Birds of a Feather Tweet Together: Integrating Network and Content Analyses to Examine Cross-Ideology Exposure on Twitter

Itai Himelboim

Department of Telecommunications, Grady College of Journalism and Mass Communication, University of Georgia, Athens, GA 30602-3018

Stephen McCreery

Department of Telecommunications, Grady College of Journalism and Mass Communication, University of Georgia, Athens, GA 30602-3018

Marc Smith

Connected Action Consulting Group, 2617 Hallmark Drive, Belmont, CA 94002

This study integrates network and content analyses to examine exposure to cross-ideological political views on Twitter. We mapped the Twitter networks of 10 controversial political topics, discovered clusters – subgroups of highly self-connected users – and coded messages and links in them for political orientation. We found that Twitter users are unlikely to be exposed to cross-ideological content from the clusters of users they followed, as these were usually politically homogeneous. Links pointed at grassroots web pages (e.g.: blogs) more frequently than traditional media websites. Liberal messages, however, were more likely to link to traditional media. Last, we found that more specific topics of controversy had both conservative and liberal clusters, while in broader topics, dominant clusters reflected conservative sentiment.

Key words: Twitter, Social networks, Social Media, Political talk, Selective exposure.

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Internet users engage in the contribution of political content via a wide range of platforms. They post on discussion forums, contribute messages on news sites' bulletin boards, add comments to discussions linked to articles, update their profiles on Facebook, post short messages on Twitter, and upload videos to video sharing sites. By contributing such content, in this sense, they participate in political talk. Much of this content is exchanged within social networks, as users reply to one another's messages, expose, and are exposed to material that has been selected on the basis of their social network connections. Since its inception, many expected that the Internet would diversify the marketplace of ideas and provide an improved platform for political participation (see Papacharissi, 2002). Others have argued that the Internet enables individuals to selectively interact with others who share political views, potentially damaging deliberative ideals (see Sunstein, 2006). Little is known, however, about whether interactions around political issues on the Internet, and in particular through social networking sites, actually lead to cross ideological exposure.

Examining the popular social networking site Twitter is one way to address the question of diversity of exposure in social media. First, Twitter is a network of users who are connected to one another via relationships formed when one user ''follows'' another user, exposing herself primarily to the messages authored by the people she selects. Such a network allows us to examine tweets with political content within the context of a web of social relationships. Mapping this network, we can examine whether Twitter users are exposed to cross-ideology based on their immediate social network. Second, the exchange of political ideas on Twitter takes place as part of users' routine activities, not in specifically designated groups or forums. Wojcieszak and Mutz (2009) found that cross political ideological interactions were more likely to take place in nonpolitical online spaces than in political spaces. Third, messages are restricted in length to 140 characters or less. As such, the use of hyperlinks is very common, which allows us to also examine the political leanings of the sources of information that tweets link to. The length restriction may also restrict the depth of such messages, but it can also make them more concise. Short political messages, it should also be noted, are a common practice in other forms of political communication, such as political advertising. And last, Twitter is very popular. According to Twitter COO Dick Costolo, in June of 2010, Twitter reached 90 million users worldwide (Schonfeld, 2010).

This study integrates network and content analyses to explore the extent to which political interactions on Twitter cross ideological lines. Twitter messages and the following relationships among users who posted them were collected for each of 10 keywords. These keywords were selected to reflect some of the the most controversial issues in the 2010 U.S. midterm elections. Some were broad: Tea Party, Obama, DNC, and GOP. Some were more issue specific: unemployment benefits, global warming, deficit, immigration reform, healthcare reform, and stimulus money. Network analysis was conducted for each keyword to reveal the top clusters of connected users. In each cluster, the political orientation of each message and the source it might link to were identified using content analysis. Overall, a total of 2,117 Twitter messages related to 10 different political keywords were found to contain 30 distinct clusters.

Literature Review

With the decline in traditional media's reach and the increase of Internet use, social media spaces are becoming increasingly popular for political communication. Specifically, about a third of American Internet users have a profile on a social networking site, and 40% of them have used these sites to engage in political activity of some kind. Among young adults (under the age of 30), 66% of Internet users have a social networking profile, and half of young profile owners use social networking sites to get or share information about political topics, including information about candidates and their election campaigns (Pew, 2009).

Examining online discussions, Delli Carpini, Cook, and Jacobs (2004) pointed out that political talk that involves the exchange of dissimilar perspectives is considered beneficial to individuals and society at large. However, the technology that enables individuals to interact with diverse perspectives also allows them to limit their exposure to like-minded individuals and information sources (Sunstein, 2006). In the following, we review literature on Internet-based political discourse, specifically in the context of exposure to cross-ideological opinions. We then turn to a discussion of Twitter as a social network, focusing on the role of clusters in examining exposure to cross-ideological political opinions. This section concludes with research questions.

The Internet and Political Discourse

The belief in the benefit of exposure to cross-ideological opinions can be traced back to John Stuart Mill (1859, p. 21), 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." 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. Habermas (1989) assumed that exposure to dissimilar views will benefit the inhabitants of a public sphere by encouraging greater interpersonal deliberation and intrapersonal reflection.

The Internet has excited discussion of the democratic potential of online discourse. As early as Corrado and Firestone (1996) it has been argued that online discussions, especially Usenet, will create a conversational democracy, where "citizens and political leaders interact in new and exciting ways" (p. 17). Hauben and Hauben (1997) suggested that online discussion groups allow citizens to participate within their daily schedules. Rheingold (1993) declared that if discussion boards are not democratizing technology, there is no such thing. Other optimistic voices suggested that the Internet could promote deliberative discourse (Paparachirissi, 2002), facilitate the distribution of information and perspectives that overcome traditional gatekeepers, such as major media outlets (Shapiro, 1999), and enable the emergence of online groups, where social actors can interact around common issues or interests (Plant, 2004). McKenna and Bargh (2000) pointed out that online interactions may facilitate exposure to opinions beyond one's immediate interpersonal social networks.

Furthermore, Blader and Tyler (2003) suggested that the increasing participation of disadvantaged individuals will diversify the views expressed. Online spaces allow the interaction of groups of individuals that otherwise could not have come together. The higher level of anonymity allowed on the Internet may encourage the expression of views, as the risk is diminished for expressing controversial or nonmainstream views. Furthermore, Mendelberg (2002) points out that minority opinions can lead majorities to consider new alternatives and perspectives (Nemeth, 1986; Turner, 1991), to seek out and process new information (Nemeth & Mayseless, 1987), and to more generally empathize with the minority's viewpoint (Moscovici, 1980).

