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Analysis of Innovation Communities of Interest for Technology Transfer and Development

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ABSTRACT

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." The *Department of the Navy Additive Manufacturing Implementation Plan* states that, "The U.S. Navy and Marine Corps are realizing the potential of additive manufacturing to transform the Department of the Navy through innovation in design, rapid prototyping, and future applications that enable warfighter readiness and self-sustainment during operations." Through the Department of the Navy's Small Business Innovation Research (SBIR) Program, small businesses of 500 people or less have the opportunity to address naval needs in more than 30 science and technology areas. SBIR provides the fleet with innovative advances in technology developed by small firms. SBIR participants benefit both from program awards as well as the further development and commercialization of the resulting products. In addition, the Navy *Small Business Technology Transfer (STTR)* program is intended to foster transitions of joint efforts between qualified small businesses and research institutions to Navy and Marine Corps, in particular navysbir.com. 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 these social innovation networks using open source data and voluntarily provided information, the Navy can amplify effects generated within additive manufacturing communities of interest to increase warfighter readiness and self-sustainment.

Researchers coded and developed *social network* matrices of US Government agencies, contracting offices, and vendors (nodes) who are currently linked together through *communities of interest* within and outside the Navy pursuing technologies aimed at improving *Navy additive manufacturing capabilities*. Through the use of commercially available social network analysis software, the matrices (of Agencies, Contracting and Requesting Offices, Vendors, and Topics) were populated and used to develop graphical two and three dimensional *topologic/sociogram depictions* of the additive manufacturing innovation community of interest network that connects these nodes. These matrices were dynamically updated by *open source databases* with information related to contracts, vendors, areas of technology, and agencies in the area of additive manufacturing (with a focus on research, development, and production contracts awarded as well as with topics of interest). Metrics of *centrality, fragmentation, constraint, cohesiveness/structural holes, and clustering* can then be longitudinally measured to determine how best to increase the network's effectiveness and integration with ongoing commercial research in order to more efficiently capitalize on collaboration, new ideas and technologies to improve additive manufacturing capabilities for the Navy.

Keywords: *social network analysis, Small Business Technology Transfer (STTR), topologic/sociogram depictions, centrality, fragmentation, constraint, cohesiveness/structural holes, clustering, communities of interest, Navy additive manufacturing capabilities, open source databases*

EXECUTIVE SUMMARY

Researchers gathered data from various government sources in order to understand how the US Navy and other Services/Agencies are funding additive manufacturing research and development. Initial data was gathered from the Small Business Innovation Research database (Small Business Administration, 2017) and the USASpending.gov database (USASpending.gov, 2017) for Prime Awards and Sub-awards that contained any of the following search terms: “Additive Manufacturing”, “Direct Digital Manufacturing”, or “3-D Printing.” The datasets were then combined using the identification numbers associated with the Prime Awards and Sub-awards and additional searches were performed in order to supplement missing information from the initial searches.

Researchers at NPS collected 302 different additive manufacturing-related contracts for financial assistance (direct grant or cooperative agreement), 464 different contracts for Prime Awards, and 93 for Sub-awards covering the government fiscal years of 2008-2017. Twenty-five different Agencies or bureaus and 119 different Contracting and Requesting Offices were involved by either funding a Prime Award or Sub-award or by requesting funding for a specific project that was fulfilled through a Prime Award or Sub-award.

Social network analysis was used to longitudinally analyze funding for projects in order to see how the community of government offices and vendors working on additive manufacturing evolved over time. Networks were initially created by graphing connections of project requests and funding sources to Prime Awards and Sub-awards, and also by connecting Prime Awards and Sub-awards to the vendors receiving them. Agencies were connected to their Contracting offices and Requesting offices. Sub-awards were also connected to their Prime Awards. Overall, the additive manufacturing network has been increasing in size and decreasing in fragmentation (a measure of disconnectedness within a network). The periods when the network size increased the most tended to have a decrease in the clustering coefficient, but this is to be expected when new Vendors or Contracting and Requesting Offices become involved in additive manufacturing. Over time, these Vendors or Contracting and Requesting Offices should be expected to have a higher level of clustering due to increased coordination and cooperation within the additive manufacturing community.

Key nodes were identified by analyzing the entire network across all time periods (2008 – 2017) and identifying nodes that spanned “structural holes” or gaps within the network. This analysis evaluates each node’s constraint, a brokerage measure for each node that calculates how infrequently a node lies in triadic brokerage positions (Burt, 1992; Everton, 2012). Nodes with low constraint have high brokerage, thereby spanning more structural holes (gaps in connectivity), and tend to be areas where new ideas or innovation may occur.

In addition to establishing contracting connections through funding requests or funding as discussed earlier, abstracts for the Prime Awards and Sub-awards were analyzed using Latent Direchlet Allocation (LDA), a machine learning algorithm that extracts sets of words that correspond to a common topic (Blei, Ng, & Jordan, 2003). This topic analysis was applied to the abstracts or product descriptions in order to determine whether the evolving communities coalesced around specific topics, or where there were potential areas for collaboration. Analyzing network topography measures over time, such as fragmentation and the local clustering coefficient, as well as measuring clustering associated with specific topics of interest could enhance the Navy's ability to improve efficiency by optimizing resources. This would potentially contribute to the rapid protoyping of additive manufacturing technologies.

Structurally, nodes with low constraint have the most potential to facilitate the exchange of ideas or information about additive manufacturing by coordinating with a variety of different Agencies, Contracting and Requesting Offices, and/or Vendors. The nodes with lowest constraint can be agencies, Contracting and Requesting Offices, or Vendors, because each of these different node types plays a different role in the network. Among the Agencies with least constraint were The National Science Foundation, The Department of Defense, The Department of Energy, the Department of the Air Force, and the Department of the Navy. Among Contracting and Requesting Offices with least constraint were NASA Shared Services Center, FA8650 USAF AFMC AFRL RQK, Office of Naval Research, DARPA, and DES DSCP Contracting Services Office. Among Vendors with least constraint were Ues, Inc, Materials & Electrochemical Research Corp, Nscrypt, Inc, Calram, Inc, and Questek Innovations LLC.

Clusters were identified within the overall Additive Manufacturing Network by analyzing contractual connections among Agencies, Contracting and Requesting Offices, and Vendors and by extracting sub-networks based on project topics. Abstracts for the Prime Awards and Sub-awards were analyzed using Latent Direchlet Allocation (LDA). Overall, the additive manufacturing network has been increasing in size and decreasing in fragmentation.

Increasing clustering of individual innovators as well as Agencies, Contracting and Requesting Offices, and Vendors around specific topics of interest across the whole of government could help eliminate redundancies or increase cost effectiveness. Searching out those who are working on similar ideas and encouraging partnerships (when practical) would help bridge individuals and organizations to clusters within the network.

BACKGROUND

In a 2015 report entitled, DOD Needs to Systematically Track Department-wide 3D Printing Efforts, the Government Accounting Office found that, "DOD has taken steps to implement additive manufacturing to improve performance and combat capability, and to achieve cost savings. GAO obtained information on multiple efforts being conducted across DOD components. DOD uses additive manufacturing for design and prototyping and for some production, such as parts for medical applications; and it is conducting research to determine how to use the technology for new applications." The report goes on to state, "However, DOD does not systematically track additive manufacturing efforts, to include (1) all activities performed and resources expended by DOD; and (2) results of these activities, including actual and potential performance and combat capability improvements, cost savings, and lessons learned. DOD has not designated a lead or focal point at a senior level to systematically track and disseminate the results of these efforts, including activities and lessons learned, department-wide. Without designating a lead to track information on additive manufacturing efforts, which is consistent with federal internal control standards, DOD officials may not obtain the information they need to leverage ongoing efforts." (Merritt, Z. D. (2015). DOD Needs to Systematically Track Department-wide 3D Printing Efforts. GAO Reports, I-44. Retrieved from http://www.gao.gov/assets/680/673099.pdf)

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." The *Department of the Navy Additive Manufacturing Implementation Plan* states that, "The U.S. Navy and Marine Corps are realizing the potential of additive manufacturing to transform the Department of the Navy through innovation in design, rapid prototyping, and future applications that enable warfighter readiness and self-sustainment during operations." Through the Department of the Navy's Small Business Innovation Research (SBIR) Program, small businesses of 500 people or less have the opportunity to address naval needs in more than 30 science and technology areas. SBIR provides the fleet with innovative advances in technology developed by small firms. SBIR participants benefit both from program awards as well as the further development and commercialization of the resulting products. In addition, the Navy Small Business Technology Transfer (STTR) program is intended to foster transitions of joint efforts between qualified small businesses and research institutions to Navy and Marine Corps, in particular navysbir.com. 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 these social innovation networks using open source data and voluntarily provided information, the Navy can amplify effects generated within additive manufacturing communities of interest to increase warfighter readiness and self-sustainment.

