Research/Studies and Analysis Area(s): Mapping the Innovation Network Formed by Members of Formal and Informal Navy Innovation Exchange Fora (Virtual and Physical) to Enhance and Accelerate Innovation for Operational and Technical Prototyping

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ABSTRACT

The so-called "*Navy Innovation Network*" consists of formal and informal collaborations that include(d) the CNO's Strategic Studies Group (SSGs), CNO's Rapid Innovation Cell (CRIC), The Athena Project, Task Force Innovation (TFI), the Naval Innovation Advisory Council (NIAC), as well as several social media groupings and innovation fora (both physical and virtual) that attract hundreds, if not thousands, of bright, motivated sailors and Navy civilians with creative ideas to share. But who are these dedicated professionals and how can we better connect them to each other and to Navy offices, agencies and programs able to adapt or rapidly prototype their innovations?

Researchers at Naval Postgraduate School (NPS) coded and developed *social network analysis* matrices of US Navy personnel (nodes) who are currently linked together through various formal and informal blogs, social media fora, information exchanges, technical fora, and command-sponsored *innovation initiatives* aimed at improving Navy combat systems, human resource polices, acquisition policies, technical, tactical and operational approaches. Through the use of commercially available social network analysis software, the matrices (of members, events, organizations, etc) were used to develop graphical two and three dimensional *topologic/sociogram depictions* of the *Navy innovation network* that connect these nodes through strong and weak ties. These matrices may now be dynamically updated by *open source databases* with information related to events being scheduled, fora available, and progress being made in specific areas of interest to Navy Innovation Network members. Metrics of *centrality, density, cohesiveness/structural holes, and clustering* can then be longitudinally measured to determine how best to increase the network's effectiveness and integration with ongoing Navy research and development at the Warfare Centers and Labs in order to more efficiently capitalize on new ideas and technologies to improve effectiveness in a variety of subject areas of interest.

Keywords: *Navy innovation network, topologic/sociogram depictions, innovation initiatives, open source databases, dark maritime network, centrality, density, cohesiveness/structural holes, and clustering, social network analysis*

EXECUTIVE SUMMARY

While there are several institutional offices within the Navy that serve as hubs for innovation (such as DUSN(M)/NIAC/Strategic Innovation Office, Navy RDT&E Strategic Cell, and others), social media is increasingly being leveraged to bring individuals, events, and organizations together. Our research found that key hubs, authorities, and nodes include individuals, official offices of the Navy and Department of Defense, commercial and non-governmental organizations, academic institutions, events, social media fora, and Twitter accounts (both official and unofficial). It was found that in many cases, ties were stronger among nodes that belonged to both the social media/Twitter network and the Events network. Of seven subgroups identified using a community detection algorithm to analyze the Retweets, Replies, and Mentions Twitter innovation network, three subgroups were of particular interest to the Navy: Subgroups 4 (Navy Innovation subgroup),3 (Navy Leadership subgroup), and 6 (Navy Topics subgroup).

Based on further Twitter subgroup analysis, the following key nodes and hubs were identified: @AthenaNavy (events and official twitter account) to access Navy innovation subgroup (Subgroup 4); @DEFConference, for accessing DoD innovation subgroup (Subgroup 1); @USNavy and @NavyInnovation, to access the upper levels of the Navy (Subgroup 3); @CIMSEC and @NavalInstitute, for accessing policy and specific areas of the Navy (Subgroup 6). It would seem logical that the Navy may benefit from using official Navy accounts in Subgroup 3 (Navy Leadership) to pass along information generated in Subgroup 4 (Navy Innovation subgroup). This information could be targeted towards accounts in Subgroup 6 (as conduits for Navy topics of interest). This could be accomplished by institutionalizing outreach to better connect the NIN to a wider community of innovation through networks of events, organizations, and social media.

It is apparent from the preliminary social network analysis conducted at NPS, that it is possible to dynamically update and periodically measure and assess the NIN network and the number and strength of ties to the wider innovation community.

BACKGROUND

In A Design for Maintaining Maritime Superiority (2016), The Chief of Naval Operations, ADM Richardson, identified, “the increasing rate of technological creation and adoption” as one of the three major interrelated global forces shaping today’s strategic environment. To achieve “high velocity learning at every level,” the paper cited the need to “Adapt processes to be inherently receptive to innovation and creativity.” Over the last decade, an unprecedented number of innovation cells have emerged throughout the Navy. Many of these innovation cells are interconnected, with members possessing attributes that include high levels of trust, adaptability, knowledge-seeking behavior, loyalty, openness, transparency, and a willingness to navigate an often daunting Navy bureaucracy.

Innovation nodes (sailors, Navy civilians, organizations, fora, events, initiatives) have self-organized over time, creating an evolving and dynamic social network. The informal Navy Innovation Network includes (or has included) the CNO's Strategic Studies Group (SSGs), Deep Blue, Disruptive Thinkers, the CNO's Rapid Innovation Cell (CRIC), TANG, CRUSER, The Athena Project, Defense Entrepreneurs Forum (DEF), and its offshoot DEFx, the SECNAV's Strategy and Innovation Department, Task Force Innovation (TFI), the Naval Innovation Advisory Council (NIAC), Defense Innovation Unit Experimental (DIUx), FabLabs and ROBO Dojo, Fleet Readiness Center Mid Atlantic (FRCMA) Junior Innovation Think Tank (JITT) and Senior Innovation Think Tank (SITT), The Bridge, The Constellation, and many others yet to be formally identified. Collaboration and brain storming methods have inspired new possibilities, critical thinking skills, and collaboration through Design Thinking (DT), User Based Design, experimentation, rapid prototyping, and intrapreneurship. By identifying and connecting the nodes in this social innovation network using open source data and voluntarily provided information, the Navy can amplify effects in areas such as unmanned vehicles, additive manufacturing, knowledge management (to include big data), wearable technology, codes and algorithms, virtual and augmented reality, and many other areas of operational interest.

A significant body of research has been conducted in the area of leveraging social networks to enhance innovation by connecting communities of interest. This work involves the study and coding of member attributes, behavior, motivations, relationships, and social media that attract new members into self-organizing clusters that constitute communities of interest (Backstrom, Huttenlocher, Kleinberg, & Lan, 2006). Further research has explored emergent behavior that can be applied as a potential strategy to increase a positive epidemic of desired behaviors within a complex organization (Horgan et al., 2010). A study of human and organizational behavior in the military provided insights into the use of electronic media and social media analysis to model human behavior, infrastructure, and information exchange in order to increase military readiness and effectiveness (National Research Council, 1998). These studies followed earlier work that sought to identify barriers to, and catalysts of, new discoveries through the mobilization of social movements (Klandermans & Oegema, 1987).

In today's hyper-connected environment of young professionals, social network analysis provides a method and tools for identifying, mapping, and measuring the emergent network of sailor-innovators eager to contribute their knowledge and Fleet experience in the pursuit of technology and process improvement through innovation. Once network membership, structure, and behavior is qualitatively analyzed and quantitatively measured, strategies can be developed to better connect sailors, command-initiatives, Naval Warfare Centers, and Labs in order to drive creative insights toward innovative and actionable solutions.

The Navy Innovation Network may be analyzed through either one mode or two made matrices: one mode analysis ties individuals to individuals for example, and two mode analysis ties, for example, individuals to fora, events, organizations, and topics they have in common. Both methods were employed in this research. While data is routinely collected on the attributes (characteristics) of individuals and stakeholders which might be helpful in link analysis, less attention has been paid to the collection of relational data. This can be achieved through algorithmic searches designed to sort large data sets from dynamic, open source (technological, news, military, and industry) databases (Franzese, Hays, & Kachi, 2012; Hays, Kachi, & Franzese, 2010; Robins, Snijders, Wang, Handcock, & Pattison, 2007). The use of social network analysis that integrates attribute data with relational data provides metrics for network analytics (e.g. eigenvector centrality, density, clustering, cohesiveness/structural holes) not possible with link analysis (Borgatti, Everett, & Johnson, 2013; Freeman, 2016; Granovetter, 1973; Kadushin, 2012; Prell, 2012; Watts, 2004).

NPS researchers coded and developed social network analysis matrices of US Navy personnel (nodes) who are currently linked together through various formal and informal blogs, social media fora, information exchanges, technical fora, and command-sponsored innovation initiatives aimed at improving Navy combat systems, human resource polices, acquisition policies, tactical and operational approaches. Through the use of commercially available social network analysis software (ORA, UCINET), the matrices (of members, events, organizations, etc) were used to develop graphical two and three dimensional topologic/sociogram depictions of the Navy innovation network that connect these nodes through strong and weak ties. These matrices were dynamically updated by open source databases with information related to events being scheduled, organizations, fora available, topics, and progress being made in specific areas of interest to Navy Innovation Network members. Metrics of centrality, density, cohesiveness/structural holes, and clustering were used to measure the network. Thesis student LT Huff, USN will use this analysis to determine how best to increase the network's effectiveness and integration with ongoing Navy research and development in order to more efficiently capitalize on new ideas and technologies to improve effectiveness in a variety of subject areas of interest.

Social Network Analysis Terminology

The following section is excerpted from an NPS thesis written by Katrina Woodhams (Advisor, Dr. Wayne Porter):

Principles associated with social network analysis are based on commonly accepted concepts of SNA identified in several studies. Although applications of SNA differ, they are generally described by the social context in which actors and ties are organized in network structures (Everton, 2012). Further, social networks function differently depending on their configuration, so it is important to identify and understand common SNA measures and metrics (Ozkan-Canbolat & Beraha, 2016). By examining the interaction between nodes and social ranking, specific metrics can be used to enhance an understanding through network analysis.

a. Actors or Nodes

The term *actors*, or *node*s, refers to distinct individuals, groups, organizations, events, and activities involved in social relations (Everton, 2012). The type of node to node transmission is perhaps the most common means for interpreting the effects of social networks (Burt, 2000). Thus, within a social network, actors (nodes) are linked together either directly or indirectly through a connection shared with another actor resulting in the behavior of a network. Conceptually, the purpose of SNA is to identify the positions of an actor (or node) in a network, ties (or links) between actors, and the manner in which an actor's behavior is influenced by the larger social network and vice versa (Carrington, Scott, & Wasserman, 2005).

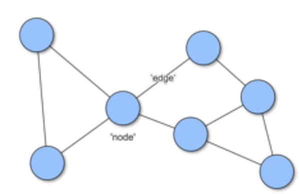

Figure 1: A network representation of nodes and edges

b. Ties

As described above, actors are connected within a network by ties. Wasserman and Faust offered the following examples of ties (1994):

- ties of sentiment (friendship, liking, respect),
- resource ties (business transactions, financial flows),
- ties of association or affiliation (members of the same church or club),
- behavioral ties (communication ties),
- ties based on geographic movement (migration, physical mobility),
- ties based on status movement (social mobility),
- formal ties (organizational hierarchy), and
- biological ties (kinship).

The type of tie is critical to understanding how social networks are affected. Mark Granovetter's 1973 groundbreaking study entitled, "The Strength of Weak Ties" identified both strong and weak ties (1973). He explained the difference between strong and weak ties as follows:

> Our acquaintances ("weak ties") are less likely to be socially involved with one another than are our close friends ("strong ties"). Thus the set of people made up of any individual and his or her acquaintances will constitute a low-density network (one in which many of the possible ties are absent), whereas the set consisting of the same individual and his or her close friends will be densely knit (many of the possible lines present) (Granovetter, 1983, pp. 1–2).

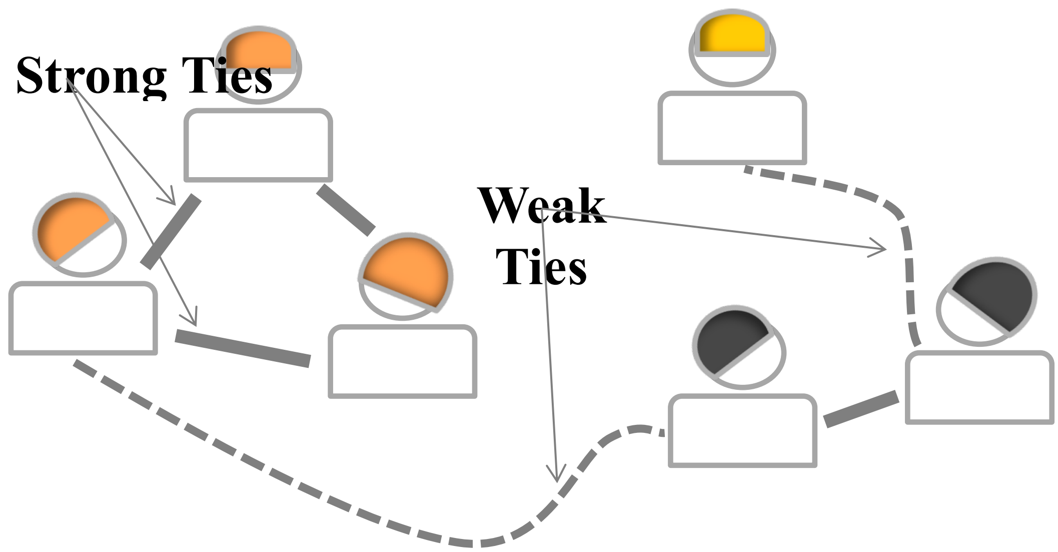

Figure 2: Strong ties and weak ties within a group

Granovetter emphasized the power of weak ties, making the argument that weak ties are "indispensable to individuals' opportunities and to their integration into communities; strong ties, breeding local cohesion, lead to overall fragmentation" (Granovetter, 1973, p. 1378). He furthermore stated, "The importance of weak ties is asserted to be that they are disproportionately likely to be bridges as compared to strong ties. . . This does not preclude the possibility that most weak ties have no such function." (Granovetter, 1983, p. 224)

c. SNA Measures and Metrics

SNA employs specific relational measures and metrics for the study of the structures of networks (Blei, Ng, & Jordan, 2003). Thus, SNA helps determine the level of an individual's or an organization's connectedness within, and the cohesiveness of, defined networks (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). Cohesion is a property of network connectedness that helps to determine the strength of relationships among actors and the resulting formation of clusters, cohesive subgroups, connected by strong ties in a network (Freeman, 1979). SNA involves both qualitative and quantitative methodologies. Using those methodologies, it first determines network membership and the nature of relationships that connect members, and then measures structural and behavioral aspects of the network. Some common SNA measurements and metrics employed in this research are noted below.