Others, however, point out that individuals tend to form new social networks connections with others who are often very similar to them. In a sense, birds of a feather flock together (McPherson et al., 2001). In fact, it is the same technology that gives the opportunity to tune out individuals and information sources one disagrees with. 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. Similarly, 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. This is in contrast to the vision of an information "commons," like public parks or the mainstream mass media, where citizens are exposed to a range of viewpoints they would not otherwise encounter. Via the Internet -- chats, forums, social networking sites, and even news -- it is easier than ever to restrict one's sources of information and discussion partners to those with whom one agrees with. Earlier studies showed that individuals selected face-to-face discussion partners that are similar to them (e.g.: Lauman, 1973; Mutz, 2002a), and avoided discussing politics when they believed others hold opposing views (Noelle-Neumann, 1984). Furthermore, Mutz (2002b) identified negative consequences of exposure to opposing opinions. Individuals who were embedded in cross-cutting social and political networks were more likely to hold ambivalent political views, which discouraged political involvement.

Do online political interactions indicate such selective exposure? Or do they diversify the marketplace of ideas? Little is known about the actual exposure to disagreement in online political discourses, and findings are mixed. 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. In contrast, McGeough (2010) found that conversations on Amazon website forums demonstrated cross ideological exposure as well as other ideals of political deliberation. Adamic and Glance (2005), analyzing 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. Furthermore, they showed 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 contrast, Kelly, Fisher, and Smith (2006), in a study of eight politically oriented Usenet discussion newsgroups, showed that individuals often preferred discussing issues with users with whom they disagreed. Wojcieszak and Mutz (2009) surveyed participation in chat-rooms and message boards. They found that whereas political discussions on political spaces indicated low levels of exposure to cross-cutting political views, political discussions on leisure-type spaces (e.g.: hobbies) have become platforms for cross-ideological exchange of opinions.

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 2 years prior to the 2008 U.S. Presidential election. Posters on each candidate's wall overwhelmingly referred readers to the website of the same candidate. Yardi and Boyd (2010) analyzed tweets about the shooting of George Tiller, a late-term abortion doctor, and the messages posted thereafter by prolife and prochoice advocates. They found evidence for replies between different-minded individuals, which reinforced in-group and out-group affiliation. They concluded that users showed a limited ability to engage in meaningful discussion. Examining Korean politicians' use of Twitter, Choi, Park, and Park (2011) found that more hyperlinks were posted to sites associated with politicians within the same party, than across parties. One overarching research question for this study is therefore:

RQ1: To what extent are Twitter users exposed to cross-ideological content within their clusters?

The Social Networks in Social Networking Sites

Social networking spaces are increasingly used for purposes of political communication. In the months preceding the 2008 elections, 10% of all American adults and 40% of social networking site users used networking services to engage in political activity, discovering political affiliations of their own friends, signing up as friends of candidates, or joining a political group (Pew, 2009). This is an increase over the 2006 elections (Pew, 2007). Social networking sites have been viewed as a new type of online public sphere (Dahlgren, 2005; Donath & Boyd, 2004; Foot & Schneider, 2006), or as a context that encourages civic discourse and debate (Westling, 2007). However, other researchers have questioned whether participants in online communities and social media are actually meeting new people, and to what degree the discourse in these communities is exposing participants to new ideas, or simply reinforcing already-held beliefs (Lampe, Ellison, & Steinfield, 2006; Nie, 2001). To examine whether cross-ideological discourse occurs within social network sites, one needs to take into account interconnections among users, namely, their social networks.

Broadly speaking, a social network is a structure created by social actors, such as individuals and organizations, when links are formed among them. Social media allow users to typically form symbolic ties among themselves. Social network theories suggest focusing on relational ties among social entities and on patterns and implications of these relationships (Wasserman & Faust, 1999). On social networking sites, users form social networks by articulating a list of other users with whom they share a connection. On Facebook, the most visible links are formed by "friendships." On Twitter, social networks are created by relationships of "following," a form of subscription to others' Twitter messages. Social networking sites allow users to display their social connections publicly to others and can be used as means to filter the streams of information generated via these services (Hogan, 2010).

Twitter as a Network of Political Talk - A Conceptual Framework

Twitter can be thought of as a conversational microblog (Barash & Golder, 2010). Like bloggers, messages posted by Twitter users are made visible to their followers, who are the collection of people who subscribe to them. Unlike blogs, messages are limited in length (140 characters or less per post), which makes message creation and consumption much less time consuming for authors and their followers. Although the quality of such a short message, in terms of its contribution for a political discourse or informed citizenry, for example, can be challenged, individuals and politicians use Twitter to express political messages (see, for instance: Gulati and Williams, 2010; Choi et al., 2011; Smith, 2011).

Twitter, like Facebook or MySpace, for example, is not designed specifically for political dialog, and most people involved in political discussions are also using the application for other social purposes. In this way, political dialog becomes embedded in other contexts in much the same way as face-to-face political discussion might take place in the context of an office, a vehicle, a sporting event, a meal, a pub, or through other public activities. This makes political discourse an extension of other realms of ongoing discourse as opposed to a special event or location. This is an important quality of political discourse on social networking services. As we recall, Wojcieszak and Mutz (2009) found that many nonpolitical online forums were used for political discussions and that political discussions on leisure-type spaces (e.g.: hobbies), not political spaces, have become platforms for cross-ideological exchange of opinions. Political talk on Twitter, then, may indeed host a wide range of opinions on a variety of topics. The mere existence of a diversity of opinions, however, does not guarantee that users will be exposed to politically heterogenous messages and individuals. In other words, unless users (a) follow or are followed by others who post messages about a certain topic, and (b) these messages reflect a range of points of view, a Twitter user is unlikely to be exposed to cross-ideological content via this social networking platform. While some users may use search features to collect messages from anyone whose tweet contains a keyword, a major and most convenient usage pattern is to read only content from people the user has selected to follow. Networks, the patterns of interconnections among users on Twitter, are therefore vital for understanding the exposure of Twitter users to political opinions on the site.

Mutz (2006b) uses the term *network* to refer to "the people with whom an individual communicates on a direct, one-on-one, basis" (p. 10). At the most basic level, then, exposure to heterogeneous individuals depends on the existence of a network connection. For example, many users may tweet about immigration reform; but only if they are connected to one another – by following or being followed – is any exposure likely to take place. Exposure to opinions about a certain issue can occur among Twitter users who are actually connected to one another and post messages on a certain topic. This does not ensure that user users will in fact read all messages posted by those they follow. It does, nonetheless, provide a framework in which such exposures *can* occur. Mapping the *following* relationships among those who tweet about a certain issue allows the identification of users who are part of highly connected subnetworks, or clusters. These are groups of users who follow or are followed by others, who also talk about a common issue as indicated by shared use of a topic, keyword, or phrase.

The latter can be exposed to a variety of opinions about a topic, as they are delivered messages from a wide range of others who post about that issue on Twitter.

