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Beyond the Red and the Blue:

Political Twitter Networks of U.S. House of Representatives

and Korean National Assembly

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Beyond the Red and the Blue:

Political Twitter Networks of U.S. House of Representatives and Korean National Assembly

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To J.K. and Seohyung

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BEYOND THE RED AND THE BLUE:
Political Twitter Networks of U.S. House of Representatives and Korean National Assembly

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This research investigates the Twitter network sphere of the 112^{th} U.S. House of Representatives and the 18^{th} Korean National Assembly members. Drawing from social network analysis, this study explores and compares structural characteristics of each legislative political network at diverse network levels – legislative, party and personal network. Mapping these networks highlights the major features of these two elite political networks grounded in a new social medium.

Findings indicate that U.S. and Korean lawmakers have created and are enjoying affluent and multi-layered digital networks. Dynamic legislative-body networks, strong party networks, and a variety of personal networks with diverse partisan and bipartisan relationships demonstrate how politicians are agile at using new mediums. This research confirmed that these newly created legislative networks go beyond partisanship. Complicated structures demonstrate active and mutual interactions among lawmakers, and the political networks with large numbers of bipartisan tie relationships indicate that

the political elite communicate, interact, and build relationships with each other rather than remaining disconnected or isolated.

This research revealed new types of leaders – digital opinion leaders – emerging from newly created digital legislative networks: the most connected lawmakers; lawmakers who have great potential to coordinate party politics; the most sought after leaders; and most sociable lawmakers. By examining lawmakers' patterns of relationship building in the network, this research tests whether these relationships are dependent on party position, ruling or opposition, in the network. In turn, this provides evidence for different uses of this new medium by party position in both legislative bodies. Detailed examination of Twitter use by political elites in Korea and the U.S. illuminate how this new media platform is being adopted by and changing politics in two distinct social and cultural settings. This new political arena, a fully digitalized and networked sphere where dynamic competition and cooperation occurs between political elites, has emerged as one of the political battlefields in politics today.

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CHAPTER 1: INTRODUCTION

Twitter, a micro-blogging service, is currently one of the most popular social media platforms. Since its award-winning appearance at the South By Southwest (SXSW) web conference held in Austin, TX, March 2007 (Makice, 2009), Twitter reached eight percent of U.S. adults daily (Smith & Brenner, 2012), and users worldwide send out 400 million tweets per day as of June 2012 (D'Orazio, 2012). The top 170 Twitter accounts, most of them belonging to celebrities and news media outlets, are followed by more than 5 million people as of August 2013 (Twitaholic, 2013).

Experts theorize that Twitter's rapidly growing popularity now permeates every corner of our daily life, including political campaigns (Fitzpatrick, 2012), both traditional and Internet media industries (Ingram, 2012), and even sporting events (Russell, 2012). For instance, Twitter's interactive UEFA Euro 2012 sites revealed that the European Championship's final soccer game, which were held in July 1st, triggered 15,358 tweets per second at its peak and more than 16.5 million tweets total from around the world, indicating world soccer fans used Twitter to share thoughts and discussion about the game and to show support for their team (Russell, 2012). In short, Twitter has become a central communication tool across many realms in citizens' daily lives. From information to mobilization, Twitter and other social media tools facilitate communication among politicians and citizens, reinvigorating the means by which people participate in the democratic process today (Gil de Zúñiga et al., 2012).

Politicians are agile in adopting this rapidly growing social media platform. For example, the President of the United States Barak Obama, the most followed political leader in the Twitter sphere, has over 35.6 million followers as of August 2013 (Twitaholic, 2013). Of his followers, 76 are heads of state or governments, more than a quarter of all world leaders and governments in the world (Lüfkens, 2012). A study also revealed that 61 world leaders and governments follow the White House Twitter feed; EU President Herman van Rompuy has 11 world leaders following; Austria's prime minister 10; the Korean president, U.K. government, and Russian prime minister all have 9 (Lüfkens, 2012). Further, Barack Obama and 2012 Republican presidential candidate Mitt Romney both launched social media campaigns, allowing them all the conveniences of a brick-and-mortar field office in cyber space (Fitzpatrick, 2012). In addition, Twitter is more popular than blogs in England (BBC, 2010), where Parliament members (MP) are often overwhelmed by the number of questions their subjects tweet at them (BBC, 2012).

Optimistic predictions that Twitter will change politics and our social lives positively are popular (Ingram, 2012), yet the new horizons of politics are still unclear. Therefore, research on how political parties and politicians are interacting through Twitter is critical to promote our understanding of new media and politics. Investigating the underlying factors and properties of political networks among politicians can determine how politicians actually use Twitter (Golbeck, Grimes & Rogers, 2010). Further, numerous critical aspects of the political communication process are rarely and hardly examined, notably the dynamics of cooperation and competition within the sub-party level, because of lack of data and closed access to hidden political arenas (Sartori, 2005). Therefore, empirical and theoretical research, trying to reveal these "invisible politics" is worth the challenge.

This study investigates the Twitter network sphere of the 112th U.S. House of Representatives and the 18th Korean National Assembly members. This research will include comprehensive topics and questions about newly created networks in both countries.

Drawing from social network analysis, this research will explore U.S. and Korean political Twitter networks and compare structural characteristics of each legislative network. Questions asking network size, density of a network, fragmentation rate, and network centralization index will be examined; findings will be compared in diverse network – whole legislative network and party network.

Mapping these networks will highlight the major features of these two elite political networks grounded in a new social medium.

This research will examine digital leaders emerging from newly created digital legislative networks: who are the most connected lawmakers; who have the great potential to coordinate party politics; who are the most sought after leaders; who are the most sociable lawmakers. Considering party politics is dominant in representative system, this research will present the top ranking lawmakers in two network levels: whole and party network.

By examining lawmakers' pattern of relationship building in the network, this research will explore whether the relationship building pattern is dependent to party position, ruling or opposition, in the network. One of the controversial tendencies in recent years, polarization and fragmentation of politics, will be examined.

The distinctive socio-political settings of Korea and the U.S. suggest useful comparisons for global trends in the use of Twitter. Both countries are home to fast Internet service, and Korea is one of the most highly connected countries in the world (OECD, 2011). The U.S. House of Representatives represents the typical bipartisan system in the tradition of Western democracy, and the Korean National Assembly represents a relatively new system in the non-Western democratic tradition (Sartori, 2005). Altogether, this detailed examination of Twitter use by political elites in Korea and the U.S. will illuminate how this new media platform is being adopted by and changing politics in two distinct social and cultural settings. Most importantly, this comparison will bring into sharp relief those aspects of the use of Twitter by political elites that are common as distinct from those aspects of the use of Twitter that are unique to one of these political settings.

The major chapters of the dissertation will be:

- Literature review, including the eight specific research questions guiding this research.
- Network analysis methodology, including a detailed presentation of the dozen measures of network properties that will be investigated for the U.S. and Korean settings.
- Two separate chapters presenting the results from these two settings.
- A chapter comparing which features of political communication in these two settings is similar and which differ. This chapter also will discuss the implications and suggestions of the findings in this study for future research.
- A final chapter presenting a normative assessment of the utility of Twitter as a platform for political communication.

CHAPTER 2: THEORETICAL BACKGROUNDS

DIGITAL TECHNOLOGY AND POLITICAL ELITE

For years, the news media's impacts and consequences have been the communication field's main research area. Numerous studies have explored its role in public agenda formation (McCombs, 2004), public opinion atmosphere (Noelle-Neumann, 1974), knowledge and information distribution (Tichenor, Donohue & Olien, 1970), formulating political attitudes (Cappella & Jamieson, 1997), and social connectedness (Putnam, 2000).

Historically, politicians have been the forerunners in new media adoption, such as newspaper, radio, television, and, more recently, the Internet, etc. (Lipinski, 2004). Researchers are now exploring the relationships between the Internet and politics. For example, how and why representatives communicate with citizens through e-mail (Goldschmidt et al., 2001) and web sites (Gulati, 2004; Jarvis & Wilkerson, 2005; Taylor & Kent, 2004).

Studies thus far have revealed that the Internet has greatly impacted politics and show a shift in communication between politicians and the public (Gulati, 2004; Fitch et al., 2005; Goldschmidt et al., 2008). Studies have shown that digital media has significantly changed the ways in which politicians connect to other party members and constituents, construct a positive image, mobilize supporters, and drum up campaign donations (Felten, 2009; Golbeck, Grimes & Rogers, 2010).

TWITTER AND POLITICS

Twitter, the latest version of popular media in politics (Tumasjan et al., 2010), allows its users to send and read short messages (up to 140-character-long) known as "tweets," which also serve as "retweets," "mentions," and so forth (Boyd & Ellison, 2008).

Researchers have examined Twitter from diverse perspectives and in numerous contexts: social network (Gruzd, Wellman & Takhteyev, 2011), social media (Boyd & Ellison, 2008; Kaplan & Haenlein, 2010), news media (Kwak et al., 2010), conversation (Boyd, Golder & Lotan, 2010; Honey & Herring, 2009), influence and power (Leavitt et al., 2009), informal communication (Zhao & Rosson, 2008), business marketing (Jansen et al., 2009), food consumption (Dixon et al., 2012), and emergency response situations (Hughes & Palen, 2009). All this research demonstrates that Twitter use varies by the gratification and utilities that the users are searching for.

Twitter is also widely used in government communication which allows the broadcasting of government policies well beyond any country's borders. For example, the late Venezuelan President Hugo Chavez used Twitter in 2012 to rally his 3.6 million followers and pursue re-election; the entire governments of Chile and Mexico, and their ministers, are on Twitter; the foreign ministries of 82 countries have Twitter accounts, and 47 foreign ministers are personally on Twitter (Lüfkens, 2012). Lüfkens (2012) asserted that Twitter has already replaced traditional diplomatic exchanges and had a massive impact on the how world political leaders interact with one another and on how diplomats connect with their host countries: Twitter provides politicians and diplomats with direct, massive, effective, and interactive ways to interact with their public.

Twitter has proven an effective tool in breaking news during China's (Bradshaw, 2008) and Japan's earthquakes (Sakaki, Okazaki & Matsuo, 2010), Iran's mass movements (Grossman, 2009; Morozov, 2009), Moldova's riots (Mungiu-Pippidi, 2009), and many other global events, while controversy remains as to whether it should be regarded as an additional media platform or is simply an open information utility (Ingram, 2012). Kwak and his colleagues (2010) found that over 85% of the topics tweeted and retweeted are headline news or persistent news in nature, indicating Twitter plays an important role in distributing news and information.

Twitter also has been demonstrated as an effective tool in civic engagement (Khan et al., 2011; Levy 2008), alternative media (Mungiu-Pippidi, 2009; Shirky, 2009), the mobilization of voters (DeBroff, 2012), and in predicting election results (Tumasjan et al., 2010). Studies also have shown that Twitter can function as a public sphere (Williamson, 2011) and suggest several political factors and motivations affecting Twitter use.

Then, why do the politicians use Twitter? What will be the gratification of Twitter use for politicians? Research on Twitter adoption by politicians revealed that U.S. representatives use Twitter mainly for "self-promotion" rather than discussion with the public or transparency of the legalization process (Golbeck, Grimes & Rogers, 2010). Another study found that representatives' Twitter adoption is closely associated with the number of bills they sponsored, which indicates that the motivations and benefits of Twitter mostly come from outreach through Twitter (Chi & Yang, 2010). Follow-up research found that accelerated Twitter adoption is closely and positively associated with successful past outcomes (Chi & Yang, 2011).

Political ideology is also an apparent underlying factor, with more labor party and liberal party members actively using Twitter than conservative members (Williamson, Miller & Fallon., 2010). Further, other research argued that motivations for Twitter use vary by political ideology: Democrats care more about transparency and amount of support, while Republicans care more about outreach and the number of bills they are sponsoring (Chi & Yang, 2010).

Studies on German Twitter use have found that a small fraction of heavy users, approximately 4% of all Twitter users, accounted for more than 40% of all messages sent and received (Tumasjan et al., 2010). A US study found approximately 20,000 elite users, comprising less than 0.05% of the use population, attracting almost 50% of all attention within Twitter (Wu et al., 2011), which strongly support the "rich-get-richer" phenomenon of the Internet (Norris, 2001).

TWITTER: WILL IT BE A NEW CONVENTION OR THE LATEST VERSION OF "ECHO CHAMBER"?

Political polarization and fragmentation phenomenon (Sunstein, 2007; 2009) are constantly found in the Twitter sphere. Wu and his colleagues (2011) found that attention in the Twitter sphere is highly homophilous. This means that celebrities, for instance, overwhelmingly follow celebrities; news media follows news media, and bloggers follow other bloggers. Another study found that during the 2010 U.S Congressional midterm elections the re-tweet network exhibited a highly polarized and segregated partisan structure having hardly any connectivity between left- and right-wing users, whereas this was not true for the “mention” network (Conover et al., 2011). The study found that the content of political discourse on Twitter was divided along partisan lines. Many messages contained sentiments more extreme than one could encounter in face-to-face interactions. Such a tendency might, the authors pointed out, actually exacerbate the problem of polarization by reinforcing pre-existing political biases (Conover et al., 2011). Researchers have found additional evidence that Twitter network structures are also grouped according to geographical proximity (Holmberg & Thelwall, 2009; Holmberg, 2010).

However, analyzing 54 million user profiles, 1.9 billion follow links among users, and all 1.7 billion public tweets, one study found social ties in the Twitter network were less dichotomous in political views than they were in the blogosphere (An et al., 2011). Most Twitter users read different views through their social ties: 75% of right-wing users received left-wing media content through Twitter friends of a different political view; 93.6% of centrists received left-wing media content and 57.4% of centrists received right-wing media; 68.7 % of left-wing users received right-wing media contents (An et al., 2011). These findings sharply contrast to findings in the blogosphere. For example Adamic and Glance (2005) found that only one in six links among the top of the left and right blogospheres linked across the ideological divide.

Yardi and Boyd (2010) also found that Twitter exposes people to diverse points of view and that a wide range of interactions occurs in the Twitter sphere, which would promote positive social outcomes. However, Yardi and Boyd (2010) argued that Twitter is insufficient for reasoned discourse and debate, privileging instead haste and emotion, although it facilitates various relationships such as shared interests, familial ties, friendships or need for orientation.

Will the Twitter network curtail the phenomenon of opinion fragmentation and political polarization? Do these findings signal an evolution of partisan media consumption (Fiorina & Abrams, 2008; Iyengar & Hahn, 2009; Prior, 2007; Stroud, 2010; 2011)? Will Twitter reinforce political partisanship or will it open new paths to the public sphere?

Like any studies on a new medium, those concerning Twitter have elements of myth, fallacy, and hyperbole about the impact it has or will have on social changes (Cha et al., 2010; Gladwell, 2010). Numerous studies have been conducted to reveal the nature and consequences of Twitter as a medium. Many of these, however, are either descriptive studies or impressionistic journal stories based on anecdotal evidence rather than solid theoretical grounds. Therefore, many aspects of Twitter use remain unexamined and several arguments need to be tested.

OPINION LEADER, INFLUENTIAL, AND NETWORK

One of the interesting findings in recent studies on Twitter is that there exist particular Twitter users who play a similar role to that of the opinion leader in the theory of the two-step flow (Katz, 1957; Katz & Lazarsfeld, 1955).

For example, Wu and his colleagues (2011) found that about 15% of tweets received by ordinary users are received directly from the media. Meanwhile, 46 % of media-originated content that reaches the masses via an "intermediary" reaches up to

490,000 users out of a million users randomly selected. The authors argued that those intermediaries, who have more followers and more actively post tweets than other users, are perfect examples of opinion leaders in classical two-step flow theory.

An and her colleagues (2011) also found that social ties broaden the types of information users receive from diverse news media. For example, they found that a user's probability of subscribing to multiple types of media was around 30.1% for direct subscription. Through social interaction such as the retweet function in the social network, however, the probability of consuming multi types of media rose to over 74.5%, even to 92.5% (An et al., 2011). They found that indirect media exposure expands the political diversity of news from 60 to 98% (An et al., 2011). Further, they found that, when direct subscription is considered alone, most Twitter users receive only biased political views they agree with. The influence of social ties dramatically changes this situation such that a majority of users have access to politically diverse views (An et al., 2011).

Another study, measuring influence in the Twitter sphere, found evidence indicating influential users intervene and mediate the process of information flow (Cha et al., 2010). Also pertaining to influence in the Twitter network, they found three critical aspects: a) Twitter users who have high in-degree (number of followers) do not necessarily spawn many re-tweets or mentions—a million follower fallacy; b) most influential users can hold significant influence over a variety of topics; c) influence in the network is not gained spontaneously but through concerted effort, (Cha et al., 2010). Leavitt (2009) suggested a Twitter-specific definition of influence online: the potential of an action of a user to initiate a further action by another user.

This raises the question of whether being influential is the same in this new medium as it is for traditional opinion leaders in classic two-step flow theory. Or is there a new type of leader in a new medium?

Watts and Dodds (2007) presented two distinctive features that distinguish opinion leaders in two-step flow theory from the influential in a networked community. These features are: a) in a classic model of two-step flow, influence can only flow from opinion leaders to followers but in an influential digital network, it can flow in either direction; b) influence in the network can propagate for many steps, whereas in the classic model it can propagate only two steps. Using a series of computer simulations of the interpersonal influence process, Watts and Dodds (2007) demonstrated the influence and its penetration varied according to the density and variance of a network. However, their arguments need more empirical evidences and tests.

RELATIONS MATTER: SOCIAL NETWORK ANALYSIS

Social network analysis can be defined as a set of relational methods for systematically understanding and identifying connections among actors (Wasserman & Faust, 1994). It is a body of theory exploring types of observable social spaces and their relation to individual and group behavior (Moody, 2012). Social network theory claims that social lives are created and maintained largely by social relationships and the patterns they form. This type of analysis differs fundamentally from perspectives based on the assumption of individualistic, attribute-based social science (Scott, 1988; Wellman, 2010).

Social network analysis assumes several things. It assumes for one that social relationships can be defined as a set of nodes that are tied by one or more types of relations (Wasserman & Faust, 1994). Social network theory considers actors, ties, dyads, triads, sub-networks, and the network itself as essential elements of the social phenomenon (Wasserman & Faust, 1994; Carrington, Scott & Wasserman, 2005). Therefore, it assumes actors' behavior depend, in large part, on how they are linked; the destiny of particular organizations may depend on the pattern of relations within the organization; patterns of relations reflect the power structure of a given setting. Clustering may reflect coalitions within the group (Moody, 2004). One of the main focuses of social network analysis is the pattern of relations among people, organizations, or nation states (Wasserman & Faust, 1994).

Since the mid-1930s, social network analysis has been used to investigate a broad range of research based on the basic notion that relations matter. Jacob Moreno introduced the ideas of sociometry in 1934; its tools were developed at the end of World War II. It was in the 1970s, when modern discrete combinatorics (especially graph theory) developed rapidly and powerful computers became readily available that the study of social networks began to flourish (Moody, 2012). Now it is used in physics, biology, medical science, sociology, anthropology, marketing, communication research, political science, terrorist and disaster networks and so forth (Borgatti et al., 2009; Carley, Reminga & Kamneva, 1998; Carrington, Scott & Wasserman, 2005; Scott, 1988).

CONCEPTS, MEASURES, AND PROPERTIES OF NETWORK

Several concepts of social network analysis are worth being noted. First, in social network theory, actors—considered to be nodes—can be ideas, events, individuals, organizations, or even nations. Relationships between nodes are often described as lines (edges) between pairs of nodes (vertex). Nodes' relationship can vary. For example, the relationship can be symmetric (two university student who share a room), asymmetric (a master who gives an order to maid), or valued (friends who see each other five times a week). Therefore, most network data are familiar to everyone. For example, a relationship can represent face-to-face contact, telephone contact, email contact, contact through faxes or wires, membership in the same organization, attendance at the same conference, or graduates of the same high school (Wasserman & Faust, 1994; Moody, 2004). Three types of network data are mainly examined: a) Ego-network, which contains the relationship of a respondent (ego) and the people they are connected to (alters); b) partial network, which contains ego-networks and some amount of tracing to reach contacts but does not include a full account of connections among all pairs of actors; and c) whole network, which includes a full account of the connections among all pairs of actors (Marsden, 2005).

When exploring a network, social network analysis focuses on a network's two features—connectivity and centrality (Borgatti, 2006). Three measures are available to examine connectivity. First, examining whether there is a chain of contact from one actor to another is reachability. Second, when they can be reached, the number of steps between them is the factor of distance. Finally, the number of different paths connecting each pair is the factor of number of paths (Borgatti, 2006). For example, in an information network, distance is the factor determining the likelihood of information passing from one end of the chain to the other. The probability of transfer information decreases over distance because information flow is not certain. Simultaneously, the probability of transfer increases with each alternative path connecting pairs of the nodes. Distance can be measured by the number of relations separating a pair (Moody, 2012).

The second feature of a network's shape – centrality — refers to one dimension of location, identifying where an actor resides in a network (Carley, Reminga & Kamneva, 1998; Everett & Borgatti, 2005). With centrality, we can compare the place where actors reside: whether an actor is at the edge (periphery) or at the center of a network, suggesting a distinction between insiders and outsiders. For instance, examining the email address and transferred data acquired by a six-year lawsuit brought by the National Security Archive and allied historians, Blanton (1995) revealed the White House information network during the early 1980s: who the insiders and the outsiders were; who were the information hub in the process of decision making.

The key topological features of any social network are the centrality measures; these also present the extent of hierarchy and clustering in a network (Borgatti 2003; 2005). It is also possible with centrality measures to examine the structure of social space. For example, these identify the core groups and the patterns of relations among them that affect the stability and resource distribution of a network. Two features of interest related to network structure are its cohesive groups and its hierarchy (Burt, 1987). Cohesive groups refer to sets of people who interact frequently with each other (Watts, 2003a). Actors belonging to these groups work together and they are often organized into positions within a network that indicate their particular roles or access to resources (Lorrain & White, 1971). Hierarchy identifies the leadership positions within a network, through either direction of ties or periphery status.

Centrality measures are often used to tap into the overall characteristics of a network and to compare different network. This process is known as centralization. The basic idea of centralization is to calculate the average deviance of each node from the most central node. Therefore, centralization calculates the extent to which a network is organized around its central nodes (Borgatti, 2005; Wasserman & Faust, 1994). Estimating the centralization of networks, we can find how a network is centralized and how different two network structures are in degree of centrality.

To compare features of networks, density is useful in measuring the overall level of network integration (Freeman, 1979; Wasserman & Faust, 1994). While centralization is the proportion of other Web sites' connections with a central site, density reflects how many sites are connected to one another in an entire network. High density implies a network is densely connected, so the complexity increases with more dynamics. Several ways of data representations are possible: the same data set can be represented via graph, adjacency matrix, arc list, node list, and so forth. Based on adjacency matrix data, this dissertation will present graphs which demonstrate what the political networks look like.

SOCIAL NETWORK ANALYSIS AND DESCRIPTIVE AND INFERENTIAL STATISTICS

The descriptive and inferential statistics for social network data are different in two distinct ways. First, social network analysis is about relations among actors, not about relations between variables. The application of statistics to social networks is about describing distributions and relations among distributions. But, social network analysis is concerned with describing the distributions of relations among actors rather than describing distributions of attributes of actors or variables (Hanneman & Riddle, 2005). Second, many of the tools of standard inferential statistics do not apply to network data directly. Most of the standard formulas for calculating estimated standard errors, computing test statistics, and assessing the probability of null hypotheses don't work with network data, which give “false positive” answers more often than “false negative” (Hanneman & Riddle, 2005). These two features mainly come about because network data are not independent samplings from populations (Hanneman & Riddle, 2005). For example, the standard formulas for computing standard errors and inferential tests on attributes generally assume independent observations. Applying them when the observations are not independent can be very misleading (Carley et al., 2011; Hanneman & Riddle, 2005). Instead, alternative numerical approaches to estimating standard errors for network statistics are used. For example, permutation approaches calculate sampling distributions of statistics directly from the observed networks by using random assignment across hundreds or thousands of trials under the assumption that null hypotheses are true (Hanneman & Riddle, 2005). Further, numerous studies have found that a networked world is composed of centers (or hubs) and peripheries. This distribution of attributes that follow scale-free power law distribution makes a networked world critically different from other scholarly research traditions based on convergence from means and regression (Barabási & Albert, 1999; Barabási, 2003).

VISUALIZATION OF NETWORK

One of the basic products of social network analysis is visualization. For instance, Moody (2004) argues that social network analysis embodies a wide range of theories relating types of observable social spaces. This is because relationships between individuals and groups create a social space that can be displayed in multiple contexts which is frequently ignored by methods of standard social science analysis.

Visualization also has numerous advantages. It facilitates an understanding of the structural features of networks (Becker, Eick, & Wilks, 1995; Freeman, 2005; Savage & Burrows, 2007). Studies indicate that visualization of network technique has the descriptive power to uncover social change and develop more analytical ways to begin to reveal some of the process at work (Freeman, 2005). It benefits an intuitive method of displaying networks, helping people to see social space. However, it lacks standards for how to display it. At the same time, large networks sometimes tend to reveal only the roughest properties of the network (Moody, 2012).

INTERNET AND HYPERLINK NETWORK ANALYSIS

With the rapid development of the Internet, a new research method has emerged—hyperlink network analysis. Hyperlink network analysis is an extension of traditional social network analysis. It focuses on the structure of a social network represented by hyperlinks on the Web. Hyperlink network analysis has added new ways to collect data by gathering it from websites, blogs, and so forth. When two websites (nodes) are connected through interlinking, they can be considered social actors and their hyperlinking activities can be analyzed as a whole.

Foot and his colleagues (2003) found that hyperlinks represent diverse relationships between websites, including preferences and agendas. Studies have found that electronic discussion groups virtually formulate a social network (Wellman, 1997) and generate the appearance of networked individuals (Wellman et al., 2003).

Scholars have argued that digital media generates networked individuals and the interconnected digital community (Rainie & Wellman, 2012). Haythornthwaite (2005) found that online connectivity creates a 'real' online community. Gruzd and colleagues (2011) showed that the Wellman's Twitter network is real one and created a virtual personal community, satisfying the preconditions of "imagined community" (Anderson, 2006), "virtual settlement" (Jones, 1997), and "sense of community" (McMillan & Chavis, 1986).

Studies have also demonstrated that hyperlink analysis is a productive research method in analyzing government online (Richards, 2005) and online relationships between politicians (Adamic & Glance, 2005; Farrall & Carpini, 2004; Halavais et al., 2003; Park & Jankowski, 2008). Hyperlink network analysis has advantages that reveal a latent network among people or organizations that might not appear when focusing only on the organization and its members' relationships (Park & Thelwall, 2003).

Hyperlink network analysis uses a set of analytical techniques and tools derived from social network analysis. Therefore, the basic hyperlink network data set is an n x n matrix**,** called adjacent matrix: n equals the number of nodes in the analysis. In hyperlink network analysis, the nodes can be websites that represent social actors like people, groups, organizations, cities, or nations. One of the important outcomes of hyperlink network analysis is to identify a central node, in this case, a central website, generally defined as the site that provides the most and/or shortest connections to other members within the group (Borgatti, 2005; Wasserman & Faust, 1994). A study found that the central website usually plays the role of hub and broker, and is an authoritative or prestigious site (Bonacich & Lloyd, 2001). Another analysis identified those groupings of websites that best represent their hyperlinked relations, producing central and periphery groups (Aldenderfer & Blashfield, 1984; Burt, 2000).

Much of the communication network research suggests a “bird of a feather phenomenon” or a “homophily principle,” the phenomenon of selecting communication partners similar to oneself (Monge & Noshir, 2003; Rogers & Bhowmik, 1970; Yuan & Gay, 2006) which corroborates with the findings that similarity brings connection (McPherson, Smith-Lovin, & Cook, 2001). These phenomena have also been found among Korean politicians and their constituencies (Park, Barnett, & Nam, 2002). The study argued that the Confucian-based South Korean culture greatly impacted the powerful homogeneity among political actors on the Web. For example, “politeness” can be an underlying factor that promotes web connections in the network (Fulk, Schmitz & Steinfeld, 1990).

Several hyperlink analyses of South Korea’s digital media use have been conducted. They include: South Korean citizen blog network (Park & Jankowski, 2008); politician’s web sites linking patterns (Park & Thelwall, 2008)); politicians’ networking patterns in blogosphere and Twitter (Park & Kluver, 2009) and legislative blogosphere in the 17th National Assembly (Bang, 2008). Especially Bang (2008) found that Korean legislative blogosphere is fragmented and polarized structure rather than bipartisan one. Cyword.com case (Park et al., 2011). Hsu and Park (2012) found that 72 South Korean National Assembly members, 25% of all members, use Twitter and in-degree and out-degree ties among politicians number, as of April 2010, 983. Hsu and Park (2012) found that liberals were dominant in Twitter use and politicians tend to link mainly by following politicians rather than through direct communication with the people. However, Hsu and Park's research stopped short of exploring party network features or digital leadership resulting from mutual follower relationships.

SOCIAL MEDIA, HYPERLINKS, AND "BIG DATA" RESEARCH

Social network analysis has diverse advantages in explaining and analyzing social phenomena, especially, a networked community and networked society, which consists of networks in all the key dimensions of social organizations and social practice (Castells, 2011).

However, one of the difficulties for empirical research is data collection (Valente, 2005); in most cases, detailed data revealing relationship like "who knows whom" is extremely difficult to come by for sufficiently large groups (Watts, 2003a). Most empirical research based on surveys or questionnaire has been egocentric research because collecting complete network data is difficult (Marsden, 1990). Whole network analysis, for example, cannot be based on respondents' reports of their behavior and in which network peers are not necessarily connected to one another and not interviewed (Valente & Vlahov, 2001; Masden, 2005). Further, respondents are notoriously bad at estimating and recalling the relationship they have in real life (Watts, 2003b).

However, several recent social network services are enabling researchers to analyze large datasets. Such datasets, on the multi-million to billion people scale, use special interfaces like the application programming interface (API) of Twitter. For example, using 58 servers at the Max Planck Institute for Software Systems, a study gathered information about users' social links and tweets, reaching up to 80 million users (Cha et al., 2010). Then, they analyzed the profiles of 54 million users; they followed 1.9 billion links among these users, as well as all 1.7 billon public tweets ever posted by the collected users (Cha et al., 2010). Then, they analyzed the profiles of 54 million users; they followed 1.9 billion links among these users, as well as all 1.7 billon public tweets ever posted by the collected users (Cha et al., 2010). They found that popular users having a high in-degree (followers) are not necessarily influential, "a million follower fallacy" (Cha et al., 2010). In the follow-up research, they explored the follow links and tweets of 80 popular news media sources and their 14 million audience members, and found 80% of Twitter users follow up to 10 media sources, typically from 2-3 different media types (An et al, 2011). They discovered that indirect media exposure via the Twitter network expands the political diversity of news to which users are exposed to a surprising extent, increasing the range by between 60 to 98% (An et al., 2011).

Further, analyzing 41.7 million Twitter user profiles, 1.47 billion social relations, 4,262 trending topics, and 106 million tweets with a follower-following topology analysis, another study found that the Twitter sphere indicated a non-power-law follower distribution, a short effective diameter, and low reciprocity, which all mark a deviation from known characteristics of human social networks (Kwak et al., 2010).

Another study tracked for 10 days 12 popular Twitter users' generated content and connections, examined a total of 134,654 tweets, 15,866,629 followers, and 899,773 followees. The study grouped a user's Twitter influence into two types: conversation based and content based (Leavitt et al., 2009). All these researches could not have been conducted without the help of computerized data gathering tools.

In these contexts, Biocca (1992) projected that communication with virtual reality will create a space for a new type of research and research method: Big data research. How will new opportunities offered by new technology and flourishing social media affect the tradition of communication research? One thing is clear, however, the fact that we have entered into the age of big data is transforming academic research on the economy, politics, and global development, and so forth (Lohr, February 11, 2012).

RESEARCH QUESTIONS

The vast majority of the research on Twitter has all been published in the last four years. Very little of this research has examined the use of Twitter by political elites. An examination of the use of Twitter by members of the Korean National Assembly and the U.S. House of Representatives should then explore significant new ground. On the other hand, such research will be guided by research questions rather than hypotheses making specific assertions about the nature of Twitter use by these political elites.

This research will include analysis of three types of network data: a) whole network; b) sub-network or partial network; c) ego network. Each level of analysis will be examined and displayed by both visualizations and network property measures.

The main topics will be as follows: a) investigate properties of each legislative body's Twitter networks; b) examine who is in what relational position in a network using five centrality measures; c) analyze sub-networks, especially major party networks in each of the countries; d) compare those properties between two legislative bodies' Twitter networks. Further, analysis of a party network will include analysis using three variables to tap detailed Twitter use of the representatives: a) ideological party identity (liberal/conservative); b) positional resources of a party in the party system (ruling party/oppositional party); and c) party relationships (intra-party/partisan and inter-party/bipartisan).

