Investigating the Efficacy of Terrorist Network Visualizations

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SUBMITTED TO THE SYSTEM DESIGN AND MANAGEMENT PROGRAM
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN ENGINEERING AND MANAGEMENT
AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

FEBRUARY 2013

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Submitted to the System Design and Management Program on January 11, 2013
in partial fulfillment of the requirements for the degree of
Master of Science in Engineering and Management

Abstract

Military intelligence analysts are increasingly tasked to sift through enormous volumes of data to identify the proverbial intelligence "needle in a haystack." One specific domain exemplifying this new intelligence paradigm is network analysis of terrorist organizations. This area of intelligence analysis uses mostly commercially available software applications to leverage the powers of social network theory against large terrorism data sets. An additional challenge is the fast paced development cycle for new sensors, which are capable of collecting data at unmanageable rates. As such, analysts are in dire need of new analytical techniques that give them the ability to *effectively and efficiently* transform the collected data into intelligible information and, subsequently, intelligence. Therefore, the primary focus of this thesis is to analyze two visualization techniques within social network analysis, with the intent to identify which mode of visualization is most effective for the intelligence tasks of: 1) identifying leaders and 2) identifying clusters.

To test the effectiveness of the visualizations, an experiment was conducted in which participants exploited matrix and node-link visualizations constructed from a surrogate terror data set. The objectives of this experiment were to test the effectiveness of the node-link visualization compared to the matrix visualization, based on two criteria: 1) effectiveness at identifying leaders and clusters within a network, and 2) the time it takes to complete each task. Participants in the experiment were all Air Force intelligence analysts and the experiment utilized a 2 (Visualization) x 2 (Task) mixed design study within-subjects on the visualization task factor and between-subjects on the visualization technique factor.

The node-link visualization resulted in statistically significantly better performance in all studied scenarios where the objective was identifying leaders. Although node-link also returned a better performance than the matrix for identifying clusters, there was not a statistically significant difference. The same lack of statistical significance holds true for the completion time dependent variable. In all cases, there was not enough difference between

the times produced by the node-link and matrix to determine if either offers a statistically significant decrease in the time it takes to complete tasks using either visualization.

At this time, the matrix should not be universally integrated into the current methodologies used by analysts to exploit terror network visualizations until more research is conducted into the respective strengths and weaknesses within the intelligence domain. However, analysts should be independently encouraged to explore and adapt new methods of visualization into their current practices and identify new or improved versions of the visualizations identified within this thesis for future testing.

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Acknowledgements

I would like to thank all those who influenced, inspired, and supported me during the development of my thesis and throughout my studies at MIT. It was only through this persistent mentoring that I was able to both excel and complete my research.

Foremost, I would like to thank my advisor Professor Missy Cummings for believing enough in my abilities to advise my thesis while away from MIT. Your insights and comments helped me transform my ideas into a well-researched thesis I can be proud of, for that I am forever thankful.

Equally important, was my thesis reader Erin Solovey. I am sincerely grateful for the time you spent reading the numerous drafts of my thesis and experimental protocols. Your insights and mentoring ensured I was able to conduct a successful human experiment. Lastly, thank you for guiding my writing and, when necessary, motivating me to create a thesis that was on par with HAL standards.

I would also like to thank my thesis advisor at Lincoln Laboratories, Dr. Peter Jones. Your guidance early-on in my writing process and during the design of my experiment was instrumental to the successful completion of both. Above all, I truly appreciate the time you sacrificed from your primary responsibilities to advise my thesis.

To my supervisors and coworkers at Hanscom, Air Force Base; thank you for your patience and support as I undertook a full-time course load at MIT in parallel with my full-time job.

To the organization of Air Force intelligence analysts who participated in my study; although you asked to remain anonymous, please know that I am forever indebted for your willingness to support my research and your encouragement for a fellow analyst. You are the heroes who I endeavored to support with this thesis.