Clusters. Theoretical work in social and other networks has involved considerable effort to uncover ways of decomposing networks into their constituent subgroups (Wasserman & Faust, 1999). Cliques and clusters refer to subgroups in a network in which nodes are substantially more connected to one another than to nodes outside that subgroup (for more discussion on clusters and cliques, see: Carrington, Scott, & Wasserman, 2005). Clusters can also be seen as community structures in networks (Newman, 2004). In the context of political talk on Twitter, users' exposure to political tweets is defined by their social network. Clusters on Twitter, which are composed of dense subgroups of interconnected Twitter users, are the context in which users are exposed to messages on Twitter, and therefore to potentially cross-ideological opinions. For example, Twitter may host a diverse list of message about the United States President's health reform proposal, but this does not mean that users are indeed exposed to the variety of standpoints expressed through the system. Mapping the relationships between Twitter users who posted messages on the topic – and specifically the clusters in which they are located – is needed to reveal the diversity of opinions within a users' *immediate network*. To continue with the same example, a cluster of individuals who tweet about health reform, including heterogeneous opinions, is an indication of exposure to cross-ideological opinions. In contrast, if clusters reflect homogeneous viewpoints, regardless of the range of opinions that might exist outside their clusters on Twitter, then this is an indication of exposure to like-minded people.

Several studies have shown that patterns of interaction on the Internet reflect distinct liberal and conservative clusters in blogs (Adamic & Glance, 2005) and Amazon.com book recommendations (Krebs, 2004), for example. The implication of these clusterings is that analysis of opinions presented in messages needs to be considered within the boundaries of clusters of connected users who are able to actually see and consume them. Approaching Twitter talk as a network, then, the next subquestion examines one aspect of the larger question of cross-ideological exposure:

RQ1a: To what extent are Twitter users exposed to cross ideological content via posted messages?

The larger network. The network of Twitter interactions is only one part of a much larger network that exists on the Internet, most notably the World Wide Web. Users are not limited to their interactions with their Twitter fellows to consume content. In fact, as Twitter limits a message's length to 140 characters, many users link to sources elsewhere on the web (Boyd & Ellison, 2007). These sources – blogs, mainstream media, governmental organizations, and others -- can add to or contradict the ideological content of a message. For example, if in a message about the recent changes to Arizona's immigration law, a user includes a hyperlink to a right-wing blog, this adds another indication of the ideological orientation of the message. In other words, user exposure to cross-ideological content via the Twitter space is not limited to immediate connections with other Twitter users, since often these connections provide links to the network outside Twitter, particularly content stored on the World Wide Web. Users may not follow all hyperlinks posted by users they follow; however these links provide us with another route through which users can be exposed to further content. Another aspect of cross ideological exposure, therefore, can be examined via the following subquestion:

RQ1b: To what extent are Twitter users exposed to cross ideological content via linked sources on the web?

In light of the importance of exposure to unlike-minded content and individuals (Mill, 1859; Arendt, 1969; Habermas, 1989) on one hand, and the potential polarization in the selection of information sources (Van Alstyne & Brynjolfsson, 1996; Sunstein, 2006) on the other, another aspect of this study's overarching question of cross-ideological exposure is:

RQ2: Is there a relationship between messages' political orientation (Liberal or Conservative) and the use of neutral ideological content sources on the web?

Last, a great potential of the Internet, as discussed earlier, is the opportunity for individuals to overcome traditional barriers of space, time, money, and traditional media, and disseminate information using a wide range of online platforms (Hauben & Hauben, 1997; Rheingold, 1993; Shapiro, 1999). However, much of this content includes personal commentary, which is often biased. Exploring the types of sources Twitter users link to (personal, governmental, and journalistic, for example) can therefore address another aspect of the question of cross-ideological exposure.

RQ3: What types of information sources do Twitter users post hyperlinks to?

Methods

This study proposes taking a multimethod approach to examining exposure to cross-ideological opinions in Twitter political discussions. First, network analysis was used to identify the main clusters in the 10 Twitter networks created by the connections among people who tweeted one of the terms selected for this study. Second, for messages in each main cluster, content analysis was performed to identify the political orientation of the content and the web resources to which they link.

Data. With the approaching 2010 United States midterm elections, we decided to select keywords that reflect controversies related to some of the most important political topics during thhe summer of 2010. The following 10 topics were selected as examples: Unemployment benefits, global warming, deficit, immigration reform, healthcare reform, stimulus money, Tea Party, Obama, DNC, and GOP. These issues are not representative of all controversial political issues, as there is no consensus of all political topics and issues one can sample from. However, they reflect some of the issues that divided the electorates in the United States approaching the 2010 midterm elections (see, for example, a review of topics on BBC, July 13, 2010). Further, data for these issues allow us to examine exposure to cross-ideological content.

Data was collected on 17 August 2010. NodeXL, a Microsoft Excel application add-in for network overview that provides support for social network analysis and visualization, was used to collect the 10 datasets from Twitter, based on the 10 topic keywords. For each, the topic itself was used as a keyword (e.g.: "Tea Party" or "Unemployment Benefits"). No variations of keywords were used for the consistency of data collection. Hashtags were not used as keywords; however, they were often included (e.g.: messages with #obama were collected, as the hashtag includes the keyword "Obama"). In order to capture a complete network of users, traditional sampling techniques were not used. Instead, for each keyword, we used NodeXL to retrieve the most recent 500 Twitter users who posted a message using that keyword, and the content of their most recent tweet in which the keyword was used. Twitter, unlike some other social media platforms, does not keep an open archive of all posted messages. However, as the selected keywords were very popular, data related to the recent 500 users who used them did not go back more than a day or two. Therefore, the data were still available. The limitation of the Twitter archiving, therefore, did not affect data collection.

Each dataset also included the following and mentioning relationships among users (i.e.: for each author, the data captured all the people who followed that person and every person that an author followed in the data set). The collection of connections associated with each term was then analyzed via NodeXL. These relationships allowed us to analyze the network and identify its main clusters, as detailed next. See Table 1 for summary of number of nodes and links per topic.

Measurements. Collecting data based on the 10 keywords led to 10 datasets that included messages and the network of relationships among the Twitter users who posted them. The network was analyzed at a macrolevel and clustered algorithmically to identify major subgroups. At the level of the individual user, messages from individuals in each cluster were analyzed for their political leaning, based on their content and hyperlinks (where available).

Table 1 *Summary of datasets*

Topic	Nodes (users)	Links (follow relationships)
DNC*	500†	3,114¥
GOP**	500	4,275
Obama	500	833
Tea Party	500	985
Deficit	500	657
Global Warming	500	482
Healthcare Reform	500	799
Immigration Reform	500	1,165
Stimulus Money	500	622
Unemployment Benefits	500	1,005

†The computer program, NodeXL, was set to collect data for the most recent 500 users who posted messages that included a given keyword.
¥Number of users that were connected to – follow or being followed by – others who posted messages about a given network.
*Democratic National Committee (the Democratic Party).
**Grand Old Party (the Republican Party).