The first step in exploring the nature of a Twitter network is to examine what each legislative Twitter network looks like. A large body of social network analysis literature suggests that the shape of a network shown by visualizations benefits intuitive ways of displaying networks, hermeneutic accessibility and descriptive power for uncovering network structure (Freeman, 2005; Moody, 2012). Visualization of each legislative body's networks will be a unique contribution of this research. This research will display network shapes in two contexts: directional networks and mutual networks. The former will display all the ties, in-and out-degree and bidirectional ties, but the latter bidirectional (mutual) ties only. Therefore this study sets RQ1 as follows:

RQ1: What does the whole network of each legislative body look like?

The next step is identifying lawmakers playing important roles in the network. A network consists of hubs and peripheries; some nodes that can be called a hub or a center are more important than others (Barabási, 2003; Watts, 2006). In the information network, these nodes work as switches, connectors or opinion leaders; in the influence network, they act as coordinators, modulators or authorities; in the friendship network, they are the popular ones or the most loved. In the classic model of information flow, information flows from opinion leaders to followers (Katz & Lazarsfeld, 1955). Considering a network of lawmakers, the lawmakers paying important roles might be digital opinion leaders.

This research uses five centrality measures developed by network analysis — degree of centrality, closeness centrality, betweenness centrality, in-degree centrality and out-degree centrality. These popular and efficient measures for analyzing node's relational position in a network are discussed in detail in the method chapter (Everett & Borgatti, 2005; Hanneman & Riddle, 2005).

Each identifies nodes playing different role in the network. For instance, a node with the highest degree of centrality, the most well-connected node, is often considered as the best "known-to-all" node or "the most influential" one because the node is in the position of being able to reach the other nodes faster than others. RQ2 consists of two sub-questions.

RQ2-1: Who are the key players in the U.S. and Korean Twitter networks?

RQ2-2: What do the key players' ego networks look like?

RQ3, H1 and RQ 5 examine the party networks in each of the legislative bodies. As Sartori (2005) noted the dynamics of cooperation and competition within the party remains "invisible politics," so it has been rarely demonstrated or empirically examined. Exploration of how each party network is organized and what the properties are can reveal some unseen aspects of party politics.

First, this study will examine the difference between conservatives' and liberals' Twitter party network and compare those properties with various social network analysis measures. Numerous studies on Twitter use by politicians reveal that Twitter use varies according to political ideology (Gulati & Williams, 2010; Williamson, Miller & Fallon., 2010). A link analysis on the elite blogosphere in the United Stated found that right wing bloggers linked to each other, tend to have more links to external sources and across the divide more than the left-wing bloggers, but they argued that the two sides of the blogosphere are mirroring each other (Adamic & Glance: 2005). Therefore, this research will examine whether the Twitter party network varies according to political ideology. This study sets RQ3 as follows:

RQ3: What is the difference between conservatives' and liberals' Twitter party networks?

Numerous studies on Twitter use by politicians reveal that Twitter use varies according to the positional resources of political elites. Studies revealed that Twitter has great potentials as an alternative media for the politicians belong to minority party (Gulati & Williams, 2010; Mungiu-Pippidi, 2009). However, little research has examined the relationship between politician's Twitter relationship building patterns and political positional resources. Therefore, this study sets H1 as follows:

> **H1**: Representatives belonging to the ruling party are more likely to have more in-degree, out-degree and mutual ties than those who belong to opposition party.

In politics, political attitudes such as "ready to hear the other side" or "willing to expose oneself to opposite opinions" are critical resources for political deliberation and political toleration, which are essential for better democracy (Mutz, 2006). A large body of social network analysis, however, reveals that similarity brings social connection (McPherson, Smith-Lovin, & Cook, 2001). Further, numerous researchers have found that social connections are guided by the "bird of a feather phenomenon" (Monge & Noshir, 2003). Communication partners select each other based on how similar they are to one another; this may be based on physical distance, beliefs, values, social status and so forth (Rogers, 2003; Rogers & Bhowmik, 1970). "Bird of a feather phenomenon" or "tendency of political homophile" is closely related to political fragmentation and polarization. Research on the blogosphere found that the blogosphere is mainly fragmented; blog use facilitates group polarization, because blogs are usually grouped with those sharing the same political ideology (Adamic & Glance: 2005). Then, what will be the political Twitter sphere created by lawmakers? Will the legislative Twitter network promote polarization and fragmentation of politics? Will the Twitter sphere be another "echo chambers of representatives"?

By comparing tie composition of party networks, this research will examine these questions. Therefore this study sets RQ5 as follows:

RQ5-1: What do the partisan and bipartisan party networks look like?

RQ5-2: What is the difference between the partisan and bipartisan connections of each party?

RQ6 investigates two comprehensive measures of two legislative bodies' political Twitter network structure, 18th Korean National Assembly and 112th U.S. House of Representatives. Two packages of social network measures will be used to compare the two legislative networks: cohesiveness and centralization. First, the cohesiveness measure includes density, reciprocal rate, fragmentation, and distance of a network. These are meant to discover how complex or connected a network is; how efficiently linked a network is and so forth. The distance of a network indicates the distance of each node suggesting the speed of information flow (Barabási, 2003). To discover the level of network's centralization, this study will use three network centralization indexes — centralization for degree, centralization for closeness, centralization for betweenness. All of these measures are discussed in detail in the method chapter.

Further, findings from RQ2 to RQ5 will be compared including measures of party network structure, tie building patterns by party position, and party network's tie composition. This study sets RQ6 as follows:

RQ6: What are the differences between U.S. and Korean representatives' political Twitter network?

This research will explore how lawmakers in the two legislative bodies are interacting in the Twitter sphere that newly created political communication landscape. Exploring the structure, the cores (the centers), and the patterns of relationship building of Twitter are the main research areas of this study. Each research questions, therefore, was set up to deal with these tasks. In terms of level of analysis, the research begins with the entire network (RQ1), goes to the core networks (RQ2), then, moves to group (party) networks (RQ3 –RQ5). RQ6 rounds up the findings and compares two legislative networks.

CHAPTER 3: METHODOLOGY

Data Collection and Analytical Procedure

Four major steps for data collection and analysis were conducted in this dissertation. First, this research collected data on attributes of representatives through the official Internet site of each country. Twitter accounts were collected from the United States House of Representatives' official Internet site (http://www.house.gov/representatives/), and the Korean National Assembly's official Internet site (http://www.assembly.go.kr/renew10/mem/mem/mem_search.jsp).

Additional information was collected from each lawmaker's official homepage, and www.twitter.com. Twitter search sites, Twitaholic.com, were also used to crosscheck the Twitter accounts. Second, this study built a Twitter engine, using a web server and a customized program interface, and collected data through Twitter API.

This provided a large body of data regarding twitter accounts managed by representatives: who follow the representative (followers), whom is followed by the representative (followees) with basic information about the Twitter accounts such as the total number of Twitter followers, followees, tweet posting, and so forth. Followees are persons who are being followed by the representatives and followers are persons who are following the representatives.

Third, Using MySQL, a database storage procedure program, this study classified and extracted Twitter tie data (followees and followings) between representatives in the United States and South Korea. MySQL is one of the most popular open source data base applications available today, which enable researchers to manage massive data (Ullman, 2006). For instance, Heer and Boyd (2005) used MySQL for analyzing and visualizing large scale online social networking services. Perera and his colleagues (2011) analyzed Twitter messages sent to President Barack Obama using MySQL.

Finally, using a social analysis package program, this study calculated a variety of measures and carried out a visualization of the diverse networks. Multiple free or commercial packages are available for network analysis today. For instance, one study tested and compared six major packages selected from 27 software packages obtainable in 2005 and concluded that there is no single best choice, most of the software packages yielded solid validity and credible results when tested using the same dataset (Huisman, & Dujin, 2005). They suggest the final choice is a matter of particular research questions or the researcher's interest.

This study used *UCINET 6.232 for Windows*, developed by Borgatti, Everett and Freeman (2002) of Harvard University. *UCINET* has become a standard network analysis program and is useful for computing measures of the network topology (Moody, 2012). This program calculates comprehensive measures of the network data as well as providing a visualization tool, *Netdraw* (Huisman, & Dujin, 2005). This study also used *ORA*, developed by the computer science department of Carnegie Mellon University, for overall network data management and visualization of the network data (Carley et al., 2011).

DESCRIPTIVE STATISTICS

Altogether this research collected data regarding 616 Korean and U.S. representatives' Twitter accounts. The amount of data collected for this research is approximately 8.50 million, including tie data such as who follows whom, how many tweets were posted by which representatives, etc.

U.S. House of Representatives data

From May 1 to 7 in 2012, I collected Twitter data from 351 representatives who have Twitter accounts: 2.48 million follower data, 353,753 followee data and 284,722 tweets data were collected. Then, using MySQL program, I extracted data on 27,877 ties among the representatives. Node attribute data were collected from the United States House of Representatives'' official Internet site (http://www.house.gov/representatives/). This site provides comprehensive and official data regarding each representative. The data collected consisted of: 1) name, 2) gender, 3) age, 4) party affiliation, and 5) district. This study collected data from both voting representatives (435 members) and non-voting representatives (6 members). Total number of representatives was 438 because of three vacancies.

Korean National Assembly data

From April 13 to 20 in 2012, I collected from 265 representatives who have Twitter accounts: 3.01 million data regarding who follow the representatives, 2.11 million data regarding who are followed by the representatives and 272,613 tweets data from Korean representatives' Twitter accounts, then extracted data on 22,934 tie data between lawmakers. Total number of Korean representatives was 293.

Node attribute data was collected from the Korean National Assembly's official Internet site (http://www.assembly.go.kr/renew10/mem/mem/mem_search.jsp) which provides comprehensive and official data. Collected data were as follows: (1) name, (2) gender, (3) age, (4) political experience (number of elected), (5) party affiliation.

MEASUREMENTS

To tap into the properties of the political network structure, this study used a wide variety of measures developed in social network analysis and hyperlink analysis. Social network analysis has diverse advantages in explaining and analyzing the networked community (Barbarasi, 2003). Studies have also demonstrated that hyperlink analysis is a productive research method in analyzing digital spheres such as online government (Richards, 2005) and digital interactions between politicians (Agamic & Glance, 2005).

Network size

Network size is often a very important measure for network analysis size is critical for the structure of social relations because of the limited resources and capacities that each node has for building and maintaining ties. In any network there are (k * k-1) unique ordered pairs of nodes (that is AB differs from BA, and leaving aside self-ties), where k is the number of nodes. The network size is important since it limits and enables nodes in what they can do or not with the network (Barabási, 2003). As range of logically possible social structures increases, complexity increases with size (Moody, 2004).

Density

The density of a network indicates its level of organization: the extent to which a network is integrated (Wasserman, Stanley & Faust, 1994). Density is defined by the total number of ties divided by the total number of possible ties.[1] For a valued network, it is the total of all values divided by the number of possible ties. In this case, the density gives the average value. Watts and Dodds (2007) have shown that the role of an influential in the network can be differentiated according to density and the variance of density of the network. As the density and variance a network increases, an influential can exercise influence over the node in the network faster.

Distance (Shortest path)

The distance between two nodes is the length of the shortest path, which is measured by constructing a distance or generalized distance matrix between all nodes of a network (graph). Watts (2003a) successively measured the distance of each citizens and suggested "six degree separation principle," the idea that everyone is approximately six steps away from any other person in the world.

Reciprocal rate

The amount of ties reciprocated in a network is the reciprocal rate. In a Twitter network, this represents how many mutual followers are in a network.

A tie is reciprocated when it is connected from node A to node B and from node B to node A. We can count the number of nodes connected by a tie (which may or may

[1] For example, let *M* be the adjacency matrix for the network of dimension m * n. If the network is a rectangular network, density can be obtained by the following equation (Hanneman & Riddle, 2005).

$$\mathrm{D} = \frac{\mathrm{Sum\ (M)}}{m * n}$$

not be reciprocated) and calculate the proportion of nodes that have reciprocated ties. Or we can count the number of nodes and calculate the proportion of nodes that are reciprocated. A common interest in looking at directed tie relationships is the extent to which ties are reciprocated. Some theorists feel that there is an equilibrium tendency toward tie relationships to be either null or reciprocated, and that asymmetric ties may be unstable. A network that has a predominance of reciprocated ties over asymmetric connections may be a more "equal" or "stable" network than one with a predominance of asymmetric connections. The reciprocal rate, therefore, reflects interconnected and shared relationships between nodes of the network (Carley et al., 2011b; Gruzd, Wellman & Takhteyev, 2011). Further, reciprocal ties are important to building a core of community and valuable resources for information and support (Grudz et al, 2011). In terms of political relationships, reciprocal ties indicate that politicians are interested in each other and willing to hear what the other has to say. This research, therefore, assumes that if reciprocal ties exist across party borders, it represents bipartisan relationships indicating that lawmakers are willing to share information and ready to hear the other side which are critical resources for political deliberation and political toleration (Mutz, 2006).

Fragmentation

The proportion of disconnected nodes in a network is known as fragmentation (Breiger, Carley & Pattison, 2003). Fragmentation indicates how many nodes are isolated and disconnected from other nodes in the network.[2]

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[2] Calculating fragmentation is straightforward. The equation is as follows:

Centrality Measures

Since the early days of social network analysis, numerous centrality measures have been developed to explain the features of network structure, the extent to which a network is centralized, which node is more influential, which node is in the most prestige position and so forth. Each measure is based on a strict mathematical formula and is used for particular research interests. The social analysis software package, *UCINET*, presents diverse centrality measures. This study uses the five most popular centrality measures—Freeman's degree of centrality, closeness centrality, the betweenness centrality, in-degree centrality and out-degree centrality. All these measures can be applied to three networks—ego network, partial network (sub-network) such as a party network, and the whole network.

When comparing two legislative networks, this study uses a network centralization index, which includes the three power indicators in the network: degree of centrality, closeness centrality and betweenness centrality (Freeman, 1979; Gruzd, Wellman, & Takhteyev, 2011).

Freeman's degree of centrality

A node's position in the network, where a node resides, can be measured by Freeman's degree of centrality which refers to the number of ties attached to the node. Simple

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Let, S_k be the number of nodes in the K^{th} Component of G, $1 \leq k \leq n$.

Then, $F = 1 - \frac{\sum_k S_k (S_k - 1)}{n\,(n-1)}$

degree can be calculated by just counting the number of tie a node has in the network. (See Appendix A to know how to calculate degree of centrality). Often it is regarded as a measure presenting the extent of a node's "known-to-all potentiality" or "power potentiality" because actors who have more ties are more likely to affect other actors directly (Carley & Reminga, 2004; Hanneman & Riddle, 2005). A node with a high degree of centrality maintains numerous contacts with other nodes in the network. A central node occupies a structural position (network location) that serves as a source or conduit for larger volumes of information exchange and other resource transactions with other nodes. In network diagrams of social space, central nodes are located at or near the center. Located spatially at the margins of a network diagram are, in contrast, the peripheral nodes, those who maintain few or no relations.

Network centralization for degree

The basic idea of centrality for a network is the average deviance of each node from the most central node. This quantifies the dispersion or variation among individual degree centralities. (See Appendix B to know how to calculate network centralization for degree) For example, Freeman's general index contrasts the gap between the largest node centrality and the other values. It ranges from 0 to 1, reaching the maximum when all others choose only one central node (e.g., a star-shaped network).[3]

[3] The minimum is reached when all nodes have identical centralities (e.g., a circle-shaped network).

Closeness centrality

A node is considered important if he/she is relatively close to all other nodes but the degree of centrality doesn't present the relative closeness of each node. Closeness centrality measurement is based on the inverse of the distance (steps) of each node to every other node in the network. (See Appendix C to know how to calculate closeness centrality and network centralization for closeness).

Betweenness centrality

Betweenness centrality presents another critical characteristic of nodes, which is calculated by how many times a player appears on the shortest path between all possible pairs of players. (See Appendix D to know how to calculate betweenness centrality and network centralization for betweenness).

A player with a high degree of betweenness functions as the gatekeeper or information broker (Freeman, 1979). Indicating the influential potentiality of a node in the network, a central node occupies a "between" position on the geodesics connecting many pairs of other nodes in the network. As a cutpoint in the shortest path connecting two other nodes, a between node might control the flow of information or the exchange of resources.

Patterns of Tie Building in the Network

Prestige node; Socialite node

Tie building patterns of a node have received major interest from network theorists. From the typology of direction of ties that each node has, in-or out-degree ties, researchers can classify a node tie building patterns: socialite and prestige. These measures represent how many relationship points a node has, which provides a simple measure of influence (Freeman, 1979). For example, if a node has a higher out-degree tie score than in-degree score, a node can be classified as a node which is a socialite, one who wants to socialize with other nodes to gain prestige (Freeman, 1979). In contrast, nodes with higher in-degree tie scores can be classified as having the prestige, nodes that are most sought after by others.

This research extends this traditional typology of network analysis to Twitter research. In the terminology of Twitter use, it can be said that if a Twitter account has more followees than followers, it can be classified as socialite Twitter account. In the contrary, if a Twitter account has more followers than followees, it can be classified as a prestige Twitter account. If a lawmaker has more followers than followees in the legislative network, this research also will classify the lawmaker as prominent. Contrary, if a lawmaker has more followees than followers in the legislative network, this research will classify the lawmaker as a socialite.

Degree of prestige and socialite

Degree of prestige can be also measured by simple calculation of how many in-degree ties a node has: degree of socialite can be measured by calculation of how may out-degree ties a node has. For instance, node A has 10 in-degree ties and 12 out-degree ties, we can say that node A's degree of prestige is 10 and A's degree of socialite is 12.

These variables are used in regression analysis examining H1. In the Korean network, lawmakers' average in-degree tie is 86.54, while lawmakers average 86.54 out-degree ties. In U.S. network, lawmakers average 79.42 in-degree ties and average 79.42 out-degree ties.

Tie Responsiveness (Mutuality)

Tie responsiveness is measured by the ratio of reciprocal ties to in-degree ties. The degree of responsiveness indicates how much each representative is responsive to other representatives' in-degree ties, demonstrating how active the lawmaker is in relationship building with others. For instance, if lawmaker A has 5 mutual ties out of 10 in-degree ties, this implies that lawmaker A responded to half of all in-degree ties with out-degree ties so lawmaker A's tie responsiveness score become .50.

Twitter Activeness Variables

To investigate relationship building pattern of representatives in the network, this research operationalized several measurements. Number of followers and followees, number of tweets are shown in Table 1 and Table 2.

Twitter Use	Mean	S.D	Minimum	Maximum	Total
Number of Tweets	813.49	2,154.42	0	9,961	284,722
Followees	1,001.41	12,063.94	0	22,594	350,496
Followers	7,010.11	22,837.95	70	298,969	2,453,541

Table 1: Twitter use of House of Representatives (N=351)

Twitter Use	Mean	S.D	Minimum	Maximum	Total
Number of Tweets	1,028.73	2,154.42	0	14,727	272,613
Followees	7,985.24	12,063.94	0	110,277	2,116,089
Followers	11,379.09	22,837.95	31	225,539	3,015,459

Table 2: Twitter Use of Korean National Assembly (N=265)

Demographics

Measurement of Age and gender are straightforward. In U.S. legislative network, mean of age is 57.91 (N =351, S.D. = 10.72); in Korean network, mean of age is 57.50 (N=265, SD=7.43). In U.S. network, 71 representative are female (16%), while 44 representative are female (15%) in Korean network.

SUMMARY

This extensive set of measures for network analysis will be used to investigate the set of research questions. Drawing a network requires all the measures of network features such as network size, density, distance, fragmentation, etc. Identifying key lawmakers in the two legislative bodies will be conducted by applying the centrality measures. Comparisons of each level of network —whole legislative body network and party network— will be conducted by applying a set of network analysis measurements. Investigations and comparisons of tie building patterns of lawmakers will be investigated by regression analysis, which includes independent variables such membership in ruling party, political experience, number of Twitter posts, number of followers and followees as well as demographic variables such as age and gender. An overview of the measures used for each of the research questions is presented in Table 3.

Measurements		Research Questions							
		1 Whole Network (Looks)	2-1 Key Players	2-2 Ego Network (Looks)	3 Conservative & Liberal Network	4 Ruling vs. Oppositional: Tie Patterns	5-1 Party Networks (Looks)	5-2 Partisan-Bipartisan Tie	6 Whole Network Comparison
Network Size	Number of Nodes	0		0	0		0	0	0
Cohesiveness	Density	0		0	0		0	0	0
	Reciprocal Rate	0		0	0		0	0	0
	Fragmentation	0		0	0		0	0	0
	Distance	0		0	0		0	0	0
Centrality	Degree (Node)	0	0	0			0	0	0
	Network Centralization for Degree	0		0	0		0	0	0
	Closeness (Node)	0	0	0			0		0
	Network Centralization for Closeness	0		0	0		0	0	0
	Betweenness (Node)	0	0	0			0		0
	Network Centralization for Betweenness	0		0	0		0	0	0
Tie Building Pattern	Sociability					0			0
	Responsiveness					0			0

Table 3: Overview of this study's investigation of Twitter network analysis

CHAPTER 4: TWITTER NETWORK OF U.S. HOUSE OF REPRESENTATIVES

THE WHOLE TWITTER NETWORK OF THE 112TH U.S. HOUSE OF REPRESENTATIVES

RQ1 asked about the overall look of the Twitter network of the U.S. House of Representatives. This research demonstrates the whole network in two ways, as shown in Figure 1 and Figure 2. Both Figures 1 and 2 deal with the level of the whole network, but they are different in the direction of relationship: directional and bidirectional network.

Figure 1 represents whole network, which includes in- and out-degree ties as well as mutual ties. Suppose a relationship where Representative A follows Representative B but Representative B doesn't reciprocate; Figure 1 displays this relationship with a line between A and B as well as mutual ties. However, Figure 2 demonstrates only mutual ties between nodes with a line. The two network figures were drawn based on relational distance of nodes included, which implies that the distance in the figure represents how closely each node is related in the network. For example, a node, displayed by a dot, standing far outside the network indicates that a node's distance to center is far. Thus, the figures demonstrate what neighborhood a particular representative belongs to in the political network and whether a node stands at the center or on the periphery. Each node is displayed by a dot signifying a representative.

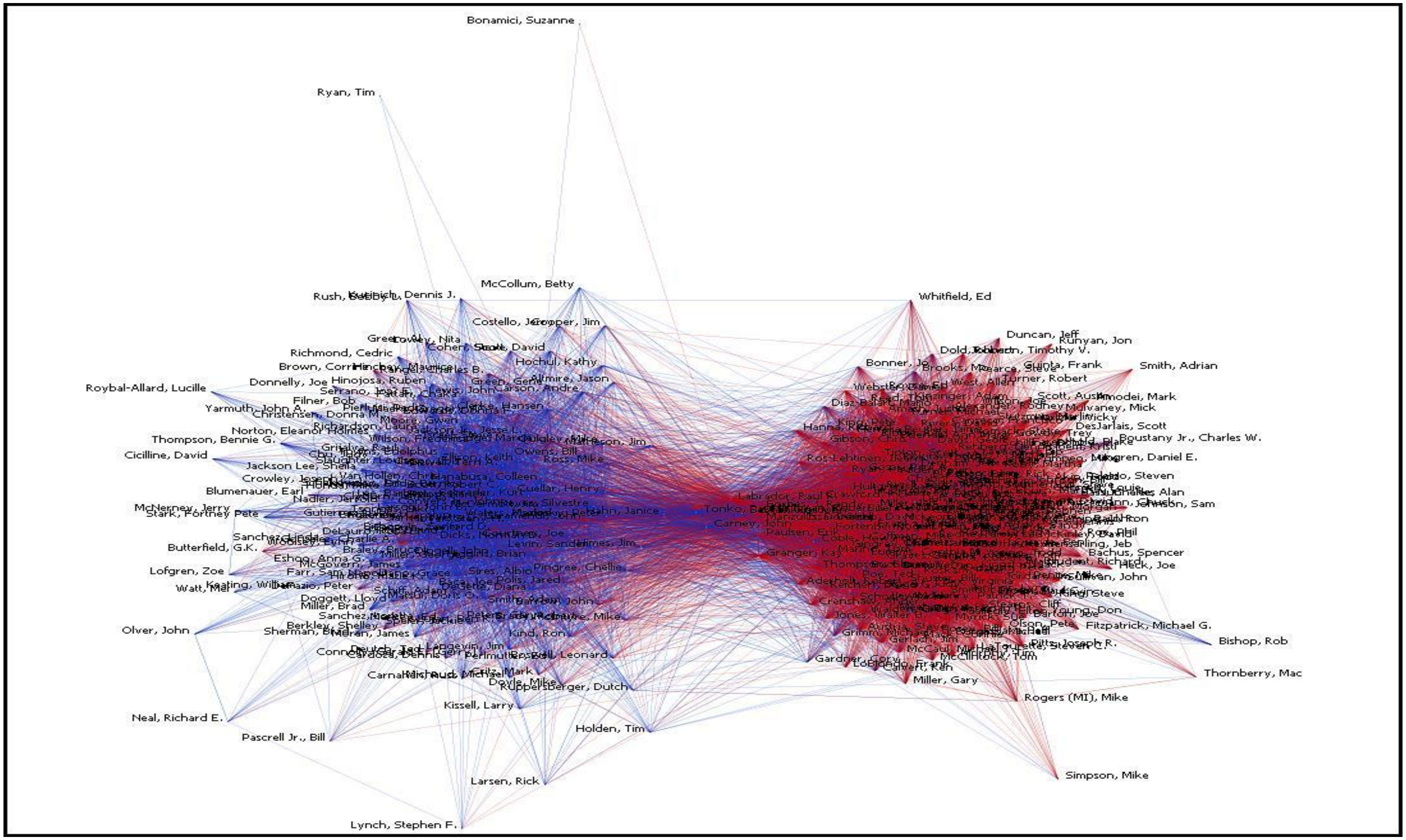


Figure:1: The Network of the 112th U.S. House of Representatives

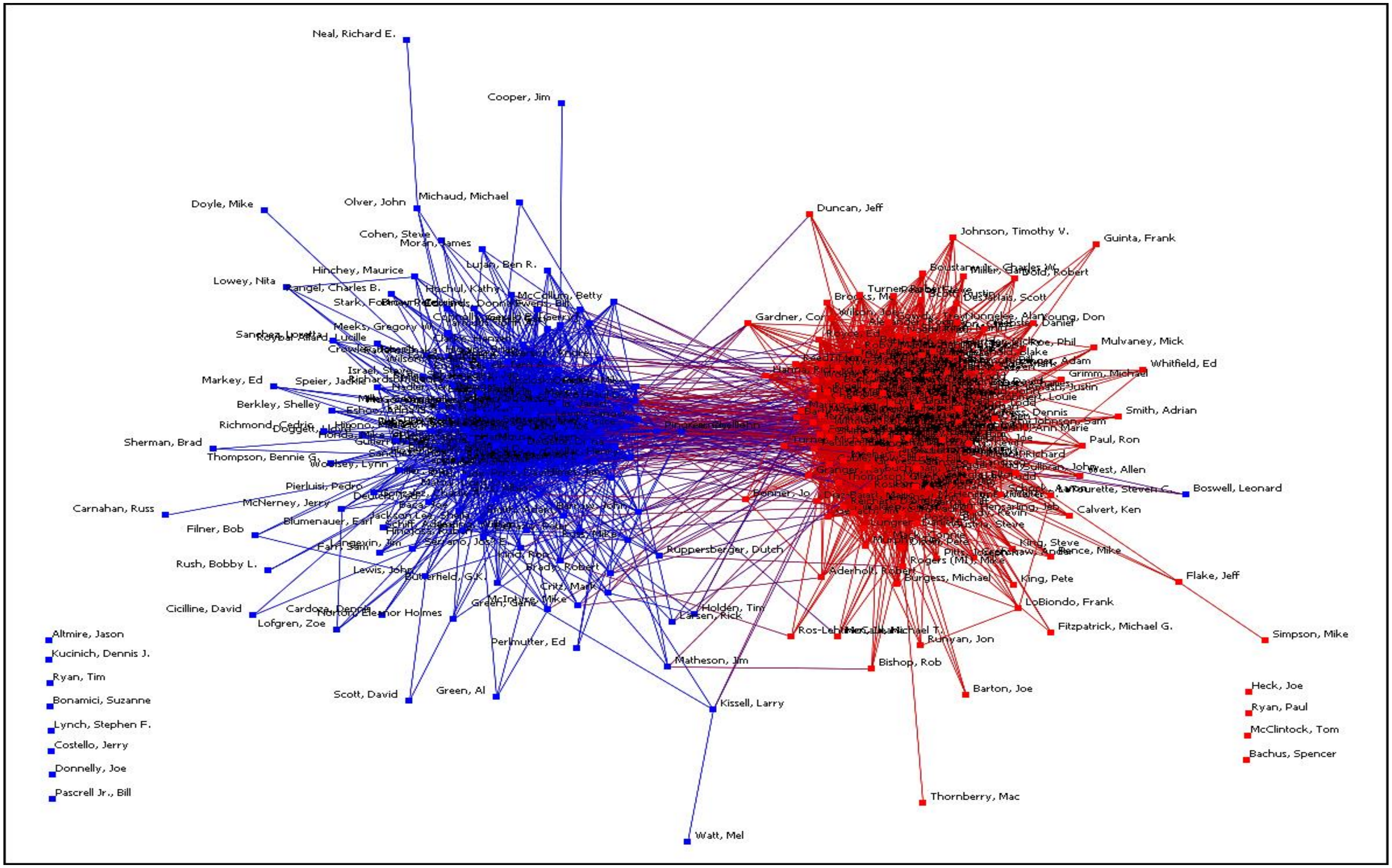


Figure2: Mutual Network of the 112th U.S. House of Representatives

The colors of nodes signify party identification: Democrats are blue, Republicans red. A line displays a tie relationship. The color of the line represents the color of the source node. For example, a blue line implies it extends from a Democrat, and a red one from a Republican. In Figure 2, showing a mutual network, every line is purple, as each line connecting two nodes represents both blue and red.

Figure 1 presents a whole Twitter network consisting of 351 U.S. representatives and 27,877 ties. This demonstrates that node position and ties are arguably bipolarized by party affiliation, showing a typical clustered network. Figure 1 indicates a large blue bloc composed of Democrats located on the left side of the network. Figure 1 also presents a large red bloc composed of Republicans on the right side of the network. By network analysis, this study found 6,670 ties connecting Democrats and 18,829 ties connecting Republicans. This research also found 2,621 ties connecting Democrats and Republicans.

Figure 1 displays a network composed of two major party blocs, a red and a blue network. Facing each other, they offer a mirror image of each bloc. On the whole, the shape of U.S. House of Representatives' Twitter network looks like a large nut containing two inner nuts or a big network containing two sea urchins. Small nuts indicate party blocs, whereas lines between two blocs indicate bipartisan relationships. Otherwise, the network looks like two sea urchins, representing the party networks, who are interacting or in the process of making nuclear fusion. Figure 1 indicates there are two core networks, clustered networks, implying that the resource of centrality such as degree of centrality or betweenness centrality is distributed across two core networks instead of across a centralized network. However, this research also discovered bipartisan ties, suggesting Twitter might serve as an information channel or a discussion network. Further implications will be discussed in the discussion section.

Figure 2 presents a mutual network among representatives, which demonstrates mutually connected nodes and ties only. A mutual network is likely to offer more critical implications as a discussion network or in community-building relationships among nodes. After all, mutual followers in a Twitter network can share and formulate stable and familiar relationships instead of one-directional relationships and rather than ties having following-only or followed-only relationships (Grud et al., 2011). Therefore, the mutual network drawn in Figure 2 can be interpreted as indicating more familiar relationships than those in Figure 1.

This research found 15,638 mutual ties between lawmakers. Different from the whole network in Figure 1, the mutual network presents 12 nodes that are outliers having no mutual ties with any other lawmakers. (They do, however, have some in-degree or out-degree ties with other lawmakers in Figure 1.) Eight of them are Democrats and four of them are Republicans. As a whole, the mutual network looks to be divided according to party affiliation, Democrats and Republicans, but each bloc is also connected. This study found 3,400 mutual ties between Democrats and 11,748 mutual ties between Republicans, suggesting Republicans are more actively connected with one another. However, this research discovered 245 pairs of bipartisan ties. This might suggest Twitter is providing an additional information or discussion network, a network that represents a more casual and instant communication channel than those found in formal relationships.