I would also like to thank my parents for their continued love and support. Your selfless understanding and support of my aspirations has always been a key component to all my successes.

Chris Berardi
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January, 2013

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Chapter 1

Introduction

"It will not be quick and it will not be easy. Our adversaries are not one or two terrorist leaders, or even a single terrorist organization or network. It's a broad network of individuals and organizations that are determined to terrorize and, in so doing, to deny us the very essence of what we are: free people. They don't live in Antarctica. They work, they train and they plan in countries. They're benefiting from the support of governments. They're benefiting from the support of non-governmental organizations that are either actively supporting them with money, intelligence and weapons or allowing them to function on their territory and tolerating if not encouraging their activities. In either case, it has to stop.

We'll have to deal with the networks…This will take a long, sustained effort. It will require the support of the American people as well as our friends and allies around the world."

Donald Rumsfeld [1]

1.1 Motivation

Since the September 11, 2001 attacks on the United States, a momentous amount of attention has shifted to the fields of intelligence and terrorism. In the 11 years since that ominous attack, the intelligence community has made substantial advancements in their ability to collect data on adversaries; however, equal progress has not been made in the analytical technologies that are required to sift through the new information. In 2010, Lieutenant General David A. Deptula, then Air Force Deputy Chief of Staff for Intelligence, Surveillance and Reconnaissance, captured this new paradigm when he remarked that in the not too distant future military intelligence organizations will be, "swimming in sensors and drowning in data" [2].

David Shedd, deputy director for the Defense Intelligence Agency, elaborated on the magnitude of the data problem within the post-September 11 intelligence community, "The day after — should we ever be attacked — you will say it was somewhere, you just couldn't either find it, or worse yet, connect it . . . It's just borne out of the enormity of the data that is out there. As a veteran of what has been termed intelligence failures and occasionally an intelligence success, I can tell you that will be viewed as failure" [3]. Shedd continued to explain that the problem is how an analyst processes all the data and finds the proverbial intelligence needle in a haystack. "The problem for that analyst today is you can't possibly [process all data] in a 24 hour day, if they were to work 24 hours a day, and get through all that data even in their area of responsibility," [3].

Today, it is all but accepted that the intelligence community is drowning in data and has recognized the presence of a "big data[1]" problem [4]. To combat this, there is a growing movement to improve the analytical tools offered to intelligence analysts. CIA spokesman Preston Golson argues, "the challenges facing our analysts today is the volume of information…Strong search tools are necessary because the signal-to-noise ratio is very high" [4]. One specific domain within this movement is network analysis of terrorist organizations. This area of intelligence analysis uses mostly commercially available software applications to leverage the powers of social network theory against large terrorism data sets.

Over the past 11 years, some software applications have made incremental improvements to the ways an analyst manipulates data and interacts with a given data set by incorporating advanced algorithms and improved user control interfaces. However, the basic methods of visualizing terror network data sets have changed very little during the same period of time. As such, the primary focus of this research is analyzing the visualizations of social network analysis in the domain of intelligence (Figure 1-1), with the

[1] Big data is an information technology term used to describe stores of data that are far too large and complex to analyze with current applications or database management tools.

intent to identify which modes of visualization are most effective for the intelligence tasks of: 1) identifying leaders and 2) identifying clusters. These two tasks were chosen because of their reoccurring importance highlighted in both the historical perspective and literature review in Chapter 2, as well as during the knowledge elicitation for a hybrid cognitive task analysis outlined in Chapter 3. Additionally, these research observations are corroborated by academic research into social network task taxonomy [5, 6] and recognized to be consistent with the primary tasks of social network analysis [7, 8].

