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Opinion Leadership on Gun Control in Social Networks: Preferential Attachment versus Reciprocal Linking

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ABSTRACT

This study involves a network analysis on Twitter discourse about gun control. In a test of competing models explaining social network dynamics, preferential attachment versus reciprocity, the latter received stronger support for the data set as a whole. Outdegree centrality at Time 1 was more closely correlated with degree centrality at Time 2 than was indegree centrality at Time 1. However, at the earliest stages of network formation, indegree centrality was the stronger force. The study further explores the process of opinion leader evolution and changes in group views on the issue of gun control.

KEYWORDS: network analysis, gun control, preferential attachment, reciprocal linking, Twitter, social media, social networking

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Introduction

On any given topic of discussion, opinion leaders will play an important role. This was true decades ago (Lazarsfeld, Berelson, & Gaudet, 1948) and remains so. Most research on opinion leadership has focused on individual traits as the causal mechanism but social media provides us with data to examine network dynamics which may also contribute. That mapping of social network connections will reveal a relatively small number of centralized vertices and a far greater number of loosely connected ones is well established. Less well understood are the dynamics of linking that lead certain voices to prominence and leave others on the periphery. In the context of an online social network, how are users connected and how does one rise to a position of influence? How does one become an opinion leader on a topic?

This study focused on one public policy issue, gun violence, and one online social network, Twitter, to examine these questions. During the summer of 2012 a series of lone gunmen made news in cities across the U.S. Nearly a hundred people were injured in four separate incidents and 22 people died including three of the gunmen. Although media coverage primarily focused on the shooters, their victims and, to a lesser extent, the issue of mental illness, some social media users were talking about gun control policy. By capturing that discourse and subjecting it to social network analysis we could test competing models of network formation and elucidate the process of opinion leadership online.

Research Literature and Theoretical Framework

Social Networks. The so-called Web 2.0 era, now at least a decade old, is epitomized by social media. Among the most popular platforms are Facebook, YouTube and Twitter. The latter has emerged as a popular platform for discussion of current events. In addition to millions of citizens around the world, Twitter is used by celebrities, comedians, and politicians, including President Obama (Marinucci, 2011). The platform's popularity is driven in part by short messages (a 140 character maximum) which are easy to read on phones and other small devices and by the first-person style of writing (Arceneaux & Weiss, 2010; Fox, Zickuhr, & Smith, 2009).

Researchers have categorized Twitter users as either one-way communicators or interactive users (Lai, Boase, & Naaman, 2010). The first type send messages "to the world" (or their followers) rather than as a direct response to someone else (Webster, 2011). This reflects Twitter's popularity as a publicity tool (Greer & Ferguson, 2011). Other Twitter users quickly created means of engaging others such as the hashtag (Segerberg & Bennett, 2011). Hashtags, or words prefixed by the hash symbol (#), are keywords used by Twitter users who share a common interest to refer to a particular topic. In July 2009, Twitter started to hyperlink all hashtags to facilitate searches containing them. Hashtags are not case sensitive and cannot contain spaces. Hashtags are topic-specific and refer to one, or a few facets of a word. For example a search for "democratic" will return all tweets that include the string "democratic," such as "a democratic system of government;" whereas a search for "#democratic" only returns results related to the Democratic Party. Hashtags are a community-driven convention for adding context and metadata (Chaudhry, Glode, Gillman, & Miller, 2012).

Since hashtags are created by users, they are not regulated. This often results in creation of competing hashtags for many popular topics, e.g. "#dem," "#dems," and "#democrats" are a few hashtags competing with "#democratic." However, some of these hashtags are used significantly more than others. A tweet may contain many of these hashtags. Hashtags may be used to aggregate, organize, and discover relevant tweets (Dizon, Thompson, Graham, Johnson, & Fisch, 2012). These features justify the use of hashtags as search queries. In this study the hashtag #guncontrol was used identify a population of Twitter messages and users.

Another means of connecting with other users in Twitter is by replying to any message. This prefixes an "at" symbol to the original messengers Twitter name (such as @BarackObama) and includes it in your response. This type of address in a Twitter message is also referred to as a "mention" and multiple @mentions can be used in any message (Twitter, 2012). In this study the @mentions are used to define directional links to other users; the users themselves are the nodes for the network analysis.

As with most networks, hubs will emerge for any given topic of conversation on Twitter. But the precise mechanism of link formation in a social network is the subject of debate in the research literature.

***Network Dynamics and Linking Patterns*.** As networks grow and evolve the connections between nodes in the network change. In the Twittersphere, these connections have been described as "cross-cutting network mechanisms" (Segerberg & Bennett, 2011, p. 201) because they rely not on a reciprocal action (such as "friending") but on shared interest in an idea. New entrants to a discussion will form links with others using @mentions and the resultant structure is likely to follow a power law. This pattern was established for links on the Internet by a number of researchers (Barabasi, 2002; Barabasi & Albert, 1999; D. Watts, 1999). Barabasi and Albert (1999) found that older nodes in a network are more likely to have collected links than ones more recently added. In this way, network *growth* favors nodes that have been around the longest. Secondly, they proposed that later joining nodes will prefer to attach to well-connected nodes, i.e., the *preferential attachment* principle. The resulting heavily skewed distribution has been found in discussion groups (Ravid & Rafaeli, 2004), collaborative tagging systems (Golder & Huberman, 2006), in the political blogosphere (Tremayne, Zheng, Lee, & Jeong, 2006), and in reader recommendation sites such as Digg (Halavais, 2009).