Density

Density is a structural element of social networks. Density is based upon "the number of *actual* direct connections [of individual members] divided by the number of *possible* direct connections in a network" (Kadushin, 2012, p. 29) and is used to determine the interconnectedness of a network (Everton, 2012). Density is a critical measure used in SNA to evaluate the sense of trust in a society, conditions of cohesive communities, social support, and high visibility, and the social capital network members share. By measuring density, the analyst can evaluate the presence or absence of ties in an effort to understand the level of diffusion of information, ideas, influence, and other materials and resources throughout a network (Kadushin, 2012). The density of a network typically grows over time and can reveal the cohesiveness of a group or community, through either the existence of highly connected actors or areas that are disparately linked, as interactions between actors or clusters of actors increase (Granovetter, 1985).

When comparing density within or to other networks, it is important to take into account the overall size of the network. Given the human limitation on the number of ties available for connection, the level of density decreases as the number of the actors within a network grows (Kadushin, 2012). Understanding whether relationships are tied directly or indirectly and the number of actors between connections can help to establish the level of network connectivity between actors (Kostiuchenko, 2011).

Path (and Path Distance)

Examining the direct and indirect connections between two nodes in a network helps to determine the *path*, or walk (i.e., a sequence of ties or links) between two connected vertices or nodes of a network (Everton, 2012). The path measurement is used to trace the route an actor has traveled to reach another member of the network (Kostiuchenko, 2011). In terms of diffusion, the links of a path might also expose redundant or inefficient flows of information or resources based on whether or not two actors have reciprocal relationships (Kadushin, 2012). Actors that can "reach their counterparts following paths of a particular direction" (Kostiuchenko, 2011, p. 695) characterize strongly structured components as opposed to weak components, in which ties are undirected or the direction of the ties is ignored. Understanding the directional nature of ties is important because it can impact the distance between connections. The path distance is defined as the number of steps needed to connect one node to another (Everton, 2012). The smallest number of steps between two nodes is referred to as the geodesic distance between them. A network commonly comprises numerous paths of varying lengths, with some shorter or longer than others; however, the path may be geodesic based on whether relationships are reciprocated or not (directed or undirected networks) (Kadushin, 2012). Thus, measuring the longest geodesic distance can reveal the overall size of the network as well provide a way to effectively analyze the network as a whole.

Structural Holes

The characteristic known as a structural hole represents a *lack* of connections (Kadushin, 2012). Ronald Burt explains, "The holes in social structure or, more simply, structural holes, are disconnections or nonequivalencies between players in the arena" (Burt, 1992, p. 2). Network members that only link to one another through a single node or "ego" indicate a structural hole is present (Burt, 1992). Depending on the ego's ability to manipulate/navigate structural holes depends in part on her/his base of support (Kadushin, 2012). If the ego node has only established a limited number of connections, it may have limited support to maximize the quantity and quality of resources it is able to obtain from the network (Borgatti & Lopez-Kidwell, 2014). The presence of structural holes in a network constrains a person's ability to gain access to, or exchange information and resources with, other network members, thereby limiting his or her social capital across the network (Burt, 1992). As such, structural holes prevent an individual or group of individuals from gaining opportunities to exchange information and inhibit those opportunities from reaching disconnected network clusters.

Centrality or "Popularity"

Centrality, or "popularity," is a measure of network topology used to determine which nodes are most connected or central to the network (Kadushin, 2012). Because of their position, nodes more central in social networks benefit from easier access to resources and an increased efficiency to disseminate information to other nodes (Everton, 2012). Hence, the greater centrality, the greater influence a node or actor has among groups, serving as a powerful relay point of information to extend an actor's influence beyond his or her original network.

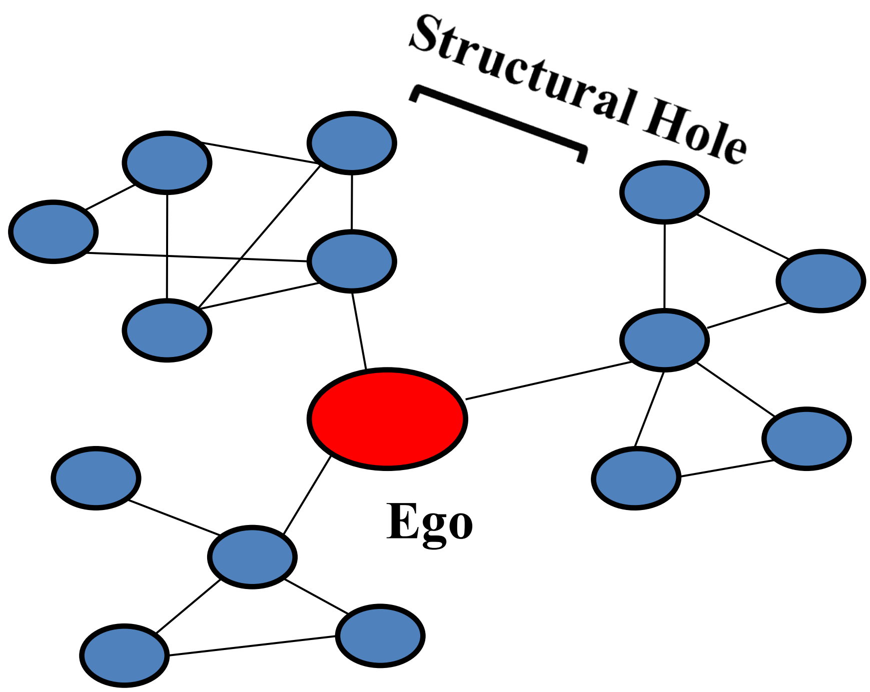

Figure 3: Example of a structural hole

Everton provides examples of commonly used measures of centrality below:

- *Degree centrality* [denotes] the count of the number of actor's ties.

- *Closeness centrality* measures (based on path distance) how close, on average, each actor is to all other actors in a network; some limitations [may affect] traditional closeness measure, but alternative measures are available.
- *Betweenness centrality* measures the extent to which each actor lies on the shortest path to all other actors in a network.
- *Eigenvector centrality* [denotes the assumption] that ties to highly central actors are more important than ties to peripheral actors, so it weights an actor's summed ties to other actors by their centrality scores. (Everton, 2012, pp. 12–13)

Sometimes nodes that have the highest centrality in one measure might have highest centrality in another measure, but that is not always the case. Often the most central node, and the order of the most central nodes, will vary by measure, as illustrated in Figure 4 (Ortiz-Arroyo, 2010, p. 30).

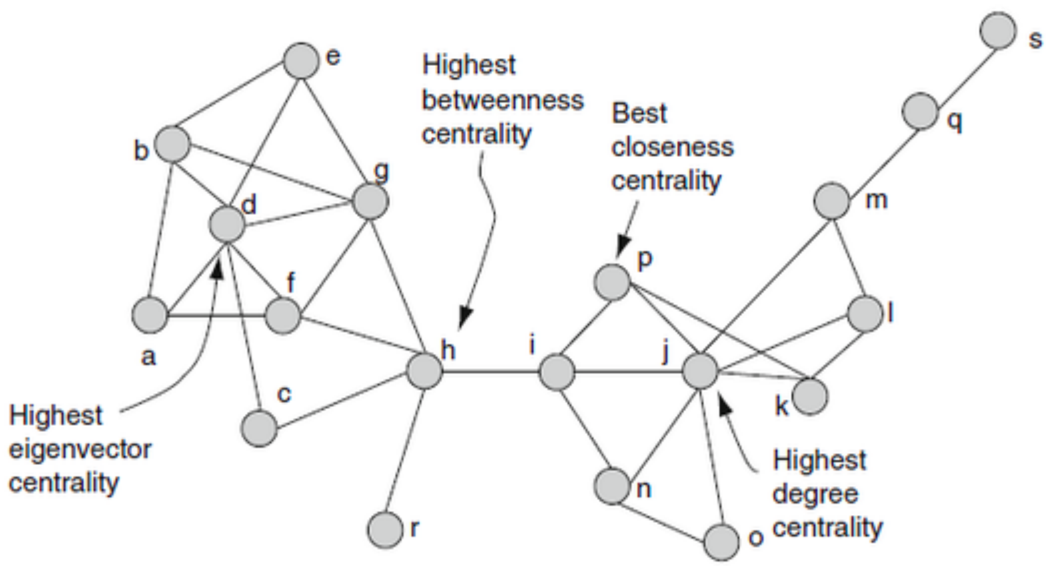

Figure 4: Example of centrality measures in SNA (Ortiz-Arroyo, 2010, p. 30)

Multiplexity

Multiplexity contributes to the identification of actors with high centrality for members of the same group with more than one kind of relationship connecting them (Kadushin, 2012). Related to the concept of homophily, in which people with like characteristics are connected and tend to have an effect on one another, multiplexity is exemplified by situations where two actors have an organizational relationship based upon employment roles (e.g. a supervisor and the supervisor's assistant) but who are also friends (Hurlbert, Beggs, & Haines, 2001). Role sets are "the set of relationships that ensue because one occupies a given role" and make up a person's status (Kadushin, 2012, p. 36). For example, a school teacher frequently engages with students, parents, school administrators, and the Board of Education. The relationships of this role vary based upon the status of a teacher (Kadushin, 2012).

Content multiplexity is a term that refers to the various flows that can occur between two pairs of nodes, for example, giving advice, making friends, or exchanging tasks for work (Hurlbert et al., 2001). Content multiplexity allows for a number of types of ideas to flow through a network that present options for resolving a problem (Cross, Borgatti, & Parker, 2001). By examining multiplexity and the actors with high centrality, network analysts can observe the consequences of multiple flows of information content and determine how nodes connect or interact in a variety of contexts (Kadushin, 2012).

Cohesive Subgroups or Clustering

The identification of dense clusters of actors is a key function of SNA. Wasserman and Faust described a cluster as consisting of actors "among whom there are relatively strong, direct, intense, and/or positive ties" (1994, p. 19). Researchers studying social networks have often referred to clusters of actors as *cohesive subgroups* or *subnetworks,* generally congregating around social interaction of actors sharing similar norms, identities, and collective behavior (Everton, 2012). Social network analysts examine patterns of ties to identify cohesive subgroups within social networks (Scott & Carrington, 2014).

Roles and Positions

The term *role* or *position* is used to identify the types of relationships that connect nodes in the wider network (Kadushin, 2012). Whether tied directly or indirectly, the roles actors play in a network explain the related behavior or social processes that result (Emirbayer & Goodwin, 1994). For example, father, mother, aunt, or uncle are typical kinship names associated with specific roles in the social system and indicate expected relationships with others. Understanding an actor's role is important in other social network measures, including centrality, clustering, and betweenness of a network. Social network analysts often study connections among particular actors to detect structurally equivalent positions (Everton, 2012).

RESEARCH OVERVIEW

By employing the tools of social network analysis and big data integration from existing databases, the collection and collation of relational and attribute data among stakeholders in physical and virtual space was analyzed for insights that might contribute to the Navy's ability to better leverage creative ideas for pragmatic solutions.

NPS CORE Lab research associates met regularly with LCDR Wheeler, USN, a former NIAC officer and a subject matter expert in the area of Navy innovation networks, and thesis student LT Huff, USN as well as other subject matter experts. These meetings were used to identify additional sources of information; to map out the processes involved in implementing Navy innovation initiatives; and, to evaluate initial analytical models used. As a result, multiple analytical models have been developed in order to determine how relevant they are to a final product and how they might be combined to provide a more complete picture.

The CORE Lab built upon the information gathered, based on knowledge and guidance from LCDR Wheeler, to construct the sociogram of nodes and ties within an identified Navy Innovation Event Network, based on a number of different events that took place to encourage innovation (Figure 5).