Network analysis. First, the major clusters in each network were identified algorithmically. Using NodeXL, we applied the Caluset Newman Moore algorithm, which identifies the main clusters in a network by placing participants into the cluster they "best" fit, based on their patterns of interconnection (for further discussion see: Wakita & Tsurumi, 2007). This method typically results in a few major clusters and several very small ones. To identify the main clusters, we used a method based on ordering clusters in descending order based on the number of Twitter users in each. A total of 30 clusters were indentified in the 10 networks. Of the 5,000 messages retrieved (500 per topic), 2,117 messages were included in the main 30 clusters (42.34%). See Figure 1 for a list of plots for all topics alongside their selected cluster sizes.

Message level content analysis. To examine cross-ideological content, we coded each message's content (including hyperlinks) from each of the main clusters. As discussed earlier, for the study we selected only messages from the main clusters identified. Each message was coded for: (1) political orientation in content, where messages were coded as neutral orientation, liberal orientation, conservative orientation, or unclear; (2) link, where messages were coded as having a hyperlink, no hyperlink, or a broken hyperlink; (3) linked source type, where hyperlinks were followed and the pages they linked to were coded as being either traditional media (media organizations that have an offline outlet), grassroots websites (individual or small group websites such as blogs, websites of interest, or other websites of independent organization), government websites, video websites, or other; and (4) orientation of the content presented on webpages that tweets linked to (e.g.: a news story or a blog entry), which was coded as no orientation, liberal orientation, conservative orientation, or unclear. Political orientation was identified based on attitudes toward a specific issue and criticism toward specific political actors or attitudes. Coding for political orientation was rather straightforward, as the intercoder reliability values indicate next. This is potentially an implication of the short length of messages. When there was a doubt, the messages were coded as "unclear." If a user posted a link to a source with, for example, conservative political orientation, while criticizing it from a liberal perspective

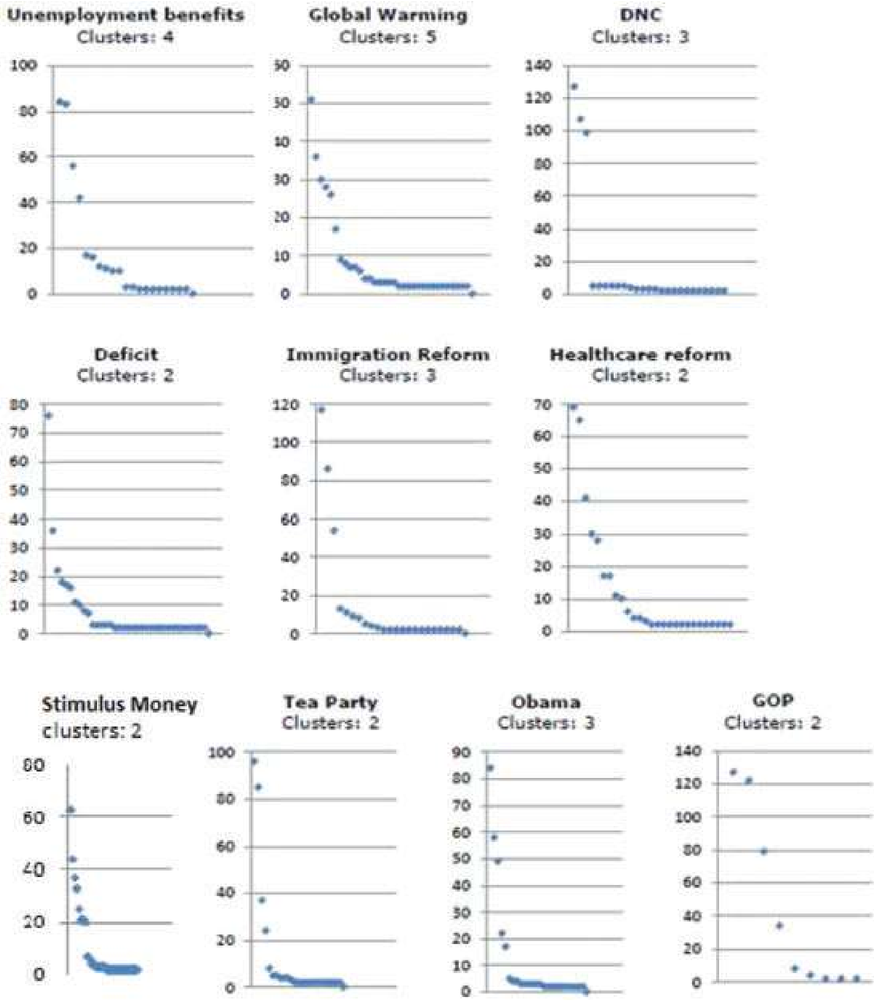

Figure 1 *Clusters in descending of size order (by topic)**
*The Caluset Newman Moore algorithm identified several clusters in each dataset. In order to identify the major ones, clusters were ordered in decreasing order. The graphs above illustrate the drop in clusters' sizes. Identifying the "drop" in clusters' sizes was helpful to identifying the larger clusters, relatively to others. The X-axis represents the number of users in a cluster and the Y-axis is the order in cluster sizes.

in the message, the message was coded as liberal and the source as conservative. For example, a link to a pro-republican video was posted next to the text: "Why are my hard-earned tax dollars paying for GOP campaign propaganda?" In this case the message was coded as liberal and the link as conservative.

Coders and intercoder reliability. Two coders were trained for purposes of content analysis. Each coder coded messages in 5 of the 10 topics. For purposes of inercoder reliability, each coder recoded 10% of the other coder's messages (a total of 212 messages). Scott's Pi was calculated per coder per item. For coder A, reliability was high for identifying retweets and replies/mentions (Scott's Pi = 1.0 for both), which is expected considering the ease of identifying these elements in messages. Values were rather high also for identifying political orientation in messages (Scott's Pi = .89), orientation of linked source (Scott's Pi = .90), and linked source type (Scott's Pi = .93). For coder B, reliability was high for identifying retweets and replies/mentions (Scott's Pi =1.0 for both). Values were rather high also for identifying political orientation in messages (Scott's Pi = .92), orientation of linked source (Scott's Pi = .88), and linked source type (Scott's Pi = .90).

Cross-ideology exposure. We integrated the cluster and content analyses to examine cross ideological exposure. We operationalized exposure to content as following users who posted that content, as by requesting to follow someone, users actively choose to be exposed that persons' posted content. This study cannot ensure that users actually read these messages or follow links in it. Retweeting or replying may be stronger indicators of exposure, as they indicate actual attention given to a message. However, the retweeting and replies are much rarer than following relationships and therefore would have reduced the data significantly. These considerations led us to choose following relationships as the better indicator of exposure.

For each topic, the major clusters were identified, as discussed earlier. Each of these clusters includes a subgroup of Twitter users that follow one another much more than they follow users in other networks. A major way in which users are exposed to messages on Twitter is by following one another; therefore, a cluster represents a group of users that are primarily exposed to one another's posted messages. Hence, in examining cross-ideological exposure, we used a cluster as a unit of analysis. For each cluster, the percentages of messages with liberal, conservative, and neutral orientations were calculated. These portions of politically oriented messages per cluster per topic were used, as will be detailed next, as an indicator for cross-ideology exposure.