KEY LAWMAKERS IN THE HOUSE OF REPRESENTATIVES TWITTER NETWORK

RQ2-1 asks about key players in the lawmakers' Twitter network. To discern key players, this research conducted five centrality measures – degree of centrality, closeness centrality, betweenness centrality, in-degree and out-degree centrality measures. These measures tapped various aspects of the relational positions of each lawmaker in the network, that is, their digital leadership. For more detailed explanations, this study presents the results of each measure at two structural levels–whole network and party network. In the mutual network, this study conducted three centrality analyses–degree of centrality, closeness centrality, betweenness centrality. These reveal representatives playing a critical role in a mutual network. The in-degree centrality measure represents who are the most sought-after lawmakers, the most prestigious lawmakers. The out-degree measure represents who are the sociable, willing-to-connect-to-others lawmakers in the network, that is, the socialites. Tables 4 and 5 show the results of the degree-of-centrality measure, revealing lawmakers most connected to other lawmakers in the mutual network. Table 4 presents the top 20 lawmakers. This research found that all the top 20 players are Republican lawmakers. For example, Eric Cantor is the leader with highest degree of centrality within the whole mutual network. Second to Cantor is John Boehner, the Speaker of the House, followed by Cathy

Rank	Name	Value(Scaled)	Party	District
1	Cantor, Eric	0.520	R	Virginia 7th District
2	Boehner, John A.	0.500	R	Ohio 8th District
3	McMorris Rodgers, Cathy	0.469	R	Washington 5th District
4	Issa, Darrell	0.466	R	California 49th District
5	Shimkus, John	0.437	R	Illinois 19th District
6	McKeon, Buck	0.420	R	California 25th District
7	Wittman, Robert J.	0.409	R	Virginia 1st District
8	Forbes, J. Randy	0.397	R	Virginia 4th District
9	Marchant, Kenny	0.389	R	Texas 24th District
10	Latta, Robert E.	0.366	R	Ohio 5th District
11	Camp, Dave	0.363	R	Michigan 4th District
12	Rooney, Tom	0.363	R	Florida 16th District
13	Bachmann, Michele	0.360	R	Minnesota 6th District
14	Manzullo, Donald	0.357	R	Illinois 16th District
15	Harper, Gregg	0.357	R	Mississippi 3rd District
16	Bilirakis, Gus M.	0.357	R	Florida 9th District
17	Rogers (AL), Mike	0.346	R	Alabama 3rd District
18	McCarthy, Kevin	0.343	R	California 22nd District
19	Lummis, Cynthia M.	0.334	R	Wyoming At-Large
20	Neugebauer, Randy	0.334	R	Texas 19th District

Table 4: Top 20 Lawmakers in Degree of Centrality
Note: R = Republican Party, D = Democratic Party

Rank	Republican Party			Democratic Party		
	Node Name	Scaled Score	Unscaled score	Name	Scaled Score	Unscaled score
1	Cantor, Eric	0.91	182	Hoyer, Steny H.	0.69	104
2	Boehner, John A.	0.88	175	Pelosi, Nancy	0.68	102
3	McMorris Rodgers, Cathy	0.81	161	Becerra, Xavier	0.53	80
4	Issa, Darrell	0.76	151	Clyburn, James E.	0.53	80
5	McKeon, Buck	0.72	144	Garamendi, John	0.47	71
6	Shimkus, John	0.69	137	Larson, John B.	0.43	65
7	Marchant, Kenny	0.67	133	Conyers Jr., John	0.43	65
8	Wittman, Robert J.	0.65	130	Tonko, Paul D.	0.43	64
9	Latta, Robert E.	0.64	127	Waters, Maxine	0.42	63
10	Forbes, J. Randy	0.63	126	Bass, Karen	0.41	62

Table 5: Party Leaders in Degree of Centrality (Authorities)

McMorris Rodgers, Chair of the House Republican Conference. Table 4 indicates several official leaders who also appear in the digital leadership list. For example, Boehner is Speaker of the House; Cantor is Republican Leader; Kevin McCarthy is Republican Whip.

Table 5 presents the top 10 players within the party network. Ranking in the party network can differ from ranking in the whole network because it calculates only ties within the party network. For example, a lawmaker who has more bipartisan ties than partisan ties will stand high in the whole network list, but his/her ranking will be lower in party network lists.

In the Republican Party's mutual network, Eric Cantor stands as the leading lawmaker with the highest degree of centrality. Second to Cantor is John Boehner, followed by Cathy McMorris Rodgers. The top four representatives are the same in both the whole network and party network. After that, the ranking order in party network begins to vary. For example, Buck McKeon, chairman of the House Armed Services Committee, is fifth in the party network, but sixth in the whole network. The centrality ranking of each lawmaker in the network can vary by the structural level of the network.

Table 5 also shows the top 10 key player list in the Democrat network. The results demonstrate that Steny H. Hoyer tops the list in terms of in-degree of centrality, indicating that within the Democratic Party, he is the leader with the most ties. Next to Hoyer is Nancy Pelosi and following her is Xavier Becerra. The Democrats list includes several party leaders in the official party hierarchy. For example, Hoyer is the Democratic Whip and Pelosi is the Minority Leader. Becerra is Caucus Vice President of the Democratic Party; Clyburn is Assistant Democratic Leader; Waters is Chief Deputy Democratic Whip; and Larson is Caucus Chairman of the Democratic Party.

Table 6 presents the top 20 lawmakers in the U.S. House of Representatives based on closeness centrality, indicating which lawmakers are relatively close to all other lawmakers. The results demonstrate that all but one of the top players are Republican. Darell Issa, a Republican and chairman of the House Oversight and Government Reform Committee, is the leader with highest closeness centrality. Second is John Shimkus, a Republican and members of House Committee of Energy and Commerce, followed by Robers J. Whittman, a Republican and member of House Committee on Armed Service. Eric Cantor who scores top in-degree of centrality stands seventh in closeness centrality; John Boehner, who scores the second in-degree centrality, stands eighth. Only one lawmaker belongs to the Democratic Party, Paul D. Tonko, member of House Budget Committee, ranks 16th in the closeness centrality measure.

Table 7 presents the top 10 lawmakers in closeness centrality for within-party networks. Eric Cantor stands top in the Republican Party network followed by John A Boehner and Cathy McMorris Rogers. Darrell Issa, who scored first in the whole network, stands fourth in the party network. In the Democratic Party network, Steny H. Hoyer tops the list for the closeness centrality score. Next to Hoyer is Nancy Pelosi and following her is Xavier Becerra. The top seven lawmakers in closeness centrality within Democratic Party network are exactly the same as those indegree of centrality.

Table 8 presents the top 20 lawmakers in the U.S. House of Representatives based on betweenness centrality. This reveals lawmakers who appear on the shortest path between all other lawmakers' tie relationships. Lawmakers who scored highly in

Rank	Name	Value(Scaled)	Party	District
1	Issa, Darrell	0.0736	R	California 49th District
2	Shimkus, John	0.0735	R	Illinois 19th District
3	Wittman, Robert J.	0.0734	R	Virginia 1st District
4	Forbes, J. Randy	0.0733	R	Virginia 4th District
5	McMorris Rodgers, Cathy	0.0732	R	Washington 5th District
	McKeon, Buck	0.0732	R	California 25th District
7	Cantor, Eric	0.0731	R	Virginia 7th District
8	Boehner, John A.	0.0730	R	Ohio 8th District
9	Manzullo, Donald	0.0729	R	Illinois 16th District
	Marchant, Kenny	0.0729	R	Texas 24th District
11	Camp, Dave	0.0728	R	Michigan 4th District
12	Bachmann, Michele	0.0727	R	Minnesota 6th District
	Lummis, Cynthia M.	0.0727	R	Wyoming At-Large
	Gibbs, Bob	0.0727	R	Ohio 18th District
15	Rogers (AL), Mike	0.0726	R	Alabama 3rd District
	Tonko, Paul D.	0.0726	D	New York 21st District
17	Paulsen, Erik	0.0725	R	Minnesota 3rd District
18	Neugebauer, Randy	0.0724	R	Texas 19th District
	Huizenga, Bill	0.0724	R	Michigan 2nd District
	Coffman, Mike	0.0724	R	Colorado 6th District

Table 6: Top 20 Lawmakers in Closeness Centrality
Note: R = Republican Party, D = Democratic Party

Republican Party			Democratic Party		
Rank	Node Name	Scaled Score	Rank	Name	Scaled Score
1	Cantor, Eric	0.1974	1	Hoyer, Steny H.	0.0975
2	Boehner, John A.	0.1961	2	Pelosi, Nancy	0.0973
3	McMorris Rodgers, Cathy	0.1932	3	Becerra, Xavier	0.0960
4	Issa, Darrell	0.1913		Clyburn, James E.	0.0960
5	McKeon, Buck	0.1899	5	Garamendi, John	0.0954
6	Shimkus, John	0.1890	6	Larson, John B.	0.0951
7	Marchant, Kenny	0.1879	7	Tonko, Paul D.	0.0950
8	Wittman, Robert J.	0.1874	8	Conyers Jr., John	0.0949
9	Latta, Robert E.	0.1872	9	Bass, Karen	0.0948
10	Rooney, Tom	0.1869		Waters, Maxine	0.0948

Table 7: Party Leaders in Closeness Centrality

betweenness centrality are usually regarded in the information network as the influential, gatekeeper, modulator, or information broker (Freeman, 1977; 1979). Different from the lists of degree and closeness centrality, on the list of betweenness centrality lawmakers from both parties appear at the top: 12 out of 20 are Republican with the remaining 8 being Democrats. Darrell Issa who scored at the top in the closeness centrality measure also stands atop the betweenness centrality measure. Next is John Shimkus, a Republican, followed by Democratic Whip Steny H. Hoyer.

Rank	Name	Value(Scaled)	Party	District
1	Issa, Darrell	0.0552	R	California 49th District
2	Shimkus, John	0.0430	R	Illinois 19th District
3	Hoyer, Steny H.	0.0407	D	Maryland 5th District
4	Pelosi, Nancy	0.0399	D	California 8th District
5	Tonko, Paul D.	0.0377	D	New York 21st District
6	Cantor, Eric	0.0302	R	Virginia 7th District
7	Wittman, Robert J.	0.0291	R	Virginia 1st District
8	McMorris Rodgers, Cathy	0.0271	R	Washington 5th District
9	Forbes, J. Randy	0.0268	R	Virginia 4th District
10	Garamendi, John	0.0265	D	California 10th District
11	Boehner, John A.	0.0264	R	Ohio 8th District
12	Manzullo, Donald	0.0209	R	Illinois 16th District
13	Levin, Sander	0.0204	D	Michigan 12th District
14	Waters, Maxine	0.0178	D	California 35th District
15	Carney, John	0.0174	D	Delaware At-Large
16	McKeon, Buck	0.0156	R	California 25th District
17	Bachmann, Michele	0.0148	R	Minnesota 6th District
18	Marchant, Kenny	0.0146	R	Texas 24th District
19	DeGette, Diana	0.0140	D	Colorado 1st District
20	Paulsen, Erik	0.0139	R	Minnesota 3rd District

Table 8: Top 20 Lawmakers in Betweeness Centrality
Note: R = Republican Party, D = Democratic Party

Rank	Republican Party			Democratic Party		
	Node Name	Scaled Score	Unscaled score	Name	Scaled Score	Unscaled score
1	Cantor, Eric	0.08	1490.14	Hoyer, Steny H.	0.15	1651.02
2	Boehner, John A.	0.07	1305.25	Pelosi, Nancy	0.14	1512.76
3	McMorris Rodgers, Cathy	0.04	692.14	Becerra, Xavier	0.05	506.44
4	Issa, Darrell	0.03	618.41	Clyburn, James E.	0.04	415.34
5	Latta, Robert E.	0.02	420.45	Larson, John B.	0.03	369.41
6	Shimkus, John	0.02	335.04	Garamendi, John	0.03	347.96
7	McKeon, Buck	0.02	327.55	Price, David	0.02	221.03
8	Marchant, Kenny	0.02	317.11	Sewell, Terri A.	0.02	214.43
9	McCarthy, Kevin	0.01	264.12	Reyes, Silvestre	0.02	209.05
10	Bachmann, Michele	0.01	240.48	Conyers Jr., John	0.02	205.60

Table 9: Party Leaders in Betweenness Centrality (Coordinators)

Table 9, a ranking of within-party networks, portrays a different landscape of major players. Eric Cantor, John A. Boehner, and Cathy McMorris Rogers appear at the top of the list in betweenness centrality within the Republican Party. In the Democratic Party, Representative Hoyer, Pelosi, and Becerra are atop the list. Representative Tonko, who stood fifth in the whole network list, is excluded from the Democratic Party network list, indicating his relational position varies in the whole network and party network.

Rank	Name	Unscaled Score	Party	District
1	Boehner, John A.	224	R	Ohio 8th District
2	Cantor, Eric	194	R	Virginia 7th District
3	Ryan, Paul	180	R	Wisconsin 1st District
4	McCarthy, Kevin	177	R	California 22nd District
5	Issa, Darrell	172	R	California 49th District
6	McMorris Rodgers, Cathy	165	R	Washington 5th District
7	McKeon, Buck	160	R	California 25th District
8	Shimkus, John	154	R	Illinois 19th District
9	Price, Tom	149	R	Georgia 6th District
10	Camp, David	144	R	Michigan 4th District
11	Wittman, Robert J.	143	R	Virginia 1st District
	Pence, Mike	143	R	Indiana 6th District
13	Latta, Robert E.	141	R	Ohio 5th District
14	Forbes, J. Randy	140	R	Virginia 4th District
14	Marchant, Kenny	140	R	Texas 24th District
16	Bachmann, Michele	138	R	Minnesota 6th District
17	Bilirakis, Gus M.	135	R	Florida 9th District
	Harper, Gregg	135	R	Mississippi 3rd District
	McHenry, Patrick T.	135	R	North Carolina 10th District
20	Chaffetz, Jason	134	R	Utah 3rd District

Table 10: Top 20 Lawmakers in In-degree Centrality

Note: R = Republican Party, D = Democratic Party

Rank	Republican Party				Democratic Party		
	Node Name	Scaled Score	Unscaled score		Name	Scaled Score	Unscaled score
1	Boehner, John A.	0.950	189	1	Pelosi, Nancy	0.740	111
2	Cantor, Eric	0.920	183	2	Hoyer, Steny H.	0.727	109
3	McCarthy, Kevin	0.854	170	3	Clyburn, James E.	0.560	84
4	Ryan, Paul	0.834	166	4	Becerra, Xavier	0.540	81
5	McMorris Rodgers, Cathy	0.809	161	5	Larson, John B.	0.493	74
6	Issa, Darrell	0.779	155	6	Garamendi, John	0.473	71
7	McKeon, Buck	0.739	147	7	Conyers Jr., John	0.467	70
8	Price, Tom	0.729	145	8	Honda, Mike	0.453	68
9	Shimkus, John	0.694	138	9	Bass, Karen	0.440	66
10	Pence, Mike	0.688	137		Waters, Maxine	0.440	66

Table 11: Top 10 Lawmakers in in-degree ties within Party

able 10 indicates the prominent lawmakers in the U.S. Twitter network calculated by in-degree centrality. Those are the most sought-after lawmakers in each party network. The results show that all belong to the Republican Party. John A. Boehner scores the most with 224 representative followers, followed by Eric Cantor with 194 representative followers and Paul Ryan with 180 representative followers.

Table 11 displays the rankings of top lawmakers in the party network, a different landscape from key lawmakers in the entire network. In the Republican network, John A. Boehner, the Speaker of the House, scores at the top and Eric Cantor, the Majority Leader, scores the second. Kevin McCarthy, Republican Whip, ranks third. McMorris Rogers ranks forth.

In the Democratic Party network, Nancy Pelosi ranks at the top, indicating she is the most followed lawmakers in the Democratic network. Steny H. Hoyer ranks second. James E. Clyburn (3rd), a former House Majority Whip and Assistant Democratic Leader, Xavier Becerra (4th), and John B. Larson (the 5th), the former chairman of the House Democratic Caucus, follow Nancy Pelosi and Steny Hoyer in the rankings.

Table 12 demonstrates the most active representatives willing to follow other lawmakers, the socialites. Paul D. Tonko, a Democrat, scores the most, following 344 representatives in the House of Representatives. Next is John Shimkus a Republican, with 320. Roscoe Bartlett, a Democrat and chairman of the Tactical Air and Land Forces Subcommittee of the House Armed Services Committee, scores third with 313, and Robert J. Wittman, a Democrat and member of Hose Committee on Armed Services, scores fourth with 308. Table 13 indicates the most active representatives in each party network. In the Republican Party, Eric Cantor scores at the top of the list, following 198 Republican representatives. Considering the total number of Republican Twitter users is 200, Erica Cantor follows 99% of all Republican representatives. All the top 10 Republican lawmakers follow approximately 97% of the total Republican Twitter users. John Garamendi scores at the top of the list in the Democratic Party network, following 147 Democratic representatives, 98% of the total Democratic Representative Twitter users (N = 150). Representative Tonko shares the top with Representative Garamendi.

Rank	Name	Value(Scaled)	Party	District
1	Tonko, Paul D.	344	D	New York 21st District
2	Shimkus, John	320	R	Illinois 19th District
3	Bartlett, Roscoe	313	D	Maryland 6th District
4	Wittman, Robert J.	308	D	Virginia 1st District
5	Forbes, J. Randy	304	R	Virginia 4th District
6	Labrador, Raul R.	298	D	Idaho 1st District
7	Manzullo, Donald	286	D	Illinois 16th District
8	Carney, John	249	R	Delaware At-Large
9	Hahn, Janice	240	D	California 36th District
10	Issa, Darrell	231	R	California 49th District
11	McMorris Rodgers, Cathy	203	R	Washington 5th District
12	Paulsen, Erik	200	R	Minnesota 3rd District
	Gibbs, Bob	200	R	Ohio 18th District
14	Marchant, Kenny	199	R	Texas 24th District
	Duffy, Sean P.	199	R	Wisconsin 7th District
16	Cantor, Eric	198	R	Virginia 7th District
	Fincher, Stephen	198	R	Tennessee 8th District
18	Terry, Lee	197	R	Nebraska 2nd District
	Walberg, Tim	197	R	Michigan 7th District
	Chabot, Steve	197	R	Ohio 1st District

Table 12: Top 20 Lawmakers in Out-degree Centrality

Note: R = Republican Party, D = Democratic Party

Rank	Republican Party			Democratic Party		
	Node Name	Scaled Score	Unscaled score	Name	Scaled Score	Unscaled score
1	Cantor, Eric	0.08	1490.14	Hoyer, Steny H.	0.15	1651.02
2	Boehner, John A.	0.07	1305.25	Pelosi, Nancy	0.14	1512.76
3	McMorris Rodgers, Cathy	0.04	692.14	Becerra, Xavier	0.05	506.44
4	Issa, Darrell	0.03	618.41	Clyburn, James E.	0.04	415.34
5	Latta, Robert E.	0.02	420.45	Larson, John B.	0.03	369.41
6	Shimkus, John	0.02	335.04	Garamendi, John	0.03	347.96
7	McKeon, Buck	0.02	327.55	Price, David	0.02	221.03
8	Marchant, Kenny	0.02	317.11	Sewell, Terri A.	0.02	214.43
9	McCarthy, Kevin	0.01	264.12	Reyes, Silvestre	0.02	209.05
10	Bachmann, Michele	0.01	240.48	Conyers Jr., John	0.02	205.60

Table 13: Top 10 Lawmakers in Out-degree Centrality

EGO NETWORKS OF THE KEY LAWMAKERS IN THE HOUSE OF REPRESENTATIVES TWITTER NETWORK

RQ 2-2 inquires about the key players' ego network. This study, for a parsimonious look at this aspect of the network, chose six lawmakers who scored at the top on the each list. Each figure indicates two levels of network: the whole ego network (above) that reveals all ties – in-degree and out-degree ties, regardless of party affiliation, and a part of the magnified network around the key player (below).

Figure 3 presents the ego networks of Eric Cantor. Eric Cantor stands atop the degree-of-centrality list in the whole network (Table4). He stands also atop the degree-of-centrality list within the Republican network. As shown in Figure 3, Eric Cantor's ego network looks like a nut colored mostly in red, which demonstrates that his ego Twitter network mainly consists of Republican lawmakers.

An analysis of ego network tie relationships indicates that Eric Cantor's ego network consists of 211 nodes and 19.469 ties. He has 194 in-degree ties and 198 out-degree ties with other lawmakers. A magnified image of Figure 3 indicates that standing near him are several Republican representatives John A. Boehner, Bill Hulzenga, Steve Stivers, and Hurt Robert. Paul D. Tonko is revealed to stand as the closest node in the network of the Democrats. Next to Tonko stands Democrat Janice Hahn.

Those lawmakers near the center of the Eric Cantor's personal network can be classified as the influential and "the core lawmakers" of Eric Cantor's personal legislative network. Furthermore, considering Eric Cantor is the lawmaker who is occupying the center of the Congressional Twitter network, these are lawmakers occupying "the cores of the core network" in the Congressional Twitter sphere. Therefore, they belong to those influential lawmakers who have distinctive advantages of engaging in information or influence flow within the Congressional network as well as the Eric Cantor's personal network.

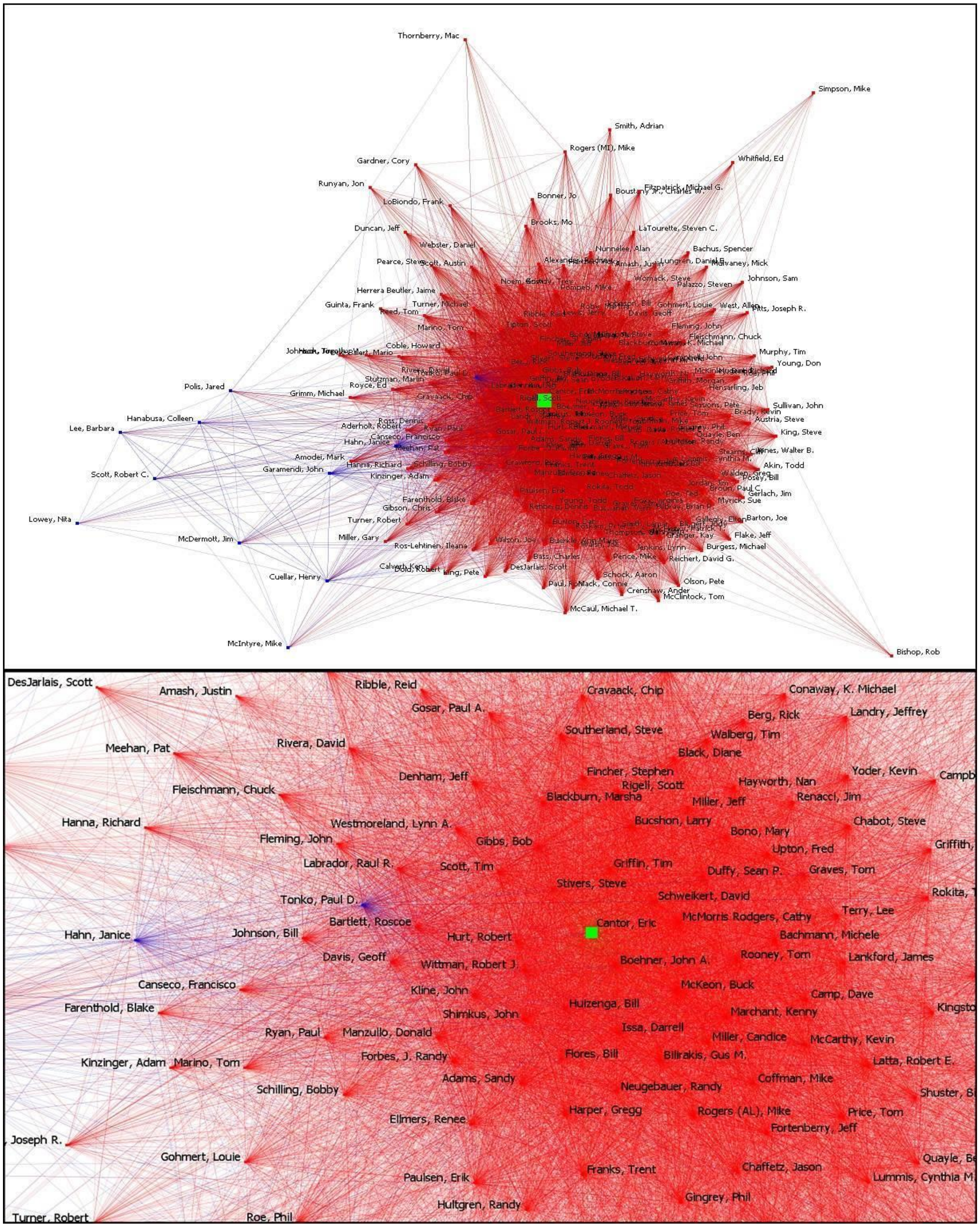


Figure3: Eric Kanto's Ego Network

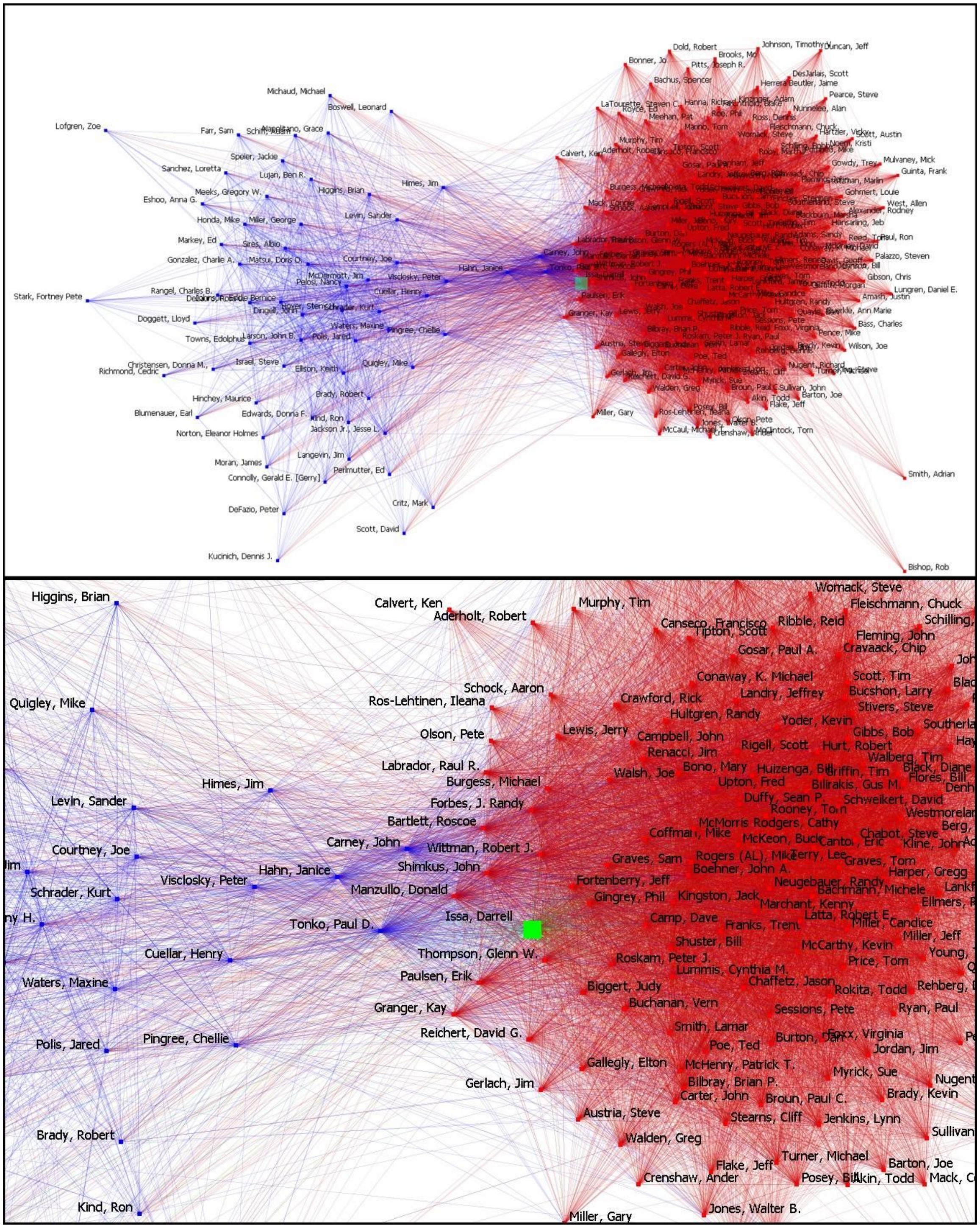


Figure 4: Darrell Issa's Ego Network

Figure 4 presents the ego networks of Darrell Issa, who stands at the top of the list of closeness centrality and betweenness centrality (Tables 6, 8). As shown in Figure 4, Darrell's ego network is composed mostly of Republican lawmakers but a fairly large part of the network consists of Democrat lawmakers. Analysis of the ego network indicates that Darrell Issa's ego network consists of 241 nodes and 20,032 ties. An analysis of the tie relationships indicates he has 178 in-degree ties and 231 out-degree ties with other lawmakers. Representative Issa has more out-degree ties than in-degree ties, which shows that he is a socialite rather than a prominent node. A magnified image of Figure 4 indicates that standing close to Issa are Republican representatives Glen W. Tomson, Donald Manzuilo, and John Shimkus and Democrats Paul D. Tonko, John Carney, and Janice Hahn.

Figure 5 presents the ego network of John A. Boehner who stands atop the list of in-degree centrality (Table 9). The degree centrality measure indicates that he is the most popular lawmaker in the House of Representatives network.

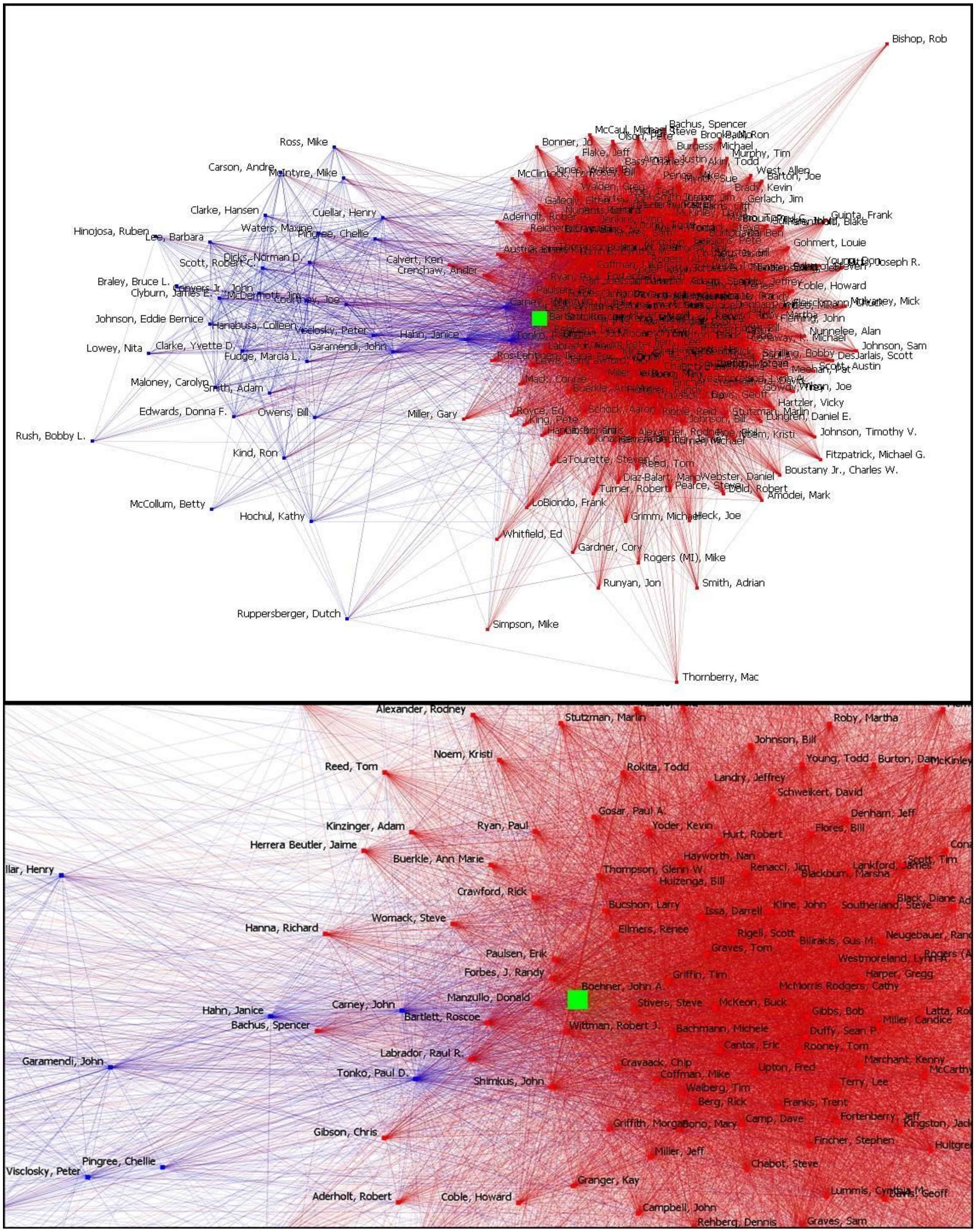


Figure 5: John Boehner's Ego Network

As shown in Figure 5, Boehner's ego network looks very similar to Issa's ego network – composed of a densely connected red nodes bloc and loosely connected blue nodes bloc – rather than Cantor's ego network which mainly consists of red nodes. An analysis of the ego network indicates that Boehner's network consists of 234 nodes and 20,557 ties with lawmakers. He has 224 in-degree ties and 184 out-degree ties with other lawmakers, which confirms Boehner is a sought-after lawmaker rather than a socialite. A magnified image of Figure 5 indicates that Republican representatives such as Robert J Wittman, Randy J. Forbes, Donald Manzuilo, and Steve Stivers stand very close to Boehner. Democrats such as John Carney and Paul D. Tonko also stand close to Boehner.