Illustrative Example: The **graph to the right** illustrates which labs in the DoD have spent the most on additive manufacturing over the last 20 years. The **graph below** illustrates how much funding SBIR contracts companies have received. Data was pulled from the SBIR website and illustrates how a rudimentary analysis of various community members could yield actionable insights for an intra- or entrepreneur, and accelerate the development of the most compelling concepts **(LT Drew Barker, USN)**.

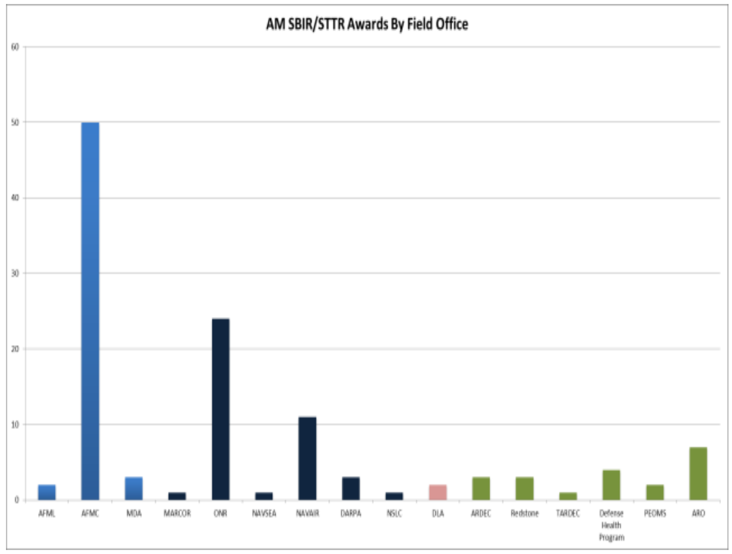

Figure 1: Number of awards by DoD labs for additive manufacturing

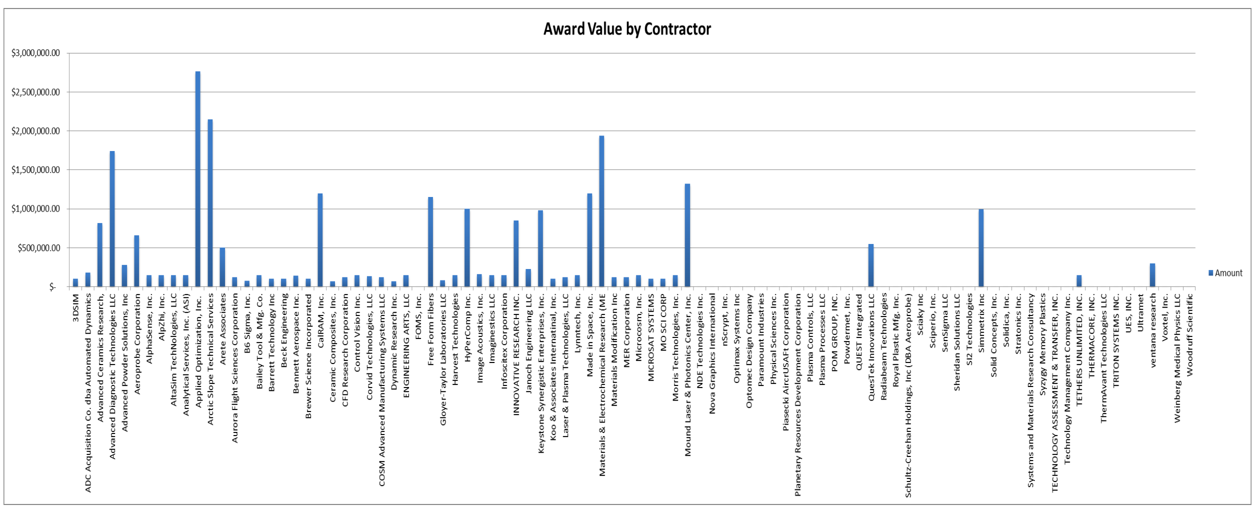

Figure 2: SBIR money received by companies for work on additive manufacturing.

Funding Received Through SBIR Contracts

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, and 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 (Carley, Horgan, Kenney, Bloom, Horne, Braddock, Vining, and Zinni, 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 (Pew, Mavor, 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 Navy professionals, entrepreneurs, intrapreneurs, and technology innovation communities of interest, social network analysis provides a method and tools for identifying, mapping, and measuring the emergent network of those eager to contribute their knowledge and experience in the pursuit of additive manufacturing 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 Navy professionals, command-initiatives, DASN RDT&E, Naval Warfare Centers, Labs and small business technology development efforts in order to drive creative insights toward innovative and actionable solutions focused on additive manufacturing.

The Navy additive manufacturing innovation communities of interest may be analyzed through either one mode or two made matrices: one mode analysis ties Vendors to Vendors for example, and two mode analysis ties, for example, Vendors to funding sources/sponsoring commands. Relational data to create networks within communities of interest can be obtained through algorithmic searches designed to sort large data sets from dynamic, open source (technological, news, military, and industry) data bases (Hays, et al, 2010; Franzese, et al, 2012; Robbins, et al, 2007). The use of social network analysis that integrates attribute data (stakeholder/agent characteristics) with relational data provides metrics for network analytics such as eigenvector centrality, density, clustering and fragmentation, and cohesiveness/structural holes (Kadushin, 2012; Watts, 2004; Borgatti, Everett, Johnson, 2013; Freeman, 2013, Granovetter, 1973; Prell, 2012).

The collection and collation of relational and attribute data among stakeholders by employing the tools of social network analysis and big data integration from existing databases could significantly contribute to our ability to identify redundant efforts, increase coordination among Contracting and Requesting Offices and Vendors, and enhance product development while potentially reducing costs.

RESEARCH OVERVIEW AND FINDINGS

Methods and Data

Researchers gathered data from various government sources in order to understand how the US Navy and other Services/Agencies are funding additive manufacturing research and development. Initial data was gathered from the Small Business Innovation Research database (Small Business Administration, 2017) and the USASpending.gov database (USASpending.gov, 2017) for Prime Awards and Sub-awards that contained any of the following search terms: "Additive Manufacturing", "Direct Digital Manufacturing", or "3-D Printing." The datasets were then combined using the identification numbers associated with the Prime Awards and Sub-awards and additional searches were performed in order to supplement missing information from the initial searches.

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Social network analysis was used to longitudinally analyze funding for projects in order to see how the community of government Offices and Vendors working on additive manufacturing evolved over time. Networks were initially created by graphing connections of project requests and funding sources to Prime Awards and Sub-awards, and also connecting Prime Awards and Sub-awards to the Vendors receiving them. Agencies were connected to their Contracting Offices and Requesting offices. Sub-awards were also connected to their Prime Awards. The network in Figure 3a provides an illustration of what these connections look like.

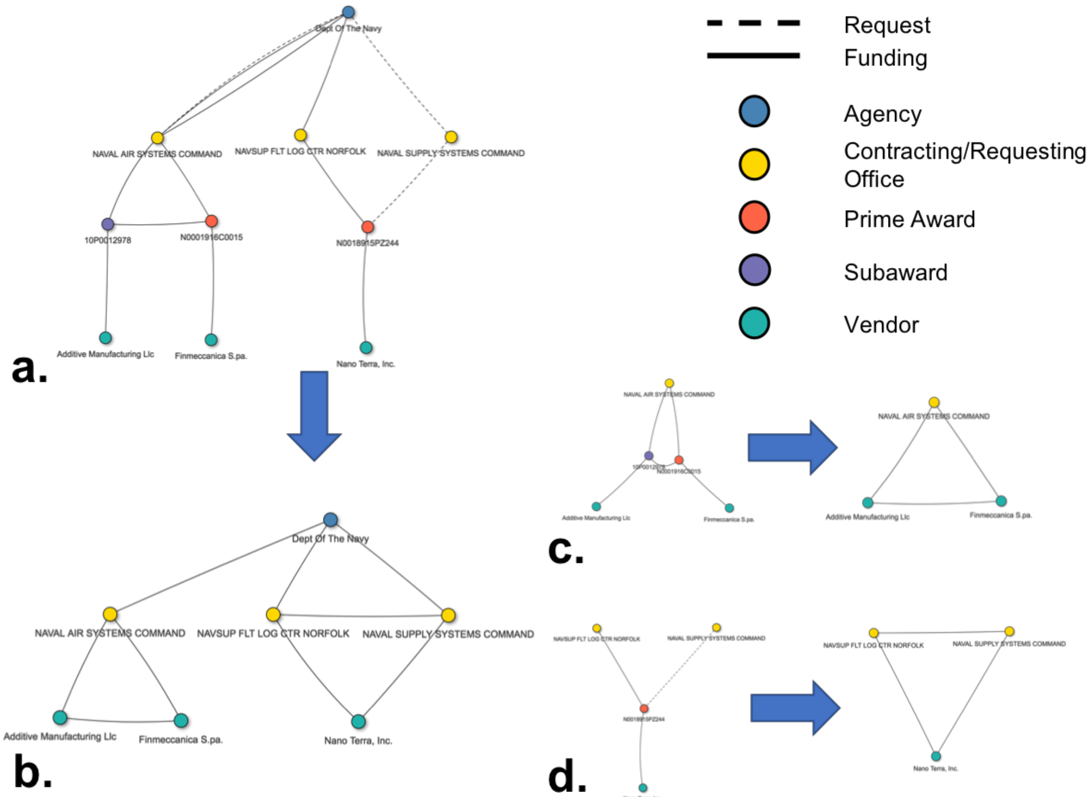

Figure 3: Example contract network (top) and folded network (bottom) within the Department of the Navy