But the preferential attachment principle has been challenged. Kim and Jo (2010, p. 376) state "a logical justification for the assumption of preferential attachment is lacking. No explanation is provided for why people prefer to attach to their links to others who have more links." Likewise Faraj and Johnson (2011) found that reciprocal exchange, not preferential attachment, explained the power distribution they found in an online community. In that case individuals were not seeking connections with prominent community members but posing questions which some well-connected members chose to answer, thus forming a tie. Further, the researchers actually found a tendency *away* from preferential attachment.

Based on this competing model of social network formation, we offer this pair of hypotheses to test via network analysis:

H1a: Indegree centrality at Time 1 rather than outdegree centrality will be more highly correlated with degree centrality[1] at Time 2.

H1b: Outdegree centrality at Time 1 rather than indegree centrality will

be more highly correlated with degree centrality at Time 2.

If the preferential attachment model is correct then Twitter users are initiating contacts via @mentions with prominent #guncontrol participants and indegree centrality at Time 1 ought to correlate with degree central at Time 2. But if the reciprocity model is correct, then outdegree centrality at Time 1 ought to provide the stronger correlation.

The Power of Social Networks. There is considerable debate over the power of social networks such as Twitter to change opinions and build popular movements. On the side of strong technological determinism are those who believe in the so-called Twitter revolutions of the last few years: Moldova in 2009, the Iranian elections protests of 2009-2010, the Tunisian revolution of 2010-2011, the Egyptian revolution of 2011 and most recently, the Occupy Wall Street protests taking place in the fall of 2011 in cities around the globe. Of Tunisia, for example, some were ready to attribute the revolution there to Twitter (Zuckerman, 2011). Others consider this view to be far too Internet-centric (Morozov, 2011).

Whether Twitter contributed to the demonstrations mentioned above or merely reflected a broader movement, there appeared to be a correlation. If the series of gun crimes in the summer of 2012 sparked a dialogue on Twitter we might expect to see an upward trend in #guncontrol messages.

RQ1: Does a gun control conversation build in size over the period of study?

We are also interested in opinion leader formation in online networks. The term "opinion leader" was originally developed by Paul F. Lazarsfeld and his colleagues during their study of the 1940 presidential election (Rogers & Cartano, 1962). Lazarsfeld et al. (1948) found that ideas can flow from media to opinion leaders and then to lower information citizens. A similar process occurs online with opinion leaders acting as filters and amplifiers of news (Himelboim, Gleave, & Smith, 2009).

Research on opinion leaders has focused largely on cognitive attributes. Opinion leaders were found to be more innovative than non-leaders (Gatignon & Robertson, 1985; Katz, 1957; Myers & Robertson 1972) and to have greater knowledge and interest than others in their communities, based on self reports. Opinion leaders are more willing to voice their views in group situations and to evaluate other people's opinions than non-leaders (Tsang & Zhou, 2005). Tsang and Zhou found that the psychographic characteristics of opinion leaders in offline communities are also present in online leaders.

But prominent online voices may not replicate offline realities. Instead of mimicking one's offline social network, social networks such as Twitter can bring together people with different backgrounds and geographic locations. The introduction of new connection mechanisms (hashtags for instance) can reorganize a network in ways previous structures would not have (Foot & Schneider, 2006; Latour, 2005; Raban, Ronen, & Guy, 2011). One example of opinion leader formation is the reader-to-leader model (Preece & Shneiderman, 2009). Users begin primarily as *readers*, actively seeking information. Some connect with others and begin collaborations until, eventually, a few become organizers or *leaders* of a movement.

Watts and Dodds (2007) offered an alternative to the idea of opinion leaders as influencers. They found that the process is more grassroots; that a critical mass of "easily influenced" individuals must exist before opinion leaders can emerge.

For the issue of gun control discourse on Twitter we asked two questions related to the process of opinion formation and leadership:

RQ2: Are pro-gun control voices or anti-gun control voices more represented in the sample and are these ratios consistent?

RQ3: How stable is opinion leadership on gun control over time?

Methodology

A longitudinal network analysis of Twitter users who used the hashtag #guncontrol during the summer of 2012 was the primary method used to test the hypotheses and answer the research questions. Traditional content analysis was also employed to code messages as positive, negative or neutral toward gun control.

Data collection. We collected Twitter data over a three-month period which encompassed four high-profile shooting incidents in 2012. The crimes are described briefly here:

1) *Aurora mass shooting*. Just after midnight on July 20, 2012, a gunman shot 70 people attending a Batman movie in an Aurora, Colorado theatre. He used several weapons including a semi-automatic rifle. Twelve of the victims died.

2) *Wisconsin Sikh temple mass shooting.* On August 5, 2012, a gunman shot ten people at a Sikh temple in Oak Creek, Wisconsin before taking his own life. The gunman had been involved with several white supremacist groups. Four of the shooting victims died.

3) *Shooting near Texas A&M University.* A gunman shot 6 people before taking his own life on August 13, 2012. Two of the victims, a constable and another bystander, died from their injuries.