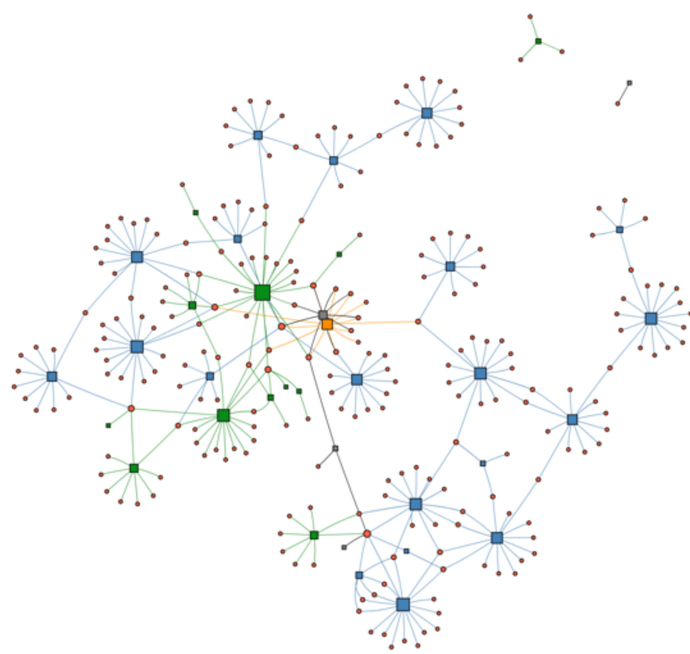

Figure 5: Two mode network or people (circles) connected to events (squares). Nodes are sized by degree centrality. Colors for the connections and events are based on the type of event: Athena (blue), DEF (green), AFCEA West (orange), other (grey).

To supplement the Event Network, social media connections were analyzed by looking at those accounts connected to The Athena Project's Twitter account. This data includes a number of different Twitter relationships ("follow," "reply," "retweet," "mention", "favorite") among previously identified and newly identified network members. Figure 6 is a sociogram for one of the initial networks identified based on social media data, with nodes sized according to their hub score, and colored according to subgroup from a community detection algorithm (Blondel et al., 2008). The community detection algorithm uses the pattern of ties to identify subgroups within the network. These subgroups were further used to find areas of homophily (attribute commonalities among subgroup members) and areas of potential brokerage between subgroups.

Finally, documents from different websites, including eight from different parts of the social media network, were analyzed based on their content. To facilitate this, Mr Schroeder and others in the CORE Lab used latent Direchlet allocation (LDA) as a method for extracting topics from the text (Blei et al., 2003; Everton, 2012). Based on the extracted topics, they created a network of individuals/topics according to how correlated their text content (blogs, proposals, etc) was to the identified topics (Figure 7). This network was then aligned with the previously identified innovation networks in order to determine where potential additional collaboration could occur.

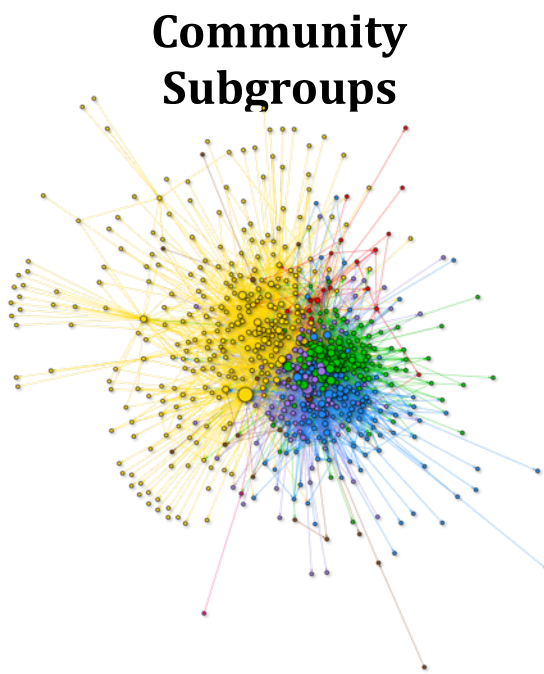

Figure 6: Retweets Replies and Mentions network with nodes colored by subgroup from community detection algorithm. Nodes sized by in degree.

LDA Topic Network

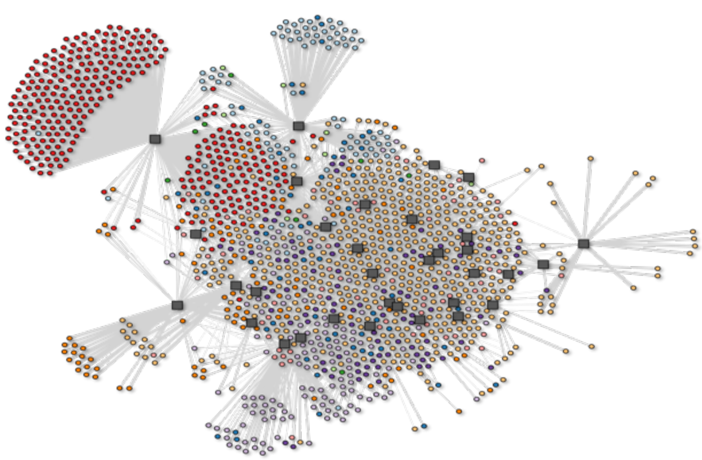

Figure 7: Topic network based on LDA analysis. Articles as circles and colored by website and topics as dark grey squares

Programs and write-ups from a number of innovation events were analyzed. A network of individuals connected to the various events was then identified, based on their role in presenting or being a part of a panel during an event. This resulted in a two-mode Event network (Figure 5), that show the connections between individuals (the red circles) and events (the squares).

Deconstructing the two-mode network (individuals tied to events) as a single mode network (events tied to other events)- based on whether individuals presented at multiple events - allows us to visualize how information can be shared and dispersed. Figure 8 shows this event by event network, with nodes sized by betweenness centrality (bridging nodes/clusters), in order to highlight which events might serve as conduits for the sharing of information.

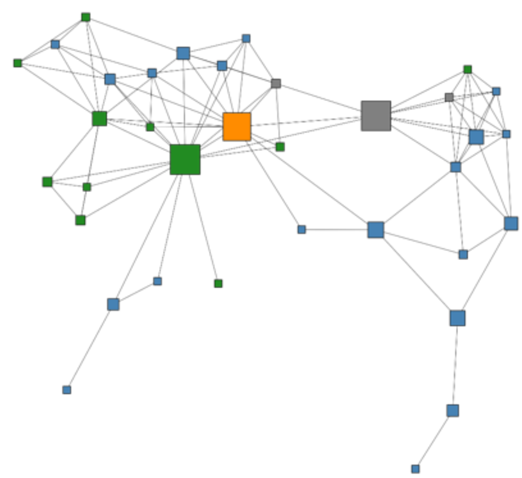

Figure 8: Event by event network, with nodes colored by event organization and sized by betweenness centrality.

The clustering in the network seems to be largely associated with where the events take place, known as proximity. Successive iterations of events tend to be connected to each other (for example ATHENA West events tend to be connected to other ATHENA West events). Further, the DEF conference that took place in San Diego is more closely connected to ATHENA West events (which also took place in San Diego) than to other DEF events held in another geographic area.

When it comes to centrality, the larger events (such as AFCEA West and the yearly DEF Conference) tend to have the highest centrality metrics. This makes sense because they often have larger attendance, more panels, and bring together people from a larger area. However, these large events are not the only ones with high betweenness centrality. One- off, smaller events can also bring together a unique group of people that might not often work together on problems. These events not only help encourage the sharing of new ideas but also work to bring the network closer together.

While participation in events is a means to share information and inspire innovation, the internet and social media also create a public forum where information and ideas can continually be shared. In order to visualize the role that social media can play in innovation, we looked at various connections between Twitter accounts of innovation network members. The Twitter accounts selected were public accounts and connected to @AthenaNavy, which is The Athena Project's Twitter account.[1]

The following networks sociograms are based on connections between accounts that either followed or were followed by the @AthenaNavy Twitter account. The three networks in Figure 9, and the results in Table 1 were created by extracting out the largest components based on the relationships analyzed (Favorite, Follow, or Retweets Replies and Mentions).

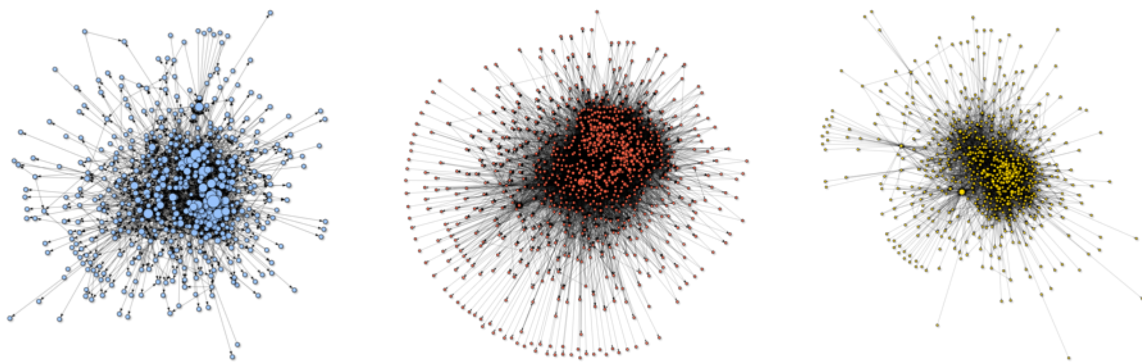

Figure 9: Favorites network (blue, left), Follows network (red, center), and Retweet Replies and Mentions network (yellow, right).

Table 1: Network topography measures of the largest component for the Favorites network, Follow network, and Retweets Mentions and Replies network.

	Favorites Network	Follow Network	Retweets Mentions and Replies
Node Count	515	869	629
Edge Count	2646	18493	6728
In Degree Centralization	0.089	0.471	0.181
Out Degree Centralization	0.162	0.571	0.131
Density	0.010	0.024	0.017
Average Degree	5.14	21.28	10.70

Many nodes found in the Event network also belong to the virtual network. By going through the accounts in the virtual networks, we identified nodes belonging to people whose accounts were also associated with the events and hosting organizations. The sociogram on the left of Figure 10

[1] Accounts with an extremely large number of followers, such as @POTUS, were not scraped; however, a large number of their connections were captured when scraping relationships from accounts that are connected to them.

depicts nodes associated with accounts that belong to people in the event (red), organizations (green), and associations (grey). The relationship ties are colored the same as the node from which they originate.

Besides the accounts associated with the event network, many were associated with official Navy accounts (for example @USNavy and @NavalWarCollege), other Department of Defense accounts (for example @USArmy and @USCG), and other US government accounts (for example @NASA and @StateDept). On the right side of Figure 10 nodes associated with Navy accounts are blue, Department of Defense are purple, and US government accounts are yellow.

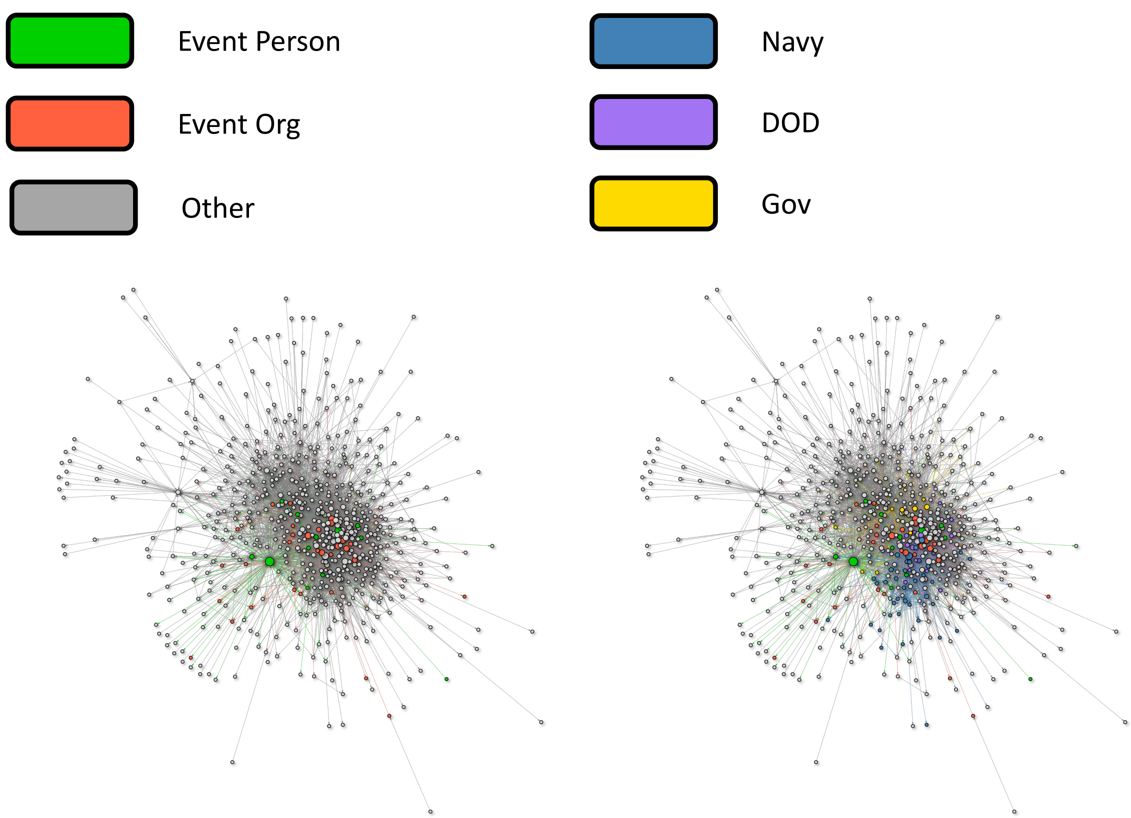

Figure 10: Retweet Replies and Mentions network with nodes colored by type, relationships colored by source type, and nodes sized by in-degree.