The network with the Prime Awards and Sub-awards was transformed into a network made up of Agencies, Contracting and Requesting Offices, and Vendors by making additional ties based on the Prime Awards and Sub-awards (Figure 3a transforms to Figure 3b). For example, in Figure 3c a Prime Award contract (red) went to one Vendor, Finmeccanica (green), and a Sub-award contract (purple) went to a different Vendor, Additive Manufacturing (green). Naval Air Systems Command, in this case, requested the funding from the Department of the Navy and created contracts for both the Prime Award and Sub-award. The two Vendors were connected to each other through the Prime Award and Sub-award. Also, both Vendors were directly connected to the Contracting and Requesting Offices (in this case the same office) that were connected to the Prime Award and Sub-award. Contracting Offices and Requesting Offices are also connected to each other if they coordinated on a Prime Award or Sub-award. In Figure 3d, Contracting and Requesting Offices were connected to each other if they were associated directly through the same Prime Award or indirectly through a Sub-award and both were connected to the Vendor that received the award. The purpose for doing these transformations was to create a network of

Agencies, Offices, and Vendors where the degree of clustering (when a node's neighbors are connected to each other) can be analyzed.

Temporal Analysis of Funding Network

The period of 2008 – 2017 demonstrated a general increase in interest and funding for projects related to additive manufacturing, as seen in Figure 4. Except for 2017, each year shows an increase in the number of Prime Awards and Sub-awards related to additive manufacturing and the number of Vendors receiving the awards. Of note, the decrease in 2017 was probably due to the data being collected in June 2017 before the 2017 fiscal year ended.

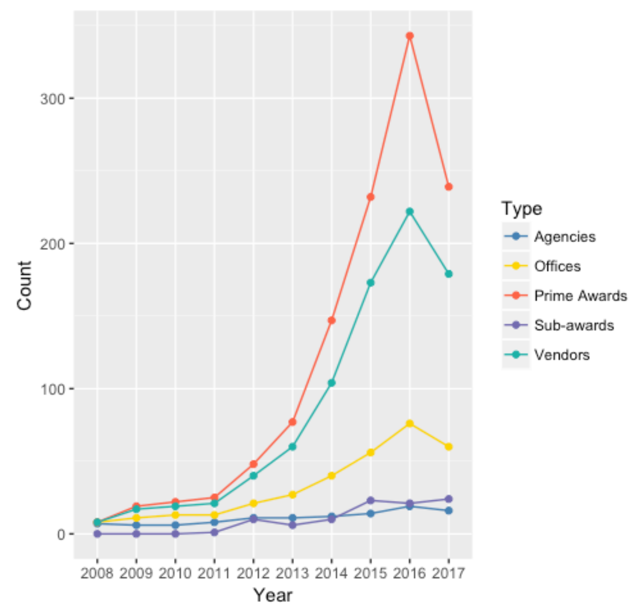

Figure 4: Count of the number of Prime Awards and Sub-awards, Agencies and Contracting and Requesting offices involved, and number of Vendors who received them for each year.

Each fiscal year's network was analyzed independently from the previous years. Network fragmentation was calculated in order to see how cohesive the network was across the entire US government. Fragmentation measures the proportion of all pairs of nodes that are not connected. A fragmentation measure of 1.0 would indicate a completely disconnected network, and a fragmentation measure of 0 would represent a network with one, fully connected, component (Borgatti, 2006; Everton, 2012). The local clustering coefficient was also calculated in order to determine how cohesive the network and sub-clusters were around each node. The local clustering coefficient measures how dense each node's ego network is, with the average then calculated across the entire network (Watts & Strogatz, 1998). Higher fragmentation would indicate that many of the different funding Agencies were focused on different aspects of additive manufacturing and/or did not fund any joint projects or share the same Vendors. A higher clustering coefficient would indicate greater coordination between Contracting and Requesting Offices and Vendors on projects or related projects. Figure 5 shows these fragmentation and clustering measures for the network over time. [See Appendix A for Social Network Analysis terminology and metrics]

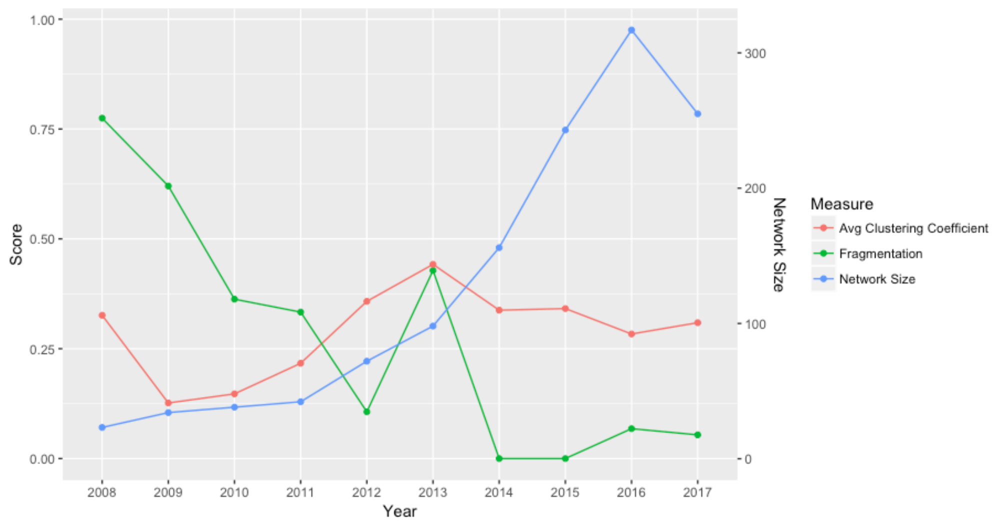

Figure 5: Measures for each year's network over time.

As seen in Figure 5, the fragmentation generally decreased over time, except for a spike in 2013. The clustering varied, with some periods having higher local clustering, and other periods having lower local clustering. The following Figures 6, 7, and 8, below, highlight three different time periods (2009, 2013, and 2017) in order to better illustrate what was happening in the funding network.

In 2009, (Figure 6), the network was fairly fragmented, with a fragmentation score of 0.62 (1.0 would indicate total fragmentation). This is largely due to the network consisting of four components (disconnected subgroups within the network), which indicates that many of the different Agencies were either not working with each other, or were not funding shared Vendors. For example, the bottom left component contains projects associated with the Air Force, the bottom right component has a project funded by NASA, and in the top right is a component that has two projects funded by the National Science Foundation. The only area where multiple Agencies are a part of the same component is seen in the upper left of Figure 6. This component contains projects for the Department of the Army, the Department of the Navy, and DARPA. The Department of the Army and the Department of the Navy both worked with Materials & Electrochemical Research Corporation and the Department of the Army and DARPA worked together on projects with Brewer Science Inc. and Tethers Unlimited Inc. The network in 2009 also had the lowest average clustering coefficient for all of the different time periods, with an average clustering coefficient of 0.13 (1.0 would indicate maximal clustering). This is largely because there were few areas where Contracting and Requesting Offices or Vendors worked together on different projects that year.

Figure 6: Funding network from 2009, nodes colored by type and sized by degree centrality. Agencies are labeled in red.