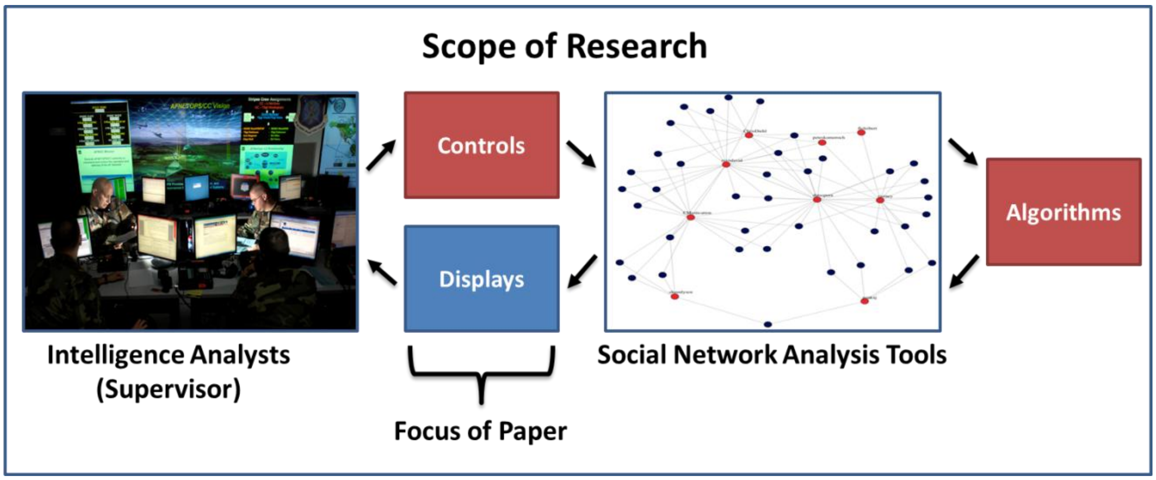

Figure 1-1: Scope of Thesis Research

In parallel with the slow development of analytical software in the intelligence domain, academia continues to make strides, particularly in the field of visualizing social networks (see Chapter 2: Literature Review for a full list of works). However, only a minority of this research has transferred into intelligence methods and techniques. As such, more research is required in this specific niche of social network analysis in the domain of intelligence.

1.2 Understanding the Problem

To understand why visualizations of social network analysis are critical, it is imperative to understand where they fit in the intelligence creation process. This process involves the transformation of data to information, then information to intelligence. Before continuing, it is important to note one key distinction between information and intelligence; intelligence is predictive in nature, allowing the anticipation or prediction of future situations. Sections 1.2.1 and 1.2.2 will build upon this difference and explain how intelligence is created and the six phase process intelligence analysts employ to create intelligence. As a result of understanding of the relationship between data, information, intelligence and the complex cognitive processes an analyst uses to transform data into intelligence, the reader will gain appreciation for the points during the process which bottleneck the production of intelligence [9].

1.2.1 Relationships between data, information, and intelligence

Intelligence is only of value when it is available and contributes to, or shapes, a decision-making process by, "providing reasoned insight into future conditions or situations" [9]. However, this same axiom does not hold true for raw data. Therefore, the burden is on the intelligence analyst to transform raw data into intelligence (Figure 1-2). This transformative process begins with the collection of data from sensors. The first step is to process the raw data into a form intelligible by an analyst. Depending on the type of raw