Active communication relationships via Twitter are established through *mentioning*, *replying to*, or *retweeting*. Therefore, in order to identify which accounts belonging to key communicators, we used the network that maps those relationships. There are a number of different ways to determine who might be key communicators in a network. We used social network analysis centrality measures in order to identify those key communicators.

The most basic measure of centrality is degree centrality (the number of a node's connections), which helps identify which nodes are extremely active (Johnson et al., 2013). Nodes with high in-degree centrality (directed connectedness) would be nodes that are mentioned, retweeted, or replied to most often. In this network, Figure 11 displays the nodes by sizing their in-degree measure, with larger nodes having higher in-degree centrality and smaller nodes having less.

Table 2 shows the four main measures of centrality (degree, betweenness, closeness, and eigenvector), as well as the hubs and centrality metrics that were applied to the Retweets, Replies, and Mentions network for the top ten Twitter accounts.

Table 2: Centrality metrics for the top ten accounts in the Retweets, Replies, and Mentions network

In Degree		**Betweenness**		**Closeness (Undirected)**	
AthenaNavy	124	AthenaNavy	0.136	AthenaNavy	0.546
DEFConference	81	USNavy	0.058	DEFConference	0.498
USNavy	80	TechCrunch	0.043	m144092	0.492
CIMSEC	67	m144092	0.041	jason_knudson	0.492
JenWalshToday	67	walsh_richard	0.033	jim_perkins1	0.490
jason_knudson	64	kelleybros	0.031	walsh_richard	0.489
jim_perkins1	64	NavyInnovator	0.026	USNavy	0.485
joshuamarcuse	62	FastCompany	0.026	JenWalshToday	0.478
m144092	55	jason_knudson	0.026	NavyInnovator	0.472
walsh_richard	54	WIRED	0.025	RogerMisso	0.472
Eigenvector		**Hubs**		**Authorities**	
DEFConference	1.000	jason_knudson	1.000	DEFConference	1.000
jim_perkins1	0.871	DEFConference	0.995	jim_perkins1	0.885
jason_knudson	0.831	jim_perkins1	0.927	jason_knudson	0.850
joshuamarcuse	0.788	august_cole	0.891	JenWalshToday	0.816
august_cole	0.780	mbgrinberg	0.790	joshuamarcuse	0.810
childersaw	0.774	m144092	0.783	childersaw	0.774
JenWalshToday	0.766	benkohlmann	0.783	august_cole	0.769
WWATMD	0.739	Casey_D120	0.774	Raphaeleads	0.757
Raphaeleads	0.733	walsh_richard	0.767	WarOnTheRocks	0.746
mbgrinberg	0.733	TroyPeterson27	0.760	WWATMD	0.746

Figure 11 displays the network with nodes colored by type and sized by various centrality measures.

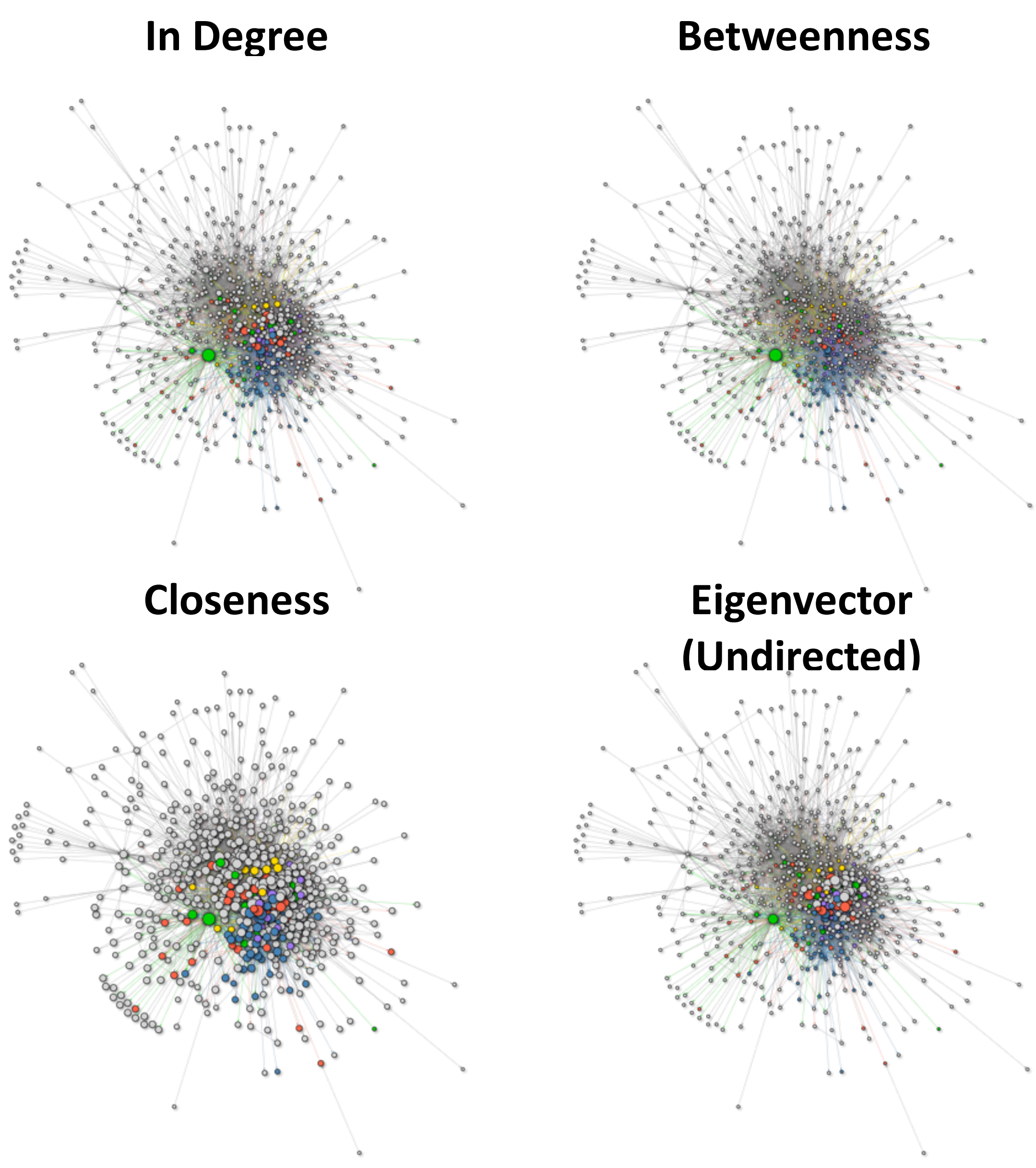

Figure 11: Retweets Replies and Mentions network with nodes sized by centrality measures and colored by node type

In addition to the four measures of centrality cited above, a metric was used to determine which accounts might be good sources of information (hubs) and which accounts might serve as authorities for information (Figure 12) (Kleinberg, 1999).

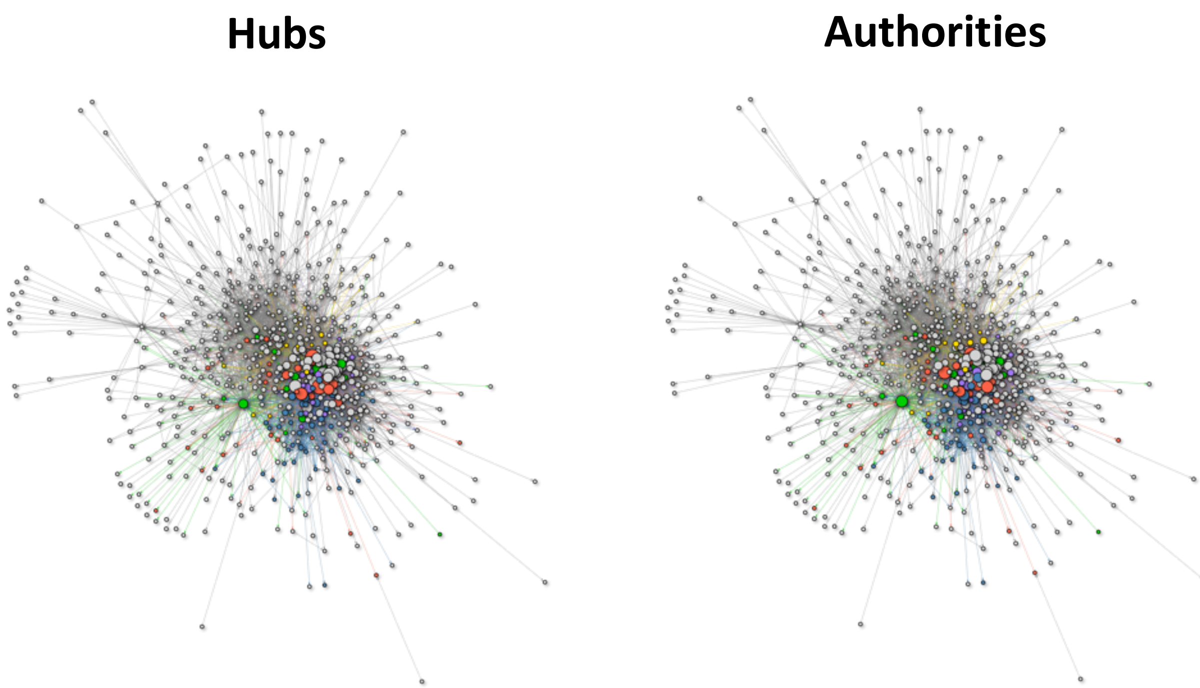

Figure 12: Retweets Replies and Mentions network with nodes sized by hubs and authorities metrics and nodes colored by type

Further to the analysis discussed above, two types of subgroup analysis were conducted. The first attempted to identify nodes within the core and nodes within the periphery of the Retweets Replies and Mentions network. The second attempted to identify communities within the network by locating internally dense pockets of interaction. Both were accomplished by analyzing the structure of the network.

In order to identify the network core, periphery, and layers in between, we used k-core analysis. K-core is an approach that identifies a "maximal group of actors, all of whom are connected to some number (k) of other group members" (Johnson et al., 2013). Instead of analyzing every k-core separately though, we identified the cores that contain about 10% of the network, 25% of the network, and 50% of the network. When pealing back the layers of the network, looking at nodes that belong to a core of layer 10 or higher, we are left with 307 nodes, or 48.8% of the network. By only looking at nodes belonging to a core of layer 20 or higher, we are left with 152 nodes, or 24.2% of the network. Finally, by looking only at nodes that belong to a core of layer 27 or higher, we are left with 61 nodes, or 9.7% of the network.

We split this network into different subgroups based on which layer they appear in as illustrated in Figure 13. Nodes that are part of a core of layer 27 or higher are categorized as being in subgroup "K-Core A". These nodes are extremely well connected to many other nodes in this network as well and are visually found at the center of the network. In Figure 13, they are colored red. This subgroup contains 61 accounts. The upper-left of Figure 14, below, visualizes this subgroup, and shows that it is a very dense network with nodes having on average 22.95 connections. Besides being well connected, it is also extremely compact, with every node belonging to the same strong component, with an average path distance of 1.62. Additionally, as can be seen both in Figure 14 and in Figure 15 below, the most common account type identified belongs to people who participated in an event in our initial event network.

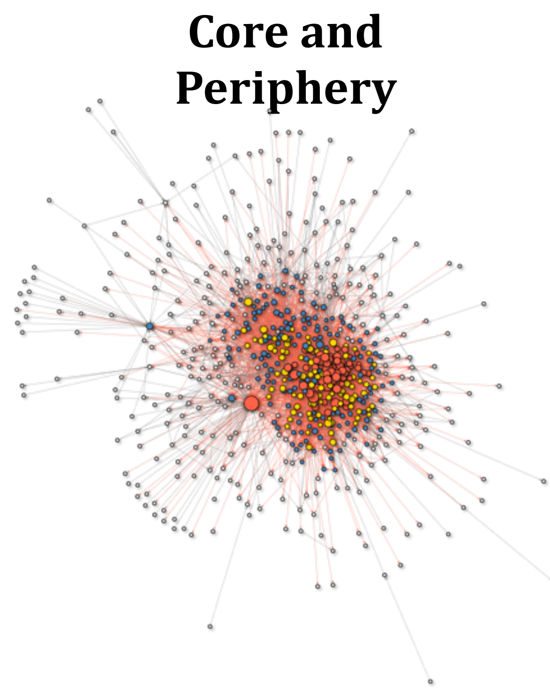

Figure 13: Retweets Replies and Mentions network with nodes colored by subgroup based on k-core, nodes sized by in-degree, and relationships colored by source node of relationship

The next layer out of our Retweets Replies and Mentions network to which we assigned a subgroup are nodes that belong to a core of layer 20 or higher, but do not belong to a core of layer 27 or higher. This subgroup, which we labeled "K-Core B", contains 91 nodes. In Figure 13, K-Core B members are the yellow nodes, as visualized in the upper right of Figure 14. Even without the central core of K-Core A being a part of the network, it is still a fairly well-connected network, with 86 of the 91 accounts (94.5%) in the network belonging to one strong component. However, it is not nearly as tightly connected as K-Core A; each account has on average 7.97 connections and the network as a whole has an average path distance of 2.74. While K-Core A was largely composed of accounts by people who were in the event network, the accounts identified in K-Core B are largely related to official Navy accounts (as illustrated in upper right of Figure 14, and in the Figure 15 bar graph). This is also the K-Core group where the most accounts associated with the organizations hosting the events are located.