Findings

As discussed in the Methods section, of the 5,000 messages retrieved (500 per topic), only 2,117 (42.34%) were associated with the main clusters and therefore selected for analysis, in order to capture participants who are exposed to other participants that post messages about a given issue. Specifically: Deficit (N = 112), DNC (N = 333), global warming (N = 171), GOP (N = 328), healthcare reform (N = 172), immigration reform (257), Obama (N = 191), stimulus money (N = 107), Tea Party (N = 181), and unemployment benefits (N = 265). A total of 30 main clusters were identified in the 10 topics (see Figure 1 for number of clusters and users per topic).

In 41.8% of messages (N = 2,117), no clear political orientation was identified. 28.3% of messages had a conservative leaning, and 20.3% showed liberal political orientation. For the rest of the messages, the political leaning was unclear. 58.2% of messages posted active links (another 4.7% of the messages posted links, which were broken by the time of the analysis). Of the 1,232 active hyperlinks, 51.3% showed no clear political orientation, 25.4% showed conservative political orientation, and 21.7% showed liberal political orientation (for the other 1.5%, the political orientation was not clear).

RQ1: To what extent are Twitter users exposed to cross-ideological content within their clusters?

For the first set of research questions, a cluster was used as the unit of analysis (N = 30) in order to capture groups of Twitter users who follow and are followed by others who post messages about a given topic. Users within each cluster are highly connected to one another, and less connected to users in other clusters. The political heterogeneity of homogeneity of content posted by users *per cluster* is therefore an indicator for cross ideological exposure. Specifically, we compare the percentages of messages with liberal and conservative orientation (RQ1a) and the political orientation of content linked to in messages, conservative versus liberal (RQ1b).

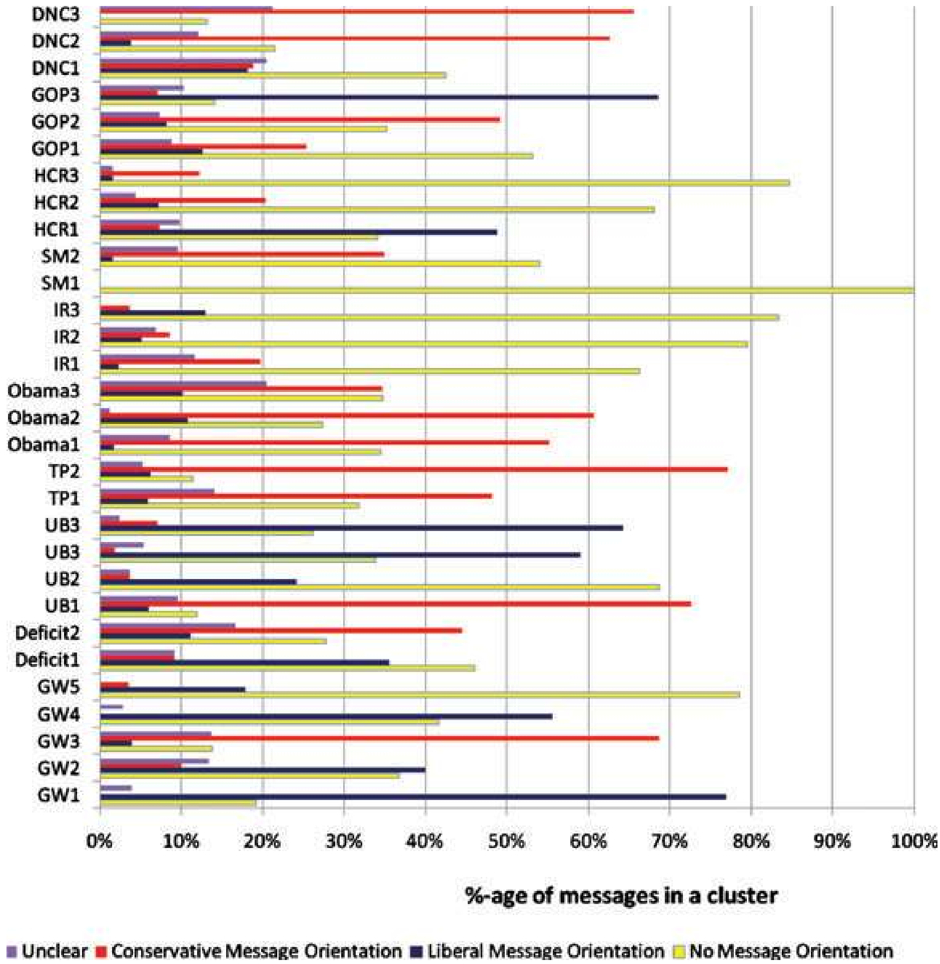

Figure 2 *Messages' Political Orientation in Percentages per Cluster*
DNC = Democratic National Committee; GOP – Grand Old Party (the Republican Party); GW = Global Warming; UB = Unemployment Benefits; TP = Tea Party; IR = Immigration Reform; SM = Stimulus Money; and HCR = Healthcare Reform.

RQ1a: To what extent are Twitter users exposed to cross ideological content via posted messages?

As Figure 2 illustrates, overall clusters reflected polarization of political opinions. A cluster was the unit of analysis, and a T-test was used to test for a difference between percentage of liberal and conservative messages in clusters. Findings showed, indeed, that the percentage of liberal messages was significantly different from the percentage of conservative messages in each cluster ($t = 8.68$, $p < .001$). In fact, the greater the percentage of messages that were labeled with either a right or left political orientation (as opposed to neutral), the greater was the difference between the percentage of messages with liberal political orientation and messages with conservative political orientation (Pearson $R = 0.87$, $p < .001$). In other words, the more that messages in clusters reflected opinions, the more one-sided those clusters were. Messages in clusters associated with global warming, deficit, unemployment benefits, Tea Party, Obama, GOP, and DNC, were mainly conservative *or* mainly liberal. In fact, of the 30 clusters, only in one cluster (one of the three DNC clusters) were the percentages of liberal and conservative politically orientated messages similar (18.1% and 18.9%, respectively). In clusters related to immigration reform, stimulus money, and healthcare reform, the vast majority of messages were lacking clear political orientation, resulting in a smaller difference between liberal and conservative messages. Whether messages in clusters were highly opinionated toward one side of the political spectrum were or mostly neutral, then, exposure to cross-ideological messages was very limited. As a side note, no significant or meaningful correlation was found between cluster size and differences between liberal and conservative messages (in percentages).

For illustration, the list of conservative messages included: "Obama says U.S. must get a handle on deficit [WSJ] Really? he has been leading it!"; and "Who Else thinks Obama's stimulus money was a hoax?" Examples of messages with a liberal orientation included: "Politicususa - Immigration Reform: The GOP's Newest Voter Intimidation Tool" (http://bit.ly/dcgP3T) More dirty tricks disguised as law"; "The deficit was caused by the recession which was caused by Bush. Grow up."