Figure 6 presents the ego network of Steny H. Hoyer who stands atop the three lists of centrality within the Democrats' party network (Tables 4, 6, 8). Figure 6 demonstrates that Hoyer's ego network looks like a nut mainly colored in blue, indicating his ego network mostly consists of Democrats. His ego network presents the mirror image of Eric Cantor's ego network with a different color composition. An analysis of the ego network relationships indicates that Hoyer's network consists of 162 nodes and 7,969 ties. He has 128 in-degree ties and 137 out-degree ties with other lawmakers. A magnified image of Figure 6 indicates that standing near him are Democrats Janice Hahn, Joe Courtney, Niki Tsongas, and Xavier Becerra.

Figure 7 presents the ego networks of Nancy Pelosi stands out in three centrality measures within the Democratic Party.

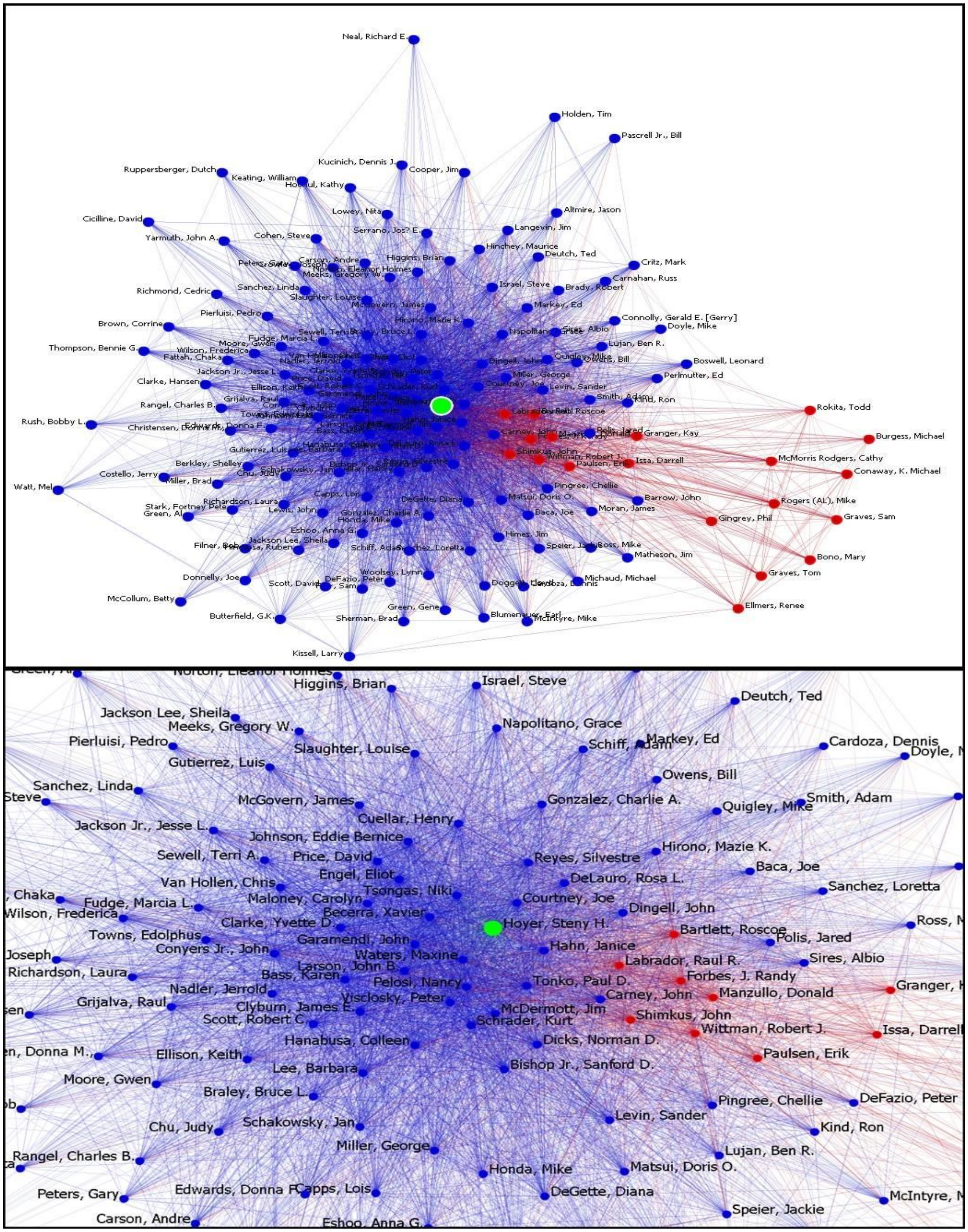


Figure 6: Steny Hoyer's Ego Network

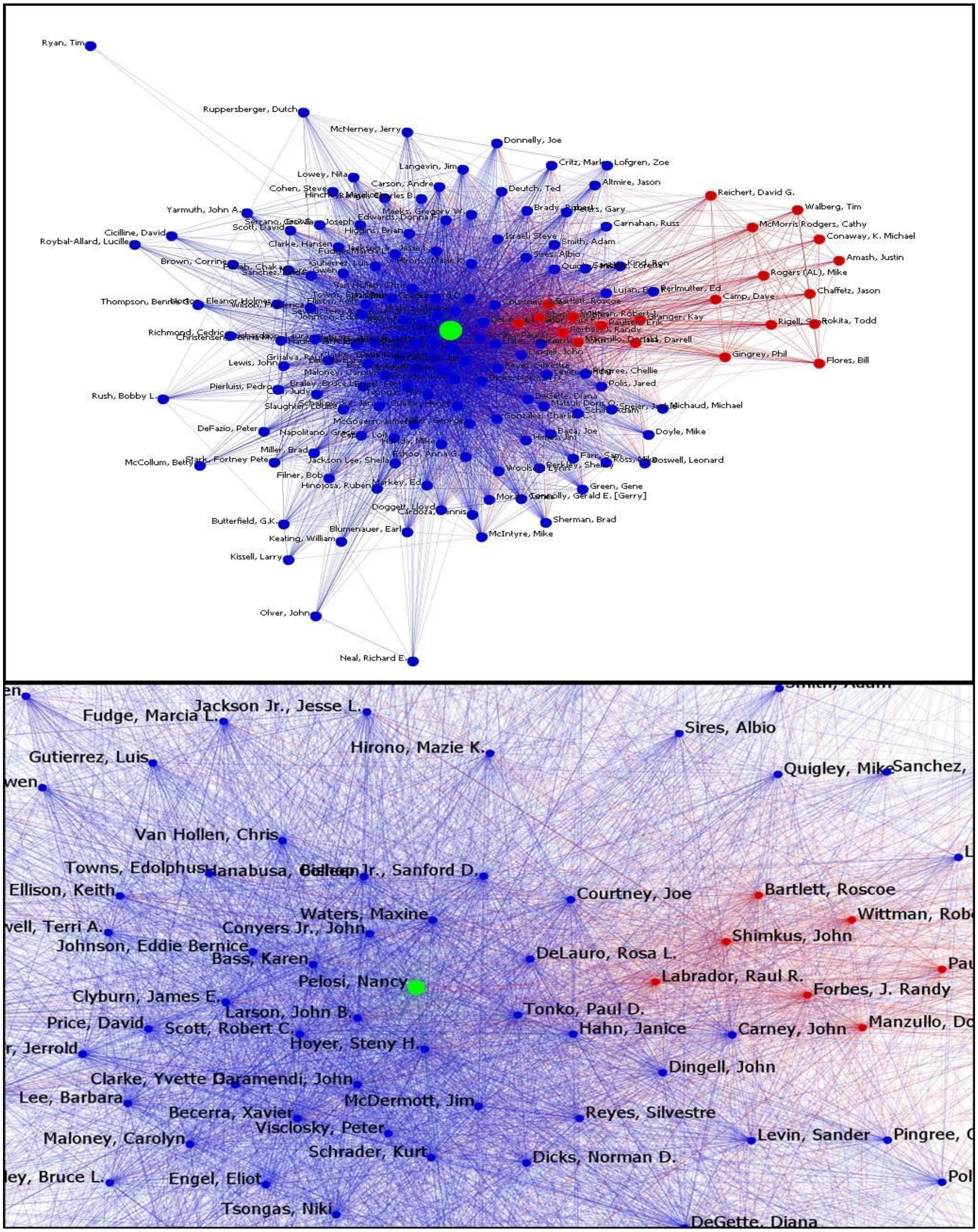


Figure 7: Nancy Pelosi's Ego Network

Figure 6 demonstrates Pelosi's ego network looks similar to that of Steny H. Hoyer's network, which looks like a nut mainly consisting of blue nodes (Democrats). An analysis of her ego network tie relationship indicates that Pelosi's network consists of 158 nodes and the total number of ties with other lawmakers is 7,729. She has 132 in-degree ties and 127 out-degree ties with lawmakers. A magnified image of Figure 7 indicates that standing close to Pelosi are Democrats Karen Bass, John b. Larson, Steny H. Hoyer, Maxie Waters, Rosa L. DeLauro, and Paul D. Tonko. Representative Raul R. Labrador is the nearest Republican lawmaker. Next to representative Labrador stands John Shimkus followed by J. Randy Forbes.

Figure 8 presents the ego network of Paul D. Tonko who stands at the top of the lists of out-degree centrality (Table 11). Figure 8 demonstrates that Representative Tonko stands at the center of a network looking like two nuts, the Democrat and Republican networks. An analysis of the ego network indicates that Boehner's network consists of 345 nodes and 27,439 lawmaker ties, revealing that Tonko's network is the largest among lawmakers. He has 87 in-degree ties and 344 out-degree ties, which indicates he is more a socialite than a prominent lawmaker. A magnified image of Figure 8 indicates that representative Janice Hahn and John Carney are positioned close to Tonko followed by Peter Visclosky, Jime himes, Chellie Pingree, and Henry Cueliar among Democrats. Among Republicans standing close to Tonko are Raul R. Labradorm, Roscoe Bartlett, John Shimukus, J. Randy Forbes, Robert J. Wittman, Darrell Issa, Donald Manzuilo, and Erik Paulsen.

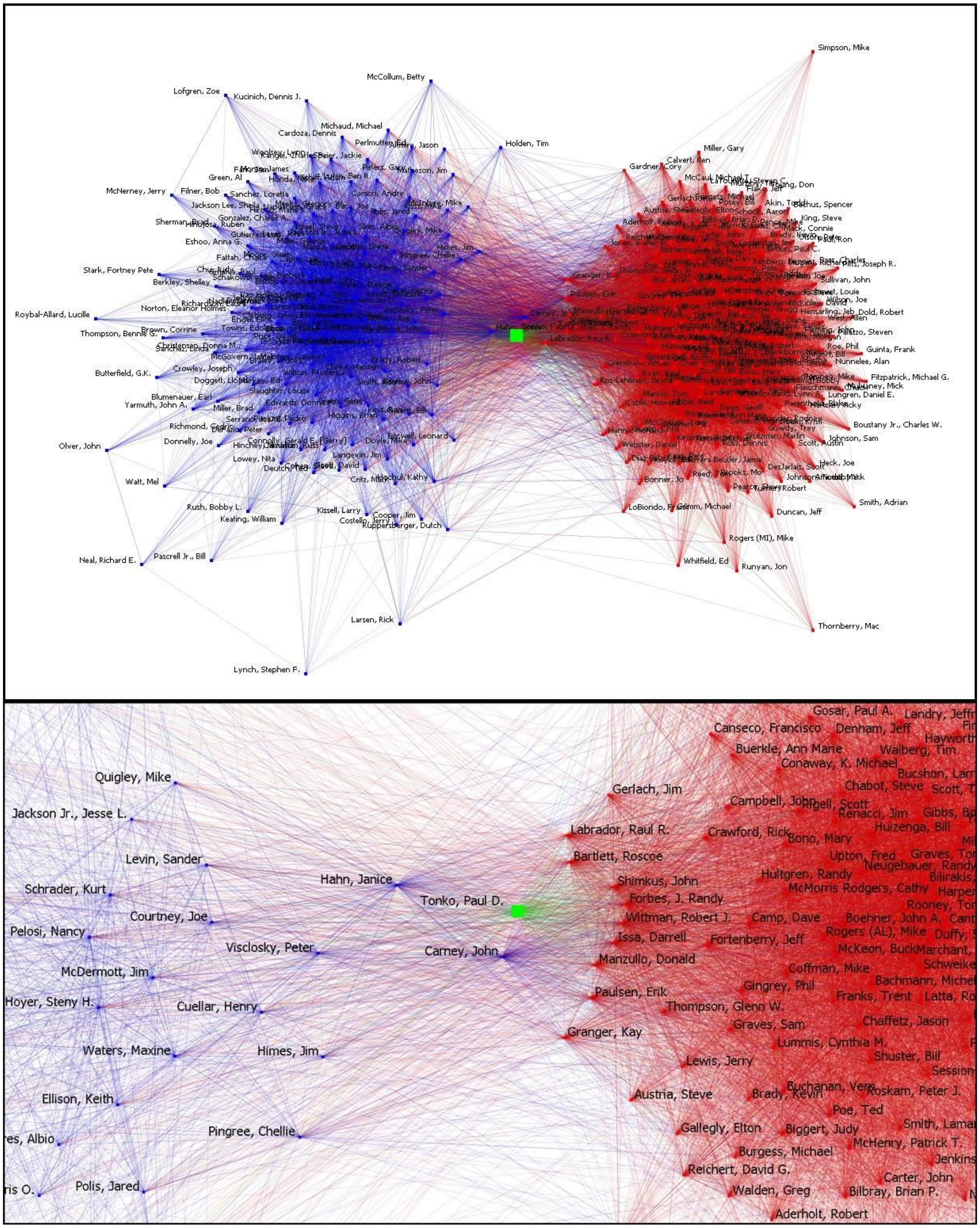


Figure 8: Paul D. Tonko's Ego Network

Network Measures	Liberal Party (Democrats Network)	Conservative Party (Republicans Network)
Network Size	151	200
Total Ties	3,400	11,748
Ties per Node	22.51	58.74
Density	.15	.30
Reciprocal Rate	1	1
Fragmentation Rate	.12	.04
Distance(Average)	1.98	1.72
Network Centralization for Degree	.551	.626
Network Centralization for Betweenness	.143	.072

Table 14: Comparisons of Two U.S. Party Mutual Networks

RED AND BLUE NETWORK

RQ3 asks the extent of the differences between conservatives' and liberals' Twitter party networks. In U.S. politics, the Republican Party is regarded as conservative and the Democratic as liberal.

Table 14 compares the properties of the Democratic and Republican mutual party network structure. First, the network analysis indicates that the size of the Republican network (N = 200) surpasses that of the Democratic Party (N = 151). Further results indicate the Republican network has a more complicated network structure.

Density, total link counts, and links per node indicate that the Republican network is more tightly knit than its Democratic counterpart. For example, the average Republican has approximately 2.6 times more mutual ties with other Republicans than do Democrats. There are nine isolated representatives in the Democrats' network but only four in the Republicans'.

Analysis of average distance shows that for both parties' networks any node can reach any other node in less than two steps, suggesting both party networks encompass a very small world. However, nodes in the Republican network are slightly closer than those in the Democrats'. The Republican network is more centralized than the Democrats' network regarding degree of centralization, meaning the degree of centrality is more concentrated there. The centralization index for betwenness centrality indicates that the Democrats network is a more centralized network in betweenness centrality, which indicates that coordinating resources are more concentrated there. In sum, Republican leadership has more resources for authority, while Democrat leadership has more resources for coordinating relationships, though the difference is not huge.

RULING PARTY AND OPPOSITION PARTY IN THE TWITTER NETWORK

H1 posited representatives belonging to the ruling party are more likely have more in-degree, out-degree and mutual ties than those who belong to opposition party. To tap the difference, this research conducted the regression analysis, shown in Table 15.

	Tie Relationship Building								
	Sociability			Prestige			Mutuality		
	t	B		t	β		t	β	
Gender	-1.24	-0.06		-0.79	-0.03		-4.46	-0.21	**
Age	0.46	0.02		0.65	0.02		0.09	0.00	
Ruling Party	5.55	0.29	**	15.29	0.56	**	5.87	0.29	**
Number of Twitts	2.05	0.13	*	4.97	0.22	**	0.51	0.03	
Number of Followees	4.78	0.30	**	3.46	0.15	**	6.34	0.39	**
Number of Follower	-2.00	-0.11	*	4.88	0.19	**	-1.05	-0.05	**
Adjusted R Square (%)		24.5			60.2			28.3	

Table15. Predictors of U.S. Lawmakers Tie Relationship (N = 351)

*Note: β = Standardized regression coefficient, *p < .05, **P < .01*

The three dependent variables are socialability, prestige, and mutuality. Degree of socialite is measured by how may out-degree ties a node has (Mean 79.42, SD = 71.89); degree of prestige is measured how many in-degree ties a node has (Mean = 79.42, SD = 35.88). Degree of mutuality is measured by the ratio of reciprocal ties to in-degree ties, indicating how each representative is responsive to other representatives' in-degree ties. Degree of mutuality, therefore, demonstrates how active lawmaker is in mutual relationship building with others (Mean = .33, SD=. 19).

Table 15 indicates that lawmakers belonging to the ruling party significantly and positively have more out-degree ties than those belong to opposition party, all else being constant ($\beta = .29$, $p < .01$). The results reveal that membership in the ruling party is a strong and significant predictor of sociability, next to the number of followees representative have ($\beta = .30$, $p < .01$). The results also show that membership to the ruling party is a significant and strong predictor of prestige (more in-degree ties) in the elite network ($\beta = .56$, $p < .01$), controlling for all other variables. Membership in the ruling party is the strongest predictor of receiving incoming ties from other lawmakers in the network. Further, the results show that lawmakers belong in the ruling party are likely to have more mutual tie relationships in the elite network ($\beta = .29$, $p < .01$), all else being constant. Ruling party membership is a strong and significant predictor of relationship-building patterns in the legislative network.

Interestingly, Table 15 indicates that female lawmakers are likely to have more mutual ties with other lawmakers ($\beta = -.21$, $p < .01$), which implies that there is a gender gap in the tie-building pattern among the U.S. legislative network.

Three activeness variables regarding Twitter use also are predictors of tie-building patterns of lawmakers. The number of followees of lawmakers is the strongest predictor for sociability ($\beta = .30$, $p < .01$) and mutual relationships of lawmakers ($\beta = .39$, $p < .01$). The number of tweets also is revealed as a predictor of lawmaker's sociability ($\beta = .13$, $p < .05$) prestige in the lawmakers network ($\beta = .22$, $p < .01$), but it fails to prove to be a predictor of mutuality. Interestingly, the number of followers of lawmakers is revealed to be a significant but negative predictor for sociability ($\beta = -.11$, $p < .05$) and mutual relationships ($\beta = -.05$, $p < .01$) in the lawmakers' network.

The number of followers of Twitter accounts is generally regarded as popularity in the Twitter network, but the results of this research reveals that lawmakers popular with the public are likely to be less sociable and have fewer mutual relationships in the elite network. However, the results indicate that the number of followers is a significant and positive predictor of prestige position in the lawmakers' network ($\beta = .19$, $p < .01$), which confirms that popularity among the Twitter public leads to a prestigious position in the elite network.

PARTISAN TIES VS. BIPARTISAN TIES

RQ5 examines the intraparty (partisan) network and interparty (bipartisan) network: how they are connected to each other and what the features are of the partisan and bipartisan networks. This research first presents overall the intraparty network and interparty network shapes, then, the network measures for intra- and interparty networks.

Figure 9 (upper image) illustrates the overall shape of the Democratic Party network. On the whole, the Democratic Party's mutual network shape looks like a typical star network: a centralized network structure with a condensed center and loosely connected peripheries, which implies that the network is organized by strong leadership. This research found nine outlier lawmakers who had no mutual relationships within the party network.

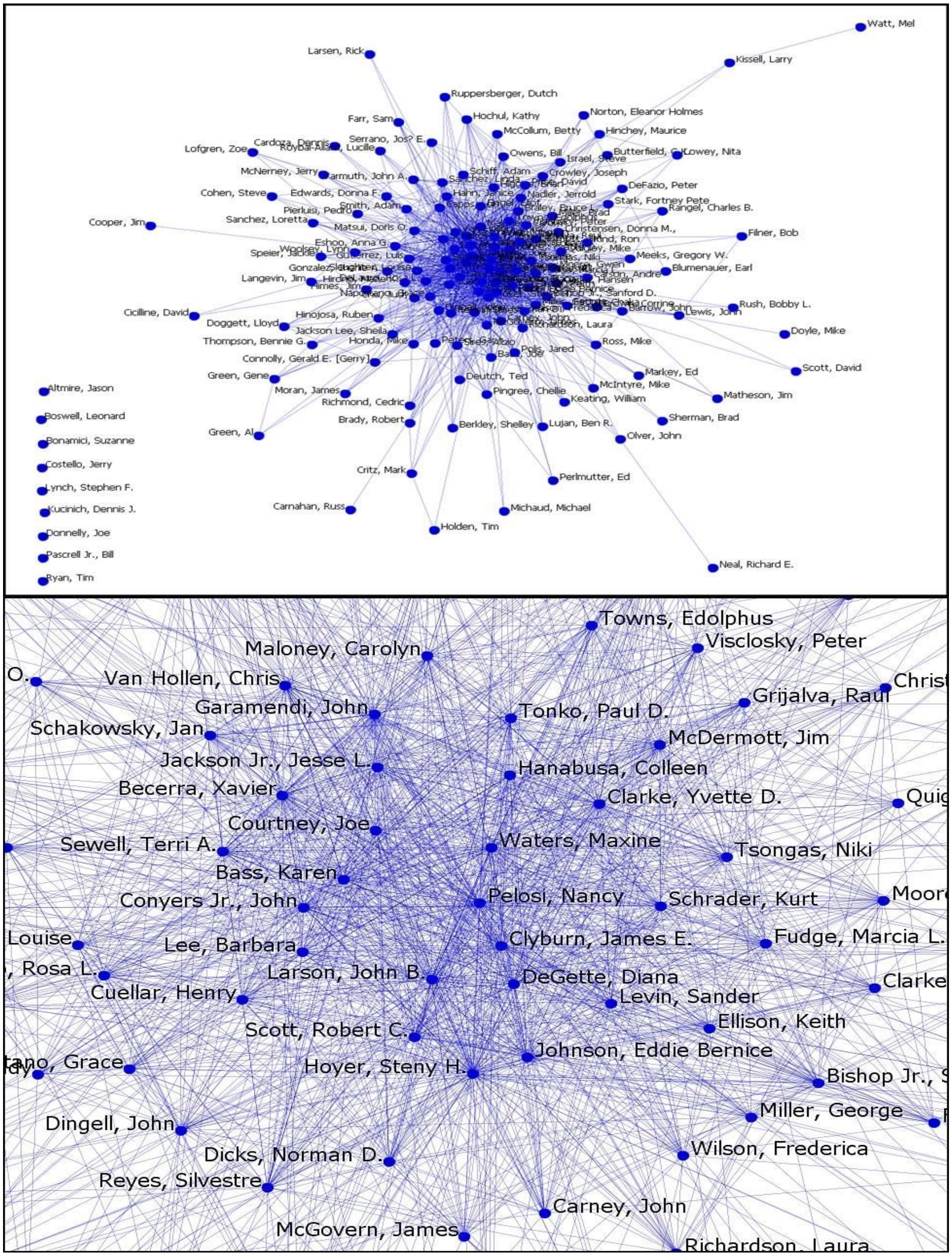


Figure 9: Democratic Party's Mutual Network

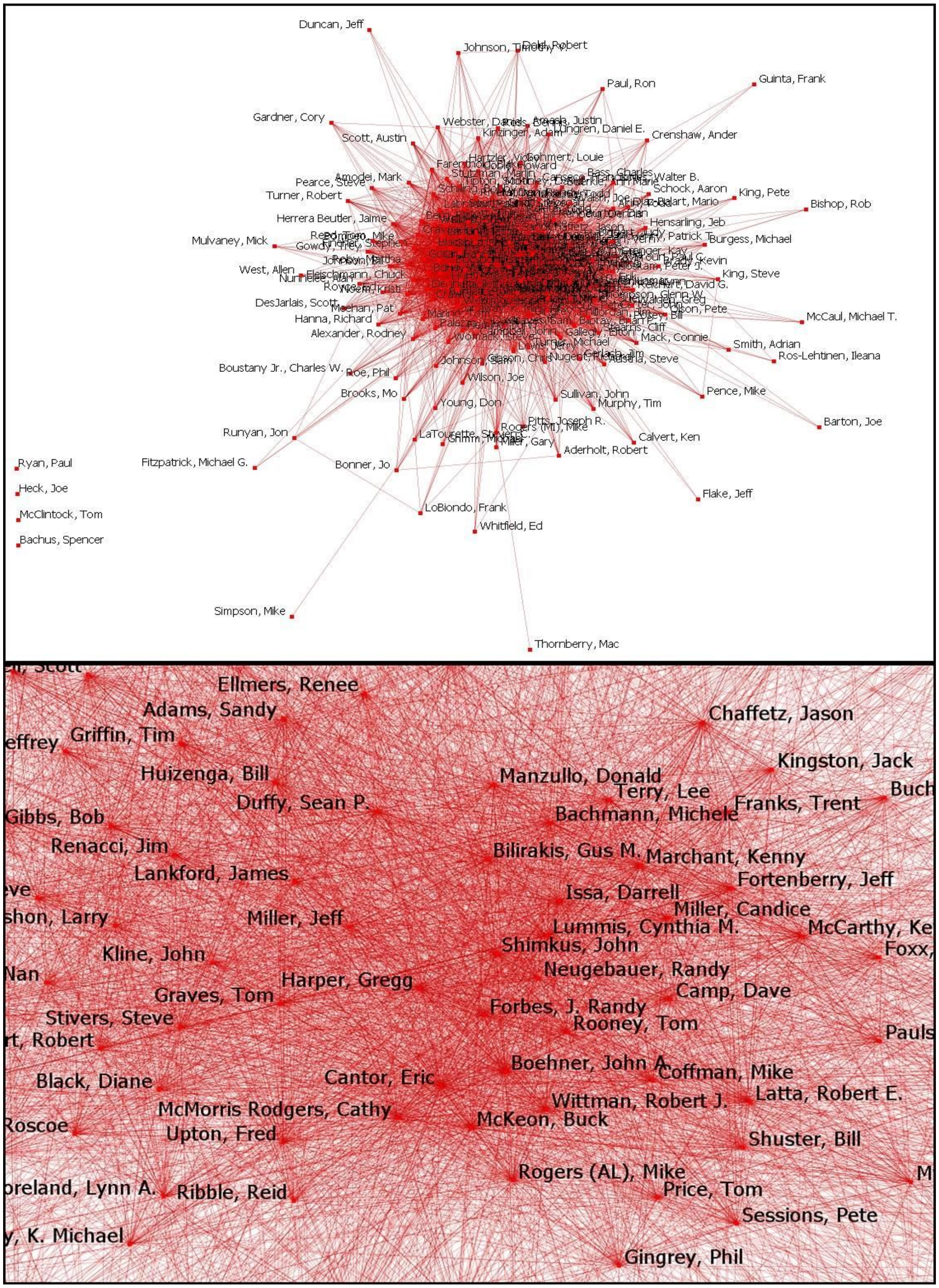


Figure 10: Republican Party's Mutual Network

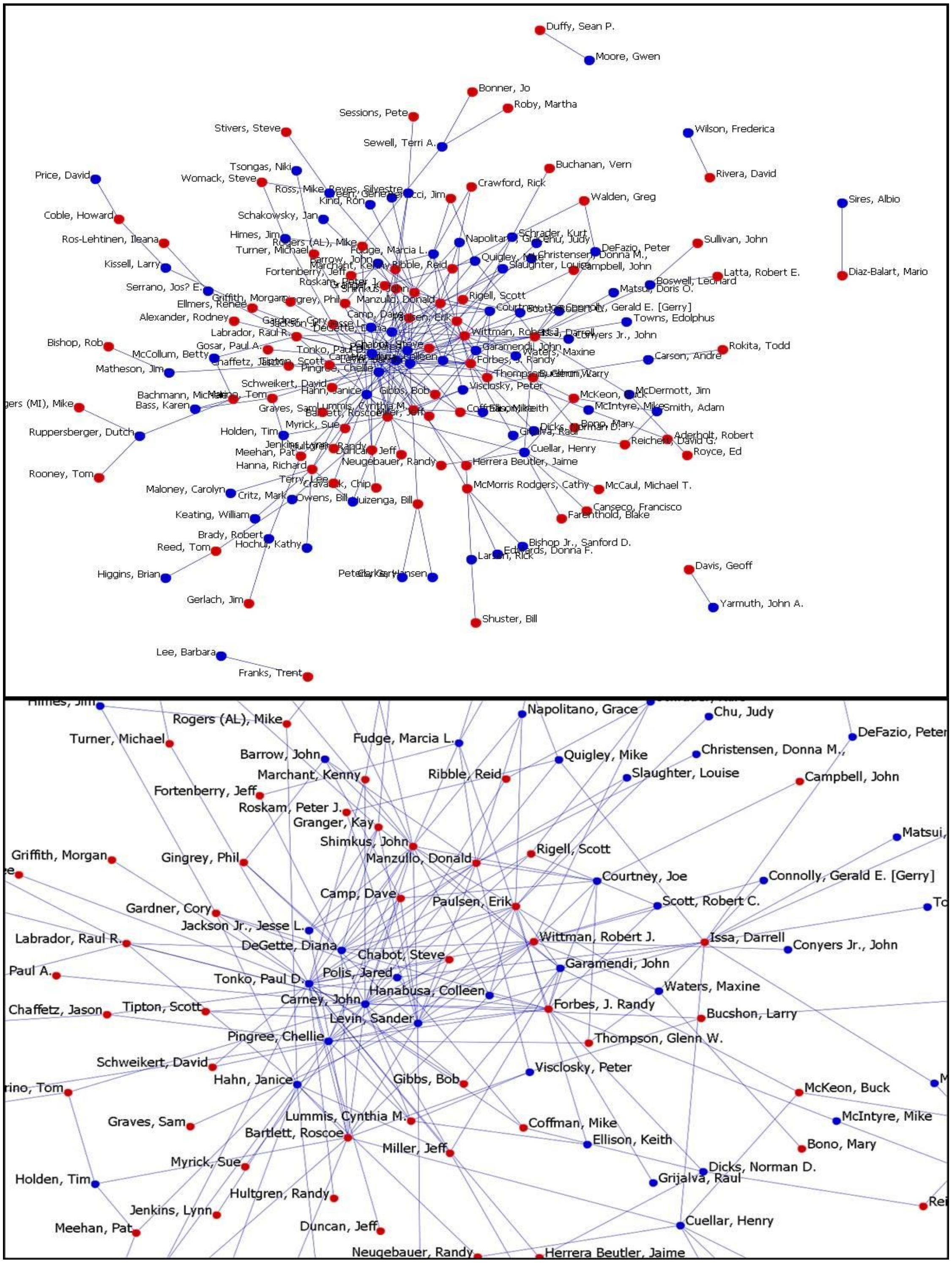


Figure 11: U.S. Bipartisan Network

The lower part of Figure 9 is a magnified image focusing on the center part of the whole party network. It shows the influence of key lawmakers such as Nancy Pelosi, James E. Clyburn, Diana DeGette, Steny h. Hoyer, Robert C. Scott, John B, Larson, Barbara Lee, John Conyers Jr., Karen Bass, and Joe Courtney.

Figure 10 illustrates the shape of the Republican Party network. The Republican network looks like a typical star network, yet network measures indicate the Republican network has a more condensed and centered network. They are more integrated to the center of the network. Four outlier lawmakers, who don’ have any ties within the party network were found by the research. A magnified network presents which lawmakers are in the center of Republican network: John Shimkus, Randy Forbes J., John Boehner, Cathy McMorris Rogers, and Eric Cantor, which corroborates with the overall centrality measure.