The next network layer to which we assigned a subgroup are nodes that belong to at least a core of layer 10 or higher, but do not belong to a core of layer 20 or higher. This subgroup, labeled "K-Core C", contains 155 nodes. In Figure 13, its nodes are colored blue as visualized in the bottom left of Figure 14. This network has one large weak component and 14 accounts being completely disconnected when the other subgroups are removed. When looking at the direction of the relationships and components, there are only two strong components larger than 1, and only one strong component larger than 2. This largest strong component contains 96 nodes (61.9%). In this subgroup located on an outer layer of the network, connections are more sparse (average number of connections for each node is 3.14). Along with having a fewer number of connections, the network is more dispersed as well, with the average path length being 4.46. When looking at the node types in both the network in the bottom left of Figure 14 and the bar graph in Figure 15, this subgroup can be seen to contain the largest number of Department of Defense-related accounts and also the most accounts related to the government in general.

The outer most layer of the network to which we assigned a subgroup are those nodes that belong to a core of less than layer 10. This subgroup, labeled “K-Core D”, contains 322 nodes. It is a relatively disconnected graph, with the largest weak component containing only 71 nodes (21.7% of the subgroup). This subgroup has a high number of individuals who were a part of the event network as can be seen in the bottom-right of Figure 14 and on the right of Figure 15. This is likely because not every person who is participating in the innovation events is active on social media. It should be noted that while social media and the virtual environment might be a useful avenue for spreading information, it is still important to have other means of spreading information about innovation events and opportunities in the Navy.

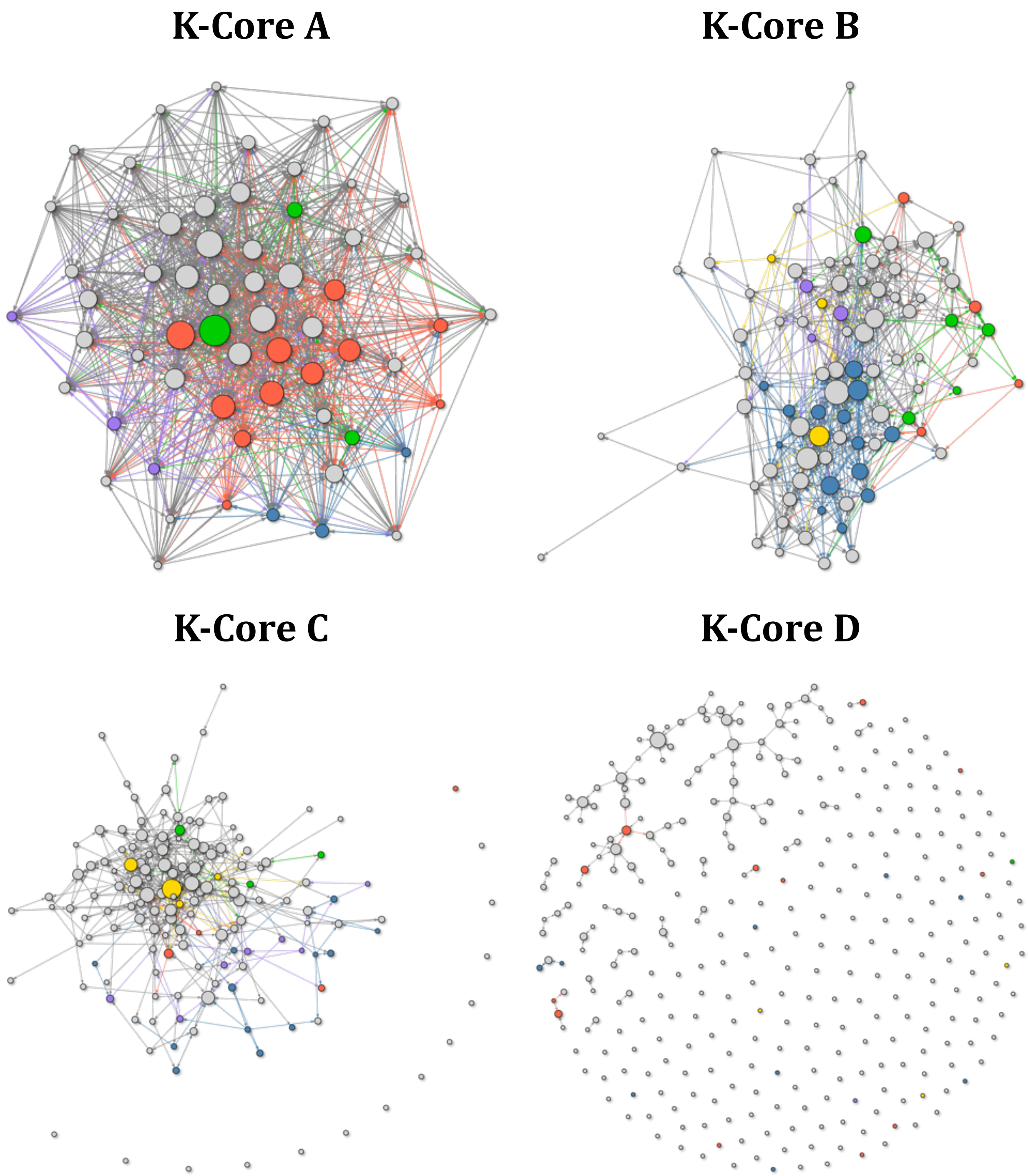

Figure 14: Graph of subgroups based on k-core. Nodes colored by type and sized by in degree.

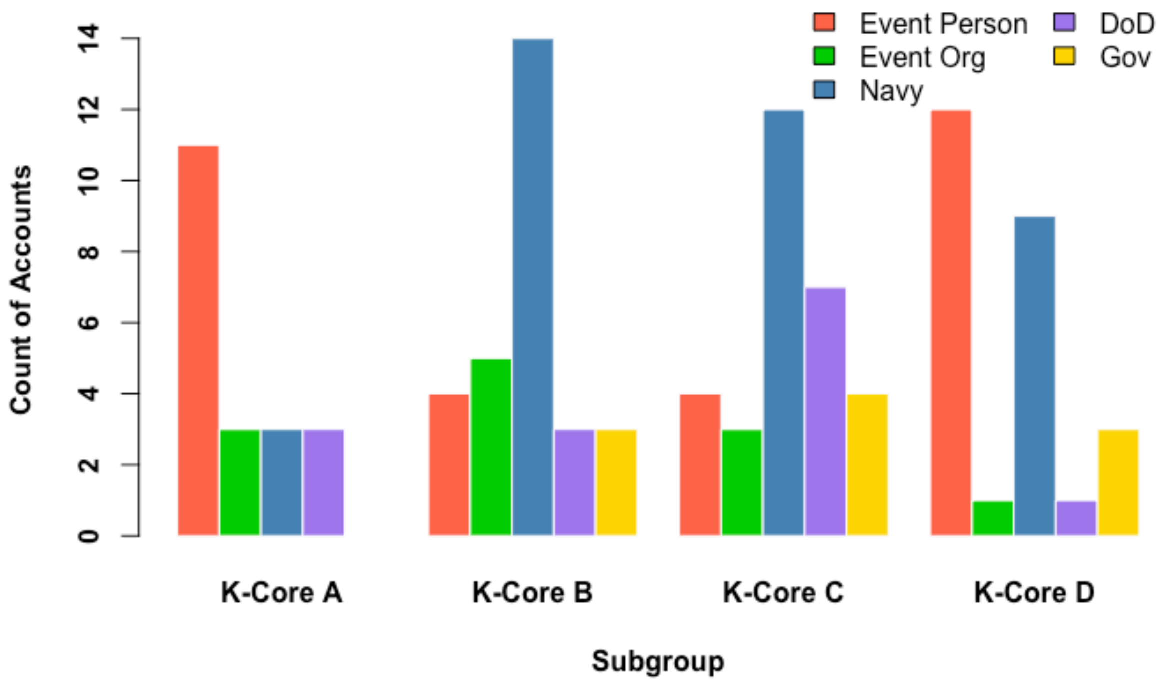

Figure 15: Counts of nodes by account type (not including "Other") for each subgroup based on k-cores

Community Detection Subgroups

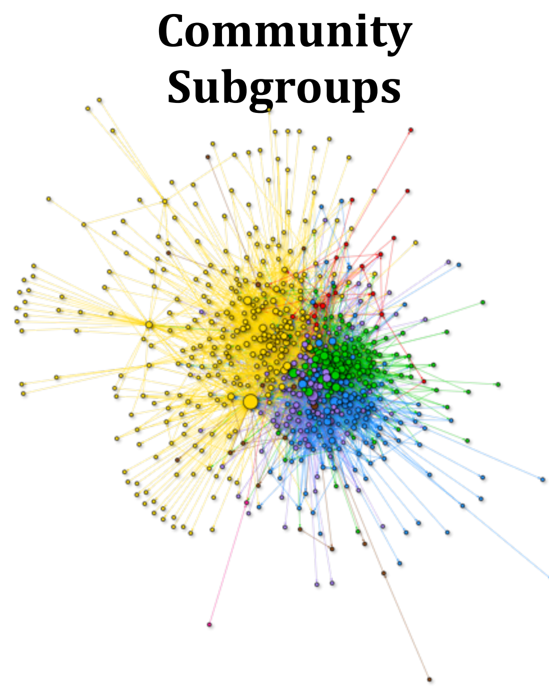

Figure 16: Retweets Replies and Mentions network with nodes colored by subgroup from community detection algorithm. Nodes sized by in degree.

The use of community detection algorithms is another approach for extracting subgroups from a network and is based on determining whether the ties between nodes are internally dense and externally sparse. The method we used was the Louvain algorithm (Blondel et al., 2008).[2] This algorithm maximized the modularity score to identify seven different subgroups, with six of them having more than two nodes.[3] The results are visualized in Figure 16, with nodes colored by their subgroup. A seventh subgroup contained two nodes only and is colored pink in Figure 16, located near the bottom left of the graph.

The first subgroup identified (colored green in Figure 16) contains 114 accounts and is the subgroup with the largest number of accounts belonging to people who attended events in the initial Event network. It is visualized on the top left of Figure 17. The most central account, in terms of in-degree centrality, is @DEFConference, which is a DoD-wide event, and the other two event-related accounts are regional DEF Conferences. The fact that the @DEFConference focuses on the entire DoD can explain why this subgroup contains accounts for other parts of the DoD but no official accounts for the Navy (as seen in the bar chart in Figure 19). This subgroup therefore can be characterized as being key to broad innovation across the DoD.

The second subgroup (colored red in Figure 16) contains only 18 accounts. It is visualized on the top right of Figure 17. None of these accounts are coded as being a part of the event network or official accounts for the US Government.

The third subgroup (colored purple in Figure 16) contains 84 accounts. It is visualized on the bottom left of Figure 17. The most central account, in terms of in-degree centrality, is @USNavy. This subgroup also contains the official accounts for the Marines (@USMC), Department of Defense (@DeptofDefense), Army (@USArmy), and Air Force (@usairforce). This subgroup contains the most official Government accounts and DoD accounts in the network (Figure 19). The one account that was also a part of the Event network is the Twitter account for DIUx (@DIU_x). Additionally, this is the subgroup that contains the official account for the Office of Strategy and Innovation, Deputy Under Secretary of the Navy (Management),

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[2] This method requires an undirected network, so the network was treated as an undirected network when executed.
[3] The modularity score from running the Louvain algorithm was 0.336.

Department of the Navy (@NavalInnovation). This subgroup can be characterized as being largely composed of official Government-related messaging, based on which accounts are central.

The fourth subgroup (colored yellow in Figure 14) is the largest, based on the Louvain algorithm, and contains 279 accounts. It is visualized on the bottom right of Figure 15. This is the subgroup that contains @AthenaNavy, which is the most central in terms of in-degree centrality. It also contains the second highest number of accounts for people from the event network and the largest number of accounts associated with events that were part of the event network (Figure 19). Unlike the first subgroup, whose events were for the entire DoD, this subgroup's events primarily focus on Navy, for example @AthenaNavy and @TANG_team. Also of note, this subgroup does not contain any official Navy or DoD accounts (except for those that organized events), but does contain the official Government account for the Small Business Administration (@SBAgov). This subgroup can be characterized as being focused on innovation, but with more of a Navy focus (based on the fact that it contains @AthenaNavy and @TANG_team).

The fifth subgroup (colored brown in Figure 16) is small, with only 18 associated accounts. It is visualized on the left of Figure 18. The connections in this subgroup are most likely based on proximity, with the two most central accounts based in San Diego.

The sixth subgroup (colored blue in Figure 16), contains 114 accounts and the most official Navy accounts (Figure 19). It is visualized on the right of Figure 18. While most of the Navy accounts in the third subgroup belonged to Navy leadership (for example @USNavy, @SECNAV, and @CNORichardson), this subgroup contains a large number of official Navy accounts for more specific communities (for example, @SurfaceWarriors, @US7thFleet, and @USPacificFleet). The most central account for this subgroup, in terms of in-degree centrality, is @CIMSEC, the account for the Center for International Maritime Security.

