions. Each dataset was analyzed individually to address the research hypotheses. Such analysis, however, cannot capture users who may follow both conservative and liberal television hosts, and are thus exposed to cross ideologies. Also, this study focused on four of the many hosts of political cable shows. Expanding the scope to a larger group of television persona will allow scholars to test whether the conclusions of this study hold in a larger population of shows.

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