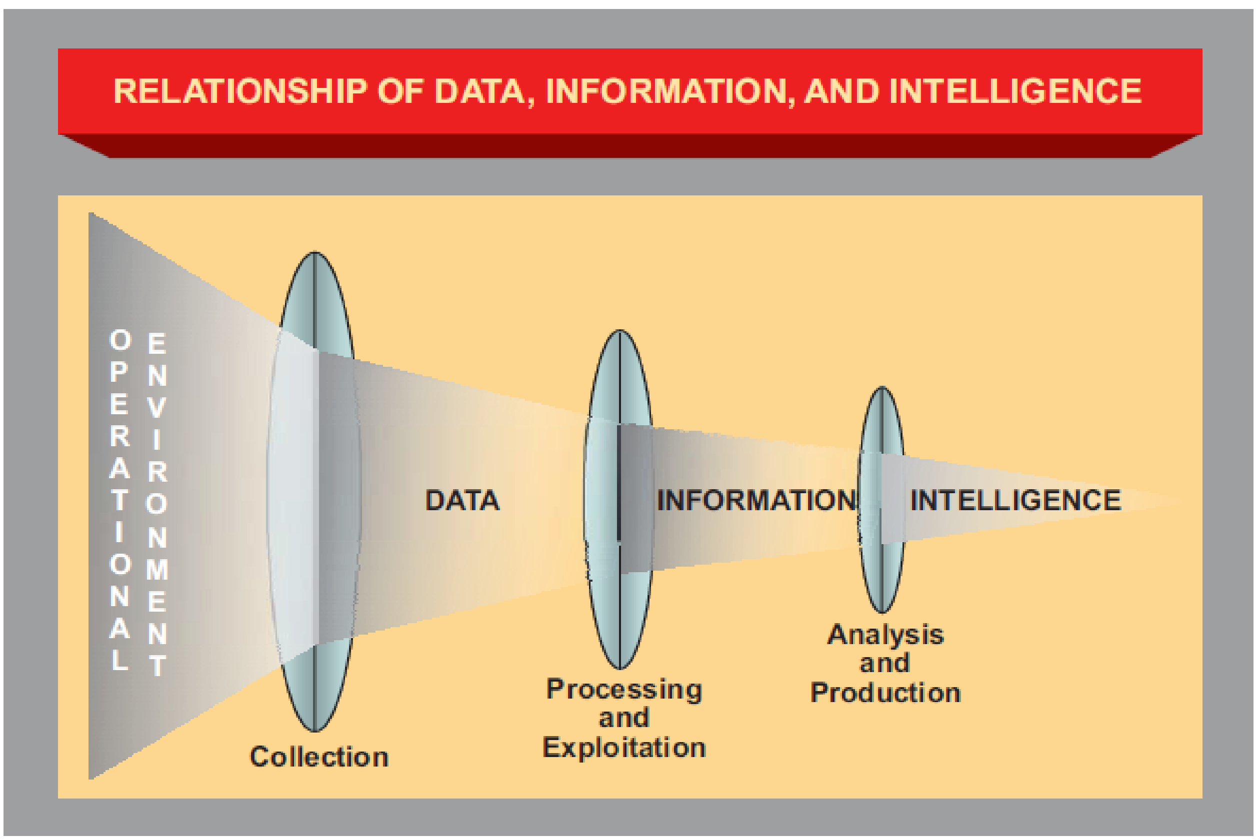

Figure 1-2: Relationship of Data, Information, and Intelligence (from [9])

data, this step is either automated as in the production of an image from a camera, requires an analyst, in limited cases, to transform the raw data into information such as language translation. In the context of social network analysis, this stage typically involves transforming the tabular raw data into a visualization, or series of visualizations. This specific transformative process (data → information) is also known within the intelligence community as *processing and exploitation*[2], which is explained in section 1.2.2.

Although seemingly simple, this stage is a key juncture in the transformative process because it produces the medium through which information is presented to an analyst and provides the basis from which intelligence is created. Errors made in the transformation of data to information will propagate throughout the process and could potentially result in misleading intelligence. Furthermore, a failure to transform data into an effective form of information limits the potential of the data and could inhibit the amount of intelligence produced.