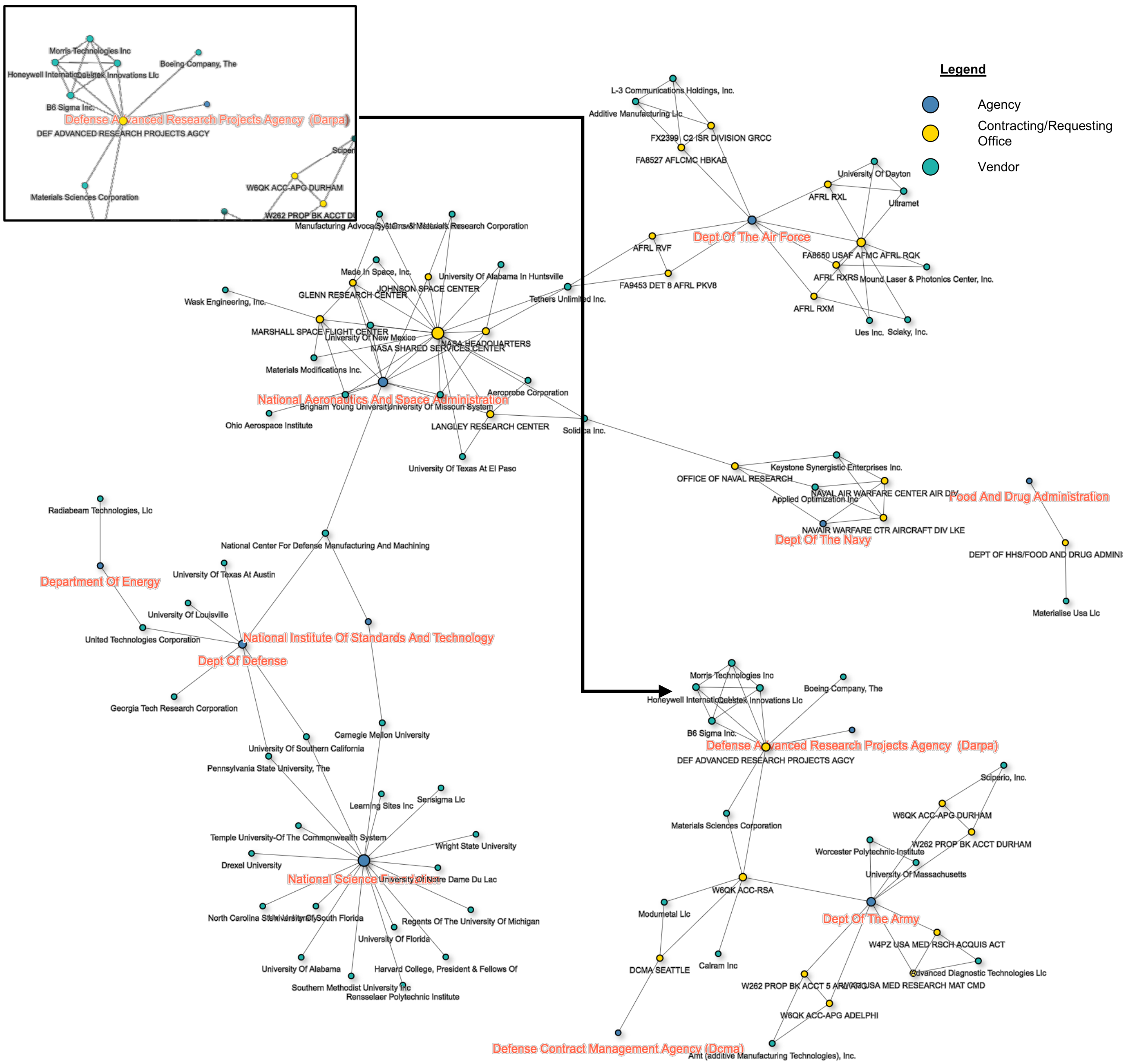

Figure 7: Funding network from 2013, nodes colored by type and sized by degree centrality. Agencies are labeled red. Inset located in upper left-hand corner.

After demonstrating relatively low fragmentation of 0.11 in 2012 (as seen in Figure 5), 2013 saw an *increase* in fragmentation. The funding network in 2013, Figure 7 above, had a fragmentation score of 0.43, and is caused by the nodes being distributed among three different components. The smallest component, at the right of Figure 7, was a project funded by the Food and Drug Administration. The other two components, on the left and lower right of Figure 7, contain the rest of the nodes. The component on the lower right has projects funded by the Department of the Army, the Defense Contract Management Agency, and DARPA. The component on the left contains projects funded by the Department of the Navy, NASA, the Department of the Air Force, the National Science Foundation, and directly from the Department of Defense. Though the network in 2013 had an increase in fragmentation, indicating relatively little coordination across the entire government, the network in 2013 had the highest average clustering coefficient of 0.44. This high clustering coefficient indicates a greater level of coordination among Contracting and Requesting Offices, and Vendors either through funding or funding requests, or by Vendors working on the same Prime- or Sub-award contracts. One area where this clustering is quite high is shown on the right of Figure 7 (inset), where four different Vendors (Honeywell International, B6 Sigma, Morris Technologies, and Questek Innovations) are all connected to each other through a Prime Award from DARPA that went to Honeywell International, as well as through three other Sub-awards that went to the other Vendors. So, while 2013 may have had less coordination across the government Agencies, it had the highest level of coordination among the Vendors and Contracting and Requesting offices.

The final year analyzed, 2017, showed a cohesive overall Government network in terms of fragmentation (score of 0.05), with almost all of the Agencies belonging to the same component. The exception was the Federal Bureau of Investigation, which is a part of the component located in the bottom right of Figure 8. Overall, the network in 2017 had a high level of clustering (though not as high as in 2012), with an average clustering coefficient of 0.31. This is because there are areas of the network that had a very high level of clustering, such inset in Figure 8, where there was coordination between Contracting and Requesting Offices from the Air Force and Defense Contract Management Agency as well as a large number of Vendors working on related projects. Other areas of the network had much lower clustering, such as shown on the upper left of Figure 8, where Vendors or universities that received funding from the National Science Foundation were not connected to each other.

Overall, the additive manufacturing network has been increasing in size and decreasing in fragmentation. The periods when the network size increased the most tended to have a decrease in the clustering coefficient, but this is to be expected when new Vendors or Contracting and Requesting Offices become involved in additive manufacturing. Over time, these Vendors or

Contracting and Requesting Offices should be expected to have a higher level of clustering due to increased coordination and cooperation within the additive manufacturing community.