4) *Empire State Building shooting.* On August 24, 2012, a gunman killed a former coworker on the sidewalk outside the Empire State Building before police shot and killed him. Nine bystanders were injured in the police crossfire.

Each of the stories received considerable national media attention and the period was judged by the authors to provide a sufficient quantity of social media content for longitudinal network analysis. The study period ran from June 19, 2012 through September 20, 2012, about a month before the first and nearly a month after the last shooting incident described above. These before and after periods were used to gauge levels of Twitter discourse and allow for comparison.

The content population. Social media messages about possible public policy response to the shooting incidents were the central interest of this study. After searching for various hashtags, several gun related hashtags relevant to public policy were discovered. Other gun-related hashtags such as #guns and #NRA were popular but not directly related to public policy discussions. Searches were conducted for the three days during and after the Aurora shooting to determine which hashtag to follow. Those results appear in Table 1.

Table 1

Gun Policy Hashtags during Aurora Shooting

Hashtag	Results (7/20)	Results (7/21)	Results (7/22)	3-day total
#GunControl	4773	1597	1831	8201
#GunRegistry	52	50	46	148
#GunLaws	233	176	150	559
#GunRights	156	146	123	425
#2ndAmmendment	47	24	30	101

Because #guncontrol was by far the most widely used public policy related hashtag concerning guns, it was selected to represent the content population.

Sampling. This study is based on data collected using PeopleBrowsr's research.ly service (http://rs.peoplebrowsr.com/). Twitter's official search engine was not used because it only returns "up to a max of roughly 1,500 results"[2] for each query. PeopleBrowsr, on the other hand, has been "collecting every tweet since 2008"[3] and allows access to the entire body of tweets generated within the most recent 1,000 days.

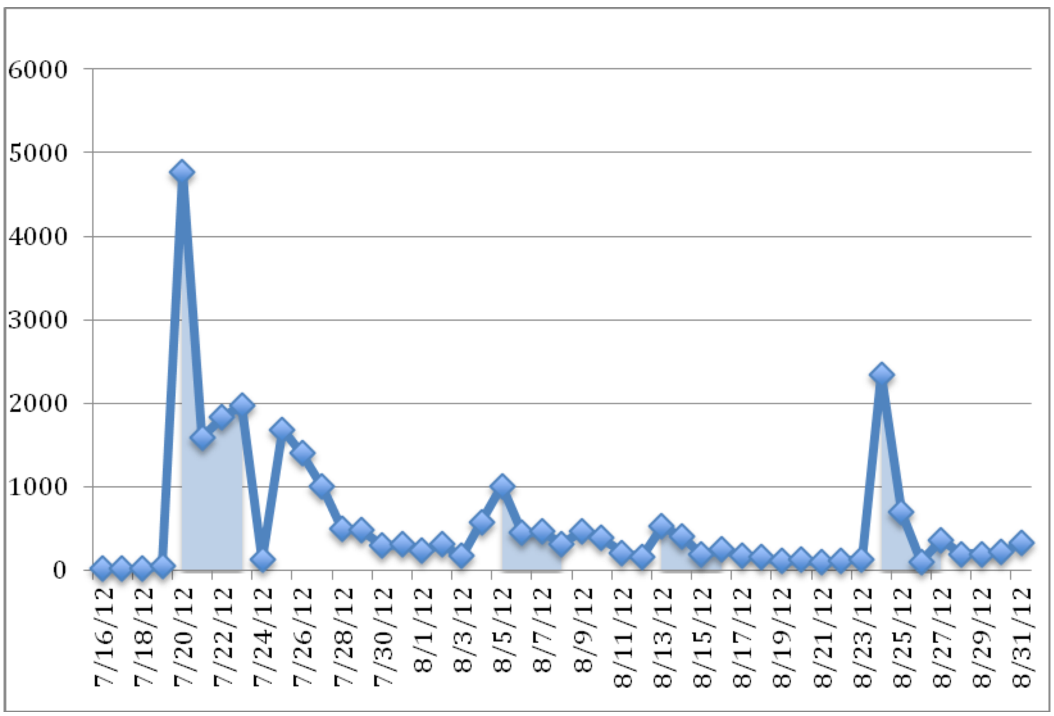
Research.ly allows users to search for older tweets by specifying the number of days they want to go back in time (up to 1,000 days) from the date they conduct the search. For example, on September 10, to retrieve tweets generated on June 19, "#GunControl" was entered in the search box and number 83 was entered in the "days ago" box; for tweets generated on June 20, number 82 was entered, etc.

Tweets returned by research.ly do not have time and date stamps. To independently verify the dates, tweets had to be found on the tweeter's page on Twitter.com. To that end, tweets were randomly selected on each day and the page of the user generating them was visited. However, there were some limitations to the random selection method. First, twitter only archives the last 3,500 tweets generated by each user and not all tweets were still available at the time of the search; second, some users lock their page and grant access only to their followers; and third, on occasions, some accounts are suspended by twitter. Whenever the randomly selected tweet could not be found on twitter, the tweet immediately following the randomly selected tweet was used for verification purposes.

Following the verification process, tweets from each day were downloaded into a separate html file. Forty-three files containing 33,528 tweets that mention the phrase "#GunControl" made up the population of this study. The population represents all the tweets containing "#GunControl" in the three-month period between June 19 and September 20. Figure 1 below depicts the distribution of these messages over the summer of 2012.