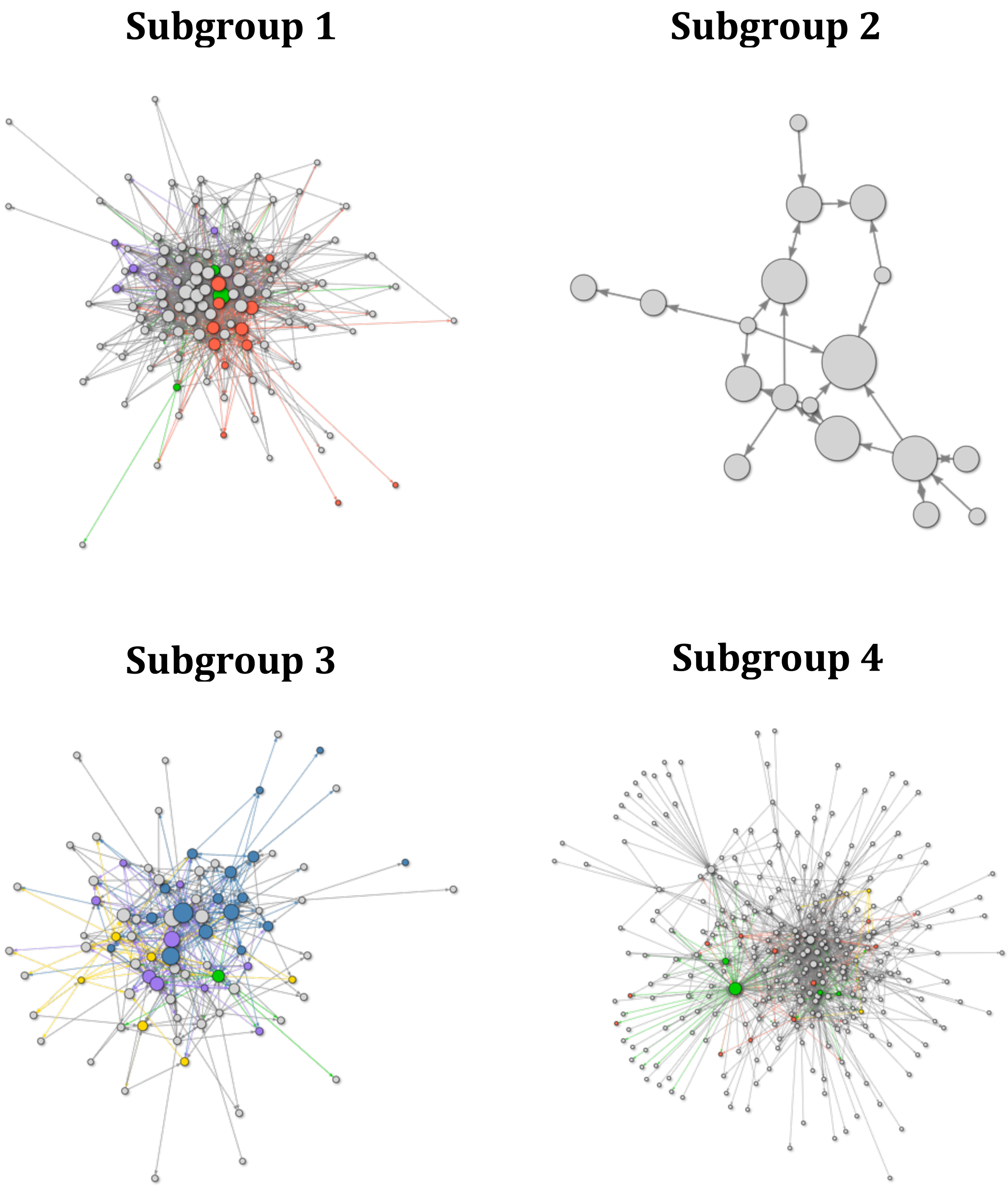

Figure 17: Graphs based on subgroups from Louvain algorithm. Nodes colored by account type and sized by in degree.

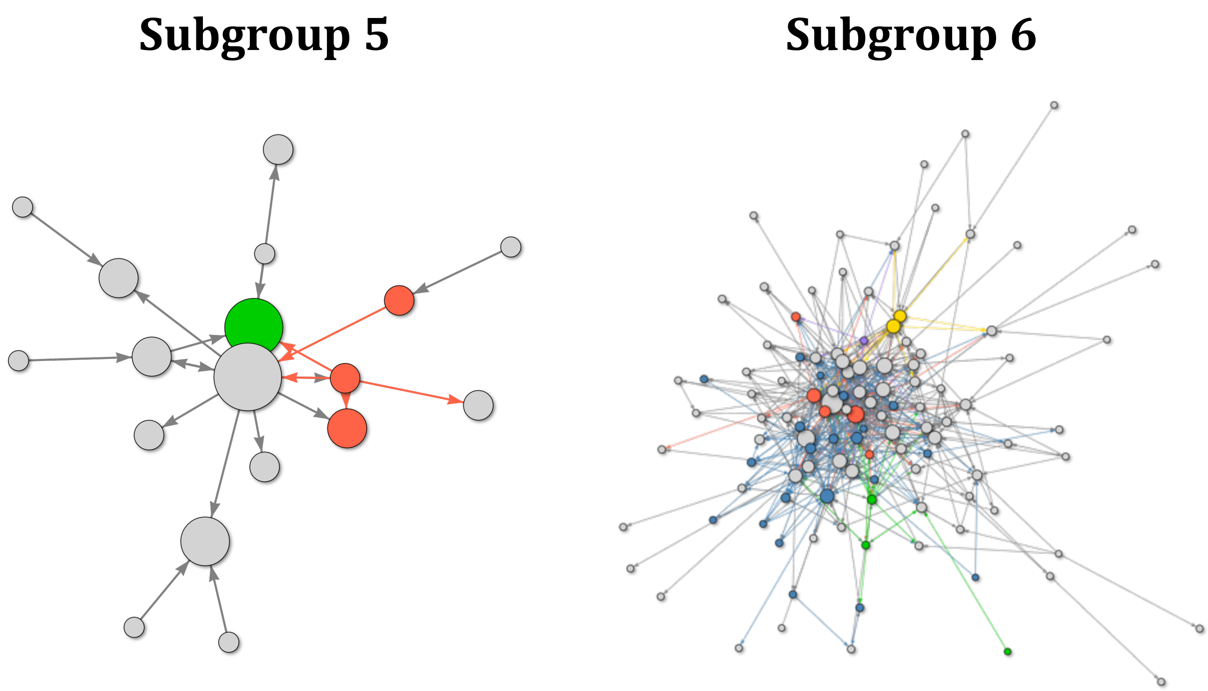

Figure 18: Graph based on subgroup from Louvain algorithm. Nodes colored by account type and sized by in degree.

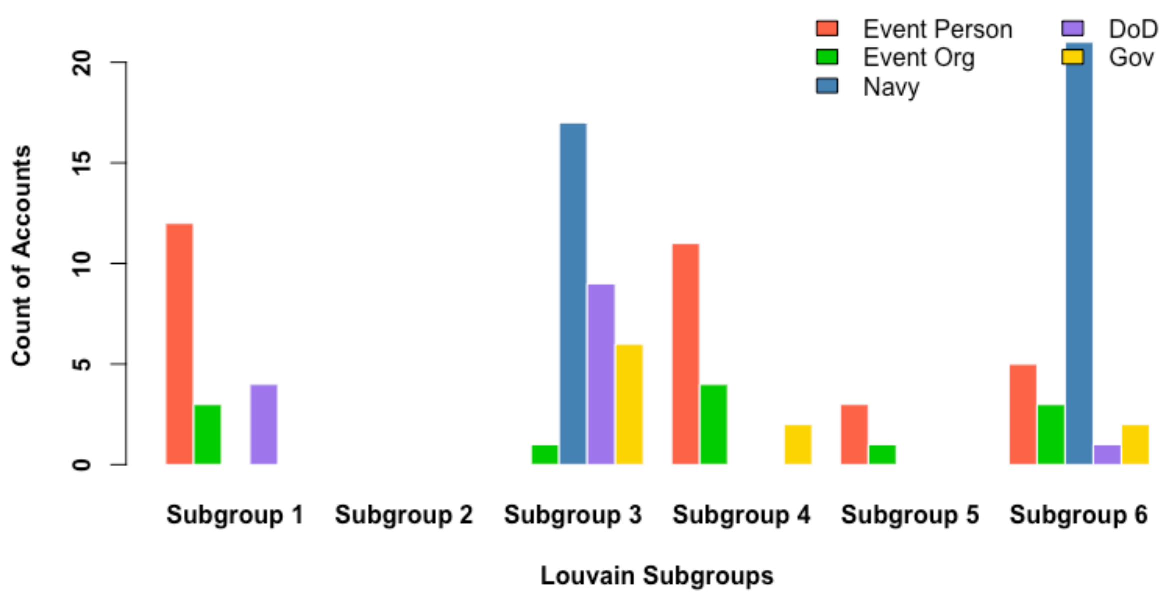

Figure 19: Counts of nodes by account type (not including "Other") for each subgroup that contained more than two nodes based on Louvain algorithm.

Content Analysis

One way to evaluate the Navy Innovation Network is analyze how people are writing about innovation in the Navy and in the DoD. Based on the social network analysis of the Twitter network and input from subject matter experts, ten blogs were identified as influential fora in which people write about innovation in the Navy and the DoD. These accounts, as well as the colors used to visualize the data, are shown in Table 3, below.

Table 3: Websites Scraped and the subgroups their Twitter handle belongs to in the Retweets Replies and Mentions network

Name	Website	Color	Twitter Account	K-Core	Subgroup
The Athena Project	athenanavy.wordpress.com		AthenaNavy	A	4
CIMSEC	cimsec.org		CIMSEC	A	6
DEF Conference	defenseentrepreneurs.org		DEFConference	A	1
General Leadership	generalleadership.com		GenLeadBlog	NA	NA
Modern Warfare Institute	mwi.usma.edu		WarInstitute	NA	NA
Sean Heritage	seanheritage.com		SeanHeritage	D	1
Small Wars Journal	smallwarsjournal.com		smallwars	A	1
Task and Purpose	taskandpurpose.com		TaskandPurpose	A	1
US Naval Institute	news.usni.org		NavalInstitute[4]	A	6
War on the Rocks	warontherocks.com		WarOnTheRocks	A	1

Most of the websites identified are a part of the Retweets Replies and Mentions network; General Leadership and Modern Warfare Institute are the exception. Twitter accounts for the websites are highlighted in the Retweets Replies and Mentions network in Figure 20. The majority of the websites' Twitter accounts are a part of the central-most core of the Retweets Replies and Mentions network (belonging to K-Core Group A), as shown above in Table 3. These Twitter accounts do not all belong to the same subgroup based on the community detection algorithm. @AthenaNavy is the site belonging to Subgroup 4, the primary Navy innovation subgroup. The twitter accounts for CIMSEC and US Naval Institute belong to Subgroup 6, which focus on specific communities of interest within the Navy. The other four websites that have Twitter accounts as part

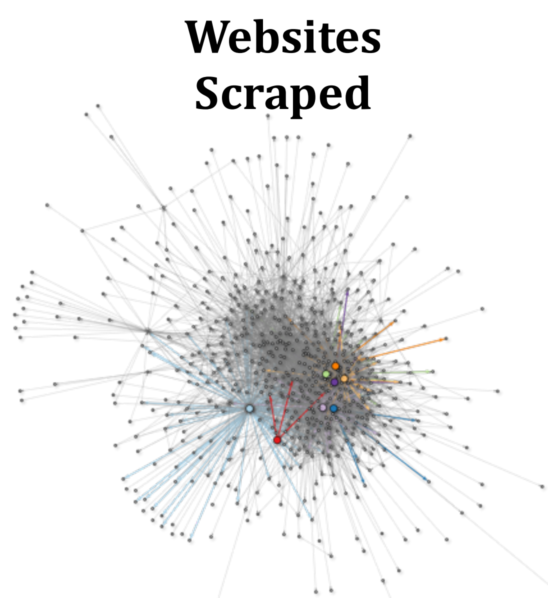

Figure 20: Retweets, Replies, and Mentions network with nodes colored by website, ties colored by node source, and nodes and ties sized to highlight websites scraped

[4] The Twitter account for the US Naval Institutes news site is @USNInews, but because that account is not in this network the account for the US Naval Institute as a whole, @NavalInstitute, is used instead.

of the Retweets Replies and Mentions network belong to Subgroup 1, which focuses on innovation across the entire DoD.

All of the ten blogs in Table 3 contain articles about innovation. Using Beautiful Soup, a Python package for scraping websites, each article or blog post that contained "innovation" or a tag associated with innovation was saved. The number of articles saved for each blog are shown in below Table 4.