Figure 11 illustrates the shape of the bipartisan mutual network in the U.S. House of Representatives, as in typical star-like network. Some 151 nodes out of 351 total lawmakers (43%) were connected with each other with 490 bipartisan ties. Further, five pairs of bipartisan ties consisting of only two lawmakers were also found, revealing that 141 lawmakers comprise the centered network in the House of Representatives. Five pair of bipartisan ties might be revealing private relationship between lawmakers but more detailed researches need to be done.

In sum, this study found six bipartisan networks: one large and five small bipartisan networks. A magnified image of the bipartisan network reveals who are at the center of the bipartisan network. Interestingly, Democrats were in the core, some Republican lawmakers stood around the center.

Party	Democrats	Republican
Democrats	6670 (3,400)	1038 (245)
Republican	1340 (245)	18829 (11,748)

Table 16: Partisan and Bipartisan Ties in the U.S. House of Representatives (N = 351)

Note. Mutual Network Ties in Parenthesis

This research also calculated how many inter- and intra-party ties connect each lawmaker and how they are distributed across the bipartisan network. Table 16 shows that approximately 91.5 % are partisan ties and 8.5% of are bipartisan ties in the directional network. The finding indicate that 98 % of mutual ties are partisan and less than 2% are bipartisan, revealing that mutual tie relationship among lawmakers is seriously partisan skewed.

SUMMARY

U.S. lawmakers have created a huge digital legislative network sphere, embracing 351 lawmakers, 80 % of the total lawmakers that are connected by 27,877 ties. The network shape vividly displays that the Congressional network consists of the two partial networks connected by bipartisan ties. This study identified the top 20 lawmakers, the core lawmakers, mostly Republicans, of the Congressional network as well as the party cores. Personal networks of the influential lawmakers indicate diverse patterns of networking within and beyond the party and the cores of the core lawmakers. Overall, the Republicans have a bigger, more tightly knitted, efficient, centralized network than the Democrats. Analysis of tie building relationships indicates that members of the ruling party are more likely sociable, prominent and active in the network. This study found 151 lawmakers connected by bipartisan ties, but the results indicate partisan ties are predominant in the network.

CHAPTER 5: TWITTER NETWORK OF THE 18TH KOREA NATIONAL ASSEMBLY

THE WHOLE TWITTER NETWORK OF THE KOREA NATIONAL ASSEMBLY

RQ1 asked about the overall look of the Twitter network of the Korea National Assembly. The whole networks of Korean lawmakers, a directional network and a bidirectional network, are shown in Figures 12 and 13. Figure 12 displays a directional network, which demonstrates in- and out-degree ties as well as mutual ties. Figure 13 displays only bidirectional (mutual) ties. Each node signifies representatives. The color of a node demonstrates party identification: a blue node signifies UDP lawmakers and red signifies SP lawmakers; green signifies Independents, and so forth.

Figure 12 presents a directional Twitter network among 265 lawmakers, which is very similar to that of the U.S. House. The network of Korean lawmakers obviously demonstrates that node distributions and tie relationships are mainly polarized by party affiliation. In general, the shape of the Korea National Assembly's network consists of two blocs, in red and blue, and reveals small node blocs belonging to five mini party members scattered around ether red or blue blocs. Two large blocks stand on opposite sides and a few bipartisan ties are connecting each node. No isolated lawmaker was found, implying every lawmaker has at least one tie with another lawmaker. This research found 22,934 ties connecting lawmakers. On the left side of Figure 12, UDP lawmakers anchor, whereas SP lawmakers anchor the right side.

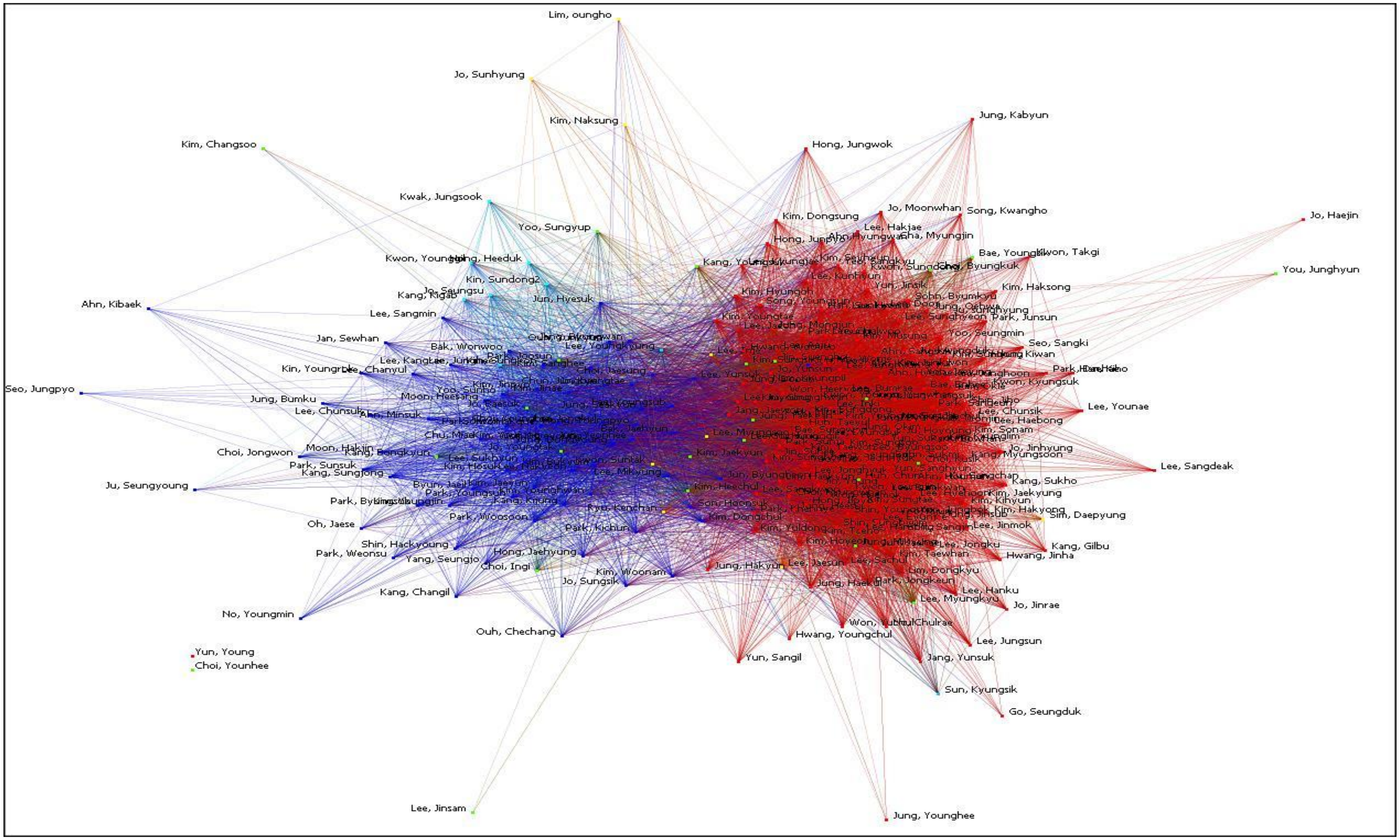


Figure 12: The Whole Network of the 18th Korean National Assembly

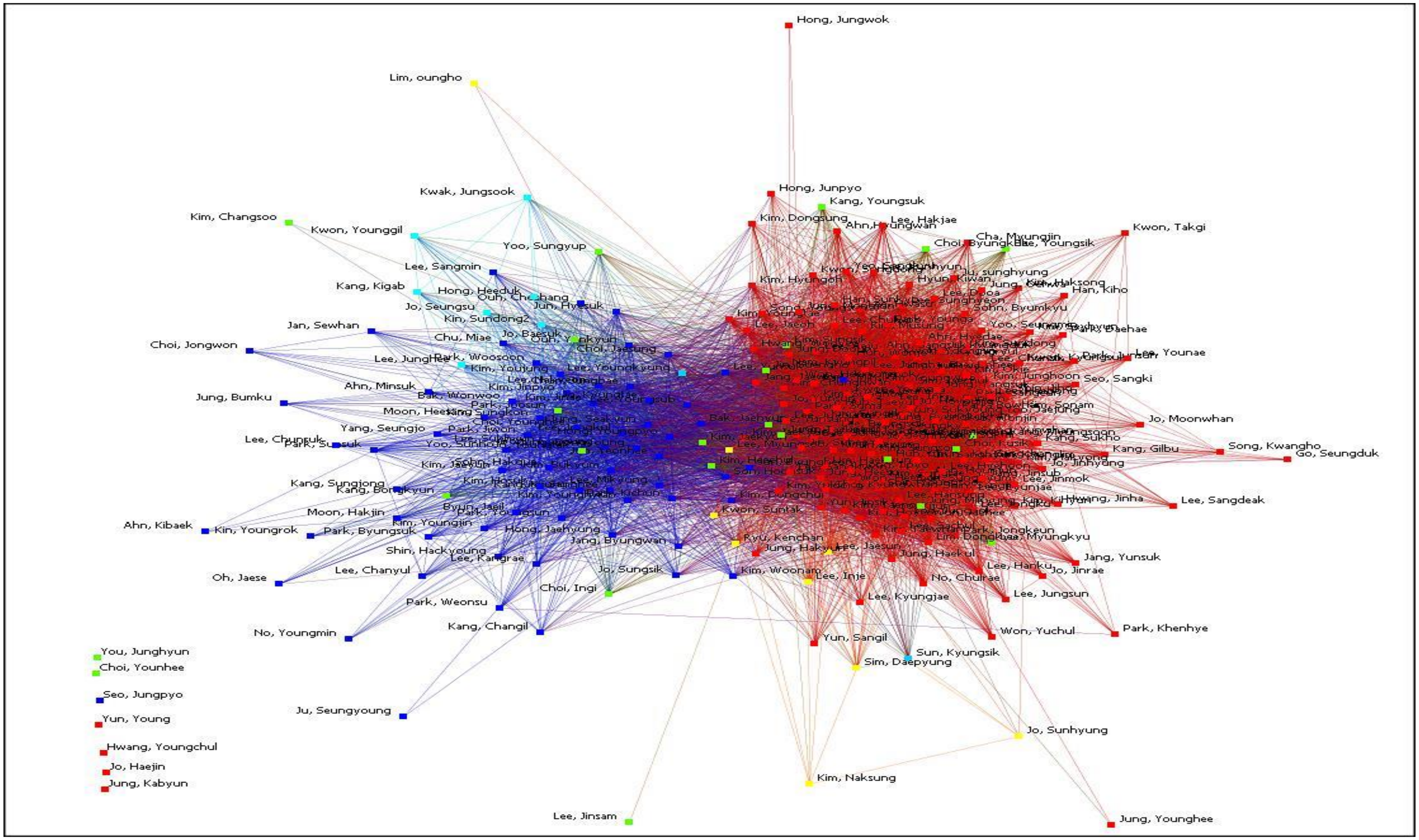


Figure 13: The Mutual Network of the 18th Korean National Assembly

Tie calculation indicates that 11,936 ties exist between SP members, while 1,457 out-degree ties go to UDP. This study also found that 2,543 ties are connecting UDP lawmakers and 1,563out-degree ties go to SP lawmakers.

Figure 12 demonstrates that the Korean legislative network consists of two large core networks headed by the two major parties, SP and UDP; however, five more political factions exist, displaying scattered dots across the whole network. Interestingly, most independents who defected from either the SP or UDP because of scandal or political dissent linger around the party network they once belonged to. For example, Representative Cho Yonhee who had once been influential in the SP party stands near the center of the SP party network, despite having defected. Figure 13 presents the Korean mutual networks between lawmakers. This research found 21,124 mutual ties between lawmakers. Different from the whole network, the mutual network reveals seven isolated, outlier lawmakers, having mutual ties with no other lawmaker. Four of them belong to SP, the ruling and conservative party, two are independent, and one belongs to UDP, the liberal and primary opposition party. Figure 13 shows that the Korean mutual network is divided by party confrontation as well as connected by bipartisan ties.

KEY LAWMAKERS IN THE KOREAN NATIONAL ASSEMBLY

RQ2-1 asks about key players in the lawmaker's Twitter network. As with the analysis of the U.S. House, this research calculated five centrality measures for all 265 lawmakers.

Rank	Name	Value(Scaled)	Value(Unscaled)	Party
1	Jun, Byungheon	0.682	180	UDP
2	Lee, Yunsung	0.659	174	ID
3	Lee, Juyoung	0.655	173	SP
4	Park, Sunja	0.648	171	SP
5	Won, Heeryong	0.633	167	SP
	Kang, Seungkyu	0.633	167	SP
7	Kim, Taewon	0.629	166	SP
8	Go, Hyunggil	0.621	164	SP
9	Kim, Chunghwan	0.610	161	SP
10	Jung, Taekean	0.591	156	ID
	Jo, Jeonhyuk	0.591	156	SP
12	Jung, Heesu	0.587	155	SP
	Lee, Byungsuk	0.587	155	SP
	Huh, Taeyul	0.587	155	SP
15	BaeK, Sungwon	0.583	154	SP
	Seo, Byungsoo	0.583	154	SP
17	Na, Sunglin	0.572	151	SP
18	Jung, Byungkuk	0.568	150	SP
	Jin, Suhee	0.568	150	SP
20	Yoo, Ilho	0.557	147	SP

Table 17: Top 20 Korean Lawmakers in Degree of Centrality
Note: SP = Saenuri Party, UDP = Unified Democratic Party,
ID = Independents,

Rank	Saenuri Party (SP)			Rank	Unified Democratic Party (UDP)		
	Node Name	Scaled Score	Unscaled score		Name	Scaled Score	Unscaled score
1	Kang,Seungkyu	0.842	128	1	Jung, Seakyun	0.853	58
2	Na, Sunglin	0.836	127	2	Jung, Dongyoung	0.824	56
3	Seo, Byungsoo	0.803	122	3	Jun, Yeonhee	0.794	54
	Kim,Taewon	0.803	122		Hong, Youngpyo	0.794	54
5	Jo, Jeonhyuk	0.796	121	5	Bak, Jaehyun	0.779	53
6	Park, Sunja	0.790	120	6	Won,Hyeyoung	0.765	52
	Won, Heeryong	0.790	120	7	Park, Jiwon	0.750	51
8	Lee, Juyoung	0.783	119		Lee Jongkul	0.750	51
9	Kim, Junkwon	0.770	117	9	Jun, Byungheon	0.735	50
	Jung, Byungkuk	0.770	117		Kang, Kijung	0.735	50

Table 18. Top 10 Lawmakers in Degree Centrality in the Party Network

Three centrality measures–degree of centrality, closeness centrality, betweenness centrality–were conducted with the mutual network, whereas in- and out-degree measures were conducted with the directional network. This research presents each result at two structural levels: the whole network to tap a lawmaker’s position in the National Assembly and party network to tap into a lawmaker’s position within their own party.

Table 17 presents the top 20 lawmakers who scored a high in-degree centrality measure. The results indicate that 17 of these representatives are SP lawmakers. Two lawmakers, prior members of SP, belong to ID, indicating that SP lawmakers are phenomenal in terms of in-degree centrality measurements at the whole network level. Only one lawmaker, Jun Byungheon who scored first in the list belongs to UDP, the largest opposition party. Second to Jung, is Lee Yunsung. Jun has 180 mutual ties with lawmakers, which reaches approximately 68% of all lawmakers in the network. Interestingly, none of the top scored representatives holds any major official party post such as party leader or floor leader.

Table 18 presents the top 10 players within each party network. As in the case of the U.S. House, the ranking of each lawmaker in the party network is not the same as the whole network level because it only represents ties within the party network; the ranking of the whole network represents all ties within the network regardless of party affiliation.

In the SP mutual network, Kang Seungkyu is shown to be the leading lawmaker with the highest degree of centrality. Second to Kang Seungkyu is Na Sunglin, followed by Seo Byungsoo. All the top 10 lawmakers in the SP network also appear to occupy high posts in the party network, although their rank order is slightly different from the whole network. Table 18 also shows the top ten players within the UDP network. Jung Seakyun scores at the top of the list, indicating he is the leader with the highest degree within UDP mutual network. Next to Jung Seakyun is Jung Dongyoung.

Rank	Name	Value(Scaled)	Value(Unscaled)	Party
1	Jun, Byungheon	0.1206	0.0005	UDP
2	Lee, Yunsung	0.1203	0.0005	ID
3	Lee, Juyoung	0.1202	0.0005	SP
4	Park, Sunja	0.1200	0.0005	SP
5	Won, Heeryong	0.1199	0.0005	SP
	Kang,Seungkyu	0.1199	0.0005	SP
7	Kim, Taewon	0.1198	0.0005	SP
8	Go, Hyunggil	0.1197	0.0005	SP
9	Kim, Chunghwan	0.1195	0.0005	SP
10	Jung, Taekean	0.1193	0.0005	ID
	Jo, Jeonhyuk	0.1193	0.0005	SP
12	Jung, Heesu	0.1192	0.0005	SP
	Lee, Byungsuk	0.1192	0.0005	SP
14	Huh, Taeyul	0.1191	0.0005	SP
	Bae, Sungwon	0.1191	0.0005	SP
	Seo, Byungsoo	0.1191	0.0005	SP
17	Na, Sunglin	0.1189	0.0005	SP
	Jung, Byungkuk	0.1189	0.0005	SP
	Jin, Suhee	0.1189	0.0005	SP
20	Yoo, Ilho	0.1188	0.0005	SP

Table 19: Top 20 Korean Lawmakers in Closeness Centrality

Note: SP = Saenuri Party, UDP = Unified Democratic Party,
ID = Independent, LPP = Liberal Progress Party

Rank	Saenuri Party (SP)		Rank	Unified Democratic Party (UDP)	
	Node Name	Scaled Score		Name	Scaled Score
1	Kang Seungkyu	0.1946	1	Jung, Seakyun	0.4690
2	Na, Sunglin	0.1934	2	Jung, Dongyoung	0.4626
	Kim, Taewon	0.1934	3	Jun, Yeonhee	0.4654
4	Seo, Byungsoo	0.1931		Hong, Youngpyo	0.4564
5	Jo, Jeonhyuk	0.1929	5	Bak, Jaehyun	0.4533
6	Won, Heeryong	0.1926	6	Won,Hyeyoung	0.4503
	Park, Sunja	0.1926	7	Park, Jiwon	0.4474
8	Lee, Juyoung	0.1922		Lee, Jongkul	0.4474
	Kim, Jungkwon	0.1922	9	Kang, Kijung	0.4444
	Lee, Byungsuk	0.1922		Jun, Byungheon	0.4444

Table 20: Top 10 Lawmakers in Closeness Centrality in Party Network

For example, both Jung Seakyun and Jung Dongyoung have been party leaders. Won Hyeyoung is the incumbent floor leader and Park Jiwon is the incumbent party leader.

Table 19 presents the top 20 lawmakers in closeness centrality. The results show that top players are almost the same as that for degree of centrality though with a slightly different ranking: 17 representatives belong to SP, 2 belong to ID, and 1 belongs to UDP. Jun Byungheon, who scored first in the degree-of-centrality list, also scores first in the closeness centrality list.

Table 20 ranks the party network showing a different landscape. In the SP mutual network, Kang Seungkyu stands atop the list. Second to Kang is Na Sunglin and Kim Taewon, followed by Sep Byungsoo. Lee Juyoung, who scored third on the whole level, scored eighth on the party network list, while Kang, fifth on the whole level, scored first in the SP network. In the UDP network, Jung Seakyun scored at the top of the list. Next to Jung Seakyun is Jung Dongyoung. Park Jiwon, the UDP party leader, scored seventh, and Won Hyeyoung, UDP floor leader, scored sixth. None of these lawmakers appears in the whole network list (Table 15), but they do appear in the party list of degree of centrality (Table 16).

Table 21 presents the top 20 lawmakers on the betweenness centrality measure. Different from the degree and closeness centrality list, several new lawmakers appear on this list. For example, Jung Seakyun and Jung Dongyoung who belong to UDP, ranked third and fourth. Ryu Kenchan, who belongs to conservative, LPP, scored ninth. On the whole, appearing on the top list of the betweenness centrality list are eight lawmakers belonging to UDP, the opposition party, seven to SP, the ruling party, three are independents, and two belong to LPP, the third largest party.

Table 22 presents another landscape of major players in the party networks. For example, Won Heeryong, who is fifth in the whole network, failed to be included in the top 10 of the SP network. On the contrary, Jin Jaehee, who does not appear in the whole network list, scored first in the SP network. In the UDP network, Jung Dongyoung scored first and Jung Seakyun scored second, while Jung Seakyun is ahead of Jung Dongyoung at the whole network level.

Rank	Name	Value(Scaled)	Value(Unscaled)	Party
1	Jun, Byungheon	0.025	850.085	UDP
2	Lee, Yunsung	0.019	660.927	ID
3	Jung, Dongyoung	0.016	544.459	UDP
4	Jung, Seakyun	0.014	500.250	UDP
5	Won, Heeryong	0.014	497.272	SP
6	Lee, Juyoung	0.013	443.296	SP
7	Bak, Jaehyun	0.012	420.074	UDP
8	Jung, Taekean	0.012	421.133	ID
9	Ryu, Kenchan	0.012	408.416	LPP
10	Park, Sunja	0.011	387.418	SP
11	Kang, Seungkyu	0.011	368.380	SP
12	Jun, Yeonhee	0.010	357.234	UDP
13	Jung, Dooun	0.010	350.093	SP
14	Kim, Jaekyun	0.010	345.325	ID
15	Kim, Dongchul	0.010	340.366	UDP
16	Kim, Taewon	0.010	328.724	SP
17	Kim, Chunghwan	0.009	323.978	SP
18	Hong, Youngpyo	0.009	301.465	UDP
19	Lee, Myungsoo	0.009	300.128	LPP
20	Lee, Youngsub	0.009	295.911	UDP

Table 21: Top 20 Korean Lawmakers in Betweeness Centrality
Note: SP = Saenuri Party, UDP + Unified Democratic Party,
ID = Independent, LPP = Liberal Progress Party

.

Rank	Saenuri Party (SP)			Rank	Unified Democratic Party (UDP)		
	Node Name	Scaled Score	Unscaled score		Name	Scaled Score	Unscaled score
1	Jun, Jaehee	0.0153	176.07	1	Jung, Dongyoung	0.0482	109.71
2	Kang, Seungkyu	0.0146	166.98	2	Jung, Seakyun	0.0359	81.89
3	Jung, Dooun	0.0133	152.86	3	Jun, Byungheon	0.0264	60.22
4	Seo, Byungsoo	0.0108	123.48	4	Kang, Kijung	0.0264	60.16
5	Jo, Jeonhyuk	0.0104	119.80	5	Jun, Yeonhee	0.0249	56.71
6	Park, Sunja	0.0096	109.68	6	Park, Jiwon	0.0227	51.75
7	Huh, Taeyul	0.0091	104.94	7	Hong, Youngpyo	0.0213	48.42
8	Na, Sunglin	0.0090	103.10	8	Kim, Hosuk	0.0202	46.01
9	Lee, Juyoung	0.0090	102.88	9	Won,Hyeyoung	0.0196	44.54
10	Kim,Taewon	0.0089	101.61	10	Bak, Jaehyun	0.0181	41.19

Table 22: Top 10 Lawmakers in Betweenness Centrality in Party Network

Table 23 presents the most sought-after lawmakers calculated by the in-degree centrality measure. Interestingly, 19 members ranked in the top 20 lists in the degree of centrality also appear in the top 20 list of in-degree of centrality. Further, the top nine lawmakers in degree of centrality rank exactly the same in in the top 20 list of in-degree of centrality. To some degree, this is plausible because degree of centrality is the sum of in-degree and out-degree but it needs more explanation regarding why in-degree ties do not always lead to out ties or vice versa.

Rank	Name	Value(Scaled)	Value(Unscaled)	Party
1	Jun, Byungheon	0.682	180	UDP
2	Lee, Yunsung	0.659	174	ID
3	Lee, Juyoung	0.655	173	SP
4	Park, Sunja	0.652	172	SP
5	Won, Heeryong	0.640	169	SP
6	Kang,Seungkyu	0.633	167	SP
7	Kim, Taewon	0.629	166	SP
8	Go, Hyunggil	0.625	165	SP
9	Kim, Chunghwan	0.614	162	SP
10	Jung, Okim	0.606	160	SP
11	Jung, Taekean	0.595	157	ID
	Jo, Jeonhyuk	0.595	157	SP
13	Huh, Taeyul	0.591	156	SP
14	Lee, Byungsuk	0.587	155	SP
	Jung, Heesu	0.587	155	SP
16	Bae, Sungwon	0.583	154	SP
	Seo, Byungsoo	0.583	154	SP
18	Na, Sunglin	0.572	151	SP
	Jin, Suhee	0.572	151	SP
20	Jung, Byungkuk	0.568	150	SP

Table 23: Top 20 Lawmakers in In-degree Centrality

Note: SP = Saenuri Party, UDP = Unified Democratic Party,
ID = Independent, LPP = Liberal Progress Party

Rank	Saenuri Party (SP)			Unified Democratic Party (UDP)			
	Node Name	Scaled Score	Unscaled score		Name	Scaled Score	Unscaled score
1	Kang,Seungkyu	0.842	128	1	Park, Jiwon	0.912	62
2	Na, Sunglin	0.836	127	2	Jung, Seakyun	0.868	59
3	Jung, Okim	0.829	126	3	Jung, Dongyoung	0.824	56
4	Kim,Taewon	0.803	122	4	Jun, Yeonhee	0.809	55
	Seo, Byungsoo	0.803	122		Won,Hyeyoung	0.809	55
6	Won, Heeryong	0.796	121		Chun, Jungbae	0.809	55
	Jo, Jeonhyuk	0.796	121		Kim, Jinpyo	0.809	55
8	Park, Sunja	0.790	120		Lee, Youngsub	0.809	55
9	Lee, Juyoung	0.783	119		Kim, Youjung	0.809	55
10	Kim, Junkwon	0.770	117	9	Hong, Youngpyo	0.794	54

Table 24: Top 10 Lawmakers in In-degree Centrality in Party Network

This is confirmed in Table 24. Park Jiwon is excluded from the Top 20 list of the whole network, yet in the UDP network he is the most sought-after lawmaker. Table 24 indicates that 62 lawmakers out of 69 UDP lawmakers (89.8%) are mutually connected to Park Jiwon, while Kang Seungkyu holds 128 out of 153 in-degree ties with SP lawmakers (83.6%).

Rank	Name	Value(Scaled)	Value(Unscaled)	Party
1	Lee, Juyoung	0.875	231	SP
2	Jun, Byungheon	0.682	180	UDP
	Won, Heeryong	0.682	180	SP
4	Lee, Yunsung	0.663	175	ID
5	Park, Sunja	0.652	172	SP
6	Kang, Seungkyu	0.644	170	SP
	Kim, Chunghwan	0.644	170	SP
8	Kim, Taewon	0.636	168	SP
9	Kim, Kyunglim	0.629	166	SP
10	Go, Hyunggil	0.625	165	SP
	Sung, Yunwhan	0.625	165	ID
12	Jo, Yunsun	0.617	163	SP
13	Jo, Jeonhyuk	0.610	161	SP
14	Jung, Taekean	0.606	160	ID
15	Jo, Wonjin	0.599	158	SP
16	Huh, Taeyul	0.591	156	SP
	Lee, Byungsuk	0.591	156	SP
	Seo, Byungsoo	0.591	156	SP
19	Jung, Heesu	0.587	155	SP
	Bae, Sungwon	0.587	155	SP

Table 25: Top 20 Lawmakers in Out-degree Centrality

Note: SP = Saenuri Party, UDP = Unified Democratic Party,
ID = Independent, LPP = Liberal Progress Party

Rank	Saenuri Party (SP)			Rank	Unified Democratic Party (UDP)		
	Node Name	Scaled Score	Unscaled score		Name	Scaled Score	Unscaled score
1	Kim, Kyunglim	0.954	145	1	Hong, Youngpyo	0.927	63
2	Lee, Juyoung	0.915	139	2	Park, Byungsuk	0.912	62
3	Jo, Wonjin	0.908	138	3	Jung, Seakyun	0.912	62
4	Won, Heeryong	0.855	130	4	Jun, Yeonhee	0.882	60
5	Kang ,Seungkyu	0.849	129	5	Bak, Jaehyun	0.838	57
6	Na, Sunglin	0.842	128	6	Jung, Dongyoung	0.824	56
7	Kim, Junkwon	0.836	127	7	Park, Jiwon	0.809	55
8	Kim,Taewon	0.816	124	8	Byun, Jaeil	0.809	55
	Jo, Jeonhyuk	0.816	124	9	Kang, Kijung	0.779	53
10	Seo, Byungsoo	0.803	122		Won,Hyeyoung	0.779	53

Table 26: Top 10 Lawmakers in Out-degree Centrality in Party Network

Table 25 exhibits the lists of lawmakers actively following other lawmakers, i.e., socialites. Lee Juyoung is first with 231 out-degree ties, 87.5% of all lawmakers (N = 265). Next is Jun Byungheon and Won Heeryong who have 180 out-degree ties, 68.2% of all lawmakers.

Table 26 indicates the lists of lawmakers actively following other lawmakers at the party level. In the SP network, Kim Kyunglim scores first with 145 SP lawmaker followees, meaning he is followed by 95.4% of all SP lawmakers; In the UDP network, Hong Youngpyo scores first with 63 UDP lawmaker followees, meaning he is followed by 92.7% of all UDP lawmakers.

EGO NETWORKS OF THE KEY LAWMAKERS IN THE HOUSE OF REPRESENTATIVES TWITTER NETWORK

RQ 2-2 asks about the key player's ego network. This study selected five lawmakers who scored at the top of each list. Each figure presents two images: the whole ego network (above) and a part of magnified network focusing on the center of the ego network (below). Each lawmaker's mutual ego network is presented.

Figure 14 displays the ego mutual network of Jun Byungheon, a liberal belonging to UDP; he scores first in in-degree of centrality, closeness centrality, betweenness centrality, and in-degree centrality. As shown in Figure 14, Jun's ego network consists of two star-like sub networks: red (conservatives) and blue (liberals). Independents (green) are scattered across the network. On the whole, Jun's ego network looks like a miniaturized form of the whole National Assembly network. A tie analysis of the ego network indicates that Jun's ego network consists of 181 nodes and 14,584 ties with lawmakers. A magnified image of Figure 14 indicates that some conservatives are located near Jun, such as Lee Myungsoo, Kim Chungwan, and Lee Juyoung. Independents are also located near Jun such as Lee Yunsung, Jung Taekean, Kim Sungsik, and Kim Haechul. The results of the centrality measures indicate that the number of his partisan node connection is 49, whereas his bipartisan node connection is 131, indicating his ego network consists largely of a bipartisan mutual network.