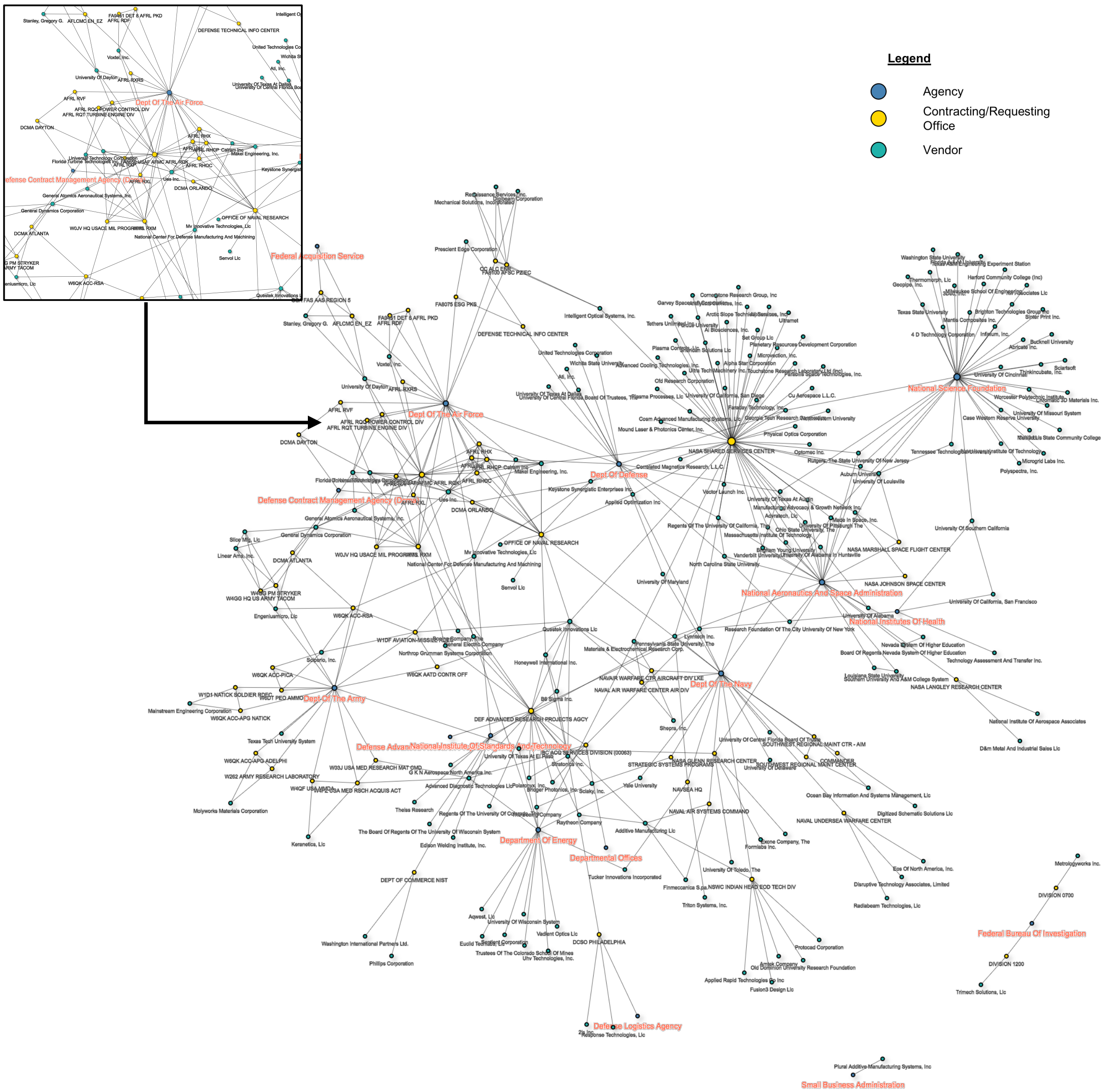

Figure 8: Funding network from 2017, nodes colored by type and sized by degree centrality. Labels for agencies are red. Inset in upper left.

Identifying Key Nodes

Key nodes were identified by analyzing the entire network across all time periods and identifying nodes that spanned "structural holes" or gaps within the network. This analysis evaluates each node's constraint, a brokerage measure for each node that calculates how infrequently a node lies in triadic brokerage positions (Burt, 1992; Everton, 2012). Nodes with low constraint have high brokerage, thereby spanning more structural holes (gaps in connectivity), and tend to be areas where new ideas or innovation may occur. Figure 9, below shows the entire network with nodes sized by the inverse of their constraint, so that nodes with low constraint are larger (have better bridging connectivity) than nodes with high constraint.

As seen in Figure 9, the nodes with the lowest constraint can be Agencies (blue), Contracting and Requesting Offices (yellow), or Vendors (green), because each of these different node types plays a different role in the network. Table 1 lists some of the nodes with the least constraint for each node type.

Structurally, nodes with low constraint have the most potential to facilitate the exchange of ideas or information about additive manufacturing by coordinating with a variety of different Agencies, Contracting and Requesting Offices, and/or Vendors.

Table 1: Top five nodes for each type with the least constraint

Agencies	Constraint
National Science Foundation	0.011
Dept Of Defense	0.031
Department Of Energy	0.032
Dept Of The Air Force	0.041
Dept Of The Navy	0.046

Contracting and Requesting Offices	Constraint
NASA SHARED SERVICES CENTER	0.015
FA8650 USAF AFMC AFRL RQK	0.046
OFFICE OF NAVAL RESEARCH	0.048
DEF ADVANCED RESEARCH PROJECTS AGCY	0.055
DES DSCP CONTRACTING SERVICES OFC	0.063

Vendors	Constraint
Ues Inc.	0.08
Materials & Electrochemical Research Corp.	0.101
Nscrypt, Inc.	0.111
Calram Inc	0.122
Questek Innovations Llc	0.126

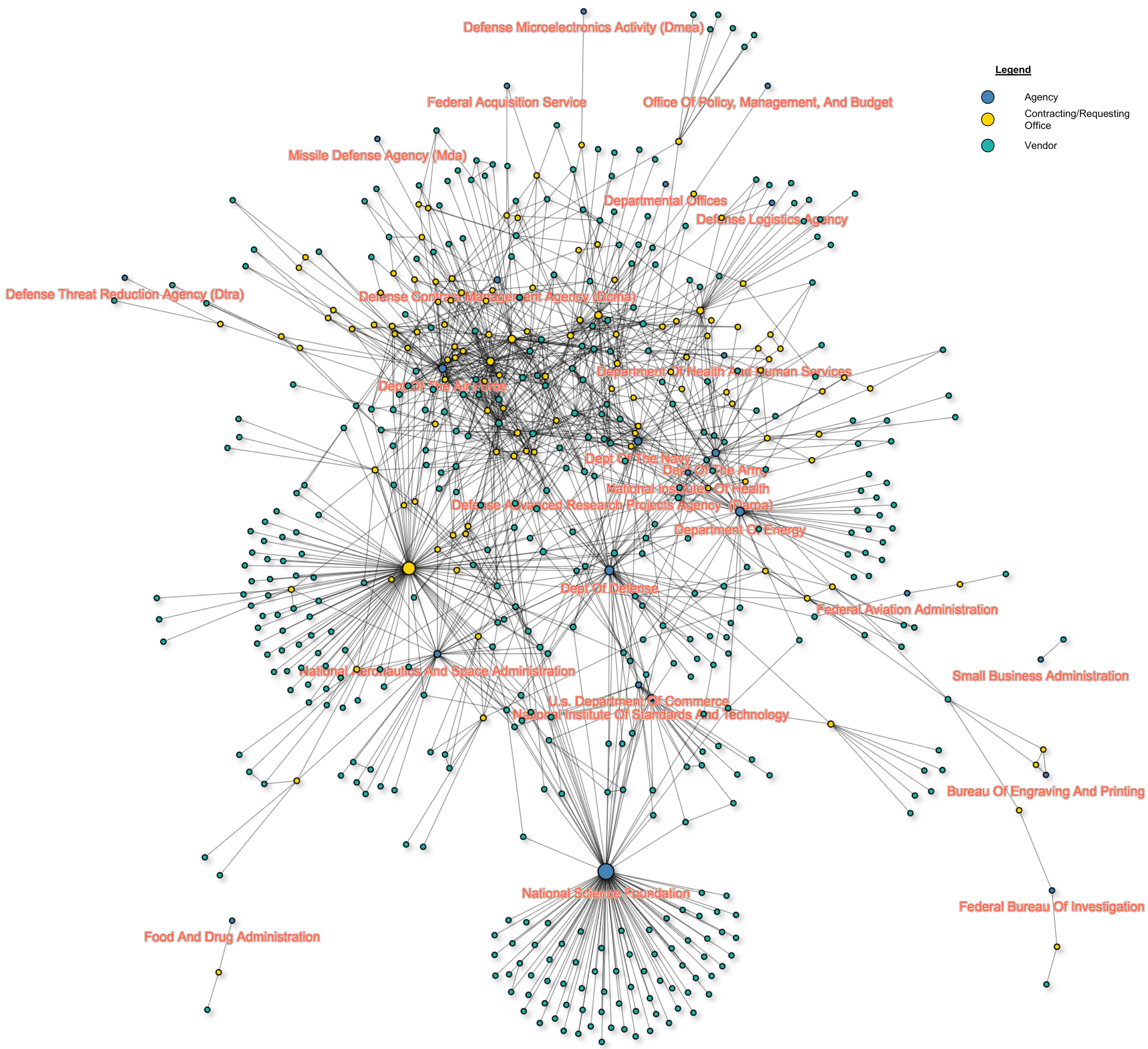

Figure 9: Network across all time periods with nodes colored by type and sized by the inverse of their constraint metric. Labels for the agencies are in red.

Topic Analysis

Besides looking at the network's structure, NPS also analyzed what research was being conducted based on abstracts or descriptions of the Prime Awards and Sub-awards. The word cloud in Figure 10 shows the most frequently used words found in the abstracts and Prime Award and Sub-award descriptions.

Figure 10: Word cloud of abstracts and descriptions before LDA analysis.

In addition to establishing the contracting connections through funding requests or funding as discussed earlier, abstracts for the Prime Awards and Sub-awards were analyzed using Latent Direchlet Allocation (LDA), a machine learning algorithm that extracts sets of words that correspond to a topic (Blei, Ng, & Jordan, 2003). This topic analysis was applied to the abstracts or product descriptions in order to determine whether the evolving communities coalesced around specific topics, or where there were potential areas for collaboration.

LDA analysis of the abstracts and work descriptions identified 16 different topics. Prime Awards and Sub-awards were then connected to each topic based on how similar they were. Some Prime Awards and Sub-awards were only connected to one topic, while others were connected to multiple topics. Figure 11 shows the network of Prime Awards and Sub-awards (circles) connected to different topics (red squares). Prime Awards and Sub-awards that were connected to the Navy are colored blue. Most of the Prime Awards and Sub-awards that were connected to the Navy are grouped in the lower right of Figure 11, with Topic 9 having the largest number of Navy related Prime Awards and Sub-awards connected to them.