Figure 1:

Distribution of Twitter Messages during Study Period



A subsample from this group was selected for manual coding via systematic sampling. Every 21st tweet was selected with a starting point selected via a random number generator (http://www.random.org).

Coding. Tweets were coded as pro-gun control (+1) and anti-gun control (-1) based on the content of the tweet as opposed to stance of the tweeter. They were coded as neutral (0) if they could not be classified under either category.

A tweet was coded pro-gun control if: 1) content explicitly stated the stance as pro-gun control; 2) the stance could be inferred from the context; 3) a link in the tweet led to explicitly pro-gun control content; 4) the content stated a negative aspect of gun-ownership or made a sarcastic or ironic remark about gun-ownership or pro-gun slogans; 5) requests for more gun-control; or 6) it contained only pro-gun control hashtags.

A tweet was coded as anti-gun control if: 1) content explicitly stated the stance as pro-gun ownership or anti-gun control; 2) it could be inferred from the context; 3) a link in the tweet led to pro-gun or anti-gun control content; 4) sarcastic or ironic remarks about gun control and pro-gun control slogans; 5) retweets of or actions urged by anti-gun control activist or opinion leader; 6) urging officials to uphold second amendment and oppose gun control; or 7) only pro-gun ownership and anti-gun control hashtags were used.

Reliability. A subsample of 100 tweets was independently coded for stance (pro-, anti- and neutral) by each author. This variable was reliable with a Scott's pi of 0.83.

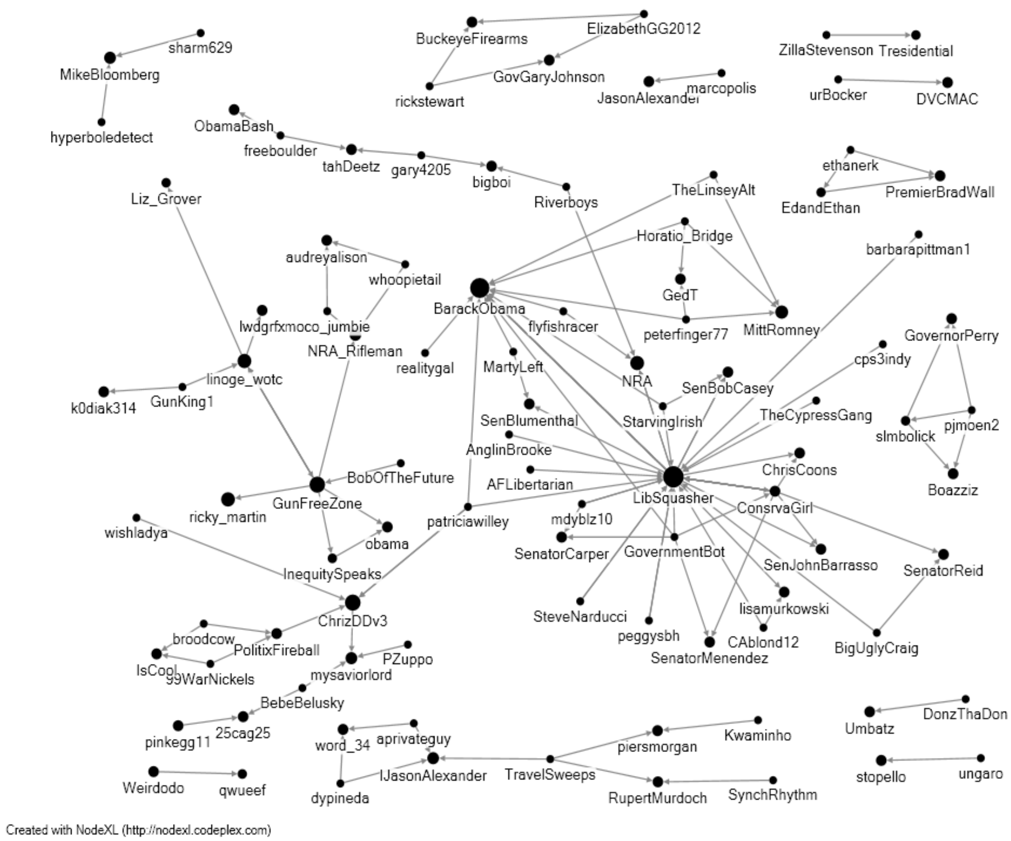
Results & Analysis

The sampling procedure described above yielded 1,577 individual Twitter messages spread over the 3-month study period. Although sampling was systematic the volume of messages found each day varied considerably depending on proximity to recent national shooting stories. The four crimes generated spikes in the use of #guncontrol on Twitter. On the day of each shooting incident, a significant increase was observed in the number of tweets generated containing "#GunControl". After a few days the conversation returned to equilibrium. With some variance, the pattern is observed for all four shooting instances. Given that the spikes for each incident lasted four days at most, the sample was broken up into nine temporal clusters: Four 4-day periods representing the day of each shooting and the following three days, and five periods of before, after, and between the shooting incidents (see Figure 1 for a graphic depiction of these periods). The tweet totals for the nine periods were, in order, 61, 488, 330, 111, 59, 67, 47, 137 and 277.