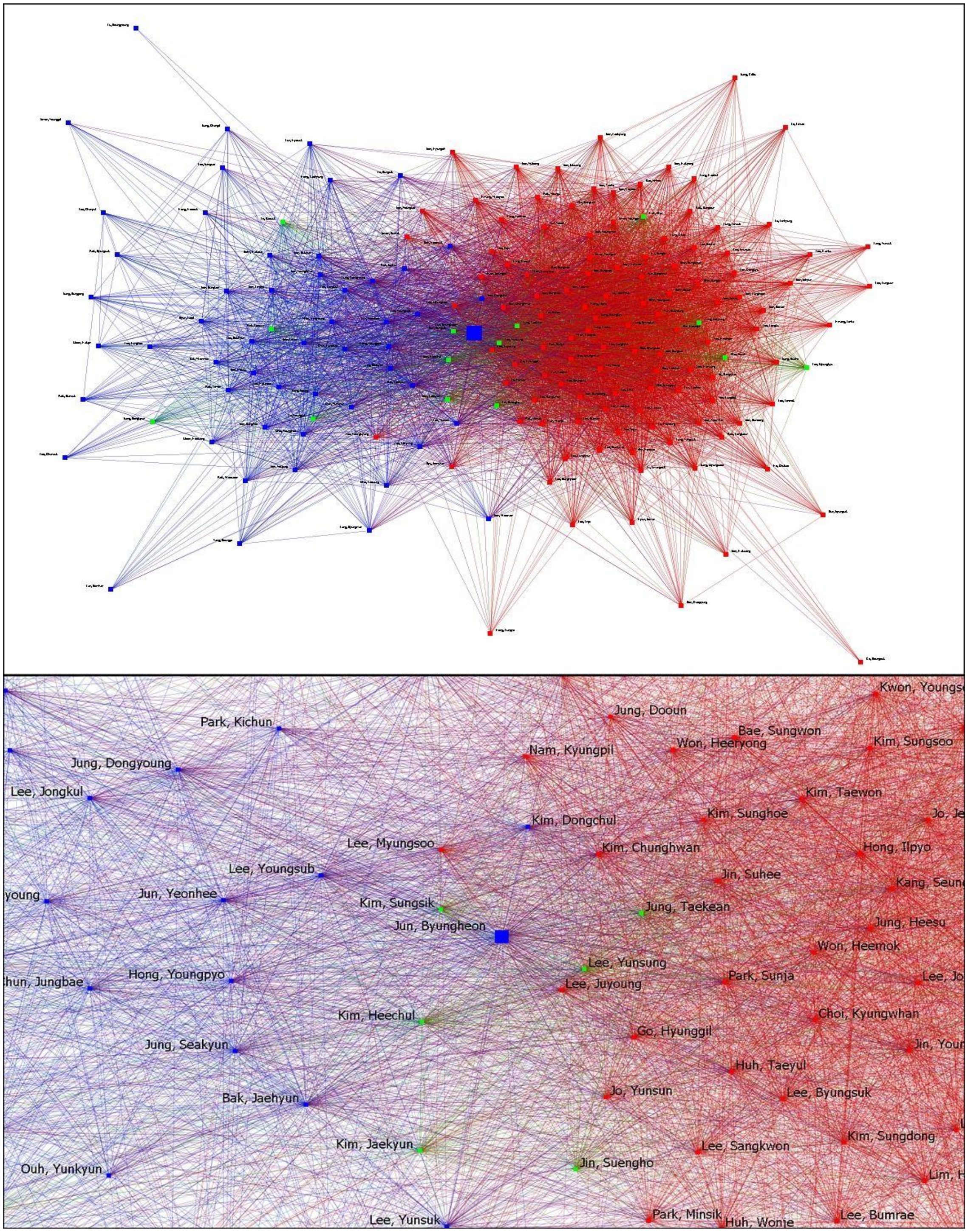


Figure 14: Jun Byungheon's Network

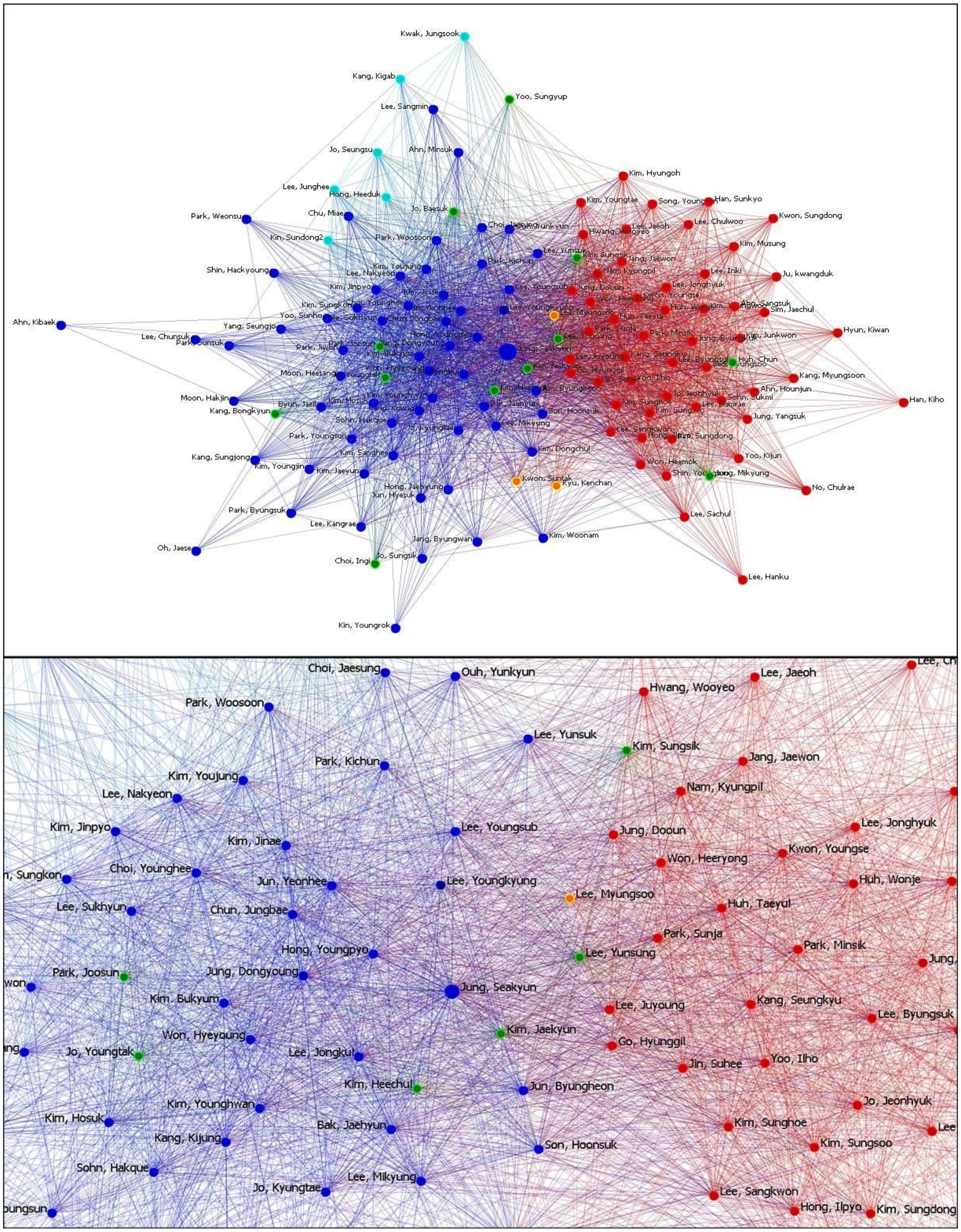


Figure 15: Jung Sekyun's Network

Figure 15 presents the ego network of Jung Seungkyun, a liberal who belongs to UDP. He stands atop the list of degree and closeness centrality within UDP. As shown in Figure 15, his network also consists of two star-like networks: a blue (UDP) and a red (SP) one. Around two large networks, lawmakers belonging to DPP (liberal) connect to Jung. A tie analysis indicates that Jun's ego network consists of 133 nodes with a total number of lawmaker ties of 7,438. The image shown in Figure 15 indicates that located close to Jung are such UDP members as Lee Yungkyung, Hong Youngpyo, and Lee Jongchul. The result also reveals that some independents – Lee Yunsung, Kim Jaekyun, and Kim Heechul – are located near Jung. The results of centrality measures indicate that the number of his partisan node connections is 57 (85% of all UDP lawmakers), whereas the number of his bipartisan node connections is 75, indicating his ego network consists largely of a bipartisan network.

Figure 16 presents the ego network of Jung Dongyoung, a liberal belonging to UDP. He is at the top of the list of betweenness centrality within the UDP network and scores high on several centrality measures. Figure 16 shows his network consists of two star-like networks: a blue and a red one. Unlike Jung Sekyun's network, he has no mutual ties with DPP lawmakers. A tie analysis indicates that Jun's ego network consists of 133 nodes and the total number of ties with lawmakers is 7,412. A magnified image of Figure 15 indicates that standing around Jung are such UDP members as Jun Younhee, Hong Youngpyo, and Jun Byungheon, as well as such independents as Lee Yunsung, Kim Jaekyun, and Kim Heechul.

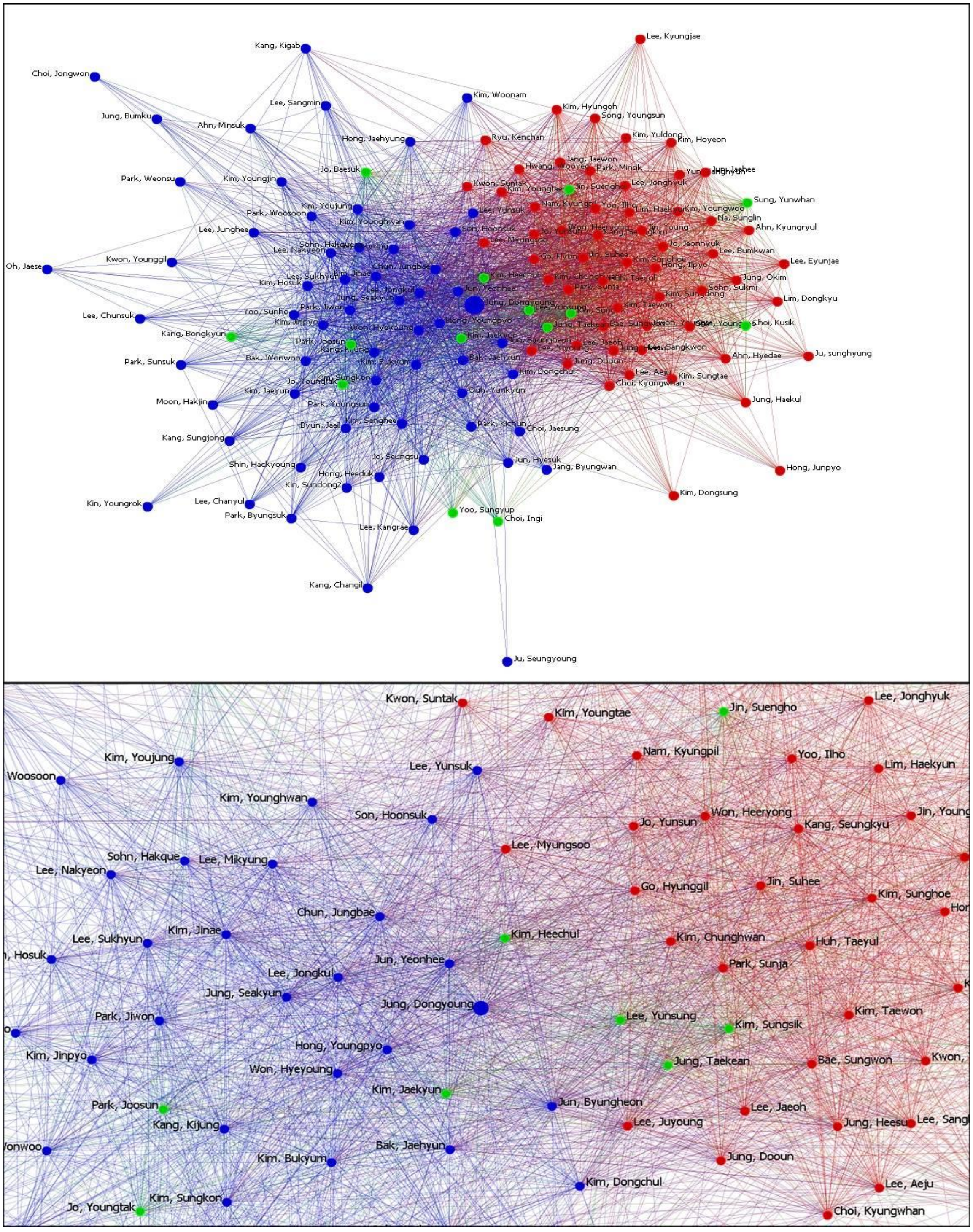


Figure 16: Jung Dongyoung's Ego Network

The results of the centrality measures indicate that the number of his partisan party network amounts to 55 (82% of all UDP lawmakers), whereas his bipartisan mutual network amounts to 79, indicating his ego network consists largely of a bipartisan mutual network rather than a partisan one.

Figure 17 presents the ego network of Kang Seungkyun who belongs to SP and is a conservative. He stands at the top of the list of degree of centrality, betweenness centrality and in-degree centrality within the SP network. Figure 17 shows that his network looks like a star-like network, largely consisting of a red (conservative) network. A tie analysis of his ego network shows that Jun's ego network consists of 168 nodes and the total number of ties with lawmakers is 14,748. A magnified image of Figure 15 indicates that standing close to Kang are SP lawmakers, such as Park Sunja, Yoo Ilho, Lee Juyoung, and Bae Byungsoo. The results of the centrality measures indicate that the number of his inner party network (SP) is 127, whereas his bipartisan network is 40, indicating his ego network largely consists of a partisan network.

Figure 18 presents the ego network of Lee Juyoung, a conservative who belongs to SP. He stands at the top of the list of out-degree of centrality with 231 lawmakers that he is following, which indicates he is the most active at seeking tie relationships with other lawmakers in Korean National Assembly. Figure 17 shows that his network looks like a star-like network, largely consisting of a red (conservative) network. Analysis of his ego network indicates that Jun's ego network consists of 174 nodes, indicating he has succeeded at building mutual ties with 173 lawmakers.

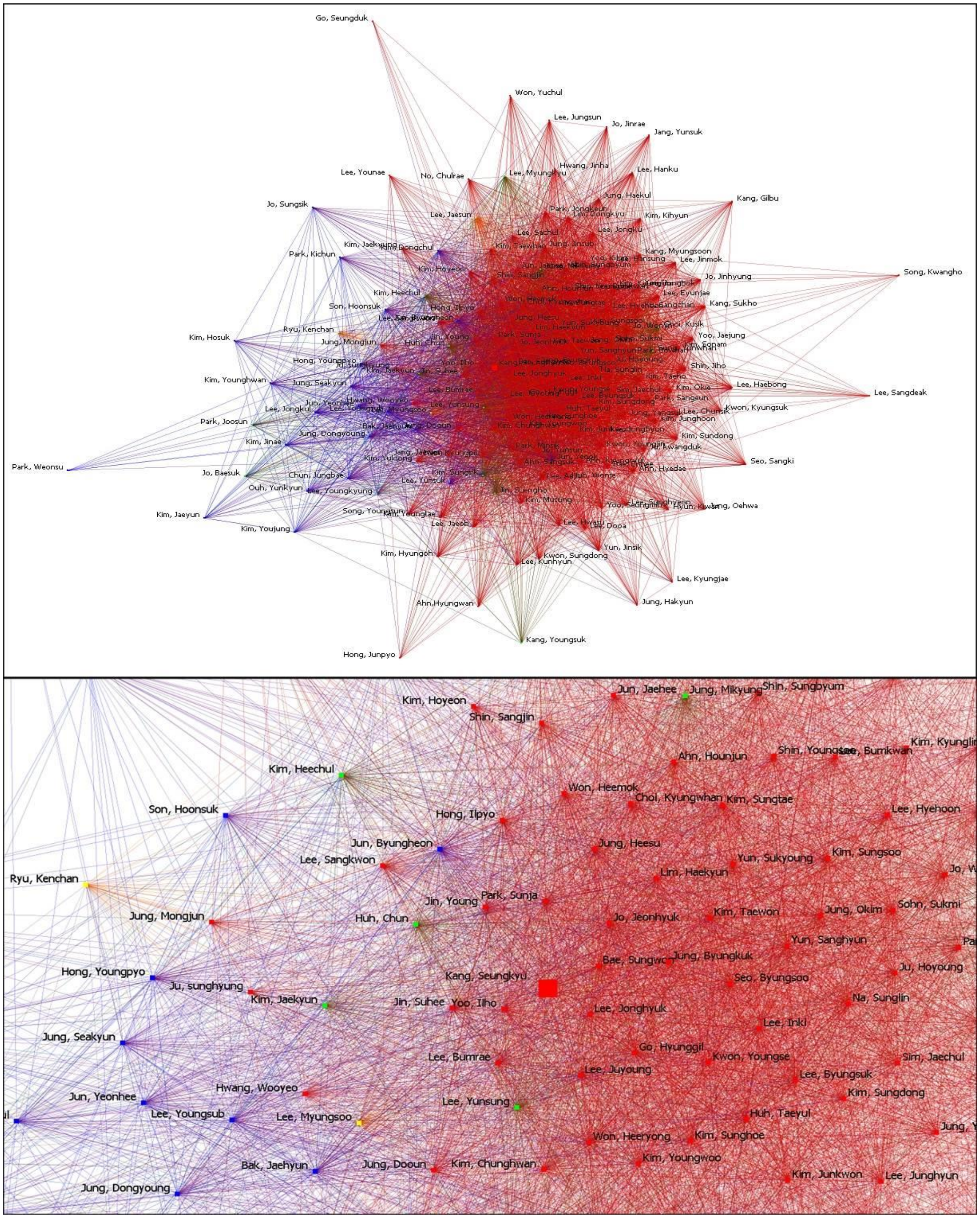


Figure 17: Kang Seungkyun's Ego Network

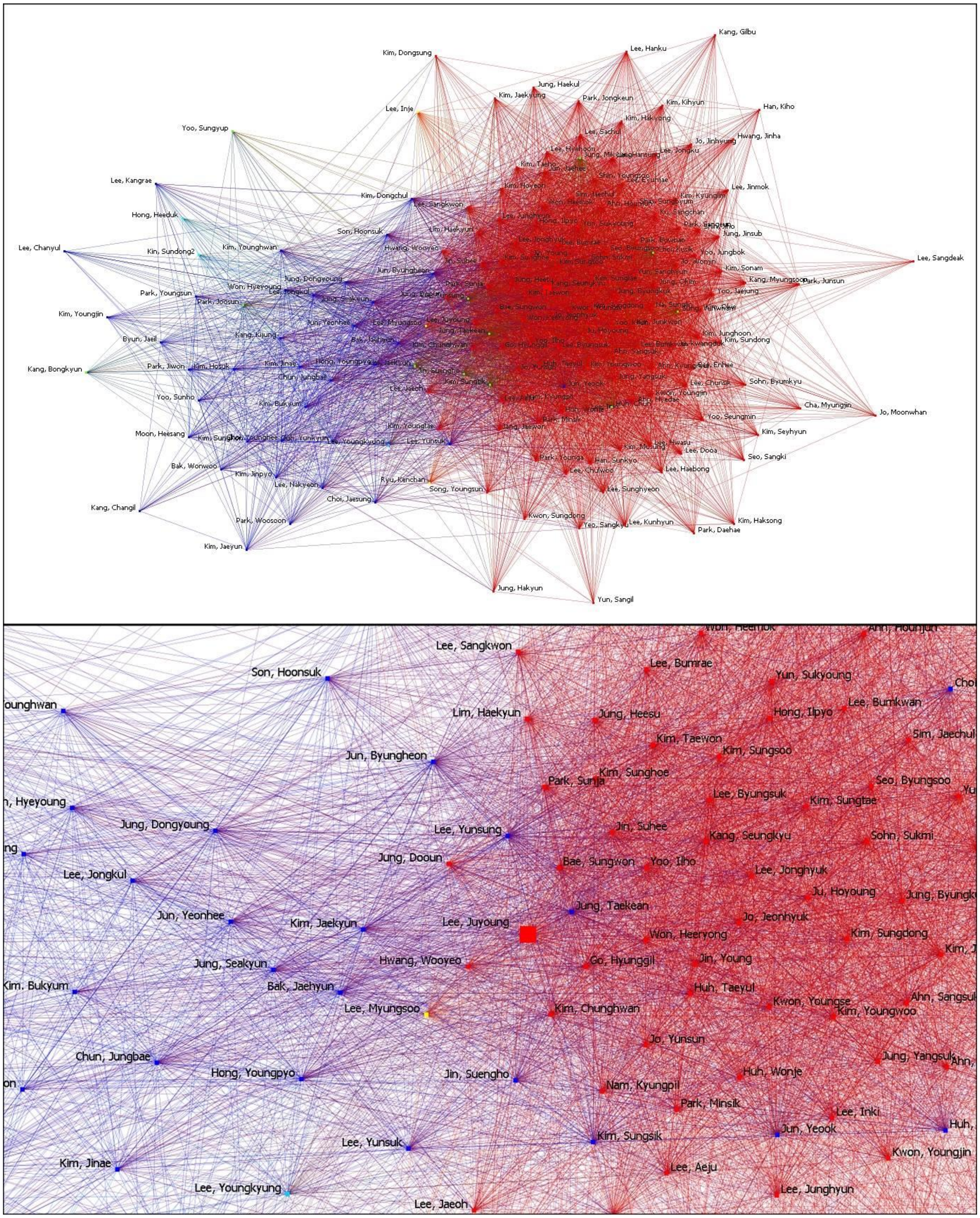


Figure 18: Lee Juyoug's Ego Network

A magnified image of Figure 18 indicates that SP lawmakers such as Jung Doowon, Hwang Wooyeo, Kim Chunghwan, and Bae Sungwoon are located around Lee. Independents Lee Yunsung and Jung Taekean are also revealed as being close to Lee. The results of centrality measures indicate that the number of his inner party ties (SP) is 118, whereas his inter-party mutual network is 55, indicating his ego network largely consists of a partisan network.

RED AND BLUE NETWORK

RQ3 asks about the extent of the differences between conservatives' and liberals' Twitter party networks. In the Korean National Assembly, this research found six parties and an independent group. To compare party networks, this study selected two major parties: SP and UDP. SP is the ruling party, widely considered as ideologically conservative, and UDP, considered as liberal, is the number one opposition party.

Table 27 compares the two major parties' mutual network structure. The results indicate that the size of the SP network (N = 153) is more dominant than the UDP network (N = 69); the SP network is 2.2 times larger than the UDP network. The results also indicate that the conservatives (N = 11,298) have 5.2 times more mutual ties than do their liberal counterparts (N = 2,170). The average SP lawmaker (73.8 ties) has approximately 2.35 times more partisan ties than does his UDP counterpart (31.4 ties). This indicates that the conservatives are more actively managing the mutual relationships between themselves.

	Saenuri Party	Unified Democratic Party
Network Size	153	69
Mutual Ties (pairs)	11,298 (5,649)	2,170 (1,085)
Ties per Node	73.8	31.4
Density	.49	.46
Reciprocal Rate	.95	.97
Fragmentation Rate	.05	.03
Distance(Average)	1.50	1.53
Network Centralization for Degree	.36	.40
Network Centralization for Betweenness	.01	.04
Average Twitts (Sum)	695 (103,343)	1,578 (108,896)
Average Followers (Sum)	8855.04 (135,4822)	13,954 (962,250)
Average Folllowees (Sum)	6687.24 (1,023,148)	11,191 (772,191)

Table27: Comparisons of Two Korean Party's Mutual Network

The density measure shows that the conservatives are slightly more tightly knitted than are the liberals. The average distance shows any node belonging to either networks can reach any other node in approximately 1.5 steps, suggesting both party networks encompass a rather small world. However, lawmakers in the conservative party network are slightly closer than their liberal counterparts. The liberal party network is more centralized than the conservative party network regarding degree of centralization, meaning their source of authority is more concentrated. The centralization index for betwenness centrality also indicates that the liberal party network is more centralized concerning betweenness centrality, which implies that coordinating or bargaining resources are more concentrated there.

RULING PARTY AND OPPOSITION PARTY IN THE TWITTER NETWORK

H1 posited representatives belonging to the ruling party are more likely have more in-degree, out-degree and mutual ties than those who belong to opposition party. To tap into this difference, this research conducted regression analysis, shown in Table 28.

Table 28 indicates that Korean lawmakers belonging to the ruling party are significantly and positively more sociable and have more out-degree ties, all else being constant ($\beta = .33$, $p < .01$). This implies that membership in the ruling party is a significant and positive predictor of sociability in the elite network.

The results also show that lawmakers belonging to the ruling party are significantly and positively in more prestigious positions in the elite network ($\beta = .40$, $p < .01$). Table 28 also indicates that membership in the ruling party is a significant and positive predictor in building mutual tie relationships with other lawmakers in the network ($\beta = .32$, $p < .01$), controlling for all other variables. Ruling party membership also is a significant and positive predictor of building active tie relationship in the lawmakers' network.

	Tie Relationship Building								
	Socialability			Prominence			Mutuality		
	t	β		t	β		t	β	
Gender	-0.59	-0.03		-0.35	-0.02		-0.59	-0.03	
Age	-0.42	-0.03		-0.96	-0.06		1.49	0.09	
Political Experience	-0.58	-0.04		-0.10	-0.01		-1.06	-0.06	
Ruling Party	6.07	0.33	**	7.56	0.40	**	5.92	0.32	**
Number of Twit	1.46	0.11		1.67	0.12		0.74	0.05	
Number of Followees	6.20	0.46	**	5.44	0.40	**	7.01	0.52	**
Number of Follower	-3.84	-0.27	**	-1.09	-0.07		-5.54	-0.38	**
Adjusted R Square (%)		25.1			29.3			27	

Table 28: Predictors of Korean Lawmakers Tie Relationship Building (N = 265)

*Note: β = Standardized regression coefficient, * p < .05,   ** P < .01*

As with the U.S. legislative network, this research found that the number of followees of a lawmaker is a positive and the strongest predictor of sociability ($\beta = .46$, $p < .01$) and mutuality ($\beta = .52$, $p < .01$). The results indicate that the number of followees for a lawmaker is a positive and a significant predictor of prestige positions in the legislative network ($\beta = .30$, $p < .01$). However, the number of postings was not a significant predictor of active tie relationships in the legislative network. Further, this study found that the popularity of lawmakers – more followers – is a significant but negative predictor of active relationship building in the lawmakers' network. The results indicate that the number of followers is a negative variable in predicting more sociability ($\beta = -.27$, $p < .01$) and mutual relationship ($\beta = -.38$, $p < .01$) in the lawmakers' network. The results revealed that gender, age, and political experience are not significant predictors of active tie building in the legislative network.

PARTISAN TIES VS. BIPARTISAN TIES

RQ5 examines intra-party (partisan) network and inter-party (bipartisan) networks. The results proceed in two steps: the overall shape of the partisan network and bipartisan network, then, the results of tie analysis.

Figure 19 (upper) displays the red, SP bipartisan network. On the whole, the SP intra-party network shape looks like a typical star network: a condensed center and loosely connected peripheries. This research also found four outlier lawmakers who were isolated and disconnected in the network. A magnified image of Figure 19 offers a look at the SP core network. Several lawmakers standing in higher positions on several centrality measures appear at the center of the network: Kang Seungkyu, Jo Jeonhyuk, Jung Okim, Jung Byungkuk, Kwon Yoingse, Won Heeryong, and Na Sunglim.

Figure 20 shows UDP's partisan network. Like the SP network, the UDP intra-party network displays a typical star shape network but a less condensed and smaller network than that of SP. This research found one outlier lawmaker.

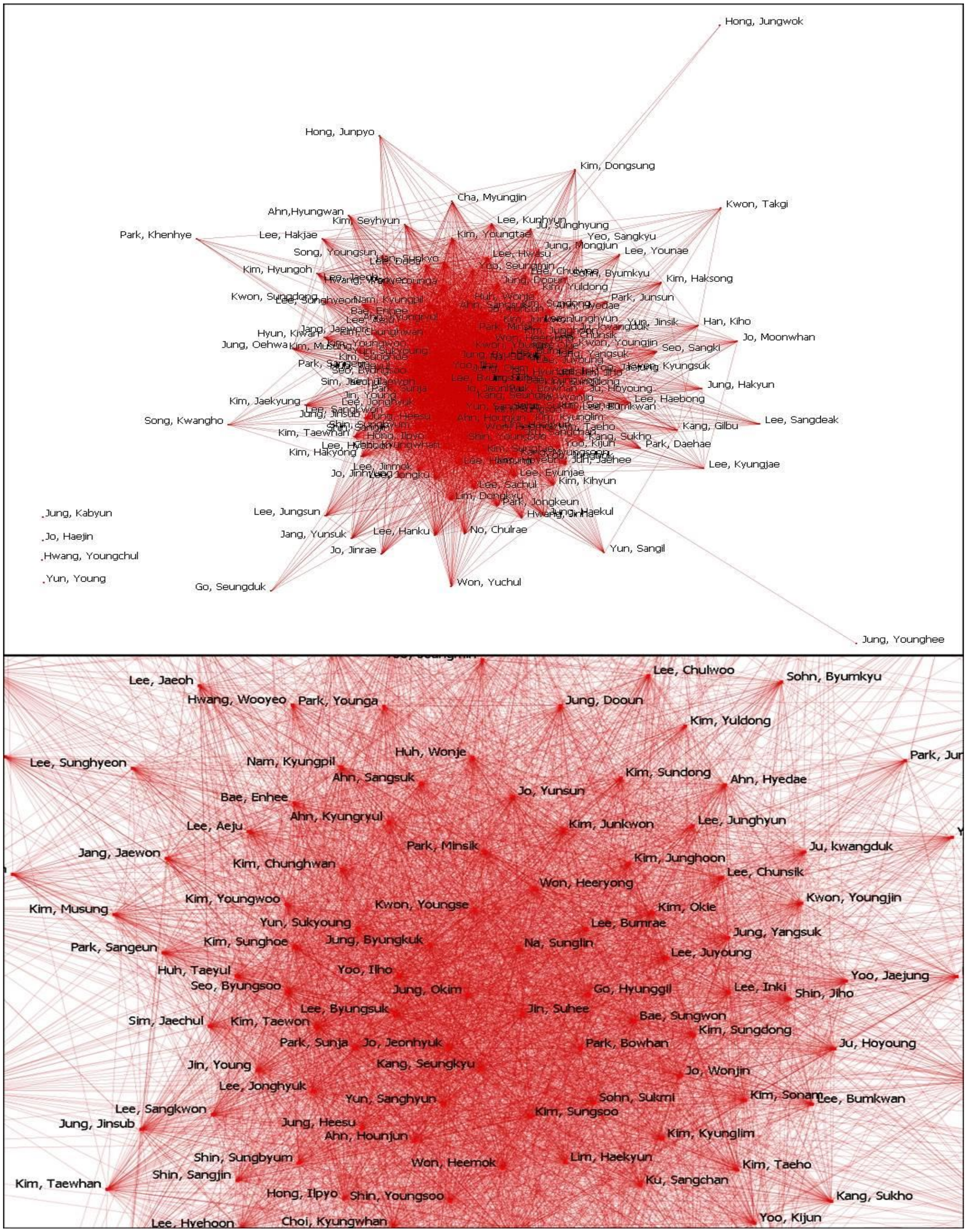


Figure 19: SP's Mutual Party Network

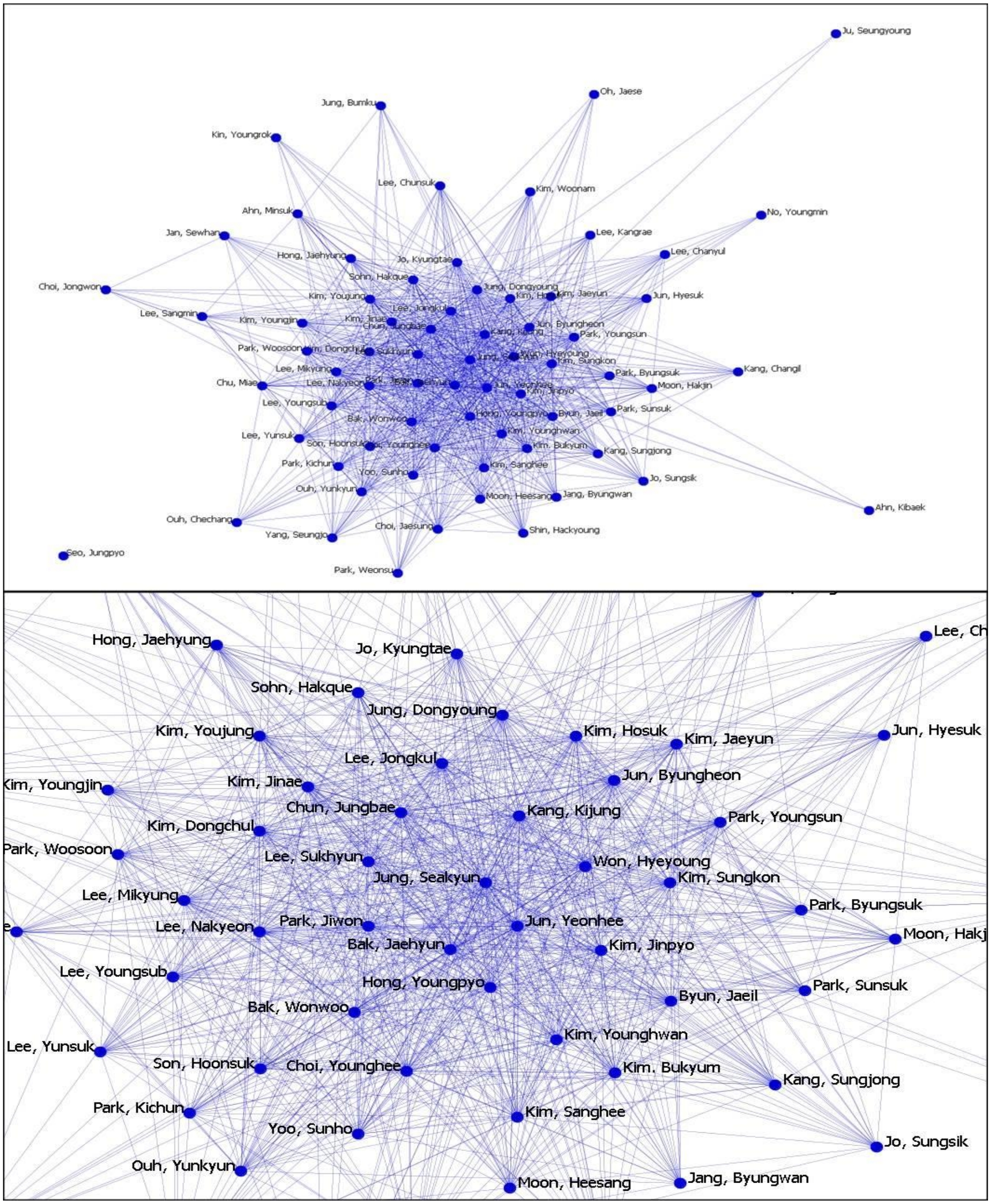


Figure 20: UDP's Mutual Party Network

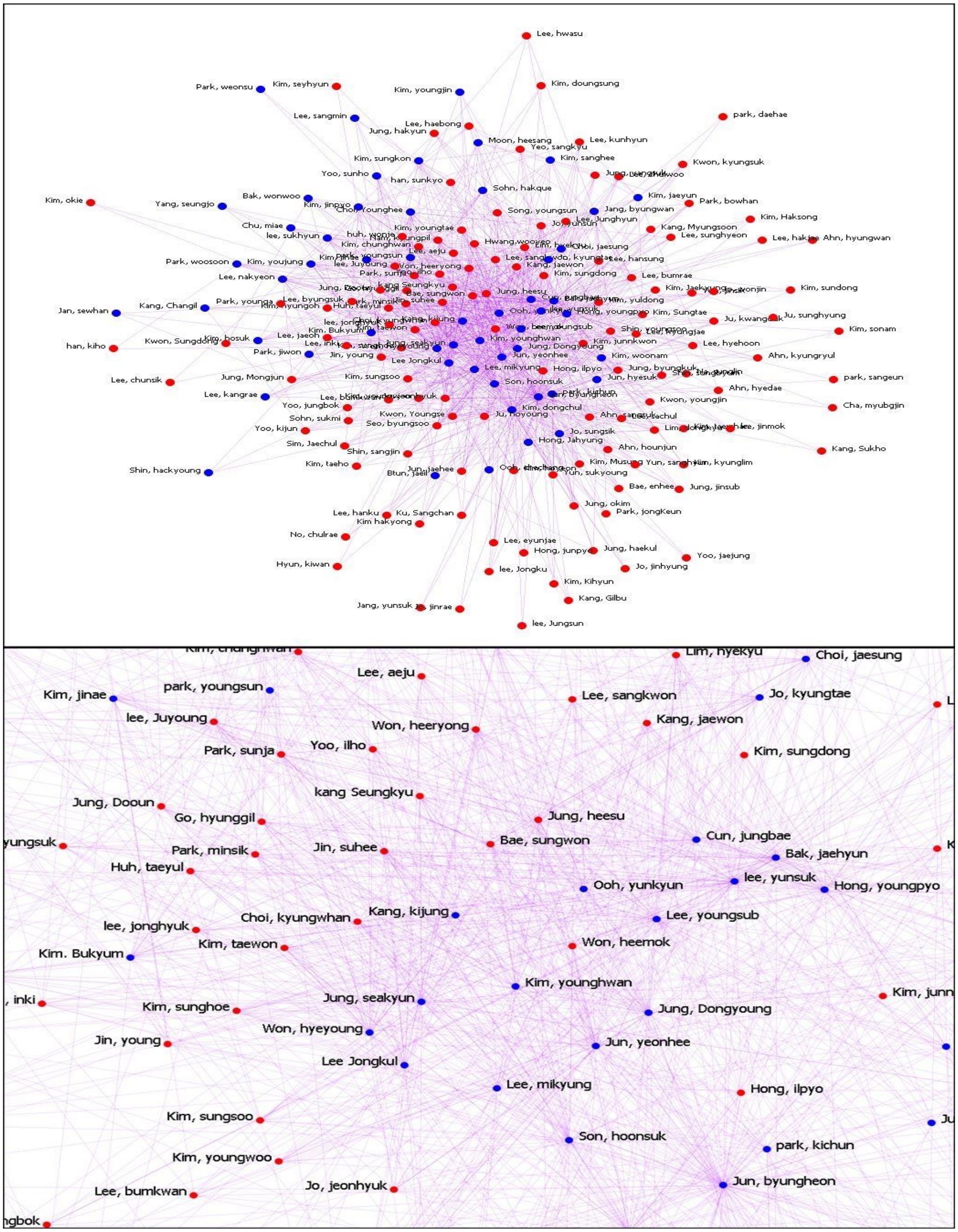


Figure 21: Korean Bipartisan Network

A magnified network presents which lawmakers are at the center of the UDP network: Jung Seakyun, Jung Dongyoung, Jun Yeonhee, Hong Youngpyo, and Bak Jaehyun.