Figure 2 indicate the portion of messages with liberal, conservative, and neutral orientation for each of the 10 topics. For illustration of how to interpret these graphs, let us examine the network created by Twitter users who posted messages that included the term "GOP." As the Figure 3 illustrates, three main clusters where created. The cluster labeled as GOP1, colored orange in the graph, includes more conservative than liberal messages (25.32% vs. 12.66%). GOP2 (in red) shows similar patterns, as 49.18% of messages had conservative orientations and only 8.2% had a liberal orientation. The GOP3 clusters (in blue), in contrast, have more liberal than conservative messages (68.5% and 7.09%, respectively). Other messages in clusters have no noticeable political orientation. "Why are my hard-earned tax dollars paying for GOP campaign propaganda?" is one example for a message related to GOP with a liberal orientation. The message, "The Enthusiasm Gap: As we move closer to Election Day, the wave of enthusiasm and support behind female Republicans," is an example of a conservative orientation.

RQ1b: To what extent are Twitter users exposed to cross ideological content sources on the web?

The hyperlinks found in many tweets point at web content that is often political oriented. By examining the political orientation of the websites that messages pointed to, a similar picture was revealed. Differences between linked content with conservative and liberal orientation in clusters were significant ($t = 7.92$, $p < .001$). Figure 4 illustrates the gaps between liberal and conservative orientation sources in clusters. Here again, in clusters related to immigration reform, stimulus money, and healthcare reform, the vast majority of sources showed no political orientation, resulting in a smaller differences between liberal and conservative oriented messages. The exposure to ideological diverse opinions via these sources was limited, as they appeared to be neutral.

For illustration, an article titled "Limbaugh smacks down Rove -- now we know who's really in charge at the GOP," in the thinkprogress.org liberal blog, is one example for a liberal link content. A link to an article on gop.com, calling to support Republican women candidates, for instance, is one example of conservative linked content.

RQ2: Is there a relationship between the political orientation of a message (liberal or conservative) and the use of neutral ideological content sources on the web?

Examining the second research question, a message was used as the unit of analysis ($N = 2{,}278$). A strong relationship was found between a message's political orientation and the orientation of the content it linked to (Pearson Chi-Square $= 1011.96$, $p < .001$). 81.7% of messages with liberal political orientation linked to content with liberal political orientation, 75.4% of conservative messages linked to conservative content, and 76.1% of messages lacking an obvious political orientation linked to content without clear political orientation. As Table 2 indicates, conservative messages (20.7%) were

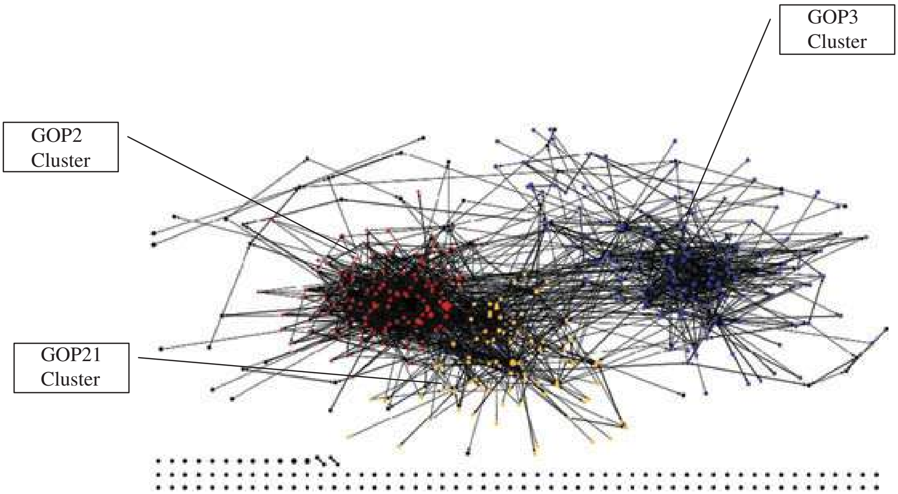

Figure 3 *Main Clusters in the GOP Network*† † GOP1 (orange) and GOP2 (Red) cluster contained predominately messages with conservative orientation. The GOP 3 cluster (Blue) contained predominately messages with liberal orientation. In the bottom of the graph are Twitter users who did not follow or were followed by others who posted messages including the term GOP.

slightly more likely than liberal messages (11.9%) to link to sources with articles without clear political orientation.

RQ3: What types of information sources do Twitter users post hyperlinks to?

Following the link posted in many tweets, we found that they pointed at a variety of web pages with content relevant to the political talk that was examined (only 1.5% did not). Although spam messages and links are quite common on Twitter in general, we did not identify such content in our analysis. Of the 1,232 links, 38.8% were directed to websites associated with grassroots sources of information, such as blogs, operated by individuals and small groups; 30.4% to websites of traditional media; 19.4% to news websites with no offline outlets (e.g.: Slate.com or Salon.com); 4.6% to video sharing sites (e.g.: Youtube), and only 1.5% to websites associated with the government, its representatives, or its candidates (see Figure 5 and Table 3).

Whereas the preferred type of website for hyperlinks – across political orientations –is what we refer to as "grassroots websites," conservative messages were more likely than liberal messages to link to such websites (59.8% and 45.9%, respectively). Websites of traditional media, in contrast, were more popular in liberal messages (23.4%) than in conservative messages (9.8%). For a more accurate test of significance, only the largest website categories -- traditional media and individuals and small groups -- were included ($N = 353$). Differences were found to be significant (Pearson Chi-Square $= 262.26$, $p < .001$).

Discussion

This study integrates network analysis and content analysis to examine user exposure to cross-ideological content on Twitter. Two major implications of this study are related to the partisan political exposure and the role that traditional media and grassroots sources play as sources of political information on this social space. We discuss them next, followed by theoretical and methodological implications.