Hypotheses testing. To test the competing pair of hypotheses, Twitter messages in each of the nine time periods were subjected to network analysis using the Social Media Research Foundation's NodeXL software (Smith et al., 2010). By plotting connections between the messages via @mentions, networks for each period were created along with measures of degree centrality for each node (see Figure 2 for an example of the clusters plotted the Aurora period). These centrality measures were then normalized to account for the different network sizes in each time period. All nodes which appeared in two adjacent time periods were collected, 119 such pairs in all. The Pearson correlation (one-tail) of indegree centrality at Time 1 and degree centrality at Time 2 was 0.295, $p=.001$, a significant correlation. The correlation (one-tail) of outdegree centrality at Time1 and degree centrality at Time2 was 0.684, $p<.001$, also a significant correlation.

Figure 2

Graph of Period 2 Clusters



*Graph depicts nodes with degree centrality 2 or higher. Unconnected nodes removed.

Both indegree and outdegree centrality at Time 1 were correlated with degree centrality at Time 2. The correlation with outdegree was much stronger. Sending out Twitter #guncontrol messages with @mentions was more important to subsequent network centrality than receiving @mentions in earlier time periods. This finding lends support to H1b but not to H1a.

Additional analysis on this issue complicates the picture, however. Repeating the above process for each pair of time periods yields a changing pattern of indegree and outdegree importance as the #guncontrol conversation evolved during the summer of 2012. See Table 2.

Table 2

Correlations with Degree Centrality Time 2

Periods	Indegree Time 1	Outdegree Time 1
1-2	.806***	.582*
2-3	.748***	.487***
3-4	.415*	.605**
4-5	.739***	.957***
5-6,6-7,7-8,8-9[4]	-.186	.640***

Note: * significant at p<.05, ** significant at p<.01, *** significant at p<.001

The strength of the association between centrality measures at Time 1 and centrality at Time 2 changes during the duration of the study. The indegree centrality of a node in the first period, the month before the Aurora shooting, is more strongly associated with that node's centrality during the second period (the four days during and after Aurora) than the outdegree centrality. That pattern holds for the next pair of adjacent time periods as well. But starting with the 3-4 time periods, encompassing the Sikh Temple shooting and the aftermath, and continuing for the duration of the study, the strength of outdegree centrality grows and indegree centrality diminishes. A possible explanation for this pattern is taken up in the discussion.

Research Question Results. The authors were interested to see if the occurrence of four high-profile gun stories in the summer of 2012 would translate into a sustained and growing conversation about gun control policy on Twitter. Further, we sought to understand who the opinion leaders were, the ratio of pro- to anti- gun control voices, and whether those opinion leaders and ratios were stable over the duration of the study. Table 3 below show the message totals for each time period. What is clear from Table 3 (and particularly Figure 1, earlier) is that each shooting incident led to a temporary spike in #guncontrol messages. The highest peak came during the Aurora shooting (period 2) with 488 sampled tweets. The next shooting incident generated 111 messages in the sample, followed by 67 for the third incident and 137 for the fourth. Based on these peaks (all 4-day periods), there was no upward linear trend and the answer to RQ1 appears to be "no."

Table 3

Pro- and Anti- Gun Control Sampled Tweets by Period

		Pro-gun control	Anti-gun control	Undetermined	All tweets
Period 1	(31days)	8	40	13	61
*Period 2	(4 days)	193	248	47	488
Period 3	(12 days)	87	200	43	330
*Period 4	(4 days)	69	33	9	111
Period 5	(4 days)	36	13	10	59
*Period 6	(4 days)	29	26	12	67
Period 7	(7 days)	10	20	17	47
*Period 8	(4 days)	68	35	34	137
Period 9	(24 days)	60	183	34	277
Total	3 months	560	798	219	1,577