After data is transformed into information, the subsequent information can be integrated and analyzed to produce intelligence. Within the intelligence community this process is referred to as *analysis* and *production*, which will be defined in the next section titled *The Intelligence Process*. The transformation of information to intelligence is accomplished through a structured sequence of actions. The first is the integration of multiple sources of information. During integration data is collated and marshaled according to predetermined criteria, which allows for comparison of similar information during the next step. Following integration is evaluation, during which each new item of information is evaluated with respect to, "the reliability of the source and the credibility of the information" [10]. Being that not all information is of equal credibility, this step is critical to ensuring the most credible information is given the highest weight during analysis. Once information is evaluated, it is ready for analysis. During analysis, assessments[3] are made by comparing already integrated and evaluated information; these assessments are combined and used to discern patterns or links. Finally, the analysis and

[2] For the purposes of this thesis exploitation is defined as, "the process by which raw data is transformed into information that can be readily disseminated, used, and transmitted by an analyst" [10].
[3] For the purposes of this thesis assessment is defined as, a prediction of the future state of an organization, individual, or adversary.

production process concludes with interpretation, which is a largely inductive reasoning process in which available information is evaluated. From this sequence of integration, evaluation, analysis, and interpretation, intelligence is finally produced. Although, this is a generic process which applies to all forms of intelligence, within the context of social network analysis, analysis would be conducted by evaluating multiple visualizations of social networks and interpreting the information resident in each of those visualizations to create a prediction about the terror network, or networks, being analyzed (see Figure 1-4).

1.2.2 The Intelligence Process

The formal intelligence process, which facilitates the transformation of data described in section 1.2.1, is defined by the Joint Chiefs of Staff in Joint Publication 2-0 as the intelligence process [9] (Figure 1-3). This process consists of six interrelated phases of intelligence operations. Each of these phases contains a wide-range of activities conducted by analysts for the purpose of providing decision-makers with timely and relevant intelligence. Each one of these phases can be deconstructed into many distinct sub-categories; however, for the purposes of this thesis only an abstraction of each category is required to gain an appreciation for the process as it pertains to social network analysis.

Figure 1-3: The Intelligence Process (from [9])

- *Planning and Direction* – "The determination of intelligence requirements, development of appropriate intelligence architecture, preparation of collection plan, and issuance of orders and requests to information collection agencies" [11]. This category specifically involves the intelligence preparation for rapid response to possible crises and contingency operations by organizing intelligence infrastructures, which are capable of responding to a range of operations set forth by a specific military unit's mission.
- *Collection* – "The acquisition of information and the provision of this information to processing elements" [11]. At this stage, it is important to note that data is acquired, not intelligence. In social network analysis, this stage consists of collecting the tabular data that is used to create visualizations.
- *Processing and Exploitation* – "the conversion of collected information into forms suitable to the production of intelligence" [11]. After raw data is collected during the collection category, it is converted into forms of information that can be readily used by analysts. A hallmark of this category of operations is the actual transformation of data into information. In the context of social network analysis, this is the stage where the raw data gathered during the collection process is transformed into visualization.
- *Analysis and Production* – "The conversion of processed information into intelligence through the integration, evaluation, analysis, and interpretation of all source data and the preparation of intelligence products in support of known or anticipated user requirements" [11]. This process results in an analyst analyzing a social network visualization for patterns, links, or other items of intelligence value.
- *Dissemination and Integration* – "The delivery of intelligence to users in a suitable form and the application of the intelligence to appropriate missions, tasks, and functions" [11]. This category is simply the compiling of intelligence products produced in the analysis and production category and delivery to the intended consumer. In the context of social network analysis, this task would result in compiling a textual report of the intelligence analysis and disseminating it to the respective consumer.

- *Evaluation and Feedback* – "Continuous assessment of intelligence operations throughout the intelligence process to ensure that intelligence requirements are being met" [11]. During evaluation and feedback, an analyst assesses the accuracy of his or her intelligence produced during the analysis and production phase.