Topic	Terms
Topic 1	engineering, students, advanced
Topic 2	potential, current, create
Topic 3	development, layer, powder
Topic 4	fuel, systems, fabrication
Topic 5	test, design, sensors
Topic 6	system, engine, propulsion
Topic 7	structures, demonstrate, structural
Topic 8	high, low, developed
Topic 9	material, modeling, microstructure
Topic 10	control, deposition, system
Topic 11	heat, energy, water
Topic 12	design, methods, processes
Topic 13	metal, laser, alloys
Topic 14	printer, material, system
Topic 15	high, power, applications
Topic 16	production, produce, costs

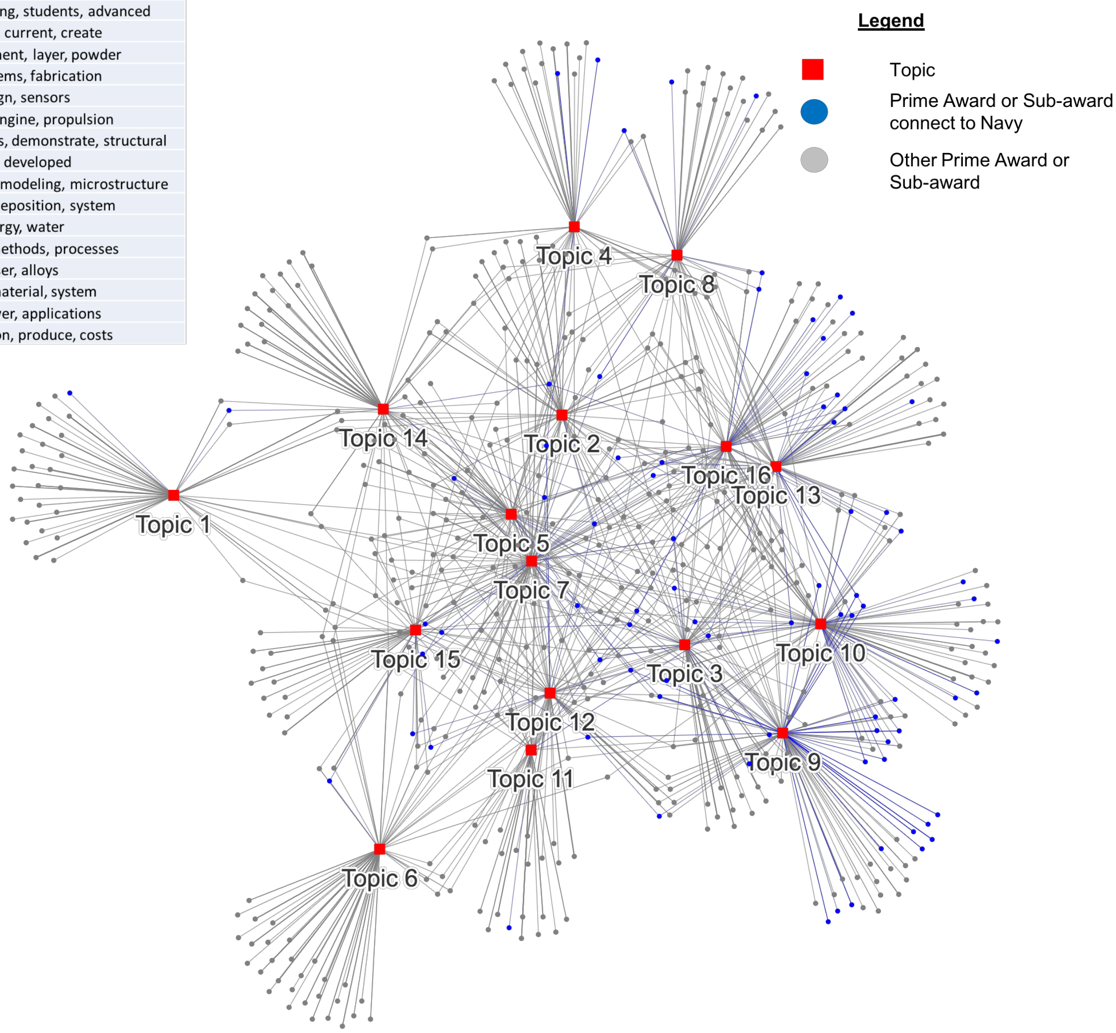

Figure 11: Prime Awards and Sub-awards (circles) connected to topics (red squares). Prime Awards and Sub-awards connected to the Navy are blue. Topics and their top three terms are in the inset in the upper left.

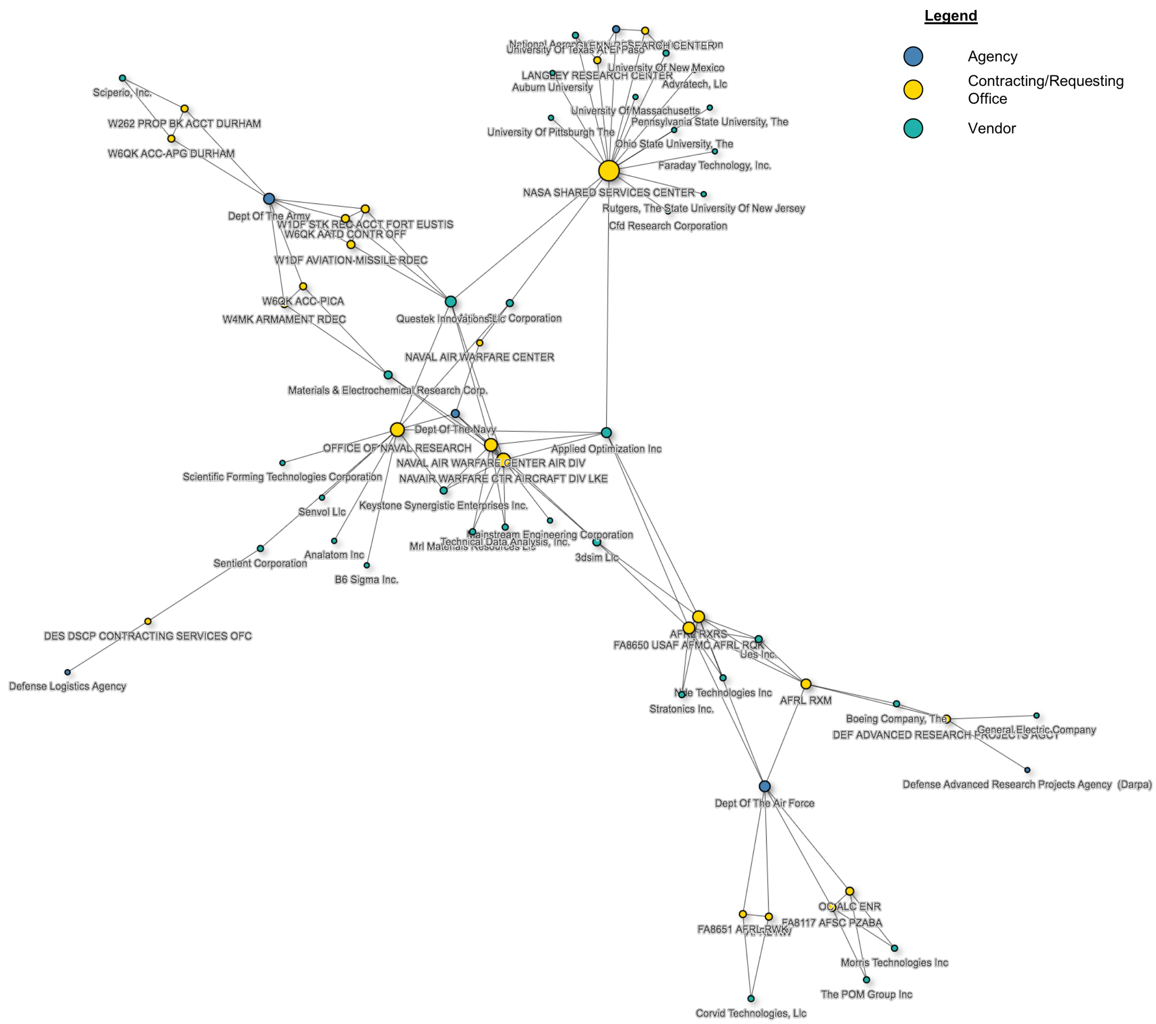

Figure 12: Subnetwork of those Agencies, Contracting and Requesting Offices, and Vendors that were connected to Prime Awards and Sub-awards dealing with Materials and Modeling (Topic 9).