*** Shooting incident periods**

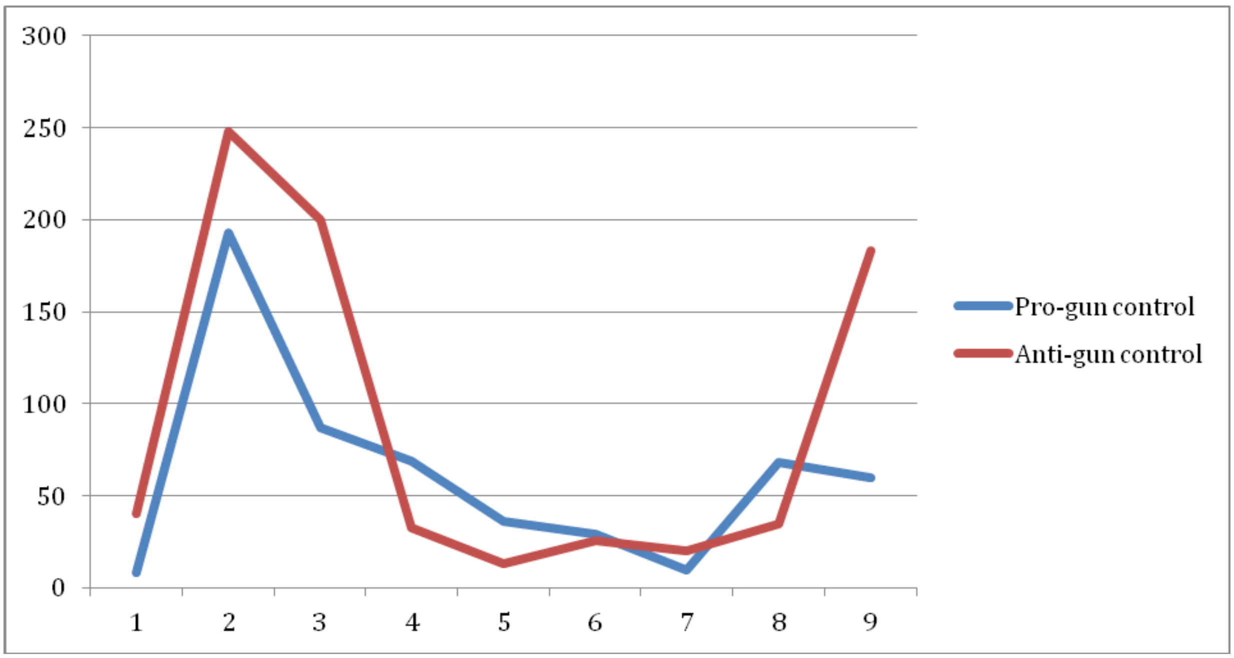
Another way to address the question is to look at the valleys between the peaks. A consistent pattern linear pattern is not discernible by this approach either. In tweets per day, period 1 was 1.97, period 3 was 27.50, period 5 was 14.75, period 7 was 6.71 and period 9 was 11.54 tweets per day. However, there was a substantial increase from the first period to the last. Caution is due when evaluating that final period, though, as it encompassed the 2012 Republican and Democratic National Conventions. Political discussions on Twitter were likely higher across all topics during this time. Although gun control was not a major topic of the 2012 presidential campaign, it was discussed during the RNC. To conclude, rather than growing consistently over the summer, the #guncontrol topic experienced short-term spikes before returning to an equilibrium state.

The second research question concerns the ratio of pro- and anti- gun control messages. The raw numbers are shown in Table 3. Anti-gun control messages account for 50.6% and pro-gun control messages were 35.5%. The remaining messages were coded as neutral. This ratio, approximately 10 anti-gun control messages for every 7 pro-gun control messages was not consistent over the summer. In period 1, the month of messages prior to the Aurora shooting, the #guncontrol conversation was dominated by anti-gun control (or pro-second amendment) voices. Just 13% of messages were pro-gun control. During the second period, the shooting in Aurora, that number rose to 40%. It fell back down to 25% during period 3 but rose to a majority, 62%, during period 4 (Sikh Temple shooting) and held steady at 61% during period 5. Pro-gun control messages were 43% during period 6 (shooting near Texas A&M) and declined to 21% during period 7. During period 8 (Empire State shooting) pro-gun control was at 50% and settled to

22% during period 9. The pattern was clear. In the days surrounding a major shooting story, gun control conversations on Twitter were evenly represented with 49% of messages pro-gun control and the rest either anti-gun control or neutral. During the periods before, after or in between, anti-gun control voices dominated; only 28%, average, were pro-gun control. See Figure 3. In answer to research question two: anti-gun control voices dominated except in the days immediately after a shooting when opinions were more evenly divided.

Figure 3

Pro- and Anti- Gun Control over Time



Research question 3 concerns the opinion leaders on #guncontrol and their stability over time. Table 4 lists the top five hubs in each of the nine time periods.

Table 4

Top 5 Vertices by Degree Centrality Rank and Period

Period	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
1	linoge-wotc	GoTimothy*	DVCMAC	jimpook	BillyRedFlower
2	LibSquasher	GunFreeZone	linoge-wotc	BarackObama	ChrizDDv3
3	BarackObama	linoge-wotc	RichardRS	ladyravens	LibSquasher
4	LipstickLibShow *	linoge-wotc	gvbowles	Lastmangoinfla *	OHIO4OBAMA *

5	LipstickLibShow*	linoge-wotc	EricBoehlert*	Implowshun*	UCguns
6	linoge-wotc	LTVConservative	k0diak314	UCguns	Weirdodo
7	linoge-wotc	urbocker	HuffingtonPost*	JustGoodNfo	DVCMAC
8	Mapsofworld	GunFreeZone	linoge-wotc	Disarm*	UCguns
9	chaotixjoe	linoge-wotc	DVCMAC	Weirdodo	UCguns

* Denotes pro-gun control opinion leader

The most dominant hub in the #guncontrol network is @linoge_wotc, whose Twitter page displays numerous gun images and the slogan "Defending individual rights, one weblog post at a time." This Twitter user appeared in all 9 time periods and was in the top 3 hubs by degree centrality and the top hub overall for the network. Other anti-gun control writers who appeared as central nodes multiple times were DVCMAC, LibSquasher and GunFreeZone.

During the first 3 time periods only one pro-gun control voice appeared as a top-five hub. It wasn't until the second shooting incident (period 4, the Sikh Temple shooting) that pro-gun control voices became more central. During both period 4 and 5 three of the top-five hubs were pro-gun control. The dominant hub during this period was @LipstickLibShow. This user is an actress/comedienne and self-described "lipstick liberal." Over the final four periods the hubs were predominantly anti-gun control; only 2 of the 20 hubs listed in Table 3 for these periods were pro-gun control.