Table 4: Number of articles saved and number of articles connected to LDA topics for each blog

Name	Color	Articles Saved	Articles in LDA Network
The Athena Project		92	92
CIMSEC		64	59
DEF Conference		8	8
General Leadership		8	8
Modern Warfare Institute		68	68
Sean Heritage		312	312
Small Wars Journal		557	510
Task and Purpose		107	105
US Naval Institute		133	131
War on the Rocks		91	91

Content analysis using the Latent Direchlet allocation method (LDA), a machine learning algorithm (Blei et al., 2003; Grün & Hornik, 2011), was performed on the document data collected in order to extract sets of words that correspond to a topic of interest. Thirty-three topics were created, each associated with a set of words.[6] Words for each topic are ranked according to the probability they are likely to appear in a document related to that topic. Table 5 gives the top ten words for four different topics. Additionally, each topic in Table 5 is named according to the highest ranked word.

Table 5: Four example topics from this analysis with the top 10 words[5]

Topic 3 "Team"	Topic 9 "Defense"	Topic 12 "Navy"	Topic 14 "Innovation"
team	defense	navy	innovation
time	dod	marine	ideas
people	technology	naval	organization
don	innovation	corps	military
life	department	ship	change
make	secretary	sea	disruptive
things	pentagon	ships	leaders
work	acquisition	fleet	innovative
opportunity	budget	marines	thinking
day	industry	maritime	culture

[5] As part of pre-processing for content analysis, common words are dropped and each word is converted to lowercase. This results in certain acronyms being lowercase; "DOD" becomes "dod" and DON becomes "don".
[6] The number of topics was automatically selected through a method that identifies the optimal number of topics (Taddy, 2012).

Each document (article or blogpost) is connected to a topic based on the words found in the document and the words assigned to the topic, resulting in a weighted two-mode network (Gretarsson et al., 2012). Weighted ties of less than 0.1 are dropped, and only those documents connected to a topic are kept. The number of articles from each website connected to a topic is found in Table 4. The resulting two-mode network, with articles (colored circles) connected to topics (dark grey squares) is visualized below in Figure 21.

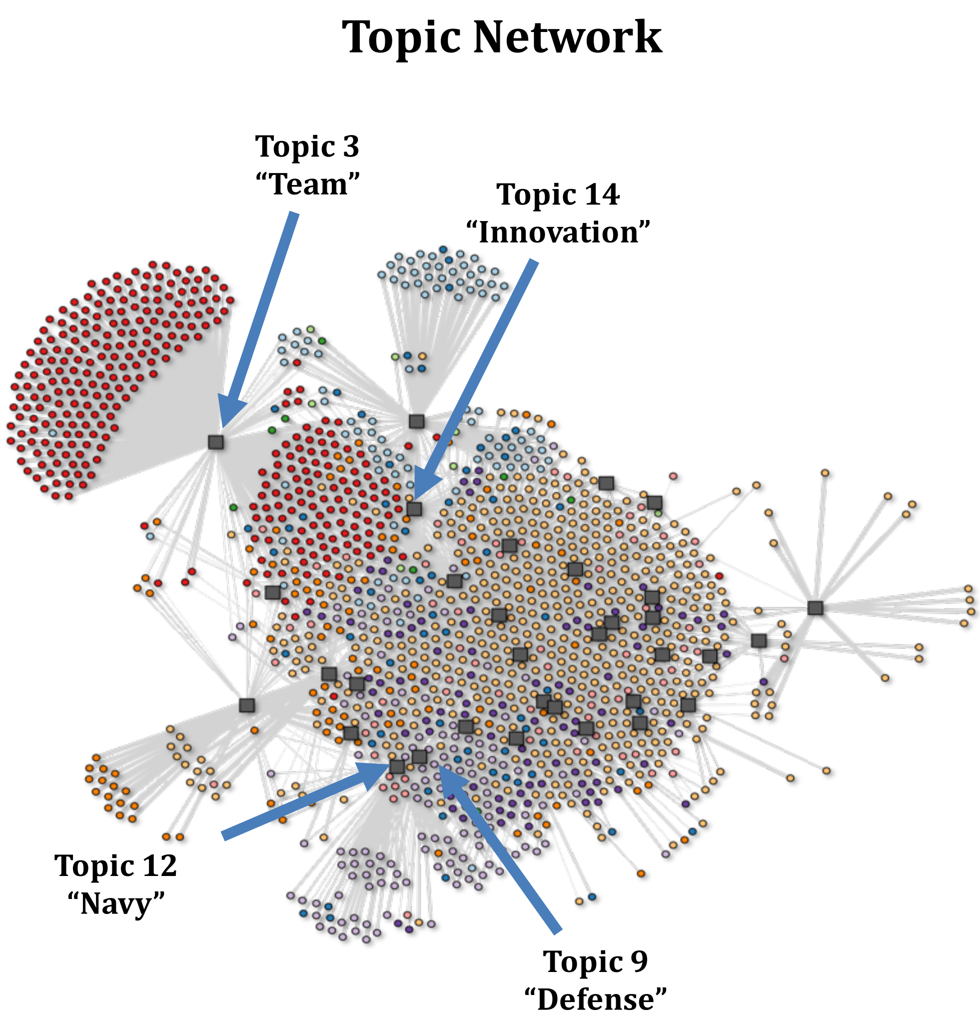

Figure 21: Topic network based on LDA analysis. Articles as circles and colored by website and topics as dark grey squares

The two mode Topic network provides the means to visualize articles written about innovation by the source-site. First, in Figure 21 the articles are colored by the originating site. This offers the ability to see which sites address unique topics and which sites share common topics. For example, the majority of Sean Heritage's articles, red in the upper left of Figure 21 and highlighted in Figure 22, are connected to Topic 3, or the "Team" topic (see Table 3 for key-words). Additionally, the topic related to teams is mostly addressed in articles from Sean

Heritage's site, with 309 of the 411 articles (75%). This suggests that Sean Heritage's site has a large number of articles that address innovation in terms that are quite different than other sites. Also, Sean Heritage's Twitter account in the Retweets Replies and Mentions network is very much on the periphery, located in K-Core Group D (Table 3), and therefore ideas related to teams (Topic 3) might not be well integrated into the overall Navy Innovation Network.

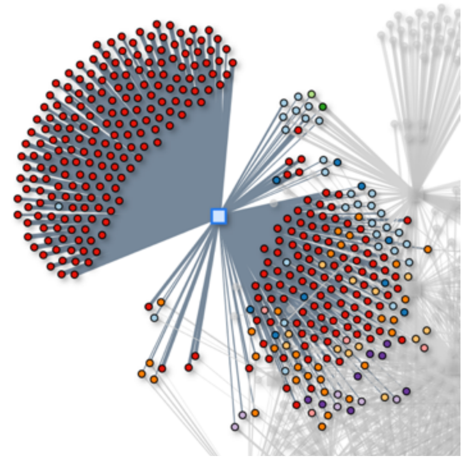

Figure 22: Highlighting Topic 3, with articles connected to the topic colored by website.

Other topics are more central to the network as a whole, with articles sourced from many different sites. Near the center of the Topic network in Figure 21, and highlighted in Figure 23, is the "Innovation" topic (see Table 5 for keywords). The central location of this topic, indicates its importance. Also, this Innovation topic is clearly relevant for the Navy Innovation Network. Additionally, as shown in Figure 23, this topic is connected to at least one article from each website.

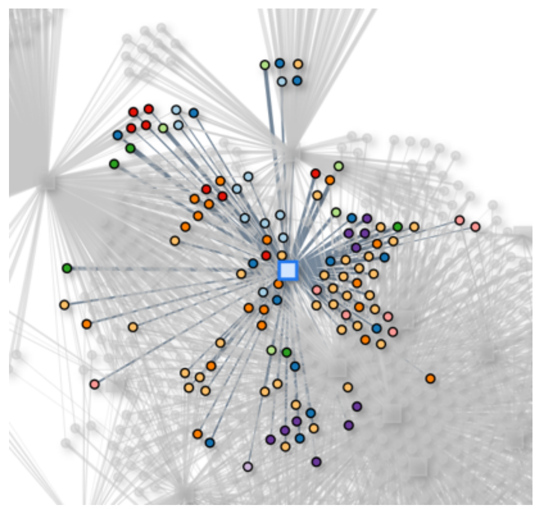

Figure 23: Highlighting Topic 14, with articles connected to the topic colored by website

As illustrated in Figure 21, topics with similar content/terminology appear closer to each other in the network. For example, the "Defense" topic and "Navy" topic (Topic 9 and Topic 12) are located close to each other in the bottom left of the network (Figure 21), because a number of articles address both topics (49 articles are connected to both topics). Based upon the words associated with the topics (Table 5) and the color coding of sources, it is possible to identify the best source that address ideas associated with the different topics. For instance, if one wanted to identify sources of articles dealing with Defense issues (Topic 9) and the Navy (Topic 12), Figure 24 indicates that US Naval Institute's has the most articles to choose from, (44 of the 49 articles come from US Naval Institute).

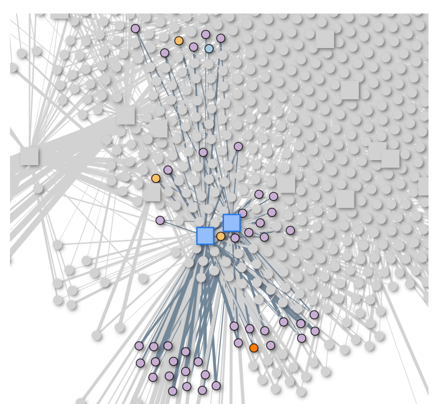

Figure 24: Highlighting Topic 9 (Defense) and Topic 12 (Navy) with articles connected to both colored by website.

Picking out key topics and sources is one method that might be used to better connect the Navy Innovation Network to a wider community of interest.

RESEARCH QUESTIONS AND FINDINGS

This research sought answers to the following the questions:

- A - What are the key nodes and networks in the Navy Innovation Network?
- B - What are the ties that link together members of the informal network?
- C - How could we more effectively bridge together individuals and clusters within the social network of Navy innovators (from the deck plates up)?
- D - How can we measure the growth and effectiveness of Navy innovation networks to enhance collaboration?
- E - Can we longitudinally measure the impact Navy formal and informal innovation networks have on enhancing the Navy's effectiveness and rapid prototyping capabilities?
- F – What strategies would be best suited to move innovation from the deck plates to those best placed to adopt new ideas for rapid prototyping?

Based on the research discussed above, the following findings are provided in response to the research questions:

A - What are the key nodes and networks in the Navy Innovation Network?
While there are several institutional offices within the Navy that serve as hubs for innovation (such as DUSN(M)/NIAC/Strategic Innovation Office, Navy RDT&E Strategic Cell, and others cited earlier) and in the Department of Defense (such as the Defense Entrepreneurs Forum, AFCEA, and DIUx) provide areas for both events and a social media presence. This brings together various individual sailors, who themselves can be central in bringing new ideas from one event to another, or be influential for spreading knowledge via social media or other public forums. Regional events can create clusters of local innovation networks, with larger events, social media, and publishing articles via blogs or websites playing a role in spreading the information across the greater community.

Based on subgroup analysis the following key nodes and hubs were identified through Twitter analysis: @AthenaNavy (events and official twitter account) to access Navy innovation subgroup (Subgroup 4); @DEFConference, for accessing DoD innovation subgroup (Subgroup 1); @USNavy and @NavyInnovation, to access the upper levels of the Navy (Subgroup 3); @CIMSEC and @NavalInstitute, for accessing policy and specific areas of the Navy (Subgroup 6).

Our research found that official, or organizational, accounts can play a role as key hubs or brokers of information; while individuals can serve as authorities, or sources of information. We identified several of these.

B - What are the ties that link together members of the informal network?
This research used the Louvain algorithm for extracting subgroups from a Twitter network by determining whether the ties between nodes are internally dense and externally sparse. This algorithm maximized the modularity score to identify five different subgroups. The location of nodes and their ties within the layered core of the network provided the means for community detection. **It was found that in many cases, ties were stronger among nodes that belonged to both the twitter network and the events network**.
Of the seven subgroups identified, subgroups three, four, and six were of particular interest to the Navy.

The third subgroup (Figure 17 above) contains 84 accounts. **The majority of official Navy Twitter accounts in this network are included in this subgroup. These Navy accounts are also relatively central in this subgroup.**

The fourth subgroup (Figure 17 above) is the subgroup that contains @AthenaNavy. **This subgroup is where many accounts that are highly involved in innovation in the Navy are likely located.**

The sixth subgroup (Figure 18 above) contains 114 accounts. **This is the subgroup that contains different regional or specialty areas for the Navy.**

Also of note, the first subgroup identified (Figure 17 above) contains 114 accounts and **is the subgroup with the largest number of accounts by people who attended events in the initial network**. It is visualized on the top left of Figure 17 above. The most central accounts, in terms of in-degree centrality, are people and events from the Event network. While there are no official Navy accounts in this subgroup, it seems to be the area where people and organizations are engaged regarding innovation in the entire DoD. Engaging this subgroup would be useful for either incorporating relevant ideas from the rest of the DoD, or injecting ideas from the Navy into the larger DoD.

C - How could we more effectively bridge together individuals and clusters within the social network of Navy innovators (from the deck plates up)?
Based on community detection analysis, **it would seem logical that the Navy may benefit from using official Navy accounts in Subgroup 3 (Navy Leadership) to pass along information generated in Subgroup 4 (Navy innovation subgroup). This information could be targeted towards accounts in Subgroup 6 (as conduits for Navy topics of interest).** This could be accomplished by institutionalizing outreach to better connect the NIN to other groups in the Navy through networks of events, organizations, and social media. Additionally, the outreach

could also be institutionalized to the larger DoD in order to capture the information generated by individuals already engaging with other parts of the military.