Each topic has a ranked set of words associated with it. For example, topic 9's highest ranked words included "material," "modeling," and "microstructure." This topic had the most Prime Awards and Sub-awards connected to it (82) and also had the most from the Navy (30). The Agencies, Contracting and Requesting Offices, and Vendors that were connected to the Prime Awards and Sub-awards related to the "Material and Modeling" topic (Topic 9) were extracted from the entire network across all time periods. In this subnetwork (Figure 12), the Navy plays a fairly central role. It is located in the middle of the network, with many Navy Offices (like Office of Naval Research and NAVAIR) working with the same Vendors used by NASA, the Air Force, and the Army.

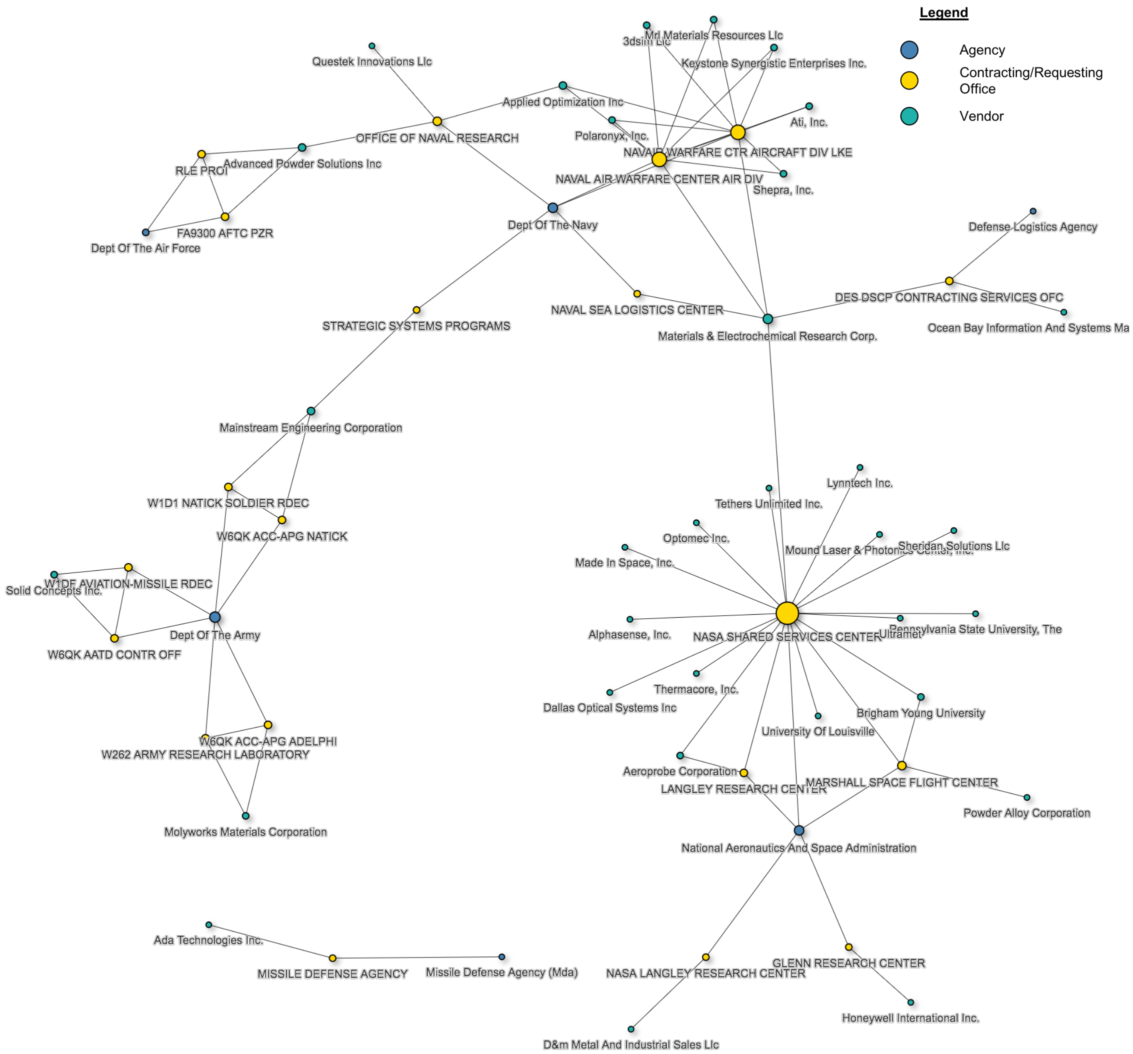

Figure 13: Subnetwork of those Agencies, Offices, and Vendors that were connected to Prime Awards and Sub-awards dealing with Metals, Lasers, and Alloys (Topic 13).

Research around Topic 13, Metals, Lasers, and Alloys for additive manufacturing seems to be a field where there might be the potential for greater collaboration. Topic 13 (located near the bottom of Figure 11) contained 67 Prime Awards and Sub-awards connected to it, with 20 being connected to the Navy. The extracted subnetwork (Figure 13) for Agencies, Contracting and Requesting Offices, and Vendors involved with those Prime Awards and Sub-awards is more dispersed. The Navy still has common Vendors with the Army, Air Force, and NASA, but many of the Vendors involved in this topic seem to work only with NASA. These Vendors may have useful knowledge that could help the Navy with their projects.

RESEARCH QUESTIONS, CONCLUSIONS, AND RECOMMENDATIONS

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 clusters in the social network of additive manufacturing communities of interest?**

Key nodes were identified by selecting nodes with low constraint. Nodes with low constraint have high brokerage, thereby spanning more structural holes (gaps in connectivity), and tend to be areas where new ideas or innovation may occur. Structurally, nodes with low constraint have the most potential to facilitate the exchange of ideas or information about additive manufacturing by coordinating with a variety of different Agencies, Contracting and Requesting Offices, and/or Vendors. The nodes with lowest constraint can be Agencies, Contracting and Requesting Offices, or Vendors, because each of these different node types plays a different role in the network. Among the Agencies with least constraint were The National Science Foundation, The Department of Defense, The Department of Energy, the Department of the air force, and the Department of the Navy. Among Contracting and Requesting Offices with least constraint were NASA Shared Services Center, FA8650 USAF AFMC AFRL RQK, Office of Naval Research, DARPA, and DES DSCP Contracting Services Office. Among Vendors with least constraint were Ues, Inc, Materials & Electrochemical Research Corp, Nscrypt, Inc, Calram, Inc, and Questek Innovations LLC.

Clusters were identified within the overall Additive Manufacturing Network by analyzing contractual connections among Agencies, Contracting and Requesting Offices, and Vendors and by extracting sub-networks based on project topics. Abstracts for the Prime Awards and Sub-awards were analyzed using Latent Direchlet Allocation (LDA), a machine learning algorithm that extracts sets of words that correspond to a topic (Blei, Ng, & Jordan, 2003).

This topic analysis was applied to the abstracts or product descriptions in order to determine whether the evolving communities coalesced around specific topics, or where there were potential areas for collaboration. Overall, the additive manufacturing network has been increasing in size and decreasing in fragmentation. The periods when the network increased the most from 2008 – 2017 tended to have a decrease in the clustering coefficient, but this is to be expected when new Vendors or Contracting and Requesting Offices become involved in additive manufacturing. Over time, these Vendors or Contracting and Requesting Offices should have a higher level of clustering due to increased coordination and cooperation within the additive manufacturing community.

B - What are the ties that link together members of these formal and informal networks?

Formal ties were identified by looking at collaboration among Agencies, Contracting and Requesting Offices, and Vendors tied through Prime Awards and Sub-Awards and through the research topics they were working. Informal networks weren't analyzed, however this research can (and should) be linked to the Analysis of Navy Innovation Network research conducted by NPS (IREF Number: NPS-N097-A), submitted as a Final Technical Report to the sponsor in December, 2017. In that Report, it was found that, "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)." Several topics of interest in the additive manufacturing community were identified in earlier in this report (Figure 11).

C - How could we more effectively bridge together individuals and clusters within the social network of Navy innovators (from the deck plates up) with the larger innovation community of interest in the area of additive manufacturing?

Increasing clustering of individual innovators as well as Agencies, Contracting and Requesting Offices, and Vendors around specific topics of interest across the whole of government could help eliminate redundancies or increase cost effectiveness. Searching out those who are working on similar ideas and encouraging partnerships (when practical) would help bridge individuals and organizations to clusters within the network. As noted in the Analysis of Navy Innovation Network (NIN) Final Technical Report cited above, "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 the Navy Innovation Network and the larger innovation community of interest in the area of additive manufacturing to enhance collaboration?