Although pro-gun control voices became much more commonplace during the Aurora shooting none rose to a prominent network position at that time; their lack of indegree or outdegree centrality at period 1 kept them on the periphery during period 2. By period 4, however, some pro-gun control voices had gained position. Later joining users like @ListickLibShow were able to quickly gain attention via outdegree centrality. This also explains the shift described earlier from a network that favored indegree centrality initially to one that later favored outdegree centrality.

The answer to research question 3 is mixed: there is some stability evident in the prominence of a few anti-gun control voices over the entire 3-month study period. But there were moments, especially after high-profile crimes, when the network changed and new voices attained prominence.

Discussion and Conclusions

In the test of competing models explaining social network dynamics, preferential attachment versus reciprocity, the latter received stronger support for the data set as a whole. Outdegree centrality at Time 1 was more closely correlated with degree centrality at Time 2 than was indegree centrality at Time 1. However, at the earliest stages of the study period, before, during and immediately after the Aurora shooting, indegree centrality was more strongly associated with subsequent degree centrality. Twitter users who were prominent before that major story were more likely to acquire links (and maintain centrality) than those who were less prominent. However, as newer pro-gun control voices joined the discussion and sent @mentions, reciprocity became a stronger force from time periods 4 through 9.

The mix of pro- and anti- gun control views likewise changed over the period of study. Before and after each shooting incident the anti-gun control voices dominated but on the days encompassing the shootings many pro-gun control users joined the discussion to result in a more even mix of views. During the first and most prominent shooting (Aurora) the newly joining pro-gun control voices remained mostly on the periphery. It wasn't until the second shooting (Sikh Temple) that a pro-gun control voice (@LipstickLibShow) attained a dominant hub position. The delayed entrance into prominence could support the view of Watts and Dodds (2007) that opinion leaders are created by a mass of like-minded "followers" waiting to be led. Those like-minded users had appeared during period 2 but it was in period 4 that a leader emerged.

Unlike other Twitter movements like #OccupyWallStreet there does not appear to have been a growing #guncontrol clamor emerging during the summer of 2012. Not long after each shooting incident the Twitter conversations would return to a much lower level. Further research, however, may be able to distinguish network dynamics common to those online movements that do manage to grow into or along with real world activity.

Although not a central focus of this study, evidence of homophily – birds of a feather flock together – was evident in the data (Himelboim, McCreery, & Smith, 2013; McPherson, Smith-Lovin, & Cook, 2001; Meraz, 2009). Anti-gun control users were more likely to @mention other anti-gun control users and the same was true among the pro-gun control users. However, there was also evidence of interaction between the members of opposing camps. This was particularly true on the days of mass shooting incidents, when more pro-gun control users entered the discussions and the balance between the two sides was more even. In these periods a reverse spiral-of-silence process (Shamir, 1997) may have been occurring. A later incident – the mass shooting an elementary school in Newtown, Connecticut – likely continued the shifting of vocalized opinions evident in the summer of 2012.

Endnotes

1. Although degree centrality is more commonly used in undirected networks, we chose to use it as a combined measure of in- and out- degree centrality in this analysis in order to determine which component at Time 1 had more impact at Time 2.
2. According to Twitter's Developers page https://dev.twitter.com/docs/api/1/get/search
3. According to Andrew Grill, PeopleBrowsr's CEO of UK operations. http://blog.peoplebrowsr.com/category/peoplebrowsr-uk/
4. Last four adjacent periods collapsed due to fewer pairs per period

References

Arceneaux, N., & Weiss, A. S. (2010). Seems stupid until you try it: press coverage of Twitter, 2006-9. *New Media & Society, 12*(8), 1262-1279. doi: 10.1177/1461444809360773

Barabasi, A.-L. (2002). *Linked: The new science of networks*. Cambridge, Mass.: Perseus Publishing.

Barabasi, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*, 509-512.

Chaudhry, A., Glode, L. M., Gillman, M., & Miller, R. S. (2012). Trends in Twitter use by physicians at the American Society of Clinical Oncology annual meeting, 2010 and 2011. *Journal of Oncology Practice, 8*(3), 173-179. doi: 10.1200/JOP.2011.000483

Dizon, D. S., Thompson, M., Graham, D., Johnson, L., & Fisch, M. (2012). Practical guidance: the use of social media in oncology practice. *Journal of Oncology Practice, 8*(5), 114-124.

Faraj, S., & Johnson, S. L. (2011). Network exchange patterns in online Ccommunities. *Organization Science, 22*(6), 1464-1480. doi: 10.1287/orsc.1100.0600

Foot, K. A., & Schneider, S. M. (2006). Web campaigning. Cambridge, Mass.: MIT Press.

Fox, S., Zickuhr, K., & Smith, A. (2009). Twitter status updating, Fall 2009. *Pew Internet and American Life Project*. Retrieved from http://www.pewinternet.org/Reports/2009/17-Twitter-and-Status-Updating-Fall-2009.aspx

Gatignon , H., & Robertson, T. S. (1985). A propositional inventory for new diffusion research *Journal of Consumer Research, 11*, 849-867.

Golder, S. A., & Huberman, B. A. (2006). Usage patterns of collaborative tagging systems. *Journal of Information Science, 32*(2), 198-208. doi: 10.1177/0165551506062337

Greer, C. F., & Ferguson, D. A. (2011). Using Twitter for promotion and branding: A content analysis of local television Twitter sites. *Journal of Broadcasting & Electronic Media, 55*(2), 198-214. doi: 10.1080/08838151.2011.570824

Halavais, A. (2009). Do Dugg diggers Digg diligently? *Information, Communication & Society, 12*(3), 444-459. doi: 10.1080/13691180802660636

Himelboim, I., Gleave, E., & Smith, M. (2009). Discussion catalysts in online political discussions: Content importers and conversation starters. *Journal of Computer-Mediated Communication, 14*(4), 771-789. doi: 10.1111/j.1083-6101.2009.01470.x

Himelboim, I., McCreery, S., & Smith, M. (2013). Birds of a feather Tweet together: Integrating network and content analyses to examine cross-ideology exposure on Twitter. *Journal of Computer-Mediated Communication, 18*(2), 40-60. doi: 10.1111/jcc4.12001

Katz, E. (1957). The two-step flow of communication: An Up-To-Date Report on an Hypothesis. *The Public Opinion Quarterly, 21*(1), 61-78.

Kim, J. Y., & Jo, H. H. (2010). A signalling explanation for preferential attachment in the evolution of social networks. *Journal of Evolutionary Economics, 20*(3), 375-393. doi: 10.1007/s00191-009-0155-7

Lai, C.-H., Boase, J., & Naaman, M. (2010). Is it really all about me? Social awareness streams on Twitter. *Conference Papers -- International Communication Association*, 1.

Latour, B. (2005). Reassembling the social : an introduction to actor-network-theory (pp. x, 301 p.). Oxford ;New York: Oxford University Press.

Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1948). The people's choice; how the voter makes up his mind in a presidential campaign. New York: Columbia Univ. Press.

Marinucci, C. (2011, July 7). Obama's Twitter forum gets thousands of tweets, *San Francisco Chronicle*. Retrieved from http://www.sfgate.com/cgi-bin/article.cgi?f=/c/a/2011/07/06/MNQH1K72JL.DTL

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27*, 415-444.

Meraz, S. (2009). Is there an elite hold? Traditional media to social media agenda setting influence in blog networks. *Journal of Computer-Mediated Communication, 14*(3), 682-707. doi: 10.1111/j.1083-6101.2009.01458.x

Morozov, E. (2011). The net delusion: The dark side of Internet freedom. New York, NY: Public Affairs.

Myers , J. H., & Robertson , T. S. (1972). Dimensions of opinion leadership. *Journal of Marketing Research*(9), 41-46.

Preece, J., & Shneiderman, B. (2009). The Reader-to-Leader framework: Motivating technology-mediated social participation. *AIS Transactions on Human-Computer Interaction, 1*, 13-32.

Raban, D. R., Ronen, I., & Guy, I. (2011). Acting or reacting? Preferential attachment in a people-tagging system. *Journal of the American Society for Information Science and Technology, 62*(4), 738-747. doi: 10.1002/asi.21490

Ravid, G., & Rafaeli, S. (2004). Asynchronous discussion groups as small world and scale free networks. *First Monday, 9*(9), Retrieved from http://firstmonday.org/article/view/1170/1090

Rogers, E. M., & Cartano, D. G. (1962). Methods of measuring opinion leadership. *American Association for Public Opinion Research, 26*(3), 435-441.

Segerberg, A., & Bennett, W. L. (2011). Social media and the organization of collective action: Using Twitter to explore the ecologies of two climate change protests. *Communication Review, 14*(3), 197-215. doi: 10.1080/10714421.2011.597250

Shamir, J. (1997). Speaking up and silencing out in face of a changing climate of opinion. *Journalism & Mass Communication Quarterly, 74*(3), 602-614.

Smith, M., Shneiderman, B., Milic-Frayling, N., Rodrigues, E. M., Leskovec, J., & Dunne, C. (2010). NodeXL: a free and open network overview, discovery and exploration add-in for Excel 2007/2010, http://nodexl.codeplex.com/ from the Social Media Research Foundation. Retrieved from http://nodexl.codeplex.com/ website: http://nodexl.codeplex.com/

Tremayne, M., Zheng, N., Lee, J. K., & Jeong, J. (2006). Issue publics on the Web: Applying network theory to the war blogosphere. *Journal of Computer-Mediated Communication, 12*(1), available: http://jcmc.indiana.edu/vol12/issue11/.

Tsang, A. S. L., & Zhou, N. (2005). Newsgroup participants as opinion leaders and seekers in online and offline communication environments. *Journal of Business Research, 25*, 1186-1193.

Twitter. (2012). What are @Replies and @Mentions? Retrieved from http://support.twitter.com/articles/14023

Watts, D. (1999). Networks, dynamics, and the small-world phenomenon. *The American Journal of Sociology, 105*(2), 493-527.

Watts, D. J., & Dodds, P. S. (2007). Influentials, networks, and public opinion formation. [Review]. *Journal of Consumer Research, 34*(4), 441-458. doi: 10.1086/518527

Webster, T. (2011). Twitter awareness nearly universal; Usage shows slight growth. *Edison Research*. Retrieved from Edison Research website: http://www.edisonresearch.com/home/archives/2011/03/twitter_awareness_nearly_universal__usage_growth_slows.php

Zuckerman, E. (2011). The first Twitter revolution. *Foreign Policy*. Retrieved from http://www.foreignpolicy.com/articles/2011/01/14/the_first_twitter_revolution