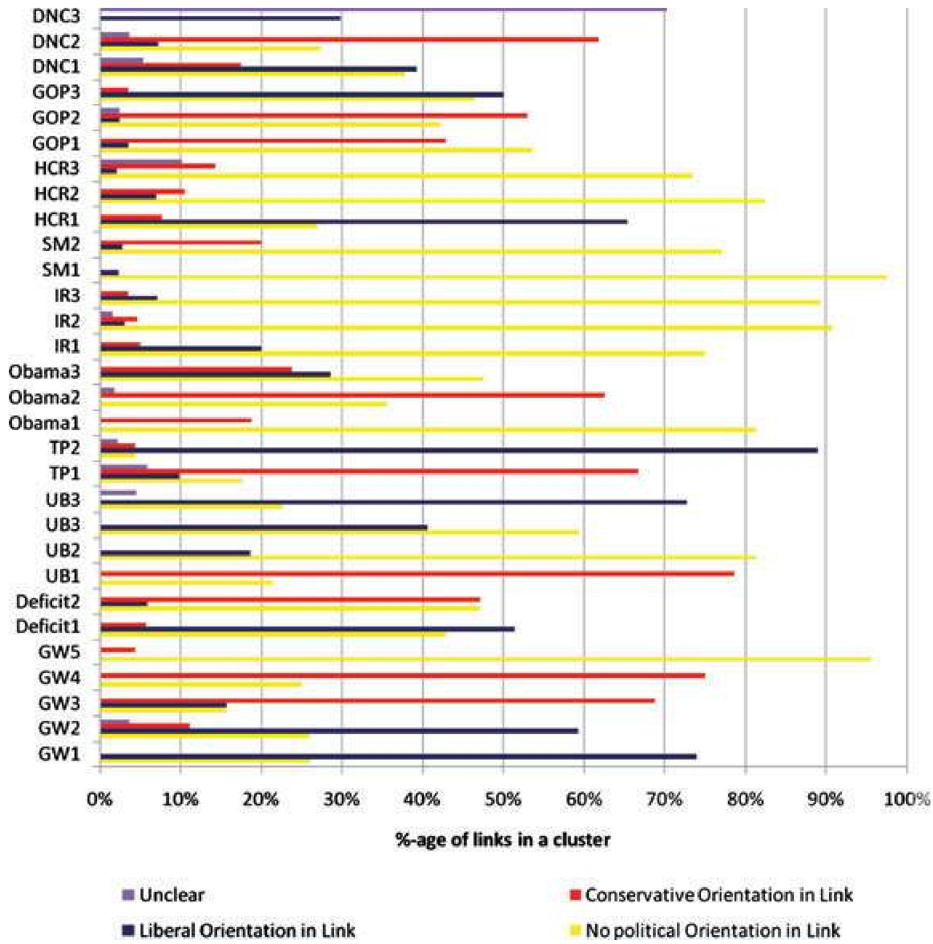

Figure 4 *Links' Source Political Orientation in Percentages per Cluster* DNC = Democratic National Committee; GOP – Grand Old Party (the Republican Party); GW = Global Warming; UB = Unemployment Benefits; TP = Tea Party; IR = Immigration Reform; SM = Stimulus Money; and HCR = Healthcare Reform.

Partisan political exposure. Exposure to messages on Twitter occurred in this study primarily within the horizons of the users' social networks, as defined by the follow-types relationships. Specifically, we identified and examined groups of highly connected users – clusters – that were loosely connected to users outside their clusters. Examining posed content within these social contexts revealed that, for most topics, messages in clusters were predominantly labeled as having either liberal *or* conservative political orientation. Furthermore, users also tended to post links to sources that corresponded to their own and their clusters' political leaning. Politically active voices, particularly younger voters, who use the Internet to express their opinions are moving away from neutral news sites in favor of those that match their own political views (Pew, 2009).

A few studies have illustrated that political online spaces that are not designated for political talk are likely to cross ideological lines (Wojcieszak & Mutz, 2009; McGeough, 2010), becoming, in Sunstein's

Table 2 *Linked Source Political Orientation by Message Source Political Orientation (N = 1232)*

		Source political orientation		
Message political orientation	N	No	Liberal	Conservative
No	633	482 (76.1%)	67 (10.6%)	75 (11.9%)
Liberal	267	32 (11.9%)	218 (81.7%)	13 (5.0%)
Conservative	313	65 (20.7%)	10 (3.2%)	236 (75.4%)

* Percentages do not add up to 100% as for some messages and sources the political leaning could not be determined (N = 19).

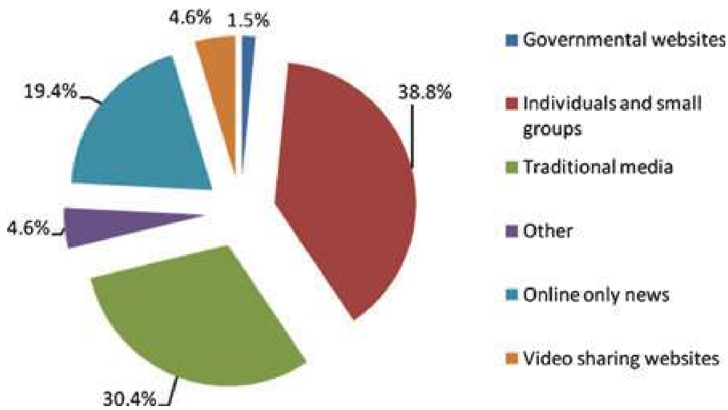

Figure 5 *Type of Sources in Links (N = 1232)*

(2006) words, "information commons," where citizens are exposed to a range of viewpoints they would not otherwise encounter. Others suggest a more partisanship position on online spaces (Adamic & Glance, 2005; Choi et al., 2010), creating spaces of "consumer sovereignty," where individuals' selective biases lead to a narrowing of the scope of news and views to which people choose to expose themselves. This study provides evidence that on Twitter, political talk is highly partisan, where users' clusters are characterized by homogeneous views and are linked to information sources. Drawing from Yardi and Boyd (2010), findings may reinforce in-group and out-group affiliations, as literally, users form separate political groups on Twitter. Any attempt to draw inferences from these findings to the political environment outside the realm of Twitter must be done with caution and requires further research. In retrospect, after the Republican Party gained power in the 2010 midterm elections, it is interesting to note that the political talk on Twitter on general topics such as Tea Party, Obama, GOP, and DNC, all reflected a strong conservative leaning, which may reflect the overall rough political environment for Democrats only a few months before the elections. The more narrowly focused issues such as healthcare reform, global warming, and the deficit, indicated polarizations, as at least one conservative and one liberal cluster was identified. In such topics, Twitter users reflected existing disagreement, while entrenching their opinions in their own like-minded social networks. Interestingly, across clusters, messages about immigration reform and stimulus money were predominately neutral, nonopinionated messages, linking mainly to neutral sources of information. In these topics, political talk was fact-based, rather than opinion-based.

Table 3 *Type of Sources in Links by Topic (N = 1232)*

	N	Gov. websites	Individuals/ small groups	Traditional media	Video sharing websites	Online only news	Other
Deficit	52	0	29 (55.77%)	14 (26.92%)	1 (1.92%)	8 (15.38%)	0
DNC*	173	0	101 (58.38%)	14 (8.09%)	13 (7.51%)	23 (13.29%)	22 (12.72%)
Global Warming	137	0	78 (0.57%)	49 (0.36%)	5 (0.4%)	4 (0.3%)	1 (0.1%)
GOP**	195	12 (6.15%)	109 (55.90%)	47 (24.10%)	4 (2.05%)	18 (9.23%)	5 (2.56%)
Health Reform	132	4 (3.03%)	46 (34.85%)	14 (10.61%)	0	49 (37.12%)	19 (14.39%)
Immigration Reform	132	0	17 (12.88%)	89 (67.42%)	1 (0.76%)	25 (18.94%)	0
Obama	109	0	25 (22.94%)	63 (57.80%)	2 (1.83%)	10 (9.17%)	9 (8.26%)
Stimulus Money	78	0	12 (0.15%)	9 (0.12%)	0	57 (0.73%)	0
Tea Party	97	0	48 (49.48%)	13 (13.40%)	25 (25.77%)	9 (9.28%)	2 (2.06%)
Unemployment Benefits	127	3 (2.36%)	18 (14.17%)	64 (50.39%)	6 (4.72%)	36 (28.35%)	0

*Democratic National Committee (the Democratic Party).
**Grand Old Party (the Republican Party).