Figure 21 displays the bipartisan network of SP and UDP. Its shape looks like a typical star like network. Some 183 lawmakers out of 222 SP and UDP lawmakers (82.4%) have 1,353 bipartisan ties. No pair-only-bipartisan ties were found. A magnified image of the network reveals who are at the center of the bipartisan network: UDP lawmakers such as Kim Youngwhan, Jung Dongyoung, Jun Yunhee, Lee Mikyung, and Son Hoonsuk and SP lawmakers such as Hong Ilpyo, Ju Hoyoung, Won Heemok, and Jo Jeonhyuk.

This study conducted tie analysis of how many partisan and bipartisan ties connect each lawmaker. Table 26 indicates that this study found 47 party networks in the Korean National Assembly, which consists of six parties and one independent group. Therefore, the maximum possible number of party networks is 49, 7 party networks and 42 inter-party ones. However, this research found that two mini parties had no partisan network. Korea Creative Party (KCP), which has two representatives, lacked any ties within party. The Korea Vision Party (KVP) has one representative, nullifying the possibility of within party ties. This research found that the total number of partisan ties is 13,676, while the total number of bipartisan ties is 7,358. Therefore, approximately 65% of total ties are partisan ties, while 35% of total ties are bipartisan, which indicates partisan relationship predominates over bipartisan relationships.

	SP	UDP	ID	LPP	DPP	KCP	KVP	Total
SP	11,298	1,353	1,124	266	43	52	95	14,231
UDP	1,353	2,170	433	109	102	34	12	4,123
ID	1,124	433	136	44	21	11	9	1,778
LPP	266	109	44	40	1	5	5	470
DPP	43	102	21	1	32	3	1	203
KCP	52	34	11	5	3	0	1	106
KVP	95	12	9	5	1	1	0	123
Total	14,231	4,123	1,778	479	203	106	123	21,034

Table 29: Partisan and Bipartisan Ties in Korean National Assembly

Note: SP = Saenuri Party, UDP = Unified Democratic Party, ID = Independents, LPP = Liberal Progress Party, DPP = Democratic Progress Party, KCP = Korean Creative Party, KVP = Korean Vision Party

However, the ratio of partisan and bipartisan relationships of each party is not homogeneous. Table 29 shows that the ruling party (SP) and the number one opposition party (UDP) have strong partisan relationships rather than bipartisan, whereas four parties and the independents have strong bipartisan relationship rather than partisan.

SUMMARY

Although Korea has a multi-party system, the Korean network shape vividly displays that the legislative network consists of two clustered networks connected by bipartisan ties. Members of small parties are scattered across the network, yet the position of each lawmaker represents their ideological stance. The results of identifying the top 20 lawmakers indicate that both ruling party members and the largest opposition party members dominate. Personal networks of the influential lawmakers indicate diverse patterns of networking within and beyond the party and the cores of the core lawmakers. The SP dominate the UDP in network size and number of average ties but the gaps in network density, path length of networks, and network centralization measures are small. Analysis of tie building relationships, however, indicates that members of the ruling party are more sociable, prominent and active in the network. This study found 35 % of the total mutual ties are bipartisan, and small party members have more bipartisan ties than partisan.

CHAPTER 6: COMPARISONS OF U.S. AND KOREAN LEGISLATIVE BODIES NETWORK

DESCRIPTIVE STATISTICS OF TWO LEGISLATIVE BODIES

RQ6 asked about the differences between U.S. and Korean representatives' political Twitter network. Before comparing the networks of the two legislative bodies, this study describes those institutions. As shown in Table 30, one of the most distinctive differences between the two legislative bodies is the party system of each: America has a bipolar party system, while South Korea has a multi-party system consisting of six parties and an independent group. The ratio of female-to-male lawmakers is nearly the same.

In the U.S. House of Representatives, the conservative Republican Party is the ruling party, and the liberal Democratic Party is the opposition party. In the Korean National Assembly, the conservative SP is the ruling party. In Korean politics several opposition parties vie for power. However, the opposition party's ideological identities are not homogeneous. For example, UDP and DPP are widely considered to be liberal, whereas LPP, CKP, and KVP are considered to be conservative. Further, a relatively large number of independent groups exist in the Korean National Assembly. Most Independents were members of large parties such as SP or UDP, but defected for a variety of reasons including political and bribe scandals, disgruntled with the authorization of candidacy, and so forth.

U.S.		Country	Korea	
%	N		%	N
		Gender		
84	367	Male	85	249
16	71	Female	15	44
		Age Group		
5	21	30s		
17	73	40s	15	43
32	139	50s	42	122
33	144	60s	38	103
14	61	More than 70s	8	25
		Party Affiliation		
44	191	Democrats		
56	247	Republican		
		Saenuri Party (SP)	55	162
		Democratic Unified Party (DUP)	27	80
		Independent (ID)	9	27
		Liberal Progress Party(LPP)	5	14
		Democratic Progress Party (DPP)	2	7
		Creative Korea Party (CKP)	1	2
		Korea Vision party (KVP)	0	1
		Twitter Use		
80	351	Yes	90	265
20	87	No	10	28
100	438	Total	100	293

Table 30: Descriptive Statistics of Two Legislative Bodies

U.S.A (N = 351)		Country	Korea (N = 265)	
Mean	Total		Mean	Total
813.49	284,722	Number of Tweets	1,028.73	272,613
1,001.41	350,496	Followees	7,985.24	2,116,089
7,010.11	2,453,541	Followers	11,379.09	3,015,459

Table 31: Comparisons of Twitter use by the Representatives

Regarding Twitter adoption, 80% of the U.S. House of Representatives are confirmed to manage their own Twitter accounts, whereas 90% of Korean lawmakers manage Twitter accounts. Both legislative bodies demonstrate high penetration rates, almost saturation stage, of Twitter use. It is fairly natural for lawmakers who belong to a social elite group, groups that are usually forerunners in new media adoption.

Table 31 presents more detailed statistics of Twitter use by the two legislative bodies. The Korean lawmakers posted an average of 1,028 tweets, whereas U.S, lawmakers posted an average of 813 tweets. Korean lawmakers average 11,379 followers and follow 7,985 twitter accounts. U.S. lawmakers average 7,010 followers and follow 1,001. All these statistics indicate Korean lawmakers are more active and popular Twitter users.

Interestingly, the Twitter relationship-building pattern is very different between the two groups, i.e., the mean ratio of in-degree-to-out-degree twitter ties of Korean lawmakers is 1 to 1.42, but that ratio for U.S. lawmakers is approximately 1:7, which implies that the average Korean lawmaker has 1 out-degree tie to every 1.42 in-degree ties, while U.S. lawmakers have 7 time more in-degree ties than out-degree ties, suggesting Twitter use differs between the two legislative bodies. Overall statistics indicate that Korean lawmakers are more active Twitter users in the penetration rate of Twitter use, number of posting tweets, number of followers and followees.

THE U.S. LEGISLATIVE NETWORK VS. THE KOREAN LEGISLATIVE NETWORK

This study compares the legislative body networks at two structural levels: directional network and mutual (bi-directional) network. Table 32 compares the network features of the two countries at the level of directional network. First, the results indicate that the U.S. lawmakers' network (N = 351) is larger than that of the Korean network (N = 265). The U.S. network outnumbers Korea's in number of ties between lawmakers. As prior researched have shown, the complexity and dynamics of a network increases as the network size increases so the results indicate that U.S. legislative network is a more complex and potentially dynamic structure than Korean network.

Conversely, the results indicate that the Korean network outscores U.S. network in density measure (32.8%) and average ties per lawmaker (Average Ties = 86.54), which indicates that it is more closely and tightly knit.

Country	Korea	U.S
Number of network size	265	351
Total Possible Ties	69,960	122,850
Ties	22,934	27,877
Average Ties per Node	86.54	79.42
Density	32.8(%)	22.7(%)
Fragmentation	1.5(%)	0 (%)
Reciprocal Rate	85.4(%)	39(%)
Path Length	1.65	1.87
Network Centralization for Degree	0.441	0.453
Network Centralization for Closeness	0.111	0.307
Network Centralization for Betweenness	0.021	0.047

Table32: Network Measures of Two Legislative Bodies

Otherwise, it can be said that the U.S. network is a more complex but looser structure, whereas the Korean network structure is smaller but more tightly knit. Lesser size but a more tightly knit network structure leads to shorter paths between lawmakers. Analysis of path length confirms that each Korean lawmaker can reach every other lawmaker within the network in 1.65 steps, while U.S. lawmakers need 1.87 steps, indicating that Korean lawmakers can more efficiently reach each other. Especially, the reciprocal rate analysis indicates that a phenomenal difference exists between the two legislative bodies. The reciprocal rate of the Korean network reaches 85.4%, whereas that of U.S. network is only at 39%. This implies that is 85.4% of Korean lawmakers are connected by mutual ties compared to America's 39%. Prior studies suggest casual and shared communication relationships occur more easily and frequently among nodes connected by mutual ties (Grudz, 2011), so the huge difference in the reciprocal rate indicates that the Twitter use of the two legislative bodies may be significantly different in a social sense. Further implications will be discussed in the discussion section.

Three measures for network centralization indicate that the U.S network has a slightly more centralized structure (Network Centralization Index for Degree = 0.45) than Korea does (Network Centralization Index for Degree = 0.44). The same goes for network centralization measures for closeness, with the U.S. network scoring 0.31 to Korea's .11. Further, Network centralization measures for betweenness indicate that the U.S. network is more centralized (Network Centralization Index for Betweenness = 0.05) in coordinative resources than that of the Korean network (Network Centralization Index for Betweenness = 0.02). Since network centralization indicates how centralized a network is, the U.S. network was shown to be a more centralized network structure. In sum, network analysis indicates that Korean lawmakers have a more compact, efficient, and decentralized network than their U.S. counterparts. This suggests that Korean lawmakers are connected more closely and efficiently, implying more familiar relationships in the network.

Country	Korea	U.S
Number of network size	265	351
Total Possible Ties	69,960	122,850
Ties	21,124	715,638
Pairs of Mutual Tie	10,562	7,819
Isolates	7	12
Average Mutual Tie pairs per Node	38.86	22.28
Density	30.2 (%)	12.7 (%)
Fragmentation	5.2 (%)	6.7 (%)
Path Length	1.71	2.24
Network Centralization for Degree	0.383	0.395
Network Centralization for Closenness	0.017	0.011
Network Centralization for Betweenness	0.022	0.052

Table 33: Mutual Network Measures of Two Legislative Bodies

Table 33 compares the two legislative bodies' mutual networks. Phenomenally different network landscapes are shown by several network measures in the mutual network. For example, gaps of network density between two networks widen nearly double. As we saw in Table 32, the gap in network density was 10.1 percent points in the directional network. In the mutual network (Table 33), the density of the Korean network was 32.29 % compared to the U.S.'s 12.7%, a gap of 17.59 %. Obviously low density of the network implies less mutual relationship within the network, so the results show that U.S. mutual network is much less tightly organized than the Korean mutual network.

Analysis of average mutual ties confirms that Korean lawmakers have an average of 38.86 mutual tie relationships with other lawmakers, while U.S. lawmakers have 22.28, which implies that the Korean network is connected to an average of 33.86 lawmakers and U.S. lawmakers is connected to 22.28. The implication is rather straightforward: Korean lawmakers have almost twice as many mutual ties as U.S. lawmakers.

Fragmentation measures also show that the U.S. network (6.7%) is more fragmented than Korea's (5.2%). The gap in path distance also widens: U.S. lawmakers (path length = 2.24) stand farther apart than do their Korean counterparts (path length = 1.71). Since lesser path length offers greater efficiency, the U.S. network is less efficiently organized than Korean network.

Two network centralization measures, network centralization for degree and betweenness, found the U.S. directional network was a more centralized structure but the gaps are marginal. However, network centralization for closeness is reversed in the mutual network: network centralization for closeness of the Korean mutual network is 0.017, whereas network centralization for closeness of the U.S. network is 0.011. In general, the gaps between the two legislative bodies are dramatically increased when we analyze the mutual network. Detailed implications of these findings will be laid out in the discussion section.

THE U.S. PARTY NETWORKS VS. THE KOREAN PARTY NETWORKS

For more detailed comparisons of the Twitter network, this research conducted network analysis of the major party's mutual network. Several differences in party networks are found.

First, the Korean major parties' mutual network is denser than that of the U.S. As Table 34 shows, the density rate of SP's (48.6%) and UDP's (46.2%) networks are much denser than those of the Democratic Party (15%) and Republican Party (29.5%).

Further, path lengths of the Korean party networks are shorter than that of the U.S. party network. Of the four parties, SP has the shortest path length (1.50), followed by UDP (1.53). Next is the Republican Party (1.72) and the Democratic Party has the longest path length (1.98).

This suggests that the Democrats' mutual network is the least efficient and has the most loosely connected network structure. Findings also show that two U.S. party networks are more centralized than their Korean counterparts. Table 34 displays the Republican Party's network centralization for degree score (.626) is the highest, followed by the Democratic Party (.551). Network centralization for betweenness also demonstrates that the U.S. parties have a more centralized network than do the Korean parties (Table 34).

Country	Korea		U.S.A	
Party	**SP**	**UDP**	**Democrats**	**Republicans**
Number of Nodes	153	69	151	200
Isolates	4	1	9	4
Total Possible Ties	23,256	4,692	22,650	398,000
Ties (Pair)	11,298 (5,649)	2,170 (1,085)	3,400 (1,700)	11,748 (5,874)
Average Ties (Pair)	36.9	15.7	11.2	29.37
Density	48.6(%)	46.2(%)	15 (%)	29.5(%)
Fragmentation	5.2(%)	2.9 (%)	11.6 (%)	4.0(%)
Path Length	1.5	1.53	1.98	1.72
Network Centralization for Degree	0.361	0.402	0.551	0.626
Network Centralization for Closeness	0.034	0.152	0.022	0.051
Network Centralization for Betweenness	0.012	0.041	0.143	0.072

Table 34: Network Statistics of Major Parties in U.S.A and Korea

Large gaps between the conservatives and liberals in tie relationship building are also found. This study found that the conservative SP lawmakers average 36.9 mutual relationships within the party network; Republican Party lawmakers are next with 29.37 mutual relationships. Both conservative parties overwhelmingly outnumber their liberal counterparts in partisan tie relationship, indicating conservative parties in both countries have much more tightly knit party network.

PARTISAN VS. BIPARTISAN TIES

For a deeper understanding of the party network structure of the two countries, this research calculated the ratios of bipartisan ties-to-partisan ties of six parties, shown in Table 35. The findings demonstrate that the Republican Party's ratio of bipartisan ties-to-partisan ties is 12.2, indicating Republican lawmakers have 12 times more partisan mutual relationships than bipartisan relationships. The Democrats' ratio of bipartisan ties-to-partisan ties is 6.4.

Table 35, however, reveals that the ratio of bipartisan ties-to-partisan ties to be relatively low in the Korean network: SP's ratio of partisan ties-to-bipartisan ties is 3.8; UDP's ratio of partisan ties-to-bipartisan ties is 2.3. Further, patterns of tie relationship building for small parties differ phenomenally from major parties. For instance, LPP, the 3rd strongest party, has roughly 10 times more bipartisan than partisan ties; DPP, the 4th party, has roughly 5 times more bipartisan ties than partisan ties.

Overall, the ratios of bipartisan ties-to-partisan ties of the two countries are significantly different. The average ratio of partisan ties-to-bipartisan ties of the Korean networks is 2.1, while that of the U.S. networks is 9.9. These findings found partisanship dominant in both countries, yet the degree of partisanship differs substantially.

Nation	Party	Partisan	Bipartisan	B-to-P ratio
Korea	SP	11,936	3,144	3.79
	UDP	2,542	1,090	2.33
	ID	150	1,802	0.08
	LPP	47	453	0.1
	DPP	34	187	0.18
	KCP	0	127	0
	KVP	0	123	0
	Total	14,709	6,926	2.12
U.S.A	Democrats	6,670	1,038	6.42
	Republican	19,006	1,552	12.24
	Total	25,676	2,590	9.91

Table 35: The ratios of bipartisan ties-to-partisan ties in U.S.A and Korean Party

Further, this research found that some lawmakers, those who largely belong to a small party, are more willing to be bipartisan rather than building partisan relationships on the Twitter network.

SUMMARY

Findings indicate Korean lawmakers are more active in using Twitter –they twit more often, they have more followers and follow more than U.S. lawmakers. Korean lawmakers created a more densely constructed, especially, more mutually connected network structure, than the U.S. network. The gaps in density and mutual relationships are far more increased in the mutual network, indicating] indicate that Korean lawmakers are sharing a very tightly constructed network. Distributions of centrality indicate that the U.S. network is a more centralized structure than the Korean network.

The party networks present different landscapes –members of the conservative party are more active in tie relationship building. The conservatives have on average more mutual ties than the liberals regardless of nationality. Network density and short paths indicate the Korean parties constructed more tightly integrated party networks than U.S. parties, whereas U.S. party structures are more centralized. In the ratios of bipartisan-to-partisan ties, parties in the two legislative bodies show differences –the Korean parties have far more bipartisan ties than their U.S. counterparts.

CHAPTER 7: DISCUSSION

BRAVE NEW DIGITAL WORLD OF POLITICAL TWITTER NETWORKS

U.S. and Korean lawmakers have created and enjoy phenomenal political networks. As evidenced in the diverse network statistics shown in the results chapters, those representatives have created affluent and multi-layered digital networks. They have created a dynamic legislative-body-scale network, and also a strong party network, a vivid bipartisan party network, and a variety of ego networks consisting of diverse compositions of partisan and bipartisan relationships. All this demonstrates how politicians are agile at incorporating and using new mediums.

A new form of digital media, Twitter, has opened a new landscape in the political arena: the digitally networked political environment. This study found that 80% of lawmakers in the U.S. network and 90% lawmakers in the Korean network are connected to one another and share tie relationships as well as with the public –they created digital community, digital networks. This could be a foreshadowing of strong and significant evidence that social media, in this case Twitter, has already reached the level of saturation stage, which implies Twitter use has great potential for creating and, maybe, are altering the political interactions of the political elites.

Before further discussion, a few theoretical assumptions of this research should be elucidated. One is that Twitter ties have certain meanings and implications that enable us to investigate the relationships among political elites. Numerous prior studies on digital media found that a hyperlink represents reference, preference, friendship, familiarity, discussion channel or information path, and so forth. Prior studies have found that digital networks created, maintained, and developed by hyperlinks function as virtual communities; these include informal communication channels, interactive discussion platforms, friendship maintaining and building networks, sometimes alternative media, and others.

What is the nature of Twitter ties in the legislative network? What are the implications of lawmakers following other lawmakers or building mutual relationships between them? Since Twitter is a relatively new medium, few studies have scrutinized the nature and use of Twitter networks.

This research assumes that Twitter ties among lawmakers are products of lawmakers' voluntary will and choice. It is highly unlikely for a lawmaker to build and share ties with other lawmakers just to show off his friendships or garner attention from the news media or mass public. Twitter relationships between lawmakers are neither well documented by scientific studies nor popular news stories. Lawmakers feel no pressure to follow a specific lawmaker. Therefore, this study argues that the tie relationships revealed here should be regarded as representing voluntary preferences and choices of lawmakers. For this reason, this research argues that Twitter ties also represent informal and casual relationships among lawmakers and that these stem from their own wills and interests.

Analysis of legislative Twitter networks reveals latent informal and volitional networks, which rarely have been investigated nor examined. Then, what will the function of this newly created digital network be? It might be an information platform or a discussion channel; it might be a digital social club or digital friendship network. The uses and gratifications of a Twitter network for lawmakers are open to future study, so follow-up studies are needed to examine the nature of the legislative Twitter network. Multiple research methods such as content analysis of survey research might be useful, and these would go far beyond the scope of this research.

NETWORK WITH TWO CORES: POLARIZED NETWORK STRUCTURE

This research, at first, asked what the political Twitter networks looked like. Visualizing the network has both pros and cons. A visualized network suggests a heuristic shortcut for understanding its nature, yet from time to time it can misrepresent its nature. Mapping a network is somewhat similar to drawing a schematic of an electronic device or blueprint of a building. They do tell a great deal about its critical features, yet sometimes fail to reveal important aspects. Therefore, this research displays diverse levels of a network from ego network to whole network.

The whole network shapes that this research presents look like a large nut containing two small nuts, or two atoms fusing into a molecule, demonstrating that legislative networks have a largely partisan structure. Both directional and bidirectional network display this polarized network structure. These findings are not unusual since clustered network structures are ubiquitous in real world (Barabási, 2003)

As has been revealed by prior studies on digital space, this research found that political digital networks represent and correlate with existing political presuppositions, especially party affiliation social relationships via social media represent, in many cases, fortifying existing relationships as well as creating new interactions.

At first glance, the look of the whole network of each legislative network demonstrates the Twitter networks are strongly polarized by political ideology or party competition. The U.S. House of Representatives network demonstrates a typical polarized network structures. Even the Korean legislative network, which has a multi-party system consisting of six parties and independents, displays a network mainly divided by party ideology. For example, LDP, the third largest party and usually classified as conservative stands between the ruling party and the main opposition party, but they are closer to the conservative ruling party. Further, UPP, the far left party, mainly shared tie relationships with the main opposition party. Independent lawmakers, most of them defectors from a large party, are shown to be close to or within the parties they had formerly belonged to.

Those figures displaying two distinctively divided forces indicate that the whole network has two sub-core or two partial networks. Each sub-network, almost exactly matching the party network, demonstrates that its shapes are extensions of a starfish-like network with a strong and condensed center and peripheries loosely connected to the center, which are shown in the party networks and their magnified images. There is nothing unusual in the fact that the nature of the lawmakers' network is fundamentally a political network striving to win electoral competitions and seize national leadership. These starfish-like networks feature a hierarchical and centralized structure.

The findings that two partial networks (sub-cores) exist in the network identifies lawmakers who are in the middle of the network, i.e., lawmakers with higher scores in closeness and betwenness centrality measures might play important roles in the network because they are the nodes that facilitate the interaction of two cores. Simultaneously, the existence of two cores represents lawmakers scoring high in degree of centrality. These might be leaders of political factions or partisan leaders rather than bipartisan leaders with cutting-edge support, explaining why the majority party members or ruling party members dominate the top of the list of degree of centrality.

NETWORKS THAT INTERACT RATHER THAN FRAGMENTED

However, this research confirmed that newly created legislative networks with their considerable number of bipartisan ties, go beyond polarized partisanship. Complicated structures of whole networks indicate how actively and mutually interacting lawmakers are. The political networks drawn by large numbers of bipartisan tie relationships indicate that the political elite communicate, interact, and build relationships each other rather than remaining disconnected or isolated. This research found that whole Twitter networks, consisting of small blue and red networks, are connected with one another. These are signified by purple lines shown in the mutual bipartisan network. In sum, this research found that these two legislative networks in the U.S. and Korea consist each of a polarized party network, yet they are considerably connected showing most lawmakers not to be fragmented and isolated.

What is the consequence of bipartisan interactions? Given lawmakers are an elite group who are highly educated and politically knowledgeable, it is highly likely to contribute and promote positive political outcomes such as advanced forms of political deliberation with political discussion and political tolerance based on mutual respect rather than negative impacts such as discouraging from political discussion or political participation (Mutz, 2006).

Assuming Twitter ties are built by voluntary and informal preferences, it is highly likely that bipartisan ties represent informal discussion channels among lawmakers, which would contribute to political deliberation as well as political tolerance. Findings of tightly knit partisan networks would also contribute to a more active and vigorous discussion channel between lawmakers because active discussion within party network would promote lawmakers competence and enhance party consensus for party policy and party agenda in the legislative process.

DIFFERENTIATION OF TWITTER USE

This study inquired about the different uses of the Twitter network according to party affiliation and party positions, and membership in ruling or opposition parties. There are significant differences in the party network structures of Democrats and Republicans. For example, the Republicans have twice the mutual ties of the Democrats; the density of the Republican network is twice that of Democrats; the size of Republican network is 30% larger than that of the Democrats. The Republicans have a more centralized party structure than do the Democrats.

In the Korean party network, SP have more than twice the mutual ties of its UDP counterparts, yet UDP's network density is only marginally denser than that of SP; UDP has a more centralized network structure than does SP. Overall, the conservatives are more willing to build tie relationships in the network than are the liberal counterparts.

Tie analysis also indicates there are significant differences in tie composition according to party affiliation. Republicans have twice as many partisan ties than do the Democrats. In the Korean network, the conservative party has far more partisan ties than the UDP.

Some parties, especially small parties, have more bipartisan than partisan ties, which might be evidence that stronger partisan relationships may be neither universal nor inherent to a network; it might be specific to a bipolar party system. Otherwise, findings suggest that the size of the party might is closely related to its tie composition. These findings confirm the legislative networks of both countries are largely divided by hard-core party networks, yet considerably connected by bipartisan ties.

Investigations of relationship-building patterns between ruling and opposition parties were examined by using regression analysis. Ruling party members, in both the U.S. and Korean networks, are more likely to be sociable, to have prestige, and to share mutual relationships. Findings indicate that tie-building patterns are significantly different by party position, when we control other variables such as age, gender, and twitter activity related variables. This confirms that the ruling party at the institutional level also dominates the digital network.

Interestingly, findings indicate that lawmakers' tie-building patterns in the network don't always correspond with their Twitter activity; in fact it can even be a negative relationship.

Findings indicate that the number of followees of lawmakers is a strong and positive predictor of lawmakers in-and out-degree relationships in the elite network. The results indicate that the number of followees is the strongest predictor of mutual relationships in the legislative network. The more a representative is willing to follow others, the more likely a representative will build mutual relationships and rise in prestige.

However, the number of followers from the public, in many journalistic articles usually regarded as popularity, is a significant but negative predictor of building out-degree tie relationships, sociability, and mutual relationships with other lawmakers. What are the implications of these findings? These findings suggest that a legislative network is a particular digital space for lawmakers, different to a relationship with the public via Twitter. These findings corroborate the findings of a prior study (Grudz et al., 2011) that indicates the global (Twitter sphere) network and the local network (legislative network) do not always match perfectly–both overlap and diversify. These findings add reasons why we need to explore the legislative network –unique networked communities that represent particular relationships among lawmakers. However more detailed studies are needed to find out how and why these patterns occur.

ADVENTS OF DIGITAL OPINION LEADERS: ARE THEY NEW POWER ELITE?

Due to its networked nature, social media opens new landscapes of research. Who are the influential or opinion leaders in the network? How and why do they raise themselves to leadership positions? What will be the consequences of the opinion formation process?

One of the core research interests in network theory as well as in communication and diffusion studies is discovering leaders, opinion leaders, or the influential in a particular network (Wasserman & Faust, 1994; Watts & Dodd, 2007). Since the legislative Twitter network has rarely been examined, there are no established research methods measuring degree of influence or leadership so this research hopes to shed new light for leadership research.

Using a variety of network analysis measures, this research has investigated who the digital leaders are in these political networks. The study presents the top 20 lists of U.S. and Korean legislative network and major party networks using five network analysis measures. Each measure reveals a different aspect of lawmakers' position in the digital network.

One of the popular measures for investigating influence in network analysis is to calculate the number of paths or ties a node has in the network: calculations of degree of centrality. The top 20 list of degree of centrality reveals which lawmakers have many ties within the network. If Node A has more ties than node B, we can say that it is more influential than Node B because more ties in the network implies more resources to reach other nodes. Further, as Node A has more ties, its position moves to the center of the network. Findings of this research indicate that lawmakers belonging to the majority party dominate the top of the list of degree of centrality. Considering that the network structure is considerably divided by party affiliation, this research conducted a more detailed degree of centrality calculation: degree of centrality in the party network.

The closeness centrality measure offers another aspect of lawmakers' position in the network. As noted conceptually in the method section, closeness centrality refers to how close a lawmaker is to other lawmakers rather than number of ties. A lawmakers' distance from other lawmakers presents a critical aspect of leadership because the closeness-of-centrality score rises when a lawmaker gets closer to the center of the network. In a network largely divided by political party, a lawmaker would get a higher score if he/she has many ties with other party members rather than just partisan ties. This suggests that lawmakers who score high in closeness of centrality may have more coordinating potentiality in the network; a lawmaker who scores only high in-degree centrality might be a leader of particular factions rather than a leader who gets broad bipartisan support.