Growth can be measured through the size of the network. Effectiveness can be analyzed across the whole of government by minimizing fragmentation through better collaboration and by encouraging each Contracting and Requesting Office and Vendor to increase local clustering through partnerships.

E - Can we longitudinally measure the impact that formal and informal innovation networks have on enhancing the Navy's effectiveness and rapid prototyping of additive manufacturing capabilities?

Yes. As was demonstrated in this research, analyzing network topography measures over time, such as fragmentation and the local clustering coefficient, as well as measuring clustering associated with specific topics of interest could enhance the Navy's ability to improve efficiency by optimizing resources. This would potentially contribute to the rapid protoyping of additive manufacturing technologies.

F – What strategies would be best suited to connect additive manufacturing innovation communities of interest to those best placed to adopt new ideas for rapid prototyping in the private sector?

Contracting and Requesting Offices, Agencies, and Vendors with low constraint (Table 1 above) are nodes where innovation is more likely to take place. By institutionalizing or encouraging connectivity among these (and others), and by aligning them with shared topics of interest, it may be possible to enhance the adoption and rapid protoyping of new ideas in the private sector. This may be further addressed in the forthcoming thesis of LT Todd Coursey, USN. The NPS CORE Lab is already pursuing follow-on research with DASN(UxS) through NPS's Consortium for Robotics and Unmanned systems Education and Research (CRUSER).

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Appendix A

Social Network Analysis Terminology

The following section is excerpted and adapted 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).

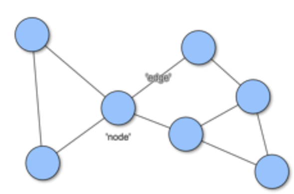

Figure 14: A network representation of nodes and edges

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).

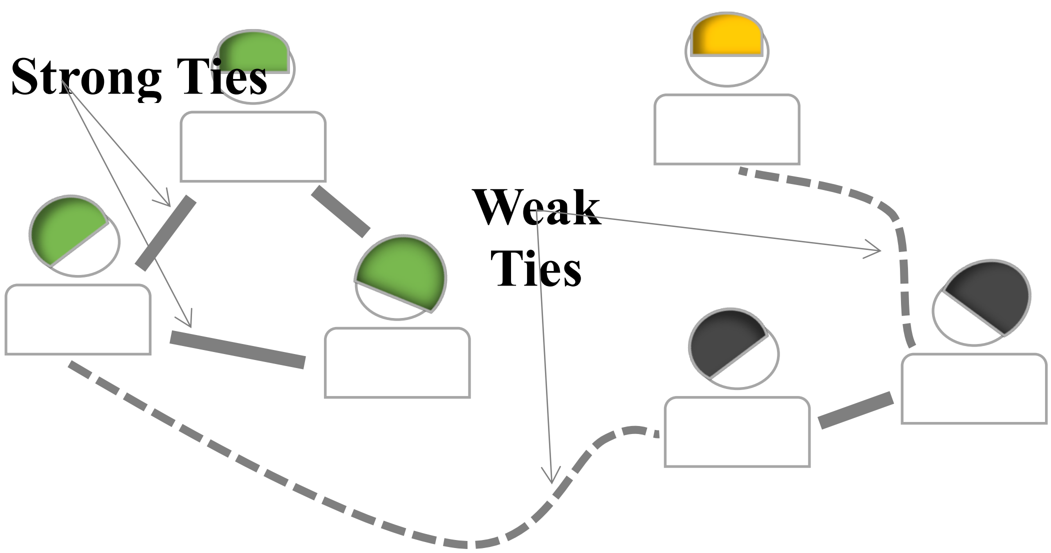

Figure 15: Strong ties and weak ties within a group

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.

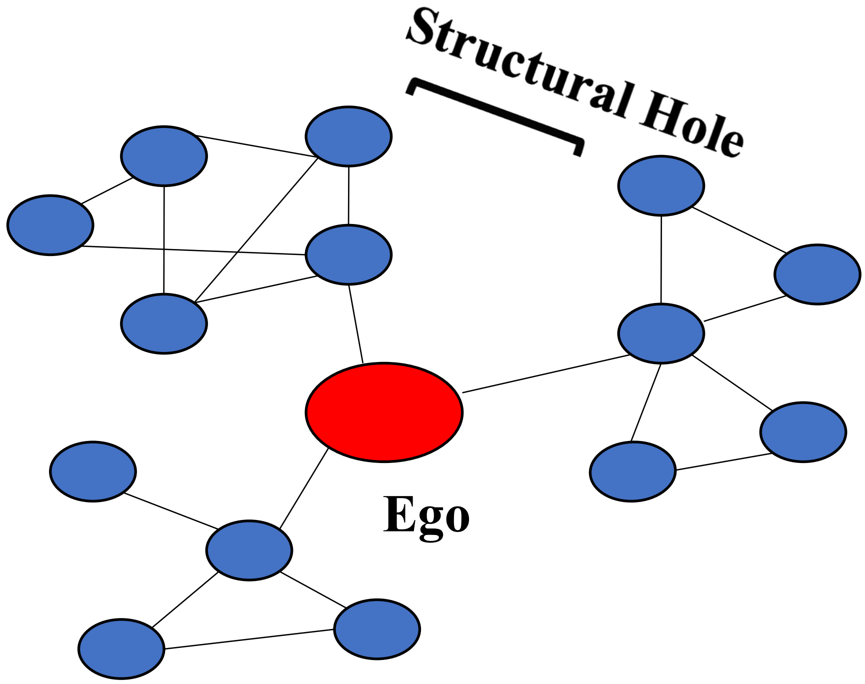

Figure 3: Example of a structural hole

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).

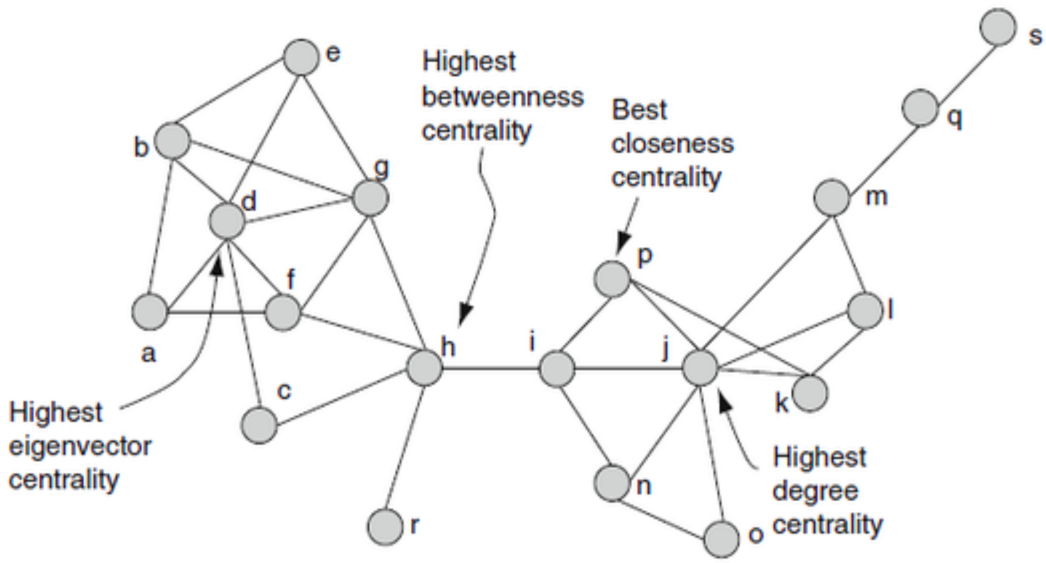

Figure 4: Example of centrality measures in SNA (Ortiz-Arroyo, 2010, p. 30)

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).

Fragmentation

Fragmentation is a network topography measure that analyzes how disconnected a network is, with disconnectedness defined as the inability to reach other nodes in the network. The result is a score between 1.0 and 0.0, with 1.0 being a completely disconnected network where each node is an isolate and 0.0 meaning that all of the nodes belong to one single component. Since a disconnected network can have multiple components of different sizes, the fragmentation score controls for that by calculating the number of pairs of nodes that can reach each other. This results in a score similar to the diversity score known as the Hirschman-Herfindahl index (Borgatti, 2006)

Constraint

Constraint is a brokerage measure for each node that calculates how infrequently a node lies in triadic brokerage positions (Burt, 1992; Everton, 2012). Nodes with low constraint have high brokerage, thereby spanning more structural holes (gaps in connectivity), and tend to be areas where new ideas or innovation may occur. The result is that nodes with low constraint tend to span structural holes, have high social capital, and develop good ideas (Burt, 2004).

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).