Information sources. About three of every five messages posted contained a hyperlink. This is a natural result of the length limitation of Twitter messages as well as common practice in online spaces (See, for example, Himelboim, Gleave, & Smith, 2009, in political newsgroups). Against the common practice on Twitter, the political talk examined here showed no spam and very few hyperlinks pointing to promotional commercial content.

Grassroots websites, such as blogs that are associated with individuals or small groups, were the most popular targets of hyperlinks posted in messages, followed by websites of traditional media. Adamic and Glance (2005), in contrast, found that political blogs were more likely to link to websites of traditional media than to other blogs. Himelboim et al. (2009) also found hyperlinks in political forums to link to websites of traditional media more frequently than to links to blogs. More research is needed to determine if there is a trend in the change from political forums favoring traditional media as a target of hyperlinks during the mid 2000's to the popularity of more grassroots websites in the current research. Such a trend, if it exists, may have important implications for the role of traditional institutions of mass communication in society, especially in light of the continuing decrease in media trust (Pew Research Center for People and the Press, 2009).

Notably, a closer analysis of hyperlinking patterns shows that conservative messages were more likely than liberal messages to include a link to grassroots websites -- mainly blogs -- where websites of traditional media were more popular among messages coded as liberal oriented. Such differences may support evidence that Republicans trust the media less than do Democrats (Pew Research Center for People and the Press, 2009).

Theoretical and research implications. Integrating network and content analyses illustrates the vital role that networks play in studying political communication and interactions, particularly those that take place online. For example, examining messages about global warming could have resulted in a rather balanced presentation of conservative and liberal messages. Without integrating network analysis, one could not have identified the polarization of Twitter political talk on this and other topics.

The short-term storage of content on Twitter has important implications on information exposure. At any given time, Twitter users are exposed only to the most recent information posted. Previous messages are not only pushed down (which is the case in almost any social media, such as blogs and Facebook), but simply disappear. Beyond a rather short period of time, these messages cannot be searched. Implications vary across users. Those who frequently read their stream of tweets can build over time a more complex understanding of the opinions of users who post them. Others are limited to only the most recent tweets, lacking of background of the issues and the users who commented about them. For researchers, it is important to capture longitudinal data. In the context of this study, however, although political orientation may change over time, they are overall stable (for example: Alwin & Krosnick, 1991). It is therefore more likely that the real-time nature of Twitter influences the extent to which users understand these issues than their cross-ideology exposure. This is, nonetheless a limitation of this study, and future studies should examined cross-ideological exposure over time.

Methodological implications. NodeXL is presented as a tool for collecting and analyzing network data and identifying and visualizing the main clusters found within them. We also illustrate the importance of a cluster-based sampling frame for the selection of messages for content analysis, as opposed to the random sampling of messages on a given topic. For practitioners, this is a simple and helpful tool for capturing and analyzing the messages posed by Twitter users on a given topic, identifying the main characters, information sources, and opinions.

Limitations. One limitation is related to the operationalization of ''exposure.'' The fact that a message appears on one's Twitter page does not ensure it will be read or that hyperlinks will be followed. Considering on one hand the reduction of data if alternative routes were taken (using replies or retweets only), and the fact that users actively choose who to follow on the other hand, we decided to use following relationships, while acknowledging the limitations. Another limitation is related to the external validity of the study. Whereas messages collected for this study represent examples of political content on Twitter during one window in time, the topics selected cannot represent all political controversies in the United States during the summer of 2010. Because of a lack of a complete inventory of political topics, a random sample of topics or keywords is impossible. Any generalization of the findings to the full range of political discussion in Twitter is therefore limited until a wider analysis is performed. Future studies may expand the list of topics for a broader understanding of political discussions on Twitter. Also, there is no reason to assume that opinions on Twitter accurately represent the distribution of American public opinion, and inferring one from another must be done with caution. Furthermore, only the most recent message that included a given keyword posted by a user was analyzed. This is a limitation of the study and the data collection tool. We may have captured one message with a political leaning, missing others with no political orientation. Acknowledging this limitation, one should also recall the rich literature in political science indicating the robustness of individuals' political attitudes and opinions (see, for example: Alwin & Krosnick, 1991). Another limitation is related to the categorization of messages as liberal or conservative, as it is a rather narrow way for conceptualizing ideology in messages. Future studies examining the different conversations within topics and clusters would add important insights for understanding political talk on Twitter. Another limitation derives from the decision to examine opinions presented only in the main clusters.

Further research should include network isolates – users who post messages with political content, but do not follow or are followed by others who post about that issue. This study included only Twitter users who linked to others who also participated in political talk, and did not include ‘‘read-only’’ users who may have consumed but did not create political content in Twitter. Further research should explore whether these ‘‘lurkers’’ are exposed to cross-ideological content on Twitter. Furthermore, following a person on Twitter does not mean that all messages will be read. Future studies, experimental or survey-based, could examine to what extent users actually read tweets posted by users they follow. Last, for data collection purposes, only keywords were used. No abbreviations, misspelling or hashtags were used. In part, this is a result of the automated data analysis. Future research can use pilot studies to identify common typos, abbreviations, and related hashtags, and include them in the data collection query.

Conclusions

Social networking sites and social media in general are becoming popular venues for political talk and interaction for individuals (Pew, 2009) and politicians (Williams & Gulati, 2007). Political talk on Twitter does not occur in a strictly political environment, and individuals create social ties based on a wide range of interests, not only based on political opinions. Political content, nonetheless, was overall confined to like-minded clusters of users. On Twitter, individuals may interact with others who do not share their political ideology. But, at least for the issues analyzed for this study, this potential does not lead to meaningful cross-ideological interaction.

Notes

1 Paper accepted for publication in *Journal of Computer-Mediated Communication*
2 Itai Himelboim is assistant professor and Stephen McCreery is a graduate student, both in the Department of Telecommunications at the University of Georgia at Athens. Marc Smith is a research sociologist at Connected Action Consulting Group.

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About the Authors

Itai Himelboim (itai@uga.edu; 120 Hooper St., Athens, GA, 30312) is an assistant professor in the Department of Telecommunications at the University of Georgia. His research interests include social media, network analysis and political communication.

Stephen McCreery (mccreery@uga.edu) is a graduate student in the Grady College of Journalism and Mass Communication at the University of Georgia. His research currently focuses on the portability of streaming mainstream video media and its effect on the consumer experience.

Marc Smith (marc@connectedaction.net) is Chief Social Scientist with Connected Action Consulting Group. His research focuses on the visualization of social media networks and computer-mediated collective action.