D - How can we measure the growth and effectiveness of Navy innovation networks to enhance collaboration?
It is apparent from the preliminary social network analysis conducted at NPS, that **it is possible to dynamically update and periodically measure and assess the NIN network and the number and strength of ties to the wider innovation community**.

E - Can we longitudinally measure the impact Navy formal and informal innovation networks have on enhancing the Navy's effectiveness and rapid prototyping capabilities?
By monitoring the number of innovations originating in the NIN that subsequently result in Fleet implementation and/or rapid protoyping, and **conducting correlation analysis, it should be possible to longitudinally assess the impact the NIN is having on the enhancement of Navy capabilities over time**.

F – What strategies would be best suited to move innovation from the deck plates to those best placed to adopt new ideas for rapid prototyping?
Thesis student LT William Huff, USN is exploring strategies to institutionalize the adoption of innovation through rapid prototyping. His thesis will be completed in Mar 18 and will be provided to DUSN(M).

TASKS

Tasks are delineated below and a Milestone Matrix with deliverables and dates is provided in another section of the proposal.

Task 1: Identify Data Requirements / Literature Review

Literature Review is provided in Appendix A. This research will be informed by earlier work done in related areas.

Task 2: Develop Conceptual Model

Social network matrices were developed for identifying and characterizing the nodes (individuals, official groups, unofficial groups, events, locations, activities, projects, research topics, twitter accounts) associated with the Navy Innovation Network. Social network analysis commercial software was used to construct graphical depictions of topologies and sociograms of the Navy Innovation Network to mathematically measure the centrality, density, clustering, cohesiveness, structural holes, and strength of ties associated with the network longitudinally over a fixed period of time using both one mode and two mode analysis.

The Louvian community detection algorithm was used to identify hubs and subgroups and the Latent Direchlet allocation (LDA) method was used for extracting topics from the text documents.

Steps in this process included:

1. Define what constitutes an innovator, innovative organization, event, community of interest, location (commons), and outcome within the context of the Navy Innovation Network.
2. Determine how to identify and characterize member-nodes and build a repository of related data.
3. Use this data to populate a matrix (or matrices) using commercially available social network analysis software (ORA, UCINET)
4. Create graphic representations of the social network topology and sociograms.
5. Determine the extent of benefit provided by network behavior and outcomes.
6. Offer suggested strategies to leverage the Navy Innovation Network in order to enhance overall readiness, effectiveness, and capacity of Naval Forces while countering internal latencies inherent in a complex and turbulent environment.

Task 3: Running the Model to Provide Empirical Evidence

The integration of open source data provided enhanced qualitative and quantitative understanding of the relational links between network nodes.

Measurement of network metrics provided detailed analysis of the Navy Innovation Network structure (e.g. eigenvector centrality, density, clustering, cohesiveness/structural holes, K-core analysis of sub-groups).

The sponsor, DUSN-Manpower, and supporting agencies including DASN RDT&E, Navy Warfare Centers and Labs, and the Naval Innovation Advisory Council were regularly consulted to ensure sponsor interests and objectives were being addressed. This iterative interaction with stakeholders was be cited in Quarterly In-Progress Reports (IPRs).

Task 4: Present Initial Findings

Initial findings were provided through Quarterly reviews and in this Final Technical Report.

Task 5: Quarterly In-Progress Reviews (IPR) Schedule.

Quarterly In-Progress Reviews were all delivered on schedule.

Task 6: Deliver Final Report/ Final Presentation Schedule

The Final Technical report represents this deliverable. The student thesis will be delivered upon completion.

Table 1: Proposal Deliverables and Task Completion Milestones

Deliverables:

1) Quarterly IPRs
2) Final Technical Report, Executive Summary, Research Poster prepared by the PI.
3) Thesis prepared by NPS student.
4) Final briefing presentation with slides prepared and presented to the sponsor by the PI, Research Associates, and NPS student.

Tasks	Tasks Description	Deliverables	Topic Sponsor Review	Final Version	Task Completion
1	Review Prior Lit.	Review of material12/16	Periodic	Lit Review	Q1 12/16
1/5	IPR#1	Dec 16	Dec 16		Q1 12/16
2	Develop Model	Graphical topologies and sociograms of the Navy Innovation Network 03/17	Periodic	Completed social network matrices and graphical depictions of network structure	Q2 03/17
2	Identify Data Bases	Identification of open-sourced data bases necessary to populate and update innovation network matrices. 03/17	Periodic	Algorithms will be developed to search these databases and integrate relevant information	Q2 03/17

2/5	IPR#2	Mar 17	Mar 17		Q2 03/17
3	Running the Model to Provide Empirical Evidence	Integration of data from various open source databases and sources of information including social media fora. 06/17	Periodic	Measure of network metrics will provide detailed analysis of the network structure and live data will contribute augment historic trend analysis.	Q3 06/17
3/5	IPR#3: Update	Jun 17	Jun 17		Q3 06/17
4	Initial Findings	Trend analysis will be conducted of longitudinal measurements of key metrics. 09/17	Periodic	Strategies to enhance the utility of the network and its outcomes will be provided in the initial technical reports and thesis.	Q4 09/17

4/5	IPR#4	Sep 17	Sep 17		Q4 09/17
6	Deliver Report	The final technical report, thesis, project briefing presentation Dec 17	Upon completion	Final Technical Report, Executive Summary, Research Poster, Thesis, and Briefing Presentation for sponsor and interested stakeholders	Q5 12/17

LITERATURE REVIEW

Backstrom, L., Huttenlocher, D., Kleinberg, J., & Lan, X. (2006). Group formation in large social networks. *The 12th ACM SIGKDD International Conference*, 44–54.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research*, *3*, 993–1022.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*(10), P10008.

Borgatti, S. P., Everett, M. G., & Johnson, J. C. (2013). *Analyzing Social Networks*. SAGE Publications Limited.

Borgatti, S. P., & Lopez-Kidwell, V. (2014). Network Theory. In J. Scott & P. J. Carrington (Eds.), *The SAGE Handbook of Social Network Analysis* (pp. 40–55). London: SAGE Publications Ltd.

Burt, R. S. (1992). *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Burt, R. S. (2000). *The Network Structure of Social Capital*. *Organizational Behaviour* (Vol. 22).

Carrington, P. J., Scott, J., & Wasserman, S. (Eds.). (2005). *Models and methods in social network analysis*. New York, NY: Cambridge University Press.

Cross, R., Borgatti, S. P., & Parker, A. (2001). Beyond answers: Dimensions of the advice network. *Social Networks*, *23*(3), 215–235. https://doi.org/10.1016/S0378-8733(01)00041-7

Emirbayer, M., & Goodwin, J. (1994). Network Analysis, Culture, and the Problem of Agency. *American Journal of Sociology*, *99*(6), 1411–1454.

Everton, S. F. (2012). *Disrupting Dark Networks*. New York, NY: Cambridge University Press.

Franzese, R. J., Hays, J. C., & Kachi, A. (2012). Modeling History Dependence in Network-Behavior Coevolution. *Political Analysis*, *20*(2), 175–190.

Freeman, L. C. (1979). Centrality in Social Networks Conceptual Clarification. *Social Networks*, *1*, 215–239.

Freeman, L. C. (2016). The Development of Social Network Analysis – with an Emphasis on Recent Events. In J. Scott & P. J. Carrington (Eds.), *The SAGE Handbook of Social Network Analysis* (pp. 26–39).

Granovetter, M. (1973). The Strength of Weak Ties. *American Journal of Sociology*.

Granovetter, M. (1983). The Strength of Weak Ties: A Network Theory Revisited. *Sociological Theory*, *1*, 201–233.

Granovetter, M. (1985). Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology*, *91*(3), 481–510.

Gretarsson, B., O'Donovan, J., Bostandjiev, S., Höllerer, T., Asuncion, A., Newman, D., & Smyth, P. (2012). TopicNets. *ACM Transactions on Intelligent Systems and Technology*, *3*(2), 1–26.

Grün, B., & Hornik, K. (2011). topicmodels: An R Package for Fitting Topic Models. *Journal of Statistical Software*, *40*(13), 1–30.

Hays, J. C., Kachi, A., & Franzese, R. J. (2010). A spatial model incorporating dynamic, endogenous network interdependence: A political science application. *Statistical Methodology*, *7*(3), 406–428.

Horgan, J., Kenney, M., Bloom, M., Horne, C., Braddock, K., Vining, P., … Bigrigg, M. (2010).

Adversarial Behavior in Complex Adaptive Systems : An Overview of ICST ' s Research on Competitive Adaptation in Militant Networks *. *APSA 2010 Annual Meeting Paper*.

Hurlbert, J., Beggs, J. J., & Haines, V. (2001). Social Networks and Social Capital in Extreme Environments. In N. Lin, K. Cook, & R. S. Burt (Eds.), *Social Capital Theory and Research* (pp. 209–232). New York: Routledge.

Johnson, J. A., Reitzel, J. D., Norwood, B. F., McCoy, D. M., Cummings, D. B., & Tate, R. R. (2013, March). Social Network Analysis: A Systematic Approach for Investigating. *Law Enforcement Bulletin*.

Kadushin, C. (2012). *Understanding Social Networks: Theories, concepts, and findings*. New York: Oxford University Press.

Klandermans, B., & Oegema, D. (1987). Potentials, Networks, Motivations, and Barriers: Steps Towards Participation in Social Movements. *American Sociological Review*, *52*(4), 519–531.

Kleinberg, J. M. (1999). Authoritative Sources in a Hyperlinked Environment. *Journal of the ACM*, *46*(May 1997), 668–677.

Kostiuchenko, T. (2011). Paths/Walks/Cycles. In *Encyclopedia of Social Networks* (pp. 696–697). SAGE Publications.

National Research Council. (1998). *Modeling Human and Organizational Behavior*. (R. W. Pew & A. S. Mavor, Eds.). Washington, DC: National Academy Press.

Ortiz-Arroyo, D. (2010). Discovering Sets of Key Players in Social Networks. In A. Abraham & V. Snášel (Eds.), *Computational Social Network Analysis: Trends, Tools and Research Advances* (pp. 27–47). London.

Ozkan-Canbolat, E., & Beraha, A. (2016). Configuration and innovation related network topology. *Journal of Innovation & Knowledge*, *1*(2), 91–98. 3

Prell, C. (2012). *Social network analysis : history, theory & methodology*. *Sage*. London, UK: SAGE Publications.

Richardson, J. M. (2016). *A Design for Maintaining Maritime Superiority*.

Robins, G., Snijders, T., Wang, P., Handcock, M., & Pattison, P. (2007). Recent developments in exponential random graph (p*) models for social networks. *Social Networks*, *29*(2), 192–215.

Scott, J., & Carrington, J. (2014). *The SAGE Handbook of Social Network Analysis*. (J. Scott & J. Carrington, Eds.). London: SAGE Publications Ltd.

Taddy, M. a. (2012). On Estimation and Selection for Topic Models. *Proceedings of the Fifteenth International Conference on Artificial Intelligence and Statistics (AISTATS 2012)*, (2003), 1184–1193.

Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge University Press.

Watts, D. J. (2004). *Six Degrees: The science of a connected age*. New York, NY: WW Norton.

Stakeholders and Sources Identified:

1. **Defense Entrepreneurs Forum**
   a. Website
      i. www.defenseentrepreneurs.org
   b. Facebook

        i. https://www.facebook.com/DefenseEntrepreneurs/
        ii. https://www.facebook.com/DEFxSD/?fref=ts
        iii. https://www.facebook.com/DEFxSV/?fref=ts
        iv. https://www.facebook.com/events/932254493568327/
        v. https://www.facebook.com/groups/1470527806557261/?fref=nf
    c. Twitter
        i. www.twitter.com/DEFConference
        ii. www.twitter.com/DEFannapolis
        iii. www.twitter.com/benningagora
        iv. www.twitter.com/uk_def

2. **Athena Project**
    a. Website
        i. http://athenanavy.com/
    b. Facebook
        i. https://www.facebook.com/athenanavy/
    c. Twitter
        i. www.twitter.com/athenanavy

3. **LinkedIn**
    a. Naval Innovation Network

4. **Bunker Labs**
    a. Facebook
        i. https://www.facebook.com/thebunkerlabs/
        ii. https://www.facebook.com/bunkerlabssiliconvalley/?fref=ts
        iii. https://www.facebook.com/bunkerlabsjax/?fref=ts
        iv.

5. **CNO's Rapid Innovation Cell (CRIC)**
    a. Facebook
        i. https://www.facebook.com/NavyCRIC/

6. **SECNAV's Strategy and Innovation Department**
    a. Website
        i. www.secnavy.navy.mil/innovation
    b. Facebook
        i. https://www.facebook.com/NavalInnovation/

7. **Tactical Advancement for Next Generation (TANG)**
8. **Strategic Studies Group**
9. **Navy Warfare Development Command's (NWDC) Navy Center for Innovation**

a. http://www.navy.mil/submit/display.asp?story_id=75060

10. Task Force Innovation (SECNAV)

a. https://www.navytimes.com/story/military/2015/04/15/navy-secretary-mabus-unveils-task-force-innovation-sea-air-space/25816721/