The potentiality of coordination can be more subtly captured by the betweenness centrality measure. Betweenness centrality refers to how many times a lawmaker appears on the shortest path between all possible pairs of players. This endows special functions to a lawmaker scoring high in betweenness centrality like a switch on an electric circuit. This feature seems to greatly enhance its importance in analyzing the legislative network. Given that Twitter networks are largely polarized by party membership, betweenness centrality measure identified who has the greatest potential to be a modulator or coordinator in the network. This research found several lawmakers scoring at the top of the list of betweenness centrality measures, which may well make them legislative modulators in the network. There are several political offices that designate the role of producing consensus in the legislative bodies; such offices are usually filled by voting within the party. The modulators, this research found, are selected by lawmaker preference, which shares common figures with official party office as well as different figures.

The prestige measure is produced by in-degree analysis, which indicates who the most sought after lawmakers are in the legislative network. Therefore, it is fairly straightforward and close to popular voting, yet it occurs in a very different political setting, voting via digital platform. Out-degree analysis shows who are the most sociable in the network. A prior study suggested that a node willing to build a tie relationship with another node usually intends to be a prestige node; therefore, a node scoring high in the out-degree measures can be classified as an ambitious lawmaker eager to get attention in the network as well (Freeman, 1979).

What do the top lists really indicate? Are the lawmakers standing at the top of the list the influential or opinion leaders in the usual sense? A few considerations should be noted. First, it is useful to keep in mind that opinion leaders in classic theory are not leaders standing at the top of formal organizations such as leaders of government. Rather they are the people involved and interacting in an informal network like a community and their influence stems from the fact that they are highly informed, respected, or simply "connected" (Watts & Dodds, 2007). Numerous underlying features of the legislative Twitter network examined by this study corroborate the concept of classic opinion leader. As shown, lawmakers have created a networked community, which might be the first and foremost social precondition for an opinion leader. Further, the networked community stems from lawmakers' informal and voluntary choices. For this reason, this study argues that lawmakers who score at the top of the lists may well be regarded as opinion leaders in the digital network, even when the network is created by the top political elites of the society. Some measures can be understood fairly easily. For instance, in-degree analysis measures the most sought after lawmakers in the network, revealing which lawmakers are the most respected lawmakers in the whole network and party network. It is very much like a popular vote. Degree-of-centrality measures provide a list of lawmakers who are the most connected with the rest of the lawmakers in the network.

However, there are some differences between traditional opinion leaders and digital leaders. In classic theory, opinion flows uni-directionally from leaders to followers (top-down), yet in the Twitter network, especially in the mutual network, the relationship is bilateral and interactive. Further, opinion leaders' scope of influence differs: the nature of face-to-face communication, where a classic opinion leader acts, limits the scope of influence to fairly narrow fields. When the network consists of heterogeneous small sub-groups, like race or religion, the scope of influence is narrowed a great deal more. For instance Brown and Reingen (1987) found that, even in a relatively small population, 38% of recommendation chains need at least four individuals to penetrate and 90% need more than one step. However, digital leaders' influence can instantly reach the whole network when we recall that every lawmaker can reach each other in two steps (as shown by the average path length measure). Even though the legislative network is divided by party affiliation, this research also confirmed that the network is connected rather than fragmented (fragmentation measure). For this reason, information flow or diffusion of innovation does not always cascade to the level of a social network in the classic opinion leader model, yet the influence of the opinion leader can easily and instantly cascade to the whole network.

These structural properties of networked community hint how news and information diffusion process occur in the new media environments connected by the social media. For instance, one prior study found that, when direct subscription is considered alone, most Twitter users consume politically biased views but the influence of social ties dramatically changes this situation such that a majority of users have access to politically diverse views (An et al, 2011). These indicate that media agenda can easily and instantly overflow to the news public via clustered but interconnected news networks created by the social media.

TYPES OF OPINION LEADERS AND DIVERSE SPHERES OF INFLUENCE

Another theoretical contribution of this research is that this study successively presents diverse types of opinion leaders and demonstrates several spheres of influence by each types of leadership. Influence/power are multi-faced concepts by nature. Thus, there can be diverse types of opinion leaders depending on the scale of community –village, city, state and national scale; the agenda of issues –foreign policy or a domestic issue; or the tasks each level of community confronts –bargaining or competition. However, those opinion leaders overlap and diverge as findings of this research indicate. Although the classic model noted that opinion leaders can differ by topics they did not present a refined analysis or typology of opinion leadership nor analysis on the variety of spheres of influence: Why some individuals rose to be opinion leaders in a particular sphere; how and different their scope of influence might be; and in which way their roles vary.

In contrast, this research succeeds to identify diverse types of opinion leaders by examining tie relationships and patterns of tie building in the network. For instance, this research identifies a lawmaker with more tie relationships than others who can distribute information faster and to larger numbers of lawmakers; a lawmaker who has greater potential to connect/disconnect information flow. As shown in CH 4 and CH5, this research demonstrates at least five different types of opinion leaders exist in the legislative networks across the Pacific Ocean. This study also demonstrates that each type of opinion leader has a different sphere of influence –some lawmakers have greater capability in broadcasting information; others have greater authority, etc. For instance, Republican Eric Cantor is the most well-connected lawmaker –1st in degree of centrality- in the U.S. House of Representatives which implies that he in the best position for distributing information faster and easier to the largest number of lawmakers, but Republican John Boehner is the one who scores top in-degree centrality, implying that he is the most prestigious lawmaker with the greatest potential to convey information authoritatively in the U.S. legislative network. Democrat Steny Hoyer scored the 3rd highest position in betweenness centrality in the Congressional network, but he failed to score in the top 20 in degree of centrality, indicating his influence will be better for the bipartisan sphere rather than distributing information to as many lawmakers as possible in the legislative bodies.

Findings of this research indicate that opinion leaders' role and sphere of influence also vary by network scale–personal, party or Congressional level. For instance, Republican Darrell Issa scored the 1st in betweenness centrality in the legislative network, but he scored 4th within the Republican Party network, indicating he has the greatest potential in coordinating bipartisan conflicts in the Congressional network but he has lesser potential than Eric Canter within the Republican Party. Leadership variations by scale of the network were also revealed by analysis of ego/personal networks. For example, analysis of Republican Darrell Issa's personal network indicates that opinion leaders in his personal network demonstrate a significantly different picture from those in the whole or party network as shown in Figure4.

Findings on different types of opinion leaders and variations of sphere of leadership provide a useful path to leadership study in the digital age. By identifying diverse opinion leaders, we can expand our understanding of the way information and public opinion formulate and interact. For instance, if we are to identify opinion leaders in the Republican Party who might play an important role in bargaining Tax Reform, we can identify those Republican lawmakers who are influential in formulating Republican policy, then, those who will actively play a role in negotiations with Democrats. Needless to say, the diverse analytical tools used in this research can be extended to other research areas such as a variety of digital spheres as well as offline community and organizations.

IDENTIFYING HIERARCHICAL STRUCTURES OF LEADERSHIP

One of the advantages of network analysis is that it can visualize the network examined. As shown in diverse network figures, each figure demonstrates a variety of hierarchical leadership structures both in the U.S. and Korean Congressional networks –how all lawmakers are integrated and interact in the legislative Twitter network. For parsimonious research, this research presents the top 20 lawmakers on five centrality measures, but the figures present the full leadership structure for diverse network scales – ego/personal network, party network, and whole legislative network.

The fact that this research identifies a leadership hierarchy in the network –from top to the lowest –sheds light on unique theoretical contributions of this research. Using network analysis, this research succeeded to produce full ranks of leadership as well as diverse types of opinion leader. This is not usual when we consider traditional leadership research that can identify only a few influential opinion leaders, mostly based on surveys or interviews. Most of all, a research method such as the random sample of a survey cannot tap the relational and full list of leadership structure. Only census data enables researchers to identify relational relationships within a network but even in this case the researcher should ask each respondent about all the relationships with the rest of the respondents in a network. Further, even a traditional census is not free from respondents' bias or disguised motivations (Herbst, 1993).

However this research presents the full influential list of each member of a network since gathered all the data using a digitalized method of data gathering, indicating the great advantages of big data research.

OPINION LEADERS IN THE LATENT NETWORK

One of the theoretical contributions of this research is the explicit identification of a latent power network among lawmakers, including identification of the core lawmakers in the network. Findings indicate distinguished Republican lawmakers such as John

Boehner, Speaker of the House, Eric Cantor, Republican Leader, Kevin McCarthy, Republican Whip stand in the center of the legislative network. In the Democratic Party network distinguished Democrats such as Steny Hoyer, Democratic Whip, Nancy Pelosi, Minority Leader stand in the center of the party network. Those findings are not unusual; lawmakers with high ranking official leadership are selected by voting so they are obviously influential lawmakers in the House of Representative. As shown in result chapter, diverse centrality positions do overlap.

Interestingly, the findings present some lawmakers who are lesser known to the public, yet play vital roles in the legislative network. For instance Darrell Issa, a Republican from the California 49th District, stands at the top of the list of closeness and betweenness centrality in the U.S. House of Representatives (Tables 6, 8), indicating he stands in the very center of the legislative network. Analysis of the ego network indicates that his ego network consists of 178 in-degree ties and 231 out-degree ties with 20,032 ties. What do these findings imply? Is Darrell Issa another type of leader playing an important but hidden role that has not been well-explored in the legislative bodies? Or is he a latent future leader who will surface in the near future?

Officially, Darell Issa is chairman of the House Oversight and Government Reform Committee which has government-wide oversight and strong legislative authority, implying that he is in charge of one of the most influential and powerful committees in the House. He led investigations into the Internal Revenue Service's scrutiny of Tea Party groups and the deadly attack on the U.S. consulate in Benghazi, Libya in 2012. He is also known as the wealthiest lawmaker in the House as of 2012, worth at least 355 million dollars. His career and official position in the Congress demonstrates that his higher position in the leadership hierarchy does not come by chance. Conversely, it may be that he is not a well-explored lawmakers, mainly because of less focus from news media even though he plays a vital role in the Congress as shown.

Whereas the Darrell Issa case indicates the strong points of this research, Republican Paul Ryan from Wisconsin's 1st district presents an interesting topic for identifying leadership in the network. He is the chairman of the House Budget Committee since 2011 and was the Republican Party nominee for Vice President of the United States in the 2012 election, which demonstrates that he is one of the most influential lawmakers in the Congress. However, as shown in Figure 2 and Figure 10, Paul is an isolated lawmaker in the legislative network and Republican mutual party network. What do these findings imply? Most of all it reveals that he has no mutual ties with other lawmakers. This does not imply that he has no ties with any other lawmakers. Conversely, the prestige measure calculated by in-degree tie reveals that he is the 3rd most sought after lawmaker in the U.S legislative bodies with 180 lawmaker followers (Table 10). He is next to John Boehner, the Speaker of the House, and Eric Cantor, the Majority Leader, and far ahead of Minority Leader, Nancy Pelosi. Findings indicate that he is the lawmaker who doesn't have any out-degree ties but has 180 lawmaker followers, demonstrating he is a prestige type of opinion leader in the Congressional network. Therefore these findings confirm the theoretical needs of diverse power/centrality measures to identify the multi-faced concept of leadership in the network. An interview or an email will reveal why he is not following other lawmakers but it goes beyond of this study.

A Korean case suggests an additional interesting example indicating the relationship between leaders in the digital network and real politics –the Jun Byungheon case. A liberal belonging to the largest opposition party, he scored first in indegree of centrality, closeness centrality, and betweenness centrality in the Korean network, indicating he is the most prestigious lawmaker with the highest coordinating potentiality in the legislative network. His ego network displays a miniaturized form of the whole National Assembly network (Figure 14). However, he was not included in the most powerful leadership group in his party as of May 2012 when this research collected network data. Further, few news media have reported that Jun is one of the most promising lawmakers who will lead his party. However, in May 2013, he was elected as the floor leaders of his party, a position the same as Democratic Whip in the U.S. House of Representatives. Does this case mean that lesser known lawmakers on the top lists are the latent but promising leaders? Prior studies found evidences that the digital community network is real and actively interacts with the offline community (Haythornthwaite, 2005; Rainie & Wellman, 2012). Therefore, it is highly plausible that digital leaders and offline leaders are positively linked.

The lawmakers' cases discussed above raise theoretical questions such as the relationship between de facto leadership and digital leadership as well as the relationship between formal and digital leadership. More follow-up studies such as longitudinal network transformation studies are needed to tap into the more precise implications and proper applicability of the findings of this research. Nonetheless, it can be said that this research has presented alternative and new ways of investigating how lawmakers interact and who rises and falls in a network since not many things occurring in the Congress or political party are known to the public. Particularly, dynamic competitions for power are usually kept behind the curtain and news media often fail to cover those news stories. Thus it shed some light on covert relationships between lawmakers.

LEGISLATIVE NETWORKS IN DIFFERENT SOCIAL SETTINGS

One of most challengeable issues of this study might be its comparison of two legislative networks: the U.S. and Korean Twitter networks. Since studies applying network analysis to newly created legislative Twitter networks are rare, this is an explanatory study in nature. However, this study found numerous notable differences between two networks worth being carefully examined. This research found considerable differences in network structure, patterns of relation-building usage, and in the composition of partisan and bipartisan connections—homogeneous or heterogeneous. Findings of this research demonstrate that Twitter use can vary significantly according to social, cultural, and political setting, even if the users examined are the top elites of society.

Significant differences in tie building pattern were found. For example, ratio of in-degree to out-degree ties shows that Korea lawmakers (1: 1.4) are roughly five times more responsive to in-degree ties than are U.S lawmakers (1:7), implying the possibilities of a Korean building mutual ties when he has an in-degree tie are five times higher than his U.S. counterpart. Findings reveal Korean lawmakers are more sociable and wiling to build mutual relationships. Findings reveal that the party networks significantly differ between the two legislative bodies. Korean party networks were revealed as much more tightly knit than U.S. parties'. Another phenomenal difference is discovered in the ratio of bipartisan-to-partisan ties of parties, which reveal the compositions of party networks: to what degree is the party network homogeneous or heterogeneous.

Findings show approximately 32.2% of total Korean lawmakers' ties are bipartisan, whereas they are only 9.1% for U.S. lawmakers. Overall Korean parties' ratio of bipartisan-to-partisan ties is higher than those of U.S. parties. This demonstrates that Korean lawmakers tend to be more exposed to cutting-edge relationships or are more likely to hear voices from other sides. These findings strongly suggest that the composition of Korean party networks is far more heterogeneous than American.

Network structures and their properties, often implicit and out of sight, limit or enhance their ability to function (Barabási, 2003). Studies have warned about various negative political outcomes of fragmented homogeneous networks that lack cross-cutting ties –group polarization (Sunstein, 2007) and political extremism (Sunstein, 2009), whereas networks can positively facilitate political knowledge and political activism (Mutz, 2006). Most of all, researchers worry about homogenous political networks–communicating with only like-minded people–having negative impacts on political moderation and deliberative democracy. Findings indicate that U.S. lawmakers uses Twitter to reinforce and expand their support rather than to hear the other side or a bipartisan discussion. New media use by the political elites significantly affects how their constituents perceive politics and decide to participate in the political process (Lipinski, 2004). Judging from the findings that Korean lawmakers are more mutually connected and have a less homogeneous network, this study suggests that the Korean network structure is more favorable to political deliberation based on mutual respect than is the U.S. network.

Then, questions arise about what causes the different use of Twitter and digital network structure between U.S. and Korean lawmakers?

One of the plausible reasons for those differences would be a different motivation for using Twitter. Prior studies indicated that U.S. lawmakers are using Twitter mainly for self-promotion (Golbeck, Grimes & Rogers, 2010) or outreach (Chi & Yang, 2010) rather than as a discussion channel. This seems to explain why U.S. lawmakers have a relatively low ratio of in-degree and out-degree ties and less mutual ties with other lawmakers. Furthermore this research found that Korean lawmakers have a relatively high ratio of in-degree and out-degree ties with other lawmakers as well as with the public, which might explain that Korean lawmakers' motivation for use of Twitter is for a discussion channel which enable them directly connect to the public, instantly and interactively share and communicate with the constituents as well as other lawmakers rather than just broadcast their own news.

Other variables such as political culture, might be a factor producing usage gaps between the two countries' political elites. Especially politics and electoral campaigns in South Korea in the 21th century have become very hot technological-driven battle fields. For example, the Internet, specifically active young internet users, played a critical role in the Presidential election held in 2004. Every party is eager to catch eyes and support from active young voters called "Netizen"; every party is running a massive special team for "digital politics" and "E-Party."; all Korean lawmakers are trying to be popular in the Internet; every politicians wants and is forced to look as a "technological savvy politician." These aspects are not particularly different in American politics but there can be significant differences in perceptions about digital politics and its future which need more follow-up studies.

"Confucianism" is one of the most popular political cultural factors among political scientists explaining the uniqueness of Korean politics since the 1950s (Henderson, 1968): a patriarchal and authoritative social structure, a state-driven industrialization model or bureaucratic authoritarianism coming from deep-rooted centralized governmental organization with an under-developed civic culture. Certainly, several values of Confucianism still remain and affect a large part of Korean society. Therefore it might be a factor creating usage gaps between U.S. and Korean lawmakers. However this research has not found any evidence that the Confucian tradition affects Korean lawmakers' Twitter use or tie building patterns. For example, several concepts examined by this research, such as mutuality or bipartisan relationships, neither come from nor are unique cultural values of Confucianism. More follow-up studies, however, are needed to find how and why social and political settings affect different use of new media by lawmakers.

LIMITATIONS AND CONTRIBUTIONS

First, "staff tweeting" might limit the validity of hyperlink research. Most politicians seem to personally enjoy Twitter, while some hire maintenance staffs. It would be proper to assume that politicians themselves decide what to post or how to interact through the help of staff rather than staff fully decide what to post or not. However, more research and empirical evidence are needed.

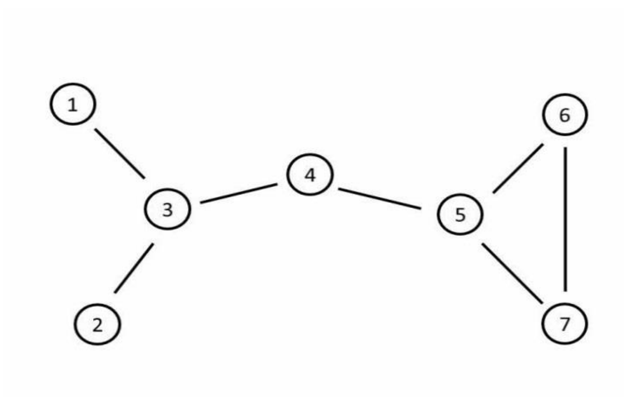
Second, Twitter has yet to become a mainstream medium, so its impact should not be overestimated (Gladwell, 2010). Most politicians employ diverse media such as letters, telephones, Internet sites, Facebook, Youtube, LinkedIn, and so forth. In the same manner, digital media's impacts on politics should not be underestimated because leaders over the world take time to engage in an unscripted and impromptu Twitter chat with their followers just as they spend time to read newspapers every day or answer letters (Lüfkens, 2012). Third, this research presents a mere snapshot (in the spring of 2012) of the Twitter network sphere. Since Twitter use by politicians is becoming more popular, longitudinal studies are needed to trace dynamic changes in the Twitter sphere. Finally, this research analyzed only tie relationships between lawmakers, so it obviously limits the validity of this research. For instance, one study found that a distinguished scholar's personal Twitter network contains at least six groups according to scholar's personal research interests by tie analysis and interview (Grudze et al., 2011). It is highly likely for lawmakers also to have multiple tiers of communities, so a follow-up study could explore a lawmaker's digital network more broadly.

Keeping all these shortcomings in mind, this research contributes to a better understanding of digitally networked politics. The former head of digital media at the World Economic Forum Matthias Lüfkens (2012) argued that no one will be able to become a leader without digital followers in the near future. This research presents a new political landscape in which most political elites interact and provides with rarely seen pictures of “invisible politics”: how parties are using digital politics; how new digital leadership is emerging and what partisan and bipartisan networks look like. These findings indicate that a new political arena, a fully digitalized and networked sphere where dynamic competition and cooperation occurs between political elites, has emerged as one of the political battlefields in politics today.

Appendix A

CALCULATION OF DEGREE OF CENTRALITY

Let's assume there is an information network of international students at the School of Journalism at UT, Austin. The network can be determined by a survey, a telephone list, email address book or Twitter tie relationship, etc. Data can be shown by graph, adjacent matrix and adjacent node list and so forth. For example, Figure below demonstrates an information network.



The network can be also addressed by an adjacent matrix and a node list shown below.

	N1	N2	N3	N4	N5	N6	N7
N1		0	1	0	0	0	0
N2	0		1	0	0	0	0
N3	1	1		1	0	0	0
N4	0	0	1		1	0	0
N5	0	0	0	1		1	1
N6	0	0	0	0	1		1
N7	0	0	0	0	1	1	

Adjacent Matrix (Non-directional Network)

Ego	Alters		
1	3		
2	3		
3	1	2	4
4	3	5	
5	4	6	7
6	5	7	
7	5	6	

Node List

Then, we calculate degree of centrality of each node as shown in below table.

Degree of Centrality		
Node	Score	Standardized Score
1	1	1/6
2	1	1/6
3	3	6/3=1/2
4	2	2/6=1/3
5	3	23/6=1/2
6	2	2/6=1/3
7	2	2/6=1/3

Degree of centrality Table above shows node 1's degree of centrality score is 1 and node 3's degree of centrality score is 3, etc. Table also indicate that we can compute rank order data using standardized scores, if we need to tap relational position of each node (relational degree score of each node). Note that, for the standardized score, you need to divide each score by n-1 (n = the number of nodes) because a node cannot has ties to itself. As the network consists of 7 nodes, 6 (7-1) is the denominator of each standard score.

However, a node's degree of centrality can vary by the nature of the relationships between each node. If the relationship between nodes is directional, several degrees of centrality measurement exist. For example, if we find lawmaker A is following lawmaker B and C, we can calculate that A's out-degree ties are two. Simultaneously, we can measure the in-degree centrality of B and C: B and C each have one in-degree tie. Further, if we found B follows A and C follows none, then, we can say that B has one out-degree tie and A has one in-degree ties. We can also count total ties that each politician has: politician A's three total degree centrality is three, B scores two and C scores one. Further, we can calculate mutual ties –bidirectional ties- that each node has. For example, given the political twitter network presented above, we can calculate that each A and B has one mutual tie but C has none. Therefore, politician C can be classified as an isolate in the mutual Twitter network because mutual network represents interconnected relationship only.

As explained above, we can calculate in-degree centrality, out-degree centrality, and total degree centrality (sums of in-degree and out-degree tie) in a directional (asymmetric) network. In a mutual network, however, we can calculate degree of centrality only because the mutual network is a symmetric network.

Appendix B

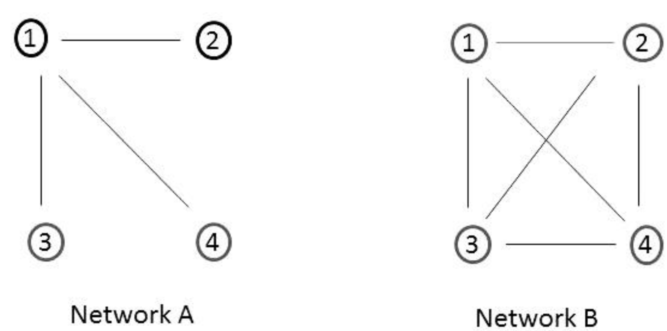
CALCULATION OF NETWORK CENTRALIZATION FOR DEGREE

To standardize or normalize the degree centrality index, so that networks of different sizes (g) may be compared, divide by the maximum possible in-degrees (= g-1 nodes if everyone is directly connected to i) and express the result as either a proportion or percentage. Therefore the formula of centralization of a network, Freeman's formula (1979), ranges from 0 to 1, and is expressed as follows:

$$C_D = \frac{\sum_{i=1}^{g}[C_D\,(n*) - \,C_D(i)]}{[(N-1)(N-2)]}$$

$$C_{D(n*)} = Maximum\ Value\ in\ the\ network$$

Suppose that there are two networks we are going to compare network A and network B shaped as follows:



In the network A, degree of centrality score of each node can be calculated: degree centrality of node 1 is 3, Node 2, 3. 4's degree of centrality score is 1. The maximum score for degree centrality of node is 3. Using the equation above, we can calculate network centrality for degree: ((3-3) + (3-1) + (3-1) + (3-1)) / (16-12+2) = (0+2+2+2)/6 = 1. Therefore, network A's network centrality score for degree is 1. In the same way, we can obtain network B's score is 0.

A network centrality 1 implies that all other nodes choose only one central node, whereas the minimum score, 0, is reached when all nodes have identical or equal centralities. As shown above, we can notice that network A has fully centralized network by node 1, whereas network B has a fully decentralized network structure.

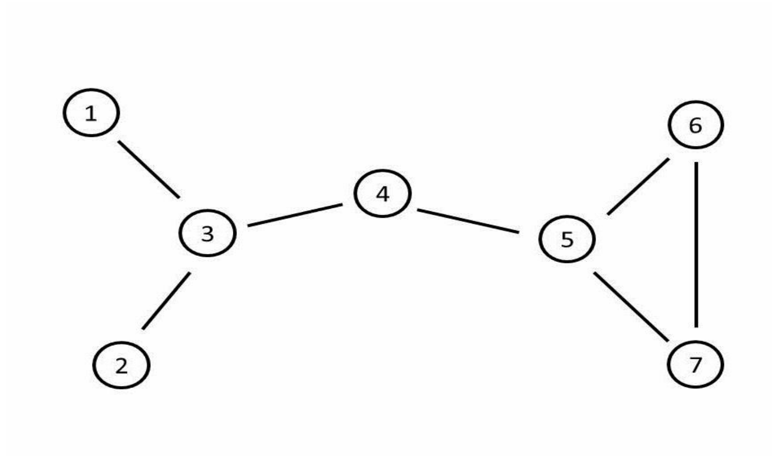
Suppose the figure above represents an information flow network, each network has pros and cons. For example, node 1 in Network A has huge control over information flow over the network A. If node 1 works well, network A will be very efficient and runs smoothly because there are no redundant edges in the network. However, if node 1 does not work or out-of-order, node 2, 3, and 4 become isolated in the network. In this sense, Network A can be risky such that the efficiency of information flow totally depends on node 1's performance. On the other hand, Network B is more flexible or stable. Even if node 1 does not work, all other nodes can still communicate and share information with each other, however, in another sense, network B has many redundant edges so the cost of managing network B can be higher than that of network A.

Supposed the network represents a decision-making network of a nation, Network A demonstrates a monolithic decision making system. In network A, all the decision-making power is concentrated in one node, a dictator, whereas Network B represents a full democratic structure of decision making. Same implications can be drawn from comparisons of two networks. Centralized decision-making network can be more efficient but less stable, whereas decentralized-decision making can be more stable but less efficient. However, it is not easy to capture or measure a decision making network because data gathering is usually very hard. Further, implication of simple network structure cannot be extended to a large scale network which has dynamically increased complexity as the size of the network increases.

Appendix C

CALCULATION OF CLOSENESS CENTRALITY

Assume an information network consists of 7 nodes.



In this network, node 3 needs 11 steps (1+1+1+2+3+3) to reach every other node, whereas node 1 need 16 steps (1+2+2+3+4+4) to reach the rest of the nodes. Therefore, we can calculate each node's closeness centrality raw score.

Closeness Centrality		
Node	Score	Standardized Score
1	1/16	6/16=3/8
2	1/16	6/16=3/8
3	1/11	6/11
4	1/10	6/10=3/5
5	1/11	6/11
6	1/15	6/15=2/5
7	1/15	6/15=2/5

We can find out that the most central node for closeness is node 4 in the network, which indicate node 4 stands at the closest point to all other nodes. Node 4 needs only 10 steps to reach every other node.

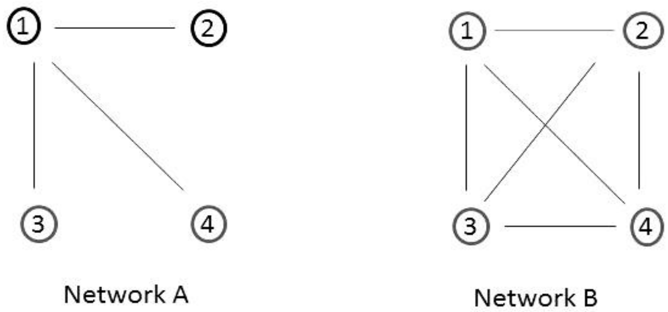
For example, degree centrality of a network above can be presented as follow table:

Degree Centrality		
Node	Score	Standardized Score
1	1	1/6
2	1	1/6
3	3	6/3=1/2
4	2	2/6=1/3
5	3	23/6=1/2
6	2	2/6=1/3
7	2	2/6=1/3

From comparisons between degree centrality and closeness centrality, we can notice another critical characteristic of nodes. The most central nodes for degree centrality are nodes 3 and 5, whereas the most central node for closeness is node 4. Node 4 can play a critical role in the network, although it has less degree centrality than node 3 or 5 because it can reach faster to the rest of nodes than any other nodes in the network.

NETWORK CENTRALIZATION FOR CLOSENESS

Given networks A and B as follows:

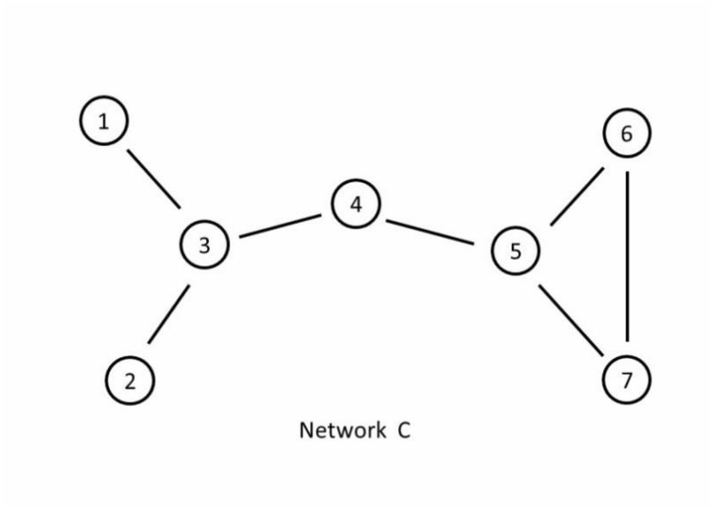


First, we can calculate the closeness score of each node. For example, node 1's closeness centrality score in the network A is 1 (1/3 + 1/3 + 1/3= 1), and each centrality score for Nodes 2, 3, 4 is 3/5. Therefore, the maximum score is 3/3 = 1. In contrast, in network B all the closeness scores are identical. The closeness score for the network is 0.

Appendix D

CALCULATION OF BETWEENNESS CENTRALITY

Assume that we calculate betweenness centrality for the network shown by graph below:

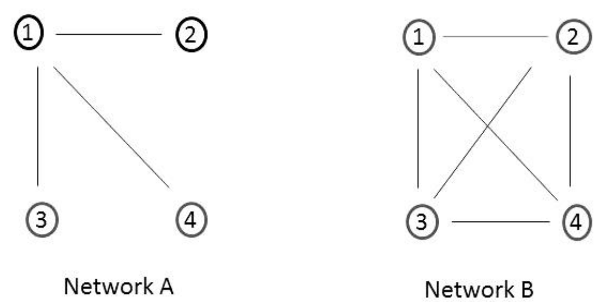


Note that each score is calculated by how frequently a node can interrupt the shortest path between two nodes. Additionally, you have to calculate weighted values for each pairs. In the network above, node 1, 2, 6, and 7 have no interruption at all. However, node 3 can interrupt the shortest paths between several pairs: A) solely interrupts pairs (1.2), (1.4), (2.4) so score is 3; B) interrupts connection between (1.5), (2.5), but node 3 shares interruption role with node 4, so score is 1 (1/2 + 1/2); C) interrupts between (1.6), (1.7), (2.6), (2.7), but it shares interruption role with node 4 and 5, so score is 4/3 (1/3 + 1/3 + 1/3 + 1/3). Therefore, the node 3's betweenness score is 16/3. You will notice that node 5 has a somewhat smaller centrality score than node 3 because the connection between node 6 and 7 reduces the controllability of node 5. Node 6 and 7 can reach each other directly.

NETWORK CENTRALIZATION FOR BETWEENNESS

As was done with the other centrality standardizations, normalize the betweenness centrality scores by dividing them by the maximum possible betweenness, expressed as a proportion or percentage. How equal are the nodes? How much variation is there in the centrality scores among the nodes?

Assume that there are two networks to compare.



In the network A, node 1's centrality score is 3/3 = 1, while Node 2, 3, 4 scored 0. So the maximum score is 3/3 = 1. Using equation, ((1-1) + (1-0) + (1-0) + (1-0)) / (4-1) = (0+1+1+1)/3 = 1, the betweenness centrality score of Network A is 1. In the network B, every node's betweenness centrality score is 0. No node can interrupt other node to connect. Therefore, the betweenness centrality score of Network B is 0. Thus, we found that Network A is more centralized than Network B for betweenness centrality.

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