1.2.3 Problem Statement

As outlined in section 1.1, the problem facing analysts today is an abundance of data and no effective means to analyze the data. This indicates a potential problem within the transition of data to information and focuses the problem down to the processing and exploitation phase of the intelligence process. During this phase, as shown in Figure 1-4, an analyst most commonly transforms the data into a node-link visualization (discussed extensively in section 2.2). However, little to no emphasis is given to creating alternating modes of

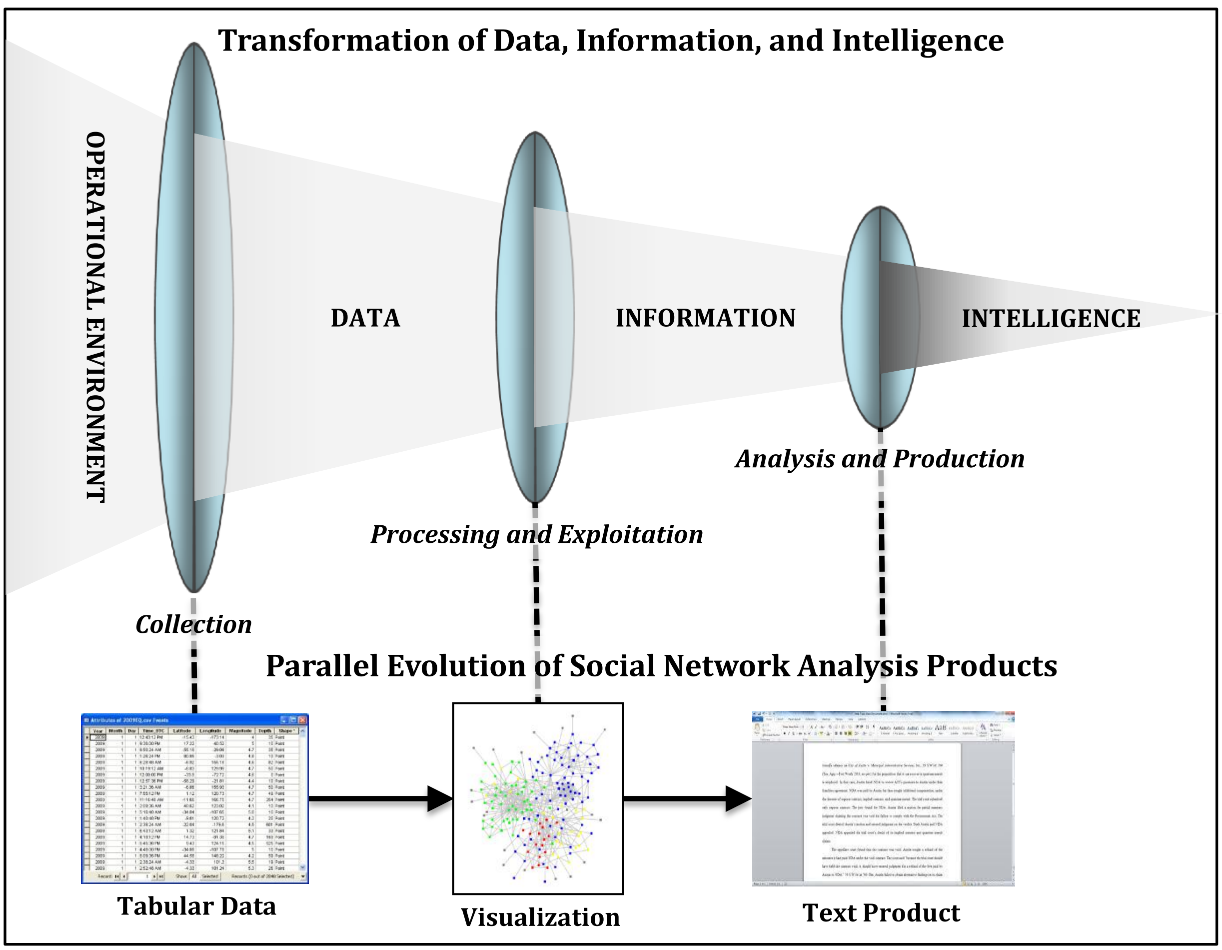

Figure 1-4: Parallel Evolution of Social Network Analysis Products

visualization that could result in a more effective transformation of data to information. