The Thesis Committee for Jin Wu
Certifies that this is the approved version of the following thesis:

A Social Network Analysis of Edward Snowden and the Diffusion of Different Media Frames

APPROVED BY
SUPERVISING COMMITTEE:

Supervisor: ______________________________
Lucinda Jane Atkinson

____
Robert Joel Lewis

A Social Network Analysis of Edward Snowden and the Diffusion of Different Media Frames

by

Jin Wu, B.A.

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Abstract

A Social Network Analysis of Edward Snowden and the Diffusion of Different Media Frames

Jin Wu, M.A.

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Supervisor: Lucinda Jane Atkinson

This paper provides insights on how five different frames of the Edward Snowden issue (Hero, Patriot, Traitor, Whistleblower, Dissident) have been diffused on the Twitter platform. This study uses *NodeXL* to collect, analyze and visualize all the tweets including the keyword "Edward Snowden" from February 17 to April 10, 2014 to examine the flow of information and the interaction between opinion leaders along with the characteristics of opinion leaders in this specific issue. Findings provide insight about future strategic communication for general branding and public image maintenance.

Keywords: Edward Snowden; Social Network Analysis (SNA), framing, visualization, Twitter, opinion leadership

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Chapter One: *Introduction*

On June 5, 2013, former Central Intelligence Agency (CIA) agent and former National Security Agency (NSA) contractor Edward Joseph Snowden disclosed top secret documents to media outlets, revealing details of Internet surveillance programs such as PRISM, XKeyscore and Tempora, as well as the interception of US and European telephone metadata (Glenn Greenwald, 2013). He leaked the documents to *The Guardian* and *The Washington Post* while he was still employed by NSA. After flying to Hong Kong on May 20, 2013, he met journalists Glenn Greenwald and Laura Poitras and also released copies to them (Glenn Greenwald, 2013).

Snowden's motivation for leaking the documents was, in his words, "to inform the public as to that which is done in their name and that which is done against them" (Glenn Greenwald, Ewen MacAskill, and Laura Poitras 2013). A subject of controversy, Snowden has been variously linked with various words including "Hero" (The Guardian 2013, The New Yorker 2013), "Whistleblower" (The New York Times 2013, Huffington Post 2013), "Dissident" (RBC Daily 2013), "Traitor" (San Francisco Chronicle 2013, Voice of America 2013), and "Patriot" (The Washington Post 2013, Politico.Com 2013). A nationwide debate about the Snowden issue lasted for several months both online and offline. Therefore, from the perspective of communication, it would be interesting to understand how these different frames influence citizens' engagement with this topic. Moreover, with the development of the Twitter platform, it would be valuable to understand how users interact with each other on this new media platform.

FRAMING THEORY

Public opinion plays a vital role. "It determines who wins elections, plays a significant role in shaping public policy, and influences the views of elected officials" (Druckman and Jacobs 2009). Therefore, it is not surprising that politicians, policy advocates, media outlets, and other interest groups put much effort to shape people's opinions and attitudes. During this process, framing matters.

Agenda Setting and Framing

There has been continuous debate that if agenda setting and framing theories are "distinct theoretical paradigms" or simply "linguistic distinctions without difference" (Chong and Wolinsky-Nahmias, 2003). Agenda-setting is "produced by repetition at the level of media texts, and accessibility at the level of audience reception" (Edy and Meirick, 2007). Essentially, it suggests that the more the media coverage an issue gets, the more noticeable that issue is for the public, and leads to higher possibility of that issue being discussed during a person's decision making process (Price, Tewksbury et al, 1997). Once an issue is made salient, it plays a larger and more vital role when people evaluate the information they receive (Iyengar and Kinder 2010).

When it comes to framing, some researchers argue that "it is no more than second-level agenda setting" that makes "aspects of the issue salient with the same mechanism" (Baumgartner, Hwang et al. 1993). McCombs, Llamas, Lopez-Escobar and Rey suggest that framing and second-level agenda setting are basically the same: "To frame is to select some aspects of a perceived reality and make them more salient in a communicating text" (McCombs, Llamas et al. 1997).

In Entman's words,

> Frames define problems—determine what a causal agent is doing with what costs and benefits, usually measured in terms of common cultural values; diagnose causes—identify the forces creating the problem; make moral judgments— evaluate causal agents and their effects; and suggest remedies—offer and justify treatments for the problems and predict their likely effects. (1993)

In general, communication researchers and political scientists use the term ''frame'' in two distinctive ways (Druckman 2001): communication/media frame; and individual frame. First of all, a communication frame or a media frame refers to "the words, images, phrases, and presentation styles that a speaker (e.g., a media outlet) uses when releasing information about an issue or event to an audience" (Gamson and Modigliani, 1989). The frame chosen by the speaker reveals what he/she sees as relevant and important to the topic. Second, a frame in thought or an individual frame represents an individual's cognitive understanding of a specific situation (Goffman, 1974).

This paper will focus on the first – the communication/media frame. By emphasizing certain information that verifies one's own opinion, opinion leaders promote their frames in various media outlets and try to make their own opinions most powerful and persuasive (Chong and Wolinsky-Nahmias, 2003). The goal of this media framing strategy is to shape the way people think about an issue and, ultimately, to lead public opinion (Scheufele, 1999).

Public opinion often depends on how opinion leaders choose to frame issues (Chong and Druckman, 2007). The literature on news framing indicates that "individuals make judgments and process new information within certain frames of reference that help them reduce the complexity of political issues" (Sherif, 1967). However, much of these works were based on experiments that constituted an ideal experimental environment in which to study framing influence because in those cases the researcher could control the messages to which individuals were exposed and could prevent people from self-selecting messages (Nelson, Bryner, et al., 2011).

Social Network Analysis and Graph Theory

A social network is defined as a social structure that consists of social players and the ties between these players (Wasserman 1994) that help researchers to understand the relationships between individuals, groups, organizations, and even countries. Social Network Analysis (SNA) is the analysis of social networks, which “views social relationships in terms of network theory, consisting of vertices and edges” (D'Andrea, Alessia et al, 2009). Studying social network is valuable when examining the broader picture of the message diffusion pattern and studying the value of individuals by evaluating the connections he/she gets (Scott and Carrington, 2011). Different messages have different diffusion paths (Denker, Garcia-Luna-Aceves, et al, 1999). Different people adopt different frames, which lead to different communication models.

In this research, graphs illustrate the results of SNA. Graphs can be used to model many types of relations and processes in physical, biological, social, and information systems (Mashaghi, Ramezanpour et al. 2004).

A graph is made up of two key elements: vertices and edges. Vertices, also called nodes, agents, entities, or items, represent things such as people, organizations, team, countries, or even keywords, etc (Smith, Shneiderman et al. 2009). This research defines the vertices as Twitter users. Adding attributes, such as number of followers and a Klout Score, to vertices could bring more insights to the network analysis by spotting influential users (Smith, Shneiderman et al. 2009).

Edges, also called links, ties, connections, and relationships, connect any two vertices together. An edge is any form of relationship or connection between any two vertices (Gross and Yellen 2004) such as citation, friendship, following, etc (Smith, Shneiderman et al, 2009). Edges may be directed or undirected. A directed one has a clear origin and destination. For instance, one Twitter user follows another Twitter user or a customer service person solves a customer’s problem. An undirected edge represents a simple relationship between any two vertices without clear starting point and destination. The relationship between two Facebook friends is an undirected one. In this research, in order to figure out the direction information flows, and to find the opinion leaders from observation, directed edges have been selected.

There are several hundred studies on opinion leadership that tried to identify the characteristics of opinion leadership (Rogers & Shoemaker, 1971). McCombs, Danielian, and Reese state in their intermediate agenda-setting theory that during the process of agenda-setting, media influence each other; media set the structure of the system in its entirety, as well as for each other (McCombs, 1989; Danielian and Reese, 1989). Therefore, the influence of media outlets on the opinions of citizens is not the only element to consider; there is also a connection that exists within the media networks. This is the “internal opinion leadership” in the media industry, which leads the framing of news content.

With the development of technology and Internet, more and more individuals get the power to influence others with their own opinions. They are the modern “opinion leaders.” During the information adoption process, opinion leaders play a vital role diffusing the message out (Richins & Root-Shaffer, 1988). They are the “agenda-setters” who are interested in influencing public opinions based on their interests (Mathes & Pfetsch, 1991). With the development of technology and new media, government and media outlets are no longer the only ones withholding the opinion leadership, more and more individuals become opinion leaders in various fields (Chan & Misra, 1990).

Although opinion leaders could influence each other, there is still a boundary for their influence. There is a tendency toward a certain amount of opinion leadership overlap across topics; however, generalized opinion leader across all areas seems not exist (Myers & Robertson, 1972). There are quite different opinion leaders in different fields.

Chapter Two: *Research Motivation and Objectives*

WHY THIS RESEARCH

Although literature on framing effectiveness by using experimental designs is rich, most studies are one-sided designs in which respondents were only assigned to one or two frames of the issue. Sniderman and Theriault (2004) stated that "framing studies have neglected the fact that frames are themselves contestable. They have instead restricted attention to situations in which citizens are artificially sequestered, restricted to hearing only one way of thinking about a political issue" (p. 145). Moreover, in the real world, people have different sources of information that provide different levels of persuasiveness, authority, and popularity. Pan and Kosicki (2001) aptly state that "resources are not distributed equally. Actors strategically cultivate their resources and translate them into framing power." Therefore, the process during which people actively seek information also should be taken into consideration. Unlike simply studying how assigned frames influenced respondents' responses, it may be valuable to examine how people take certain messages out of the overwhelming amount of information in a real world information search.

Moreover, unlike the manipulated conditions in experimental designs, in real world conditions, people actively seek information. Therefore, some people's frames are more likely to reach bigger audiences because of their popularity and authority. For example, when the message comes from a credible source (Druckman and Bolsen, 2011), it resonates with consensus values (Chong, 2000) and does not contradict strongly held prior beliefs, the frame gains more credibility (Haider-Markel and Joslyn, 2001; Druckman and Nelson, 2003: Himelboim, Smith et al, 2013). Therefore, it is a good complement to study framing effects by collecting real-world data.

Moreover, social media is increasingly home to civil society (Himelboim, Smith et al. 2013), providing users platforms for public discussions, debates, and information sharing. Therefore, conversations on social media platforms are as important as those on other traditional media channels. Another advantage of using social media networks conducting analysis would be the fact they provide the possibility for researchers to observe the spread of a certain message through which metrics like communication patterns, opinion leadership, and popularity of a certain frame can be observed.

Although there is a huge debate about the Edward Snowden issue, there is still no study about how people respond to its five different frames. Therefore, this paper examines how the presence of multiple competing frames affects the engagement of the audience by extracting real-world data addressing the Edward Snowden issue from the Twitter platform.

RESEARCH QUESTIONS AND HYPOTHESES

To explore more about the diffusion of the five frames on the Twitter platform, the research collects tweets with key word "Edward Snowden" and also separately collects tweets with key words "Edward Snowden" and any of the five frames: "Hero" (The Guardian 2013, The New Yorker 2013), "Whistleblower" (The New York Times 2013, Huffington Post 2013, Fox News 2013), "Dissident" (RBC Daily, 2013), "Traitor" (San Francisco Chronicle 2013, Voice of America 2013), or "Patriot" (The Washington Post 2013, Politico.com 2013), in order to create both a general diffusion network and specific networks for every frame. From these networks, it could be observed how different frames distribute within the general network: how many users are talking about this topic with these key words? Which frame gets the most tweets? Who are the opinion leaders (users that have most number of re-tweet/comment/mention)? How many re-tweet/comment/mention relationships existed surrounding these opinion leaders? Are there sub-groups based on keywords they use?

Research Question 1: Media outlets and opinion leaders have defined Edward Snowden in five different frames: Hero (The Guardian 2013;The New Yorker 2013); Whistleblower (The New York Times 2013; Huffington Post 2013;Fox News 2013); Dissident (RBC Daily 2013); Traitor (San Francisco Chronicle 2013;Voice of America 2013); and Patriot (The Washington Post 2013;Politico.Com 2013). How do these different frames distribute on Twitter? How do individual users respond to different frames on Twitter?

A variety of researcher discussed the influence opinion leaders have on people who seek information (Flynn, Goldsmith et al, 1996); however, little research examines the relationship among opinion leaders and the conduct of social network analysis. This study could provide some insight about this relationship. Based on the general network, it could be observed whether opinion leaders with different frames are connected to each other. Based on each specific frame network, it could be observed whether opinion leaders with the same frame connect with each other. The relationship between opinion leaders would raise insight on the values of partnership. If relationships do exist, then what kinds of opinion leaders connect with each other? Are they in the same field or not? In this research, by observing if there is edge linking each other, these connections could be illustrated via the graph illustration.

Research Question 2: What is the relationship between opinion leaders? Are they connected?

Twitter is a highly visible social media platform that can be used as a measure of influence and Klout is the most popular software utilized to calculate Twitter user influence (Anger and Kittl, 2011). In this paper, the general influence will be based on users' Klout score. Information source quality could be evaluated through reputation of the source and authority of it (Druckman, Fein, et al, 2012). Social media reputation refers to its public image (if it has the good reputation providing the true and valuable information) (Madden and Smith, 2010). Expertness refers to the field the user focuses on (if it has expertness on this topic and frame) (Maddux and Rogers, 1980). These criteria would be evaluated by examining a leader's Twitter profile. It is hypothesized that opinion leaders with different frames should have different profiles. For example, maybe opinion leaders who use the frame "hero" would be liberal, while opinion leaders use the frame "traitor" would be conservative. In the research, if a Twitter user re-tweets another user's tweet, or comments under it, or mentions the information source in the user's own tweets, then he/she is defined as engaged.

Hypothesis 1: Field related source quality (reputation, expertness) on specific topic is more important than the general influence (Klout Score) when engaging individual users to the issue.

Since this is a political issue, information sources have been categorized into two groups: government opinion leaders (NSA, American government, etc), and non-government opinion leaders (journalist, broadcaster, liberal activist, etc). If a Twitter user re-tweets another user's tweet, or comments under it, or mentions the information source in the users' own tweets, he/she is defined as paying attention to that piece of information.

Hypothesis 2: Individual users pay more attention to non-government opinion leaders' tweets than government opinion leaders' tweets.

Chapter Three: *Methodology*

Influence is defined as the power or capacity of causing an effect in indirect or intangible ways (Solis and Webber, 2012). There is a large amount of literature that examines theories of influence, but there is still no good solutions to measure influence in a tangible way (March, 1955). Now, Twitter has provided a great platform. All the Twitter data is publicly available; it has clear relationships established among various users, and its 140-word limitation makes the analysis more manageable. Therefore, Twitter has been utilized as a tool in this research, which can be regarded as a representation of 'influence.'

In this research, Social Network Analysis software *NodeXL* was used to extract Twitter data, conduct the following social network analysis, and visualize data sets. Twitter posts from February 17 to April 10, 2014 have been extracted by using the following key words: "Edward Snowden;" "Snowden;" "NSA;" "Snowden" + "hero;" "Snowden" + "traitor;" "Snowden" + "whistleblower;" "Snowden" + "patriot;" and "Snowden" + "dissident." This study collected and analyzed only publicly available information. Direct messages or other private content were excluded.

In this study, social network interactions were treated as a graph and graph metrics were used to describe importance within the network. There were two common visualization approaches. One was to illustrate the actors by vertices and connect two actors whenever they shared an interaction. Another one was a bipartite graph, which defined both actors and interactions as vertices and connecting actors with interactions (Ediger, Jiang et al, 2010). In this paper, the former representation connecting actors to actors was used. Twitter users (@XX) were illustrated as vertices, and interactions including any "re-tweet," "mention," and "comment" activities were illustrated as edges.

The analysis mainly addressed the size and structure of the network, and sub-groups based on various key words and hash-tags used. The results are illustrated via graphs, which highlight the opinion leaders and key words that drove conversations.

METRICS BEING MEASURED

Density

Density is “an aggregate network metric used to describe the level of interconnectedness of the vertices” (Hansen, Shneiderman et al, 2010). It is calculated by dividing number of edges observed in the network by total number of possible relationships that could be present (Smith, Shneiderman, et al. 2009). Different densities decided if the network was or sparse. If the network had a high density, that meant most of the components inside were connected.

Centrality

Centrality refers to “a group of metrics aim to quantify the ‘importance’ or ‘influence’ of a particular node (or group) within a network” (Smith, Shneiderman, et al, 2009; Tsvetovat and Kouznetsov, 2011). There are two kinds of Centrality. One is for the evaluation of the whole network. Centrality can tell if most of the users are connecting with one specific user. A highly centralized network has many edges emanating from several important vertices while a decentralized network has “little variation between the numbers of edges each vertex possesses” (Opsahl, Agneessens, et al, 2010). Another Centrality is a metric for each individual user within the network describing whether a particular vertex could be said to be in the “middle” of the network (Newman 2005). In this study, Between-ness Centrality, Degree Centrality, and Eigenvector Centrality have been measured to evaluate values of individual vertices.

Between-ness

Between-ness Centrality is a useful measurement for the importance of a vertex. It is calculated via counting the number of shortest paths from all vertices to all others that pass through this specific vertex (Freeman, 1977). Some vertices with average degree of centrality, but high between-ness centrality, are also important because they are the ones that connect the whole network together. Degree Centrality is measured through the number of links a vertex has. It consists of In-Degree, which represents the influence of a specific vertex, and Out-Degree, which represents the number of interactions including “comments,” “mentions,” and “re-tweets” that each tweet of a vertex has. Out-Degree also represents number of ties that the vertex directs to others. In this research, it would be the number of tweets that the vertex re-tweets from others or the number of comments and mentions this vertex include in his/her tweets.

Chapter Four: *Results*

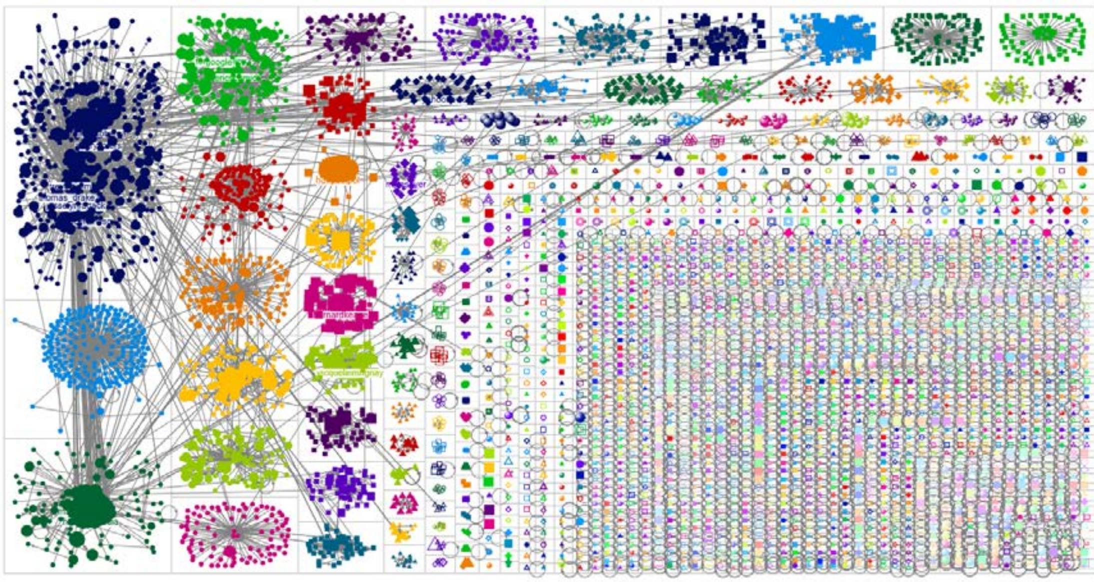
After collecting all the Twitter data, in order to get a clear picture about the distribution of the messages, data sets have been grouped into clusters. *NodeXL* provides three of the clustering algorithms from the Stanford Network Analysis Platform (SNAP) library for calculating network metrics from graphs (Marc Smith, 2011), which are the Wakita-and-Tsurumi algorithm, the Girvan-Newman algorithm, and Clauset-Newman-Moore algorithm. These algorithms all try to place densely connected vertices into different groups.

Although the Clauset-Newman-Moore algorithm is the first to be proposed to find community structure in social networks, it is limited to the number of nodes within the network and it would take a long time to move forward with the analysis. The Girvan-Newman algorithm focuses more on edges that are most likely between different communities instead of trying to create a measure that tells which edges are the most central within communities. In short, it pays more attention on "between-ness" rather than "centrality." The Wakita-and-Tsurumi algorithm improved Clauset-Newman-Moore algorithm's problem by trying to balance the sizes of the communities being merged and it emphasized "centrality," helping to find vertices with higher diffusion influence (Wakita & Tsurumi, 2007). Therefore, the Wakita-and-Tsurumi algorithm was most appropriate to use in this study's analysis process to produce clearly-separated clusters.

RQ1: Media outlets and opinion leaders have defined Edward Snowden in five different frames: Hero, Whistleblower, Dissident, Traitor, and Patriot. How do these different frames distribute on Twitter? How do individual users respond to different frames on Twitter?

Figure 4.1 provides the network visualization of connections among the 6013 Twitter users who tweeted "Edward Snowden" over a period from February 17 to April

10, 2014. Grey edges represent for “replies-to,” “mention,” and “re-tweet from” relationships. There are also self-loop edges for each tweet that was not a “replies to,” “mention,” or “re-tweet from” relationship. There were 11,543 different relationships among them.



Created with NodeXL (http://nodexl.codeplex.com)

Figure 4.1 Relationships between Twitter users who tweeted “Edward Snowden” over the period February 17 to April 10, 2014. *This graph visualizes the 11,543 different relationships among the 6013 Twitter users who tweeted “Edward Snowden” over a period from February 17th, 2014 to April 10th, 2014. Grey edges represent for “replies-to”, “mention”, “re-tweet from” relationships. A structure called “Community Clusters” has been observed. A collection of medium sized groups, rather than a crowd of mostly unconnected Twitter users, were formed. The number of unconnected users illustrates the high popularity of this topic because it means many users were expressing their opinions about this topic although they were not influential on the platforms.*

According to Figure 1, it could be observed that the whole “Edward Snowden” network formed a structure called “Community Clusters” (Smith, Rainie, Shneiderman & Himelboim, 2014). Community Clusters are the defining quality of networks that feature a collection of medium sized groups, rather than a crowd of mostly unconnected Twitter users. Understanding its structure is important for us to identify where the groups are, how they formed, and how many unconnected users there are in the network. More unconnected users mean higher popularity of this topic (Himelboim, Smith, et al, 2013).

To further examine the diffusion of messages with different key words, sub-groups have been separated out of the whole network to conduct another analysis. All the tweets under different key words were collected during the same period. The most salient keywords related to Edward Snowden are “Hero,” followed by “Traitor,” “Patriot,” “Whistleblower,” and “Dissident,” as illustrated in Table 4.1.

Table 4.1 Overall metrics for social networks based on different keywords

Metrics	**Value**				
	Hero	**Patriot**	**Traitor**	**Whistleblower**	**Dissident**
Vertices	3,177	998	1,971	882	43
Total Edges	4,952	1,563	3,594	1,378	56
Unique Edges	2,295	771	1,519	687	19
Graph Density	0.00023627	0.000802005	0.000447092	0.00079275	0.012735327
Connected Components	1,188	342	719	402	22
Maximum Vertices in a Connected Component	1,158	512	1,758	320	8

To better observe the flow of the message and find opinion leaders, self-loops (any user who is the original publisher, or any user who re-tweet/mention/comment his/her own tweet) have been eliminated and visualized data into the graphs.

Figures 4.2 through Figure 4.6 provide the visualizations of tweets collected from February 17 to April 10, 2014 talking about “Edward Snowden” and keywords including “Hero” (Figure 4.2), “Patriot” (Figure 4.3), “Traitor” (Figure 4.4), “Whistleblower” (Figure 4.5), and “Dissident” (Figure 4.6).

Each user who contributed to the Twitter conversation was located in a position in the networks among all participants in the conversation. The bigger the vertex size means the higher in-degree it has. From these figures, it could be clearly figured out that there were opinion leaders whose tweets had gained lots of responses (re-tweet/comment/mention). It could also be observed from the following figures that within all these networks, although all these five networks had strongly centralized networks, not all the sub-groups were connected together. In the “Patriot” network and the “Traitor” network, there were several isolated groups that were defined as “islands.” They were not connected to the rest part of the network, which meant there were several opinion leaders in these two networks whose active followers were a special group of people and these people had such a high loyalty and trust in these opinion leaders that they didn’t pay attention to others.

From the visualizations, readers could observe the frame of the “Hero” as the most discussed one on Twitter, while the frame of the “Dissident” was the least discussed one.

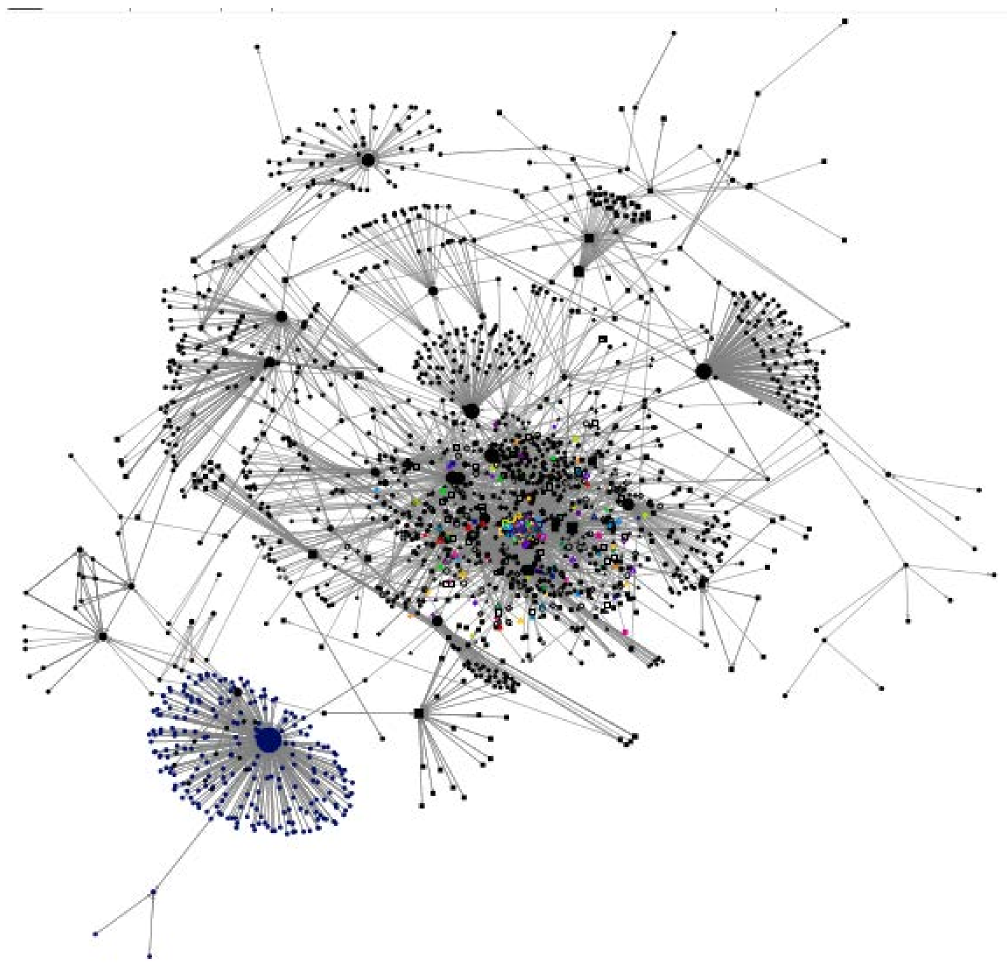


Figure 4.2 *NodeXL* visualization of the connections among users who posted tweets including key words, “Edward Snowden” and “Hero” between February 17 and April 10, 2014. *Self-loops have been eliminated during the visualization process. Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. According to this graph, a quite centralized network could be observed. Opinion leaders whose tweets have gained lots of responses (re-tweet/comment/mention) have been observed.*

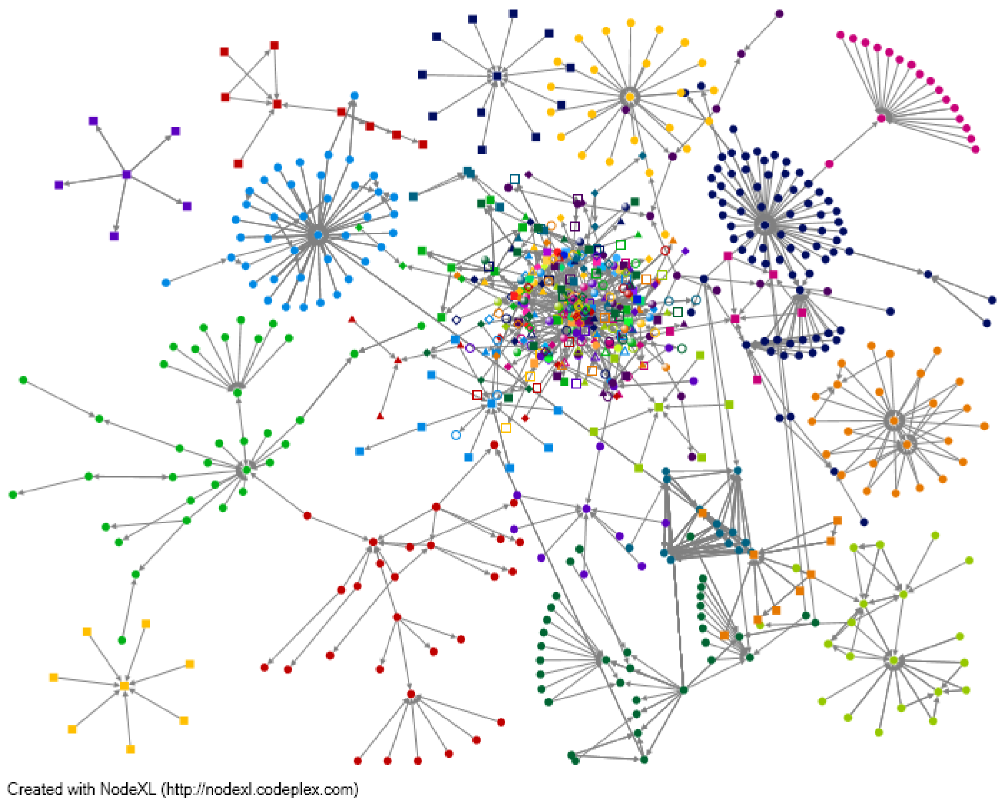


Figure 4.3 *NodeXL* visualization of connections among users who posted tweets including key words “Edward Snowden” and ”Patriot” from February 17 to April 10, 2014. *Self-loops have been eliminated during the visualization process. Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. According to this graph, although a quite centralized network could be observed, not all the sub-groups are connected together. There are several isolated groups which are defined as “islands”. They are not connected to the rest part of the network. It means there are several opinion leaders in this network whose active followers are a special group of people and these people have such a high loyalty and trust in these opinion leaders that they don’t pay attention to others.*

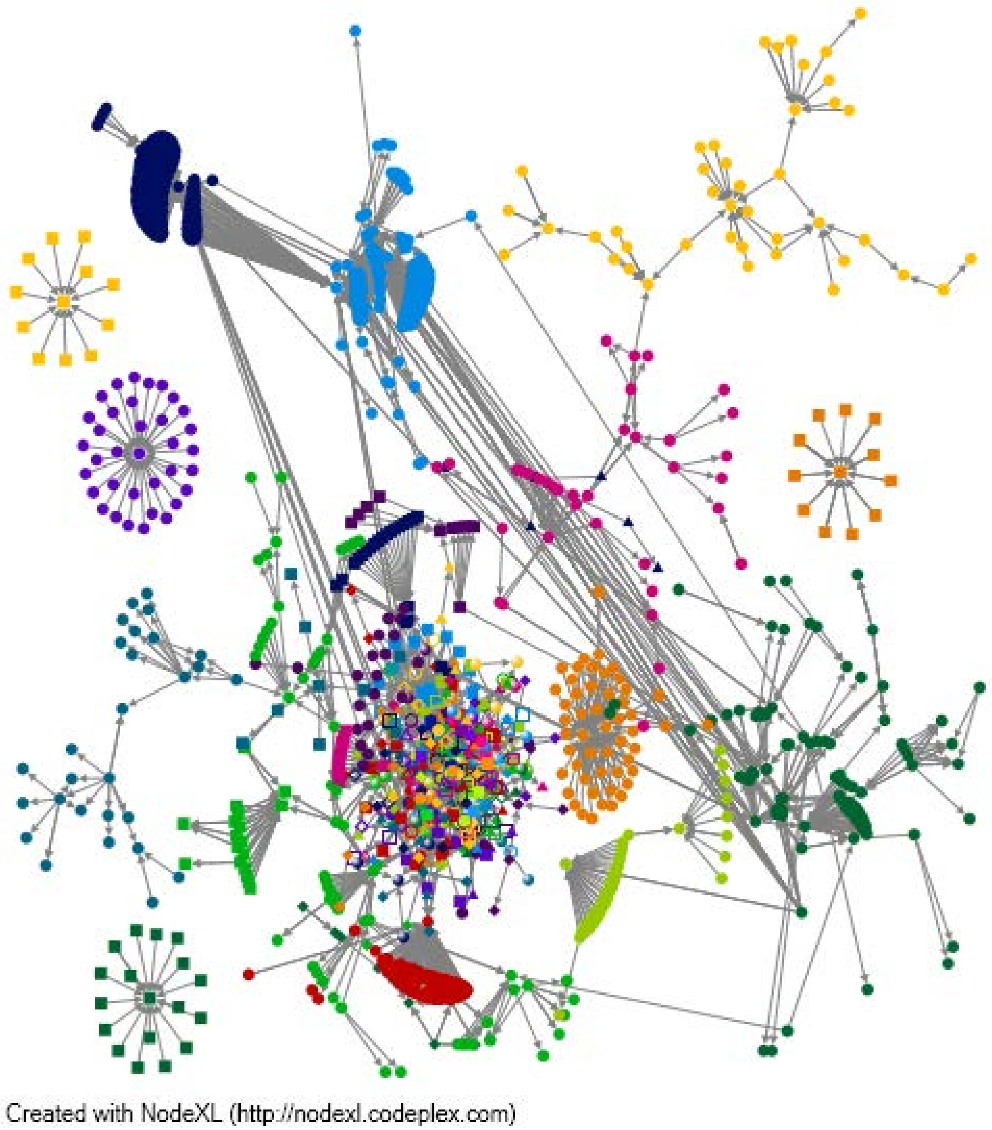


Figure 4.4 *NodeXL* visualization of connections among users who posted tweets including key words “Edward Snowden” and ”Traitor” from February 17 to April 10, 2014. *Self-loops have been eliminated during the visualization process. Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. According to this graph, although a quite centralized network could be observed, not all the sub-groups are connected together. There are several isolated groups which are defined as “islands”. They are not connected to the rest part of the network. It means there are several opinion leaders in this network whose active followers are a special group of people and these people have such a high loyalty and trust in these opinion leaders that they don’t pay attention to others.*

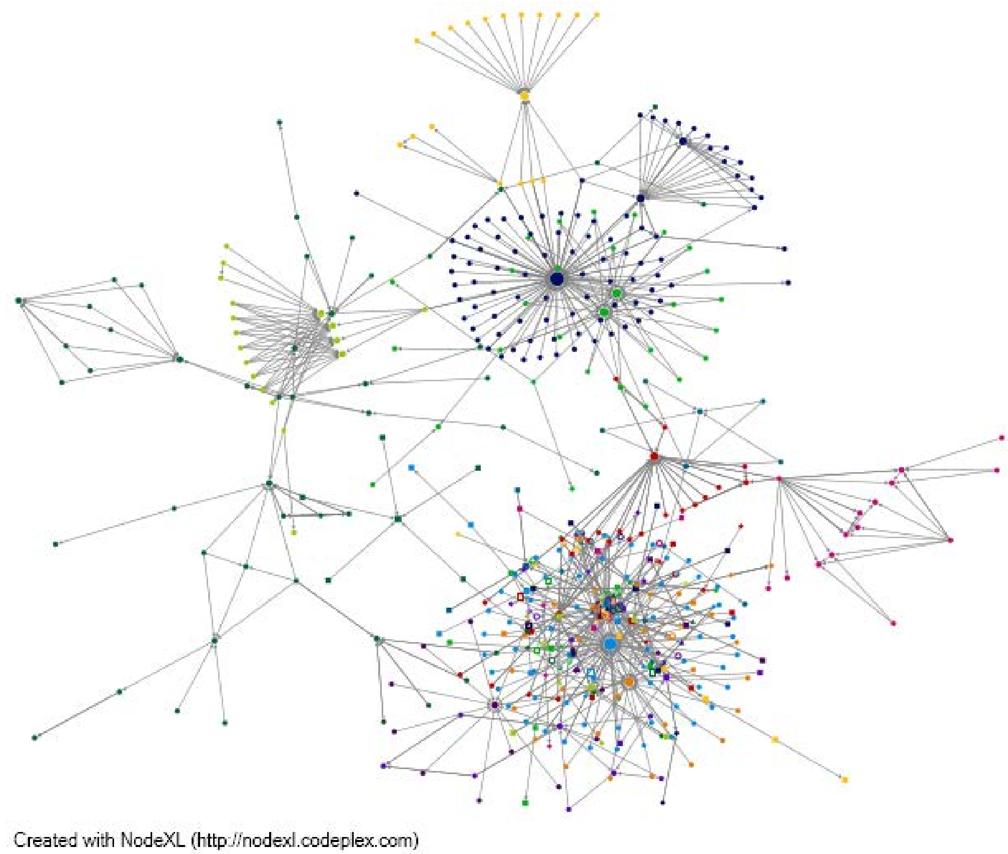


Figure 4.5 *NodeXL* visualization of the connections among users who posted tweets including key words “Edward Snowden” and “Whistleblower” from February 17 to April 10, 2014. *Self-loops have been eliminated during the visualization process. Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. According to this graph, a quite centralized network could be observed. Opinion leaders whose tweets have gained lots of responses (re-tweet/comment/mention) have been observed. However, not like the “Hero” network, “Whistleblower” has not been widely used in relevant tweets.*

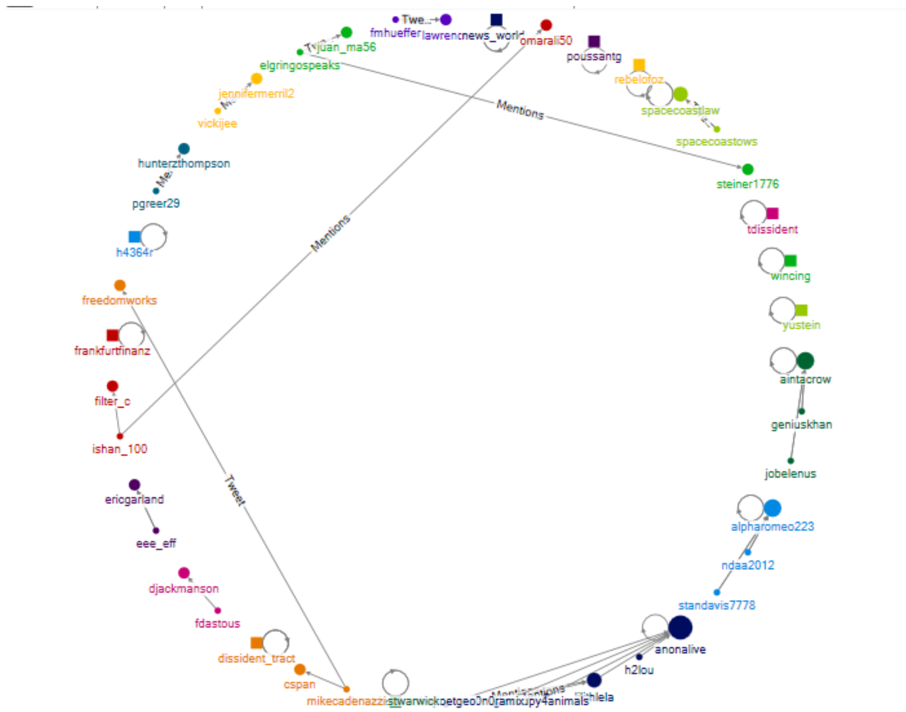


Figure 4.6 *NodeXL* visualization of the connections among users who posted tweets including key words "Edward Snowden" and "Dissident" from February 17 to April 10, 2014. *Self-loops have been kept during the visualization process because lack of interaction among each user. Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. According to this graph, a quite loose network could be observed. Only one opinion leader whose tweets have gained lots of responses (re-tweet/comment/mention) has been observed.*

Research Question 2: What is the relationship between opinion leaders? Are they connected?

To examine the relationship between opinion leaders, in-degree was filtered as the criteria. Minimum requirements varied from network to network. For the "Hero" network, the top 20 most influential Twitter users were picked out based on their in-degree metrics ranging from 21 to 220. Among these opinion leaders, most of them were "liberal" and working in science industry, non-profit sector, or social justice sector (see *Appendix).*

According to Figure 4.7, all of the sub-groups were connected. Most of the groups were linked by the followers they shared, and there was no apparent information flow between these influential users. However, connections between BBC News US (@bbcnewsus) and BBC Senior Writer Anthony Zurcher (@awzurcher); as well as between U.S. Senator Sen Dianne Feinstein (@senfeinstein) and An Angry Democrat (@angryvoters), were still observed.

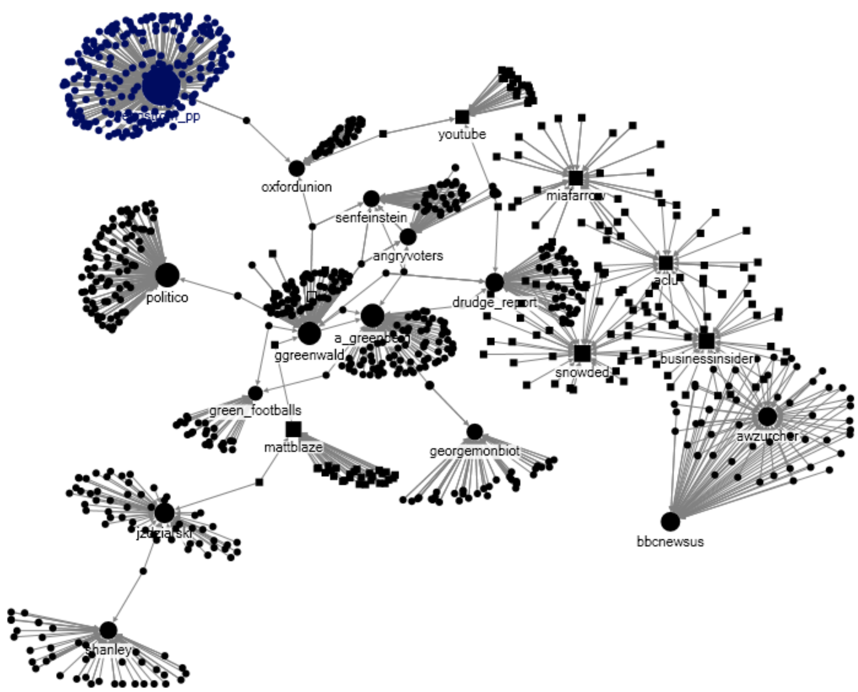


Figure 4.7 *NodeXL* visualization of the connections among Top 20 most influential people (based on their In-Degree metrics) who posted tweets including key words "Edward Snowden" and "Hero" from February 17 to April 10, 2014 and vertices that are linked to these opinion leaders. *Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. The account names of these opinion leaders were noted within each subgroup. All of the sub-groups are connected. Most of the groups are linked by the followers they share, and only several connections have been observed among these influential users.*

Figure 4.8 visualized the information distribution network within the "Patriot" network after narrowing down to vertices that had at least 10 in-degrees and vertices that were linked to these "influential" vertices. Among these 17 opinion-leader-centered sub-groups, 16 of them were somehow connected to the rest. Only the network surrounding Dan Gillmor (@ *dangillmor)* was totally isolated from the whole network. When it came to the relationships among opinion leaders, NSA Whistleblower Drake (@thomas_drake1) and National Security and Human rights lawyer Jesselyn Radack (@jesselynradack) were connected; Political News website Politico.com (@politco) and Politico.com Report Josh Gerstein (@joshgerstein) were connected; Politics Blogger and Writer for Guardian Greg Jericho (@grogsgamut) and European journalist Jacquelin Magnay (@jacquelinmagnay) were also connected. Therefore, not only were regular Twitter users connected to these opinion leaders, but various opinion leaders had connections with each other, as well.

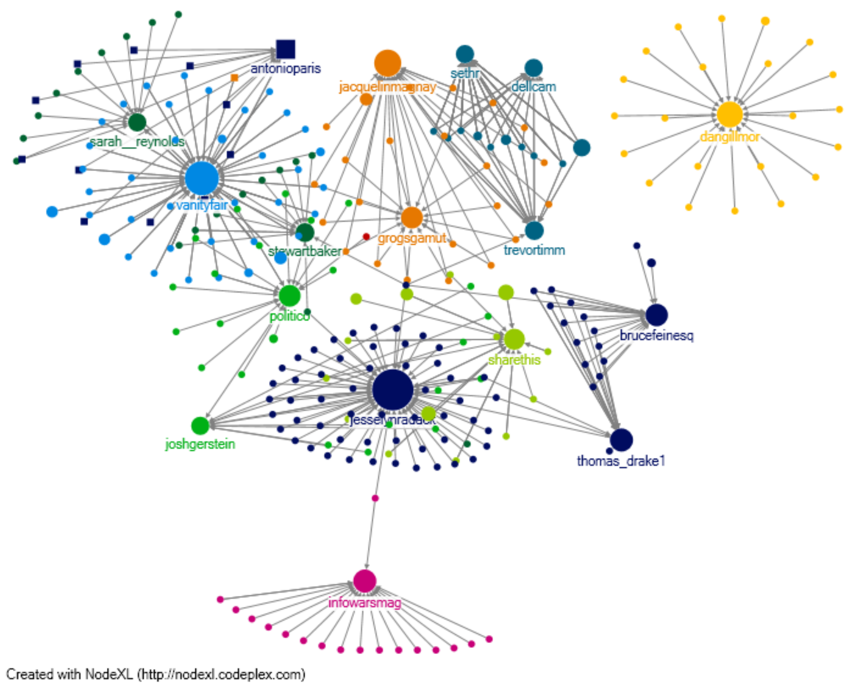


Figure 4.8 *NodeXL* visualization of the connections among users with a 10-and-above in-degree metric who posted tweets including key words "Edward Snowden" and "Patriot" from February

17 to April 10, 2014 and vertices that are linked to these opinion leaders. *Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. The account names of these opinion leaders were noted within each subgroup. All of the sub-groups are connected. Among these 17 opinion-leader-centered sub-groups, 16 of them are somehow connected to the rest. Only the network surrounding Dan Gillmor (@ dangillmor) is totally isolated from the whole network.*

Figure 4.9 visualized the information distribution network within the "Traitor" Network after narrowing down the top 20 in-degree vertices or vertices that were linked to these "influential" vertices. Among these 20 opinion-leader-centered sub-groups, 17 of them were somehow connected to the each other. There were two networks totally isolated from the rest, which were networks surrounding Founder of Cognitive Edge Dave Snowden (*@snowded)* and Cyber-Philanthropist Myles Dyer (@mylesdyer). When it came to the relationships among opinion leaders, NSA Whistleblower Thomas Drake (@thomas_drake1) mentioned Constitutional Attorney Bruce Fein (@brucefeinesq) 11 times in its tweets, mentioned Jesselyn Radack (@jesselynradack) eight times, mentioned Jacquelin Magnay (@jacquelinmagnay) for 10 times, and mentioned Executive Director at FreedomOfPress Trevor Timm (@trevortimm) seven times. Trevor Timm (@trevortimm) re-tweeted HuffPost Media (@huffpostmedia)'s tweets twice; writer for Crikey Bernard Keane (@bernardkeane) mentioned Scott Ludlam (@senatorludlam) once in his tweet; Jesselyn Radack (@jesselynradack) mentioned Stewart Baker (@stewartbaker) and Trevor Timm (@trevortimm) in her tweet; an Angry Democrat (@angryvoters) re-tweeted three tweets from Thomas Drake (@thomas_drake1); and @Foreign Policy Magazine (@foreignpolicy) mentioned former CEO of Google Eric Schmidt (@ericschmidt) and Google (@google) in his tweets. Therefore, not only were regular Twitter users connected to these opinion leaders, but various opinion leaders had connections with each other as well.

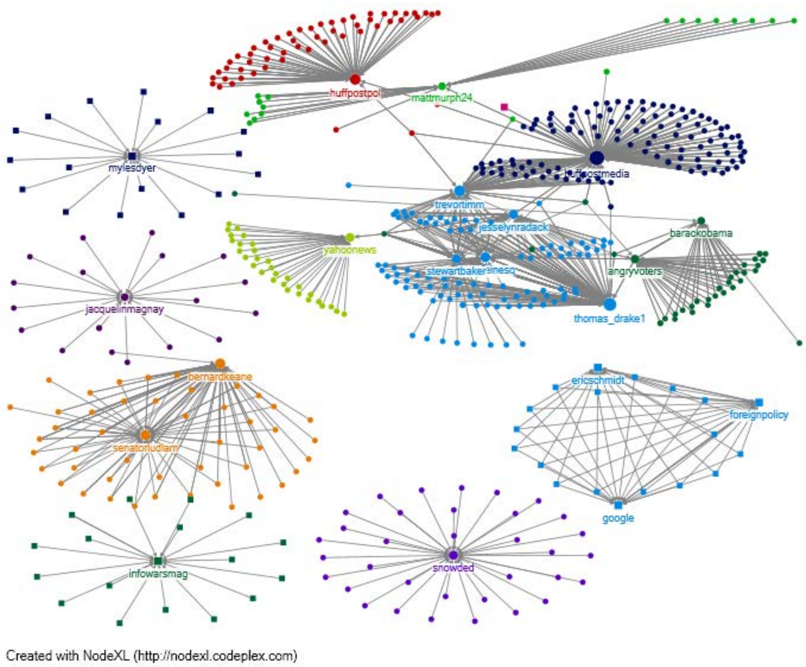


Figure 4.9 *NodeXL* visualization of the connections among Top 20 most influential people (based on their In-Degree metrics) who posted tweets including key words "Edward Snowden" and "Traitor" from February 17 to April 10, 2014 and vertices that are linked to these opinion leaders. *Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. The account names of these opinion leaders were noted within each subgroup. Among these 20 opinion-leader-centered sub-groups, 17 of them are somehow connected to the each other. Therefore, not only regular Twitter users are connected to these opinion leaders, various opinion leaders have connections with each other as well. However, there are still 2 subgroups are totally isolated from the rest.*

Figure 4.10 visualized the information distribution network within the "Whistleblower" Network after narrowing down vertices with in-degree higher than 10 and vertices that were linked to these "influential" vertices. Among these 14 opinion-leader-centered sub-groups, 11 of them were somehow connected to the each other. There were three networks that were totally isolated from the rest – networks surrounding Mashable (@mashable), Love Bytes (@lovebytess), and Time Magezine (@time). When it came to the relationships among opinion leaders, Thomas Drake

(@thomas_drake1) mentioned James O'Beime (@jamesob) and Jesselyn Radack (@jesselynradack) twice in his tweets; James O'Beime (@jamesob) mentioned Thomas Drake (@thomas_drake1) in his tweet.

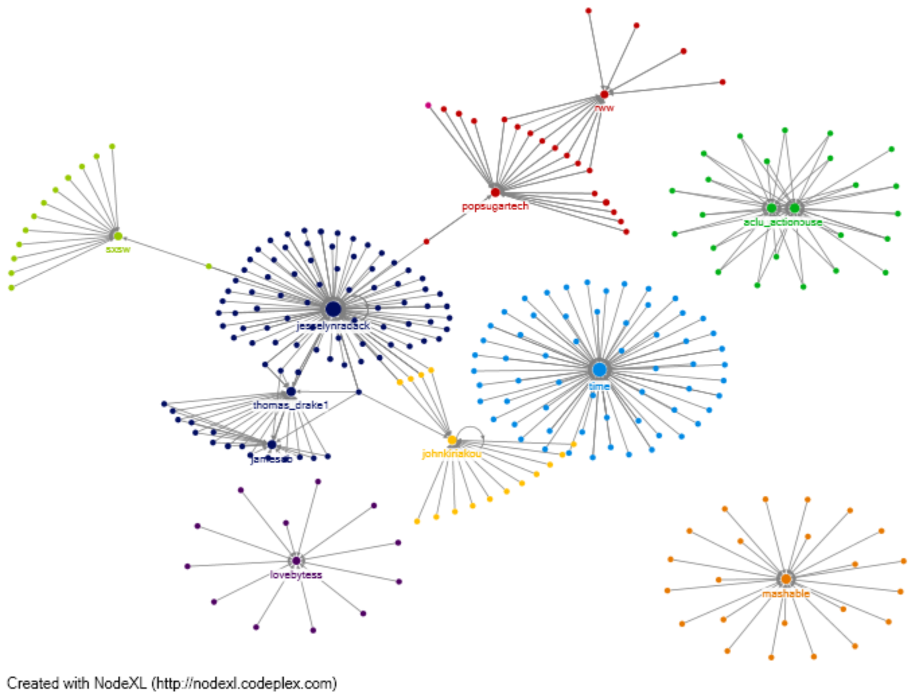


Figure 4.10 *NodeXL* visualization of the connections among users with a 10-and-above in-degree metric who posted tweets including key words "Edward Snowden" and "Whistleblower" from February 17 to April 10, 2014 and vertices that are linked to these opinion leaders. *Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. The account names of these opinion leaders were noted within each subgroup. Among these 14 opinion-leader-centered sub-groups, 11 of them are somehow connected to the each other, and the other 3 networks are totally isolated from the rest.*

Figure 4.11 visualized the information distribution network within the "Dissident" Network, after narrowing down to vertices with bigger than two in-degree, which means that vertices that with at least two re-tweets/mentions/comments would be shown in the visualization. According to figure 4.12, these vertices, which have been defined as "opinion leaders" within this "dissident" condition, don't have apparent relationships with each other.

Figure 4.11 *NodeXL* visualization of the connections among users with a 2-and-above in-degree metric who posted tweets including key words "Edward Snowden" and "Dissident" from February 17 to April 10, 2014 and vertices that are linked to these opinion leaders. *Each user who contributes to the Twitter conversation is located in a position in the networks among all participants in the conversation. Bigger the vertex size is, higher in-degree it has. The account names of these opinion leaders were noted within each subgroup. No apparent connection between opinion leaders has been observed.*

Hypothesis 1: Field related source quality (reputation, expertness) on specific topic is more important than the general influence (Klout Score) when engaging individual users to the issue.

According to the Twitter data, within all the Twitter users who tweeted about Edward Snowden and either of the other five key words ("Hero," "Patriot," "Traitor," "Whistleblower," and "Dissident"), Twitter users with the highest Klout Score were not the ones that gained the most attention and engagement on the Edward Snowden topic. In the following discussion, users with the most followers were defined as "popular;" while users with the most re-tweet/comment/mention were defined as “influential” on this specific topic.

In the “Hero” case, within the top 10 popular (which means with highest Klout Score) Twitter accounts, only YouTube and Glenn Greenwald were in the Top 20 list (appendix) while YouTube was the 20th one. In the “Patriot” case, only @sharethis was in “popular” and “influential.” In the “Traitor,” “Whistleblower,” and “Dissident” cases, there was not a single user listed on both lists.

Table 4.2 Top 10 Most Influential Twitter Accounts that Tweeted “Snowden” and “X” (X=hero, patriot, traitor, whistleblower, or dissident)

Hero		Patriot		Traitor		Whistleblower		Dissident	
User	**Klout Score**	**User**	**Klout Score**	**User**	**Klout Score**	**User**	**Klout Score**	**User**	**Klout Score**
New Yorker	97	USA Today	96	NY Times	99	YouTube	99	Tony Yustein	53
CBS News	94	Vice	91	Anonymous	91	Wiki Leaks	90	The Dissident	55
YouTube	91	Wiki Leaks	90	Wiki Leaks	90	Hala Gorani	80	Ryan Onstott	45
Market Watch	91	Share This	87	SFGate.com	86	foGuardian	99	Mitch Melnick	67
Vice	91	John Cusack	86	Lawrence O’Donnell	80	Glenn Greenwald	88	Michael Cadenazzi	43
Wiki Leaks	90	The Heritage Foundation	83	Tread Stone 3	67	Cenk Uygur	82	Lawrence O’Donnell	80
Glenn Greenwald	88	NY Times World	74	Mike Golic	67	BuzzFeed	95	Genevieve Hebert	65
John Gruber	83	Andrew Sullivan	73	Po.st	67	Anonymous Operations	74	Freedom Works	83
Owen Jones	83	Jon Wexford	58	Tom O’Halloran	63	Alan Rusbridger	85	C-SPAN	82

Within all five of the networks, only several opinion leaders appear in more than one network (see Appendix), which may indicate that people who spoke about different frames found different opinions leaders trustworthy. Users who talked about the frame defining Edward Snowden as a “Hero” and “Dissident” were more willing to engage with the tweets from liberal people who were working in science industry, non-profit sector, and social justice sector. Influential opinion leaders that tweeted “Edward Snowden” together with “Patriot,” were more likely to be politicians, journalists, or bloggers who focused on human rights, justice, and freedom.

On the other hand, users who accepted the frame defining Edward Snowden as a “Traitor,” were more willing to engage with the tweets from politicians, media outlets, lawyers, and Google (who used to be enrolled in a privacy crisis).

Hypothesis 2: Individual users pay more attention to non-government opinion leaders’ tweets than government opinion leaders’ tweets.

Among all the 74 opinion leaders (hero: 20; patriot: 17; traitor: 20; whistleblower: 12; dissident: 5), six users were government related accounts. Therefore, in the Edward Snowden case, Twitter users were more engaged with non-government accounts’ opinions and comments.

Figures 4.12 and 4.13 display the vertices based on their In-Degree and Between-ness Centrality from the networks of “Hero” and “Patriot.” The user with the highest in-degree and the user with the highest Between Centrality was not the same.

From Figure 4.12, it could be observed that without @ggreenwald or its followers, information distribution would be slowed down because of the need to go through links to various opinion leader groups. On the other hand, although @engstrom_pp has the most re-tweets/comments/mentions, its Between-ness Centrality metric was just within average because if it had been cut from the network, the rest of the network wouldn’t be influenced at all. It only connected to @oxfordunion.

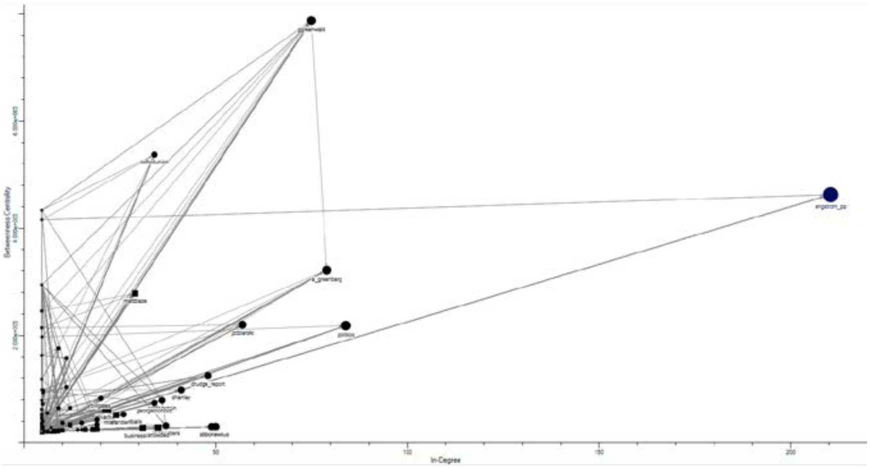


Figure 4.12 *NodeXL* visualization of the positions of top 20 opinion leaders in the "Snowden"+ "Hero" network based on their in-degree metric and number of followers. *The X-axis represents the In-Degree value. The value increases while the dots moving right. The Y-axis represents the number of followers which reveals the general popularity of these users on Twitter platform. The value increases while the dots moving upward. The graph shows that user with the highest in-degree value and the user with the highest Between Centrality are not the same one. Different users have different roles in the information diffusion process.*

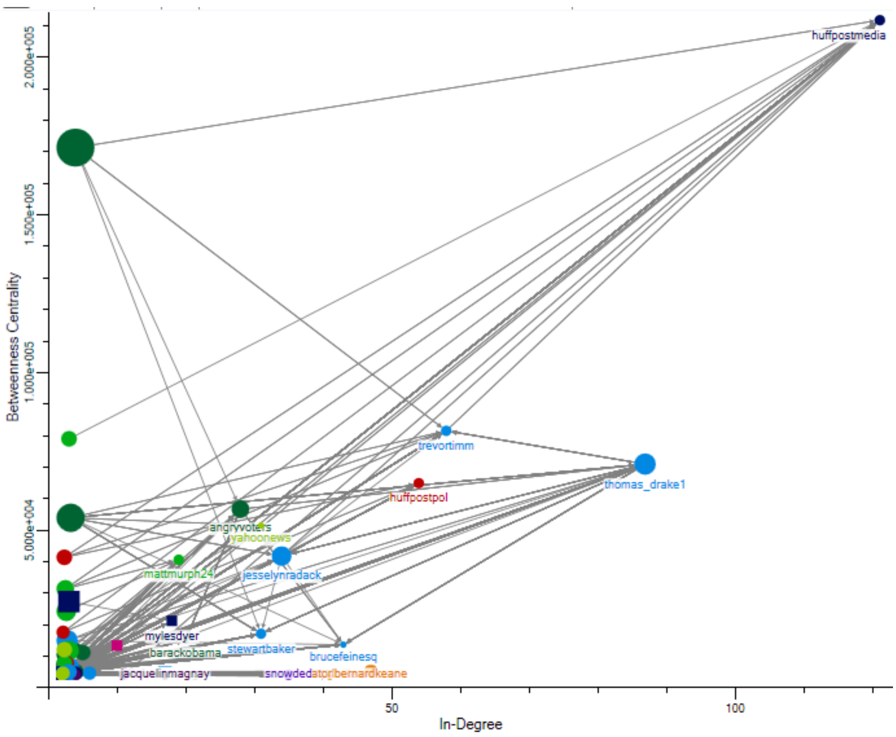


Figure 4.13 *NodeXL* visualization of the positions of top 20 opinion leaders in the "Snowden"+ "Patriot" network based on their in-degree metric and number of followers. *The X-axis represents the In-Degree value. The value increases while the dots moving right. The Y-axis represents the number of followers which reveals the general popularity of these*

users on Twitter platform. The value increases while the dots moving upward. The graph shows that user with the highest in-degree value and the user with the highest Between Centrality are not the same one. Different users have different roles in the information diffusion process.

Chapter Five: *Discussion and Implication*

The analyzed datasets and network graphs revealed information at the level of both individuals and groups.

In the whole network, including all the tweets talking about Edward Snowden during certain period of time, a big amount of self-loops were observed. The high number of self-loops represented the popularity of this topic. Not only did users follow opinion leaders' discussions, but some users also made their opinions about this political issue known independently without being influenced by others.

When it came to the five different message frames, there were several specific findings. The most mentioned key words were "Hero" and "Traitor." Although "Hero" was the most mentioned word, it didn't reflect the idea that most of the Twitter users respected Edward Snowden's behavior because they may have been debating whether he was a hero or a traitor. The same concern became apparent within the traitor network. Other words, which were not so extremely emotional, including "Patriot," "Whistleblower," and "Dissident" were less discussed.

Although the "Dissident" network had the least vertices, it had the highest density within the five networks, which meant it had the highest interconnectedness of its vertices. Therefore, it suggested that people who were talking about the "Dissident" frame shared things in common that united them into a well-communicated group. Although the opinion leaders in the "Dissident" network were not so influential as the ones in other networks, there were many interactions among regular users and that was the effect that made the network interconnected.

In the "Hero" network, its low density indicated that it had quite a few isolated sub-groups defined as 'islanders.' Because too many people framed Edward Snowden as a "Hero," the sentiment spread broadly, which made it hard to connect everyone together into a solid group. The "Hero" network was great for raising awareness of the topic, whereas the “Dissident” network had advantages on creating a loyal group that supported the idea.

Generally speaking, no apparent relationship had been found among opinion leaders, however it still differed from frame to frame. The “Traitor” network was the one in which most opinion leader interactions were found. The “Hero,” “Patriot,” and “Whistleblower” networks had several interactions existing in each network. No interactions between opinion leaders were found within the “Dissident” network. Because not so many people accepted the “Dissident” frame, the opinion leaders within that network had no big difference from other regular users based on their in-degree metric. Although it cannot be concluded that opinion leaders were the group that pushed the “Hero,” “Patriot,” “Traitor,” and “Whistleblower” frames into broader discussion, it could be suggested that the number of opinion leaders who engaged and the extent of opinion leader connectedness influenced the message diffusion.

The research also showed that if the connection was between two similar opinion leaders, such as The Guardian and the journalist of The Guardian, then it did not greatly broaden the network; however, it was great to solidify the relationships and to make the audience persuaded. On the other hand, if the connection was between different kinds of opinion leaders, such as The Guardian and Google, the target this frame reached was much bigger.

From the contrast analysis about between-ness centrality and in-degree, it could be observed that not only vertices with most responses were the most important ones. There were two kinds of notable users: “hubs” and “bridges” (Smith, Rainie, Shneiderman & Himelboim 2014). In this research, “Hubs” means that vertices have a great amount of interactions with other vertices; in another words, a high in-degree. For example, its tweets have been re-tweeted/commented many times. “Bridges” refer to vertices with a high between-ness centrality. These users have links across sub-group boundaries and have the capability passing information from one group to another. Those successfully diffused frames need both "hubs" and "bridges." Although the "bridges" don't have many connections, they were the ones that could diffuse message from opinion leaders to a broader area, dramatically expanding the influence.

Just like an important user may not get both high in-degree and high between-ness centrality, if a user was defined as an "opinion leader" in this study, that didn't mean he/she was the most influential Twitter account on the Internet. In all the networks based on different keywords, there was little duplication observed between Top 10 Twitter users, who have the highest Klout score, and Top 20 opinion leaders who got most responses from their followers (re-tweet/comment/mention) on the Edward Snowden related tweets. Therefore, there were topic-related influence and authority. Although some Twitter users had high general popularity on the platform, they may not have been influential on this specific topic. When topics/fields/industries vary, different groups of opinion leaders are observed. The "expertness" from their occupation, political ideology, or personal interest, provided users credibility.

IMPLICATIONS FOR STRATEGIC COMMUNICATION

This research revealed how different frames of the same issue were communicated and flowed on the Twitter platform. Several implications could be concluded from the findings to shed light on strategic communication.

Establish Opinion Leaders Together Would Lead to Much Bigger Influence.

According to the data visualization, not many connections between any two opinion leaders were observed. However, once any two opinion leaders were linked, the message could expand into a much bigger influence. Therefore, from the perspective of strategic communication, partnership with other brands, organizations, or individuals could bring into huge amount of assistance and increase brand awareness. Different forms of partnerships have different benefits. If the primary goal was to expand the market and reach more target audience, partnering with another corporate/organization/individual, which are different from your current brand, was more effective. For instance, Coca Cola may partner with a non-profit organization such as WWF in order to engage people who were concerned about environment into fans of Coca Cola. On another hand, if the primary goal for partnership was to solidify the current target market, establishing a relationship with a similar player on the market would be more effective. For instance, Hermes may partner with La Mer because its target audience was very similar. People who purchase Hermes have high possibility that they were also consumers of La Mer. Therefore, this partnership would strengthen the image of both brands and the consumer perception.

Who Knows You, and Who You Know – They Are Both Important.

According to the comparison based on Between-ness Centrality and In-Degree, it was clearly illustrated that some Twitter users, although they didn't have an in-degree as high as others, had a really high Between-ness Centrality, which meant they were the essential dots that bridged different groups. These "bridgers" were equally important when any brand/organization/individual wanted to increase its awareness and preference. Through these bridgers' messages could be transmitted to much more remote fields and might lead to a much bigger influence.

The golden rule of networking was that "The most important thing is not who you know, but always who knows you" (Daly 2008). Therefore, in the strategic communication field, it was always important to find the perfect opinion leaders to help diffuse the brand message. For example, University of Texas at Austin could ask Matthew McConaughey (UT Alumni) to send out any message discussing the achievements of UT. Since McConaughey won the Oscar for Best Actor, he would act as the "hub" to influence teenagers who may be a potential market for UT.

However, in some occasions, finding the "bridges" was equally important. For example, the LBJ School of Public Affairs at University of Texas at Austin wanted to launch its new executive graduate program. It would be more efficient to use someone who knew all the stakeholders to persuade others. Then the key stakeholders could continue diffusing the message to a broader audience.

Different Topics Have Different Criteria for "Persuasiveness."

The research revealed that different frames needed different opinion leaders to make them salient. When it came to strategic brand communication, it could be implied that figuring out the right person to be the opinion leader was vital and necessary. There were different "influential" and "trustworthy" individuals in different fields. For example, if Nike wanted to launch a new campaign connecting sports and fashion together, Nike wouldn't go to Sean Connery, despite his fame and influence, because consumers do not connect him to sports. Under this situation, any less-famous and sporty model would be more effective in expressing the brand message.

Public Image Establishment and Maintenance

This research provided implications for organizations, corporates, and individuals about how to establish and maintain their public image. Finding the most suitable "messenger" and communicating the correctly framed message from a well-established angle were two key factors influencing people's perception on perception and image within an issue, which is especially important for crisis management. For example, PepsiCo suffered an image crisis because of its not-environment-friendly issue. To change that public image, PepsiCo partnered with several non-profits and social enterprises to engage itself into environment protection movements.

Chapter Six: *Limitations and Future Research*

There were limitations with this research. First of all, it cannot be ignored that people who take their time posting and interacting on Twitter are a quite special group, especially those who are eager to talk about politics on social media platforms. They may be different from other Twitter users. Therefore, their performance cannot represent all the Twitter users. Moreover, Twitter users are only 18% of Internet users and 14% of the overall adult populations (Smith, Rainie, Shneiderman & Himelboim, 2014), so Twitter users' behavior cannot represent the total Internet users or the total population (Pew Internet 2014).

Second, the tweets collected by *NodeXL* in this research were just snapshots of related tweets in a certain period of time. The data sets did not represent the larger period of discussion beyond the time frame during which the data was collected.

Since this research focused on users' responses on the Twitter platform, in order to further this research, other social media platforms could be studied to see if there is any difference among different social media platforms. Do people on Facebook have different responses from people on Twitter about the exactly same issue? How do different social media platforms influence the message framing?

Moreover, people's perception was impossible to measure with social network analysis alone. Survey or experimental design could be conducted to understand people's attitudes towards Edward Snowden issue. The results could be compared with Social Network Analysis results. Does users' social media engagement, including re-tweet/comment/mention, really reflect their attitude and perception? What factors influence their decision? Are they exposed to all the different frames? Or is there a filter bubble (Pariser, 2011) caused by users' active social media following preference to block them from other different frames?

These potential research questions are valuable to help researcher to gain a deeper and more accurate understanding about how different frames are influencing people's attitudes towards public issues and to figure out a better communication strategy to tackle it.

Chapter Seven: *Conclusion*

The research raises several insights on the message diffusion pattern of five different frames (Hero, Patriot, Traitor, Whistleblower, Dissident) of the Edward Snowden issue. The integration of social network analysis and framing theory and the findings of that integration provide insights about future strategic communication for general branding and public image maintenance.

However, since the result are based on a small part of the Twitter users' responses, it is still valuable to put the research into a broader context to see if the results go along with the ones in this paper.

Appendix

Table 7.1 Top 5 Twitter Accounts (with an in-degree no less than 2) that Tweeted “Snowden” and “Dissident”

Username	**Real Name**	**Profile**	**In-Degree**	**Between-ness Centrality**	**Page Rank**
@anonalive	Anon Animal	Against the fuckin Gov, Big Brother and Censorship	6	15	2.29
@aintacrow	Raven Rakia	Freelance Journalist	3	2	1.723
@alpharomeo223	Domestic Terrorist	We are all domestic terrorists now! Unless you donate to Harry Reid	3	2	1.723
@lilithlela	Lilith Lela	Gather intelligence and share information on bypassing Internet censorship and reconnaissance practices of the inter-web	2	1	1.156
@spacecoastlaw	SpaceCoastLaw	Law, Bankruptcy	2	0	1.298

Appendix 7.2 Top 20 Twitter Accounts (gained most re-tweets/mentions/replies) that Tweeted "Snowden" and "Hero"

Username	**Real Name**	**Profile**	**In-Degree**	**Between-ness Centrality**	**Page Rank**
@engstrom_pp	Christian Engstrom	Member of the European Parliament for the Pirate Party	220	462306.000	98.895
@politico	POLITICO	Political News	84	217613.833	33.710
@a_greenberg	Andy Greenberg	Tech Reporter for Forbes; Author of This Machine Kills Secrets: How WikiLeakers, Cypherpunks, and Hacktivists Aim to Free the World's information	79	321193.862	33.661
@ggreenwald	Glenn Greenwald	Journalist with Liberty and Justice	75	821435.184	28.910
@JZdziarski	Jonathan Zdziarski	Forensic scientist; author for O'Reilly Media, hacker	57	219318.000	25.959
@BBCNewsUS	BBC News US	International News Media	50	2172.000	12.356
@awzurcher	Anthony Zurcher	BBC senior writer; blogger	49	1916.000	12.032
@DRUDGE_REPORT	DRUDGE REPORT	U.S. based news aggregation website	48	124052.898	20.509
@shanley	Shanley	Silicon Valley's last cultural critic; founder @modelviewmedia	41	97596.000	18.640
@AngryVoters	An Angry DEMOCRAT	N/A	37	30791.319	9.262
@SenFeinstein	Sen Dianne Feinstein	U.S. Senator from California	36	78069.359	8.872
@snowded	Dave Snowden	Founder and Chief Scientific Officer at Cognitive Edge	35	1122.000	16.377
@OxfornUnion	Oxford Union	Most famous debating society in the world	34	536998.304	14.033
@GeorgeMonbiot	George Monbiot	Unreconstructed idealist	34	72992.000	15.121
@businessinsider	Business Insider	The latest business news and analysis	31	870.000	14.540
@mattblaze	Matt Blaze	Scientist, safecraker	29	277651.000	13.013

@Green_Footballs	Charles Johnson	Scientist, Co-started PJ Media, Code Monkey	26	51715.440	10.423
@MiaFarrow	Mia Farrow	Actress, Activist, UNICEF ambassador	24	50402.000	10.942
@ACLU	ACLU National	Nonprofit, nonpartisan, public interest org devoted to protecting the basic civil liberties of everyone in America	22	59428.000	9.312
@YouTube	YouTube	Video-sharing website	21	61006.527	8.876

Appendix 7.3 Top 12 Twitter Accounts (with an in-degree no less than 10) that Tweeted "Snowden" and "Whistleblower"

Username	**Real Name**	**Profile**	**In-Degree**	**Between-ness Centrality**	**Page Rank**
@jesselynradack	Jesselyn Radack	National security and human rights lawyer	81	25332.643	32.035
@time	TIME	American weekly news magazine	61	3660	28.568
@mashable	Mashable	British-American news website, technology and social media blog	23	506	11.108
@whitehouse	The White House	Follow for the latest from President Obama and his administration	23	472	6.147
@aclu_action	ACLU Action	It is on the front lines in the fight for freedom	21	270	5.537
@thomas_drake1	Thomas Drake	NSA whistleblower	20	4455.595	5.706
@jamesob	James O'Beirne	Resident caveman @percolate	18	328.429	4.795
@popsugartech	POPSUGAR Tech	From simple how-tos, to geek culture, cool websites	18	10395	5.305
@johnkiriakou	John Kiriakou	Anti-torture whistleblower; CIA officer	17	3611.5	6.581
@sxsw	SXSW	A set of film, interactive, and music festivals and conferences that take place early each year in mid-March in Austin	13	2282	2.887
@lovebytes	Love Bytes	N/A	12	132	6.054
@rww	ReadWrite	The latest news, analysis and conversation in all things	12	1365	3.748

Appendix 7.4 Top 20 Twitter Accounts (gained most re-tweets/mentions/replies) that Tweeted “Snowden” and “Traitor”

Username	**Real Name**	**Profile**	**In-Degree**	**Between-ness Centrality**	**Page Rank**
@huffpostmedia	HuffPost Media	Liberal American online news aggregator and blog	123	215987.154	38.882
@thomas_drake1	Thomas Drake	NSA whistleblower	87	70746.115	21.586
@trevortimm	Trevor Timm	Executive director @FreedomofPress	58	81310.874	14.347
@huffpostpol	HuffPost Politics	The latest political news from The Huffington Post’s politics team	54	64682.067	23.821
@bernardkeane	Bernard Keane	Writer for Crikey	47	4984.000	12.878
@brucefeinesq	Bruce Fein	Constitutional Attorney	43	13360.311	9.174
@senatorludlam	Scott Ludlam	Authorized by Australian Greens Senator	41	1242.000	10.748
@snowded	Dave Snowden	Founder and Chief Scientific Officer of Cognitive Edge	35	1122.000	16.377
@jesselynradack	Jesselyn Radack	National security and human rights lawyer	34	41508.323	8.355
@stewartbaker	stewartbaker	Former General Counsel of NSA, blogger	31	16828.358	7.090
@yahoonews	Yahoo News	Internet-based news aggregator by Yahoo	31	51228.000	13.554
@angryvoters	An Angry DEMOCRAT	N/A	28	56414.933	7.293
@barackobama	Barack Obama	Run by Organizing for Action staff	20	14896.476	4.873
@mattmurph24	Matt Murphy	Political Junkie	19	40361.416	6.336
@mylesdyer	Myles Dyer	Cyber-Philanthropist; @ChannelFlip YouTube Marketing	18	20912.000	7.512
@ericschmidt	Eric Schmidt	Executive Chairman & former CEO of Google	18	90.667	3.202
@google	A Googler	Google	18	90.667	3.202
@foreignpolicy	Foreign Policy	The magazine for global politics, economics and ideas	17	90.778	3.354
@infowarsmag	Infowars Magazine	We are not Left or Right. We are Constitutionalists.	17	272.000	8.351
@jacquelinmagnay	Jacquelin Magnay	Journalist in Europe	17	1843.000	4.758

Appendix 7.5 Top 20 Twitter Accounts (gained most re-tweets/mentions/replies) that Tweeted “Snowden” and “Patriot”

Username	Real Name	Profile	In-Degree	Between-ness Centrality	Page Rank
@jesselynradack	Jesselyn Radack	National security & human rights lawyer	58	26836.595	24.387
@vanityfair	Vanity Fair	American monthly magazine of pop culture, fashion, and politics	40	2235.000	13.956
@jacquelinmagnay	Jacquelin Magnay	Journalist in Europe	25	403.000	6.534
@dangillmor	Dan Gillmor	American technology writer and columnist	23	504.000	10.582
@thomas_drake1	Thomas Drake	NSA whistleblower	17	3045.571	5.436
@infowarsmag	Infowars Magazine	We are not left or right. We are Constitutionalists	17	6512.000	8.052
@brucefeinesq	Bruce Fein	Constitutional Attorney	16	4628.000	4.568
@politico	POLITICO	Politics, Political News	16	13104.000	7.040
@grogsgamut	Greg Jericho	Blogger on politics, movies, books, and sports. Writes for Guardian Australia	15	105.000	4.253
@sharethis	Share This	Uses large-scale social data to deliver breakthrough insights, audience building and advertising solutions across mobile and desktop environments	14	262.333	4.111
@stewartbaker	stewartbaker	Former General Counsel of NSA, blogger	12	16147.833	4.383
@trevortimm	Trevor Timm	Executive director @ FreedomofPress	11	3091.467	2.090
@antonioparis	Antonio Paris	Founder of Aerial Phenomena, Author, Filmmaker	11	110.000	5.595
@sarah_reynolds	Sarah Reynolds	Progressive patriot	11	3522.000	4.436
@joshgerstein	Josh Gerstein	POLITICO reporter covering the White House, Justice Department	11	3726.000	4.779
@sethr	Seth Rosenblatt	CNET News Senior Writer on Google and security	10	329.800	1.817

@dellcam	Dell Cameron	Reporter @dailydot	10	329.800	1.817
@pbc_hollywood	Poweredby Comedy™	TV Network focusing on movies	10	370.4	2.043
@samsteinhp	Sam Stein	Political editor and While House correspondent	10	106	4.767
@dellcam	Dell Cameron	Reporter @dailydot	10	329.800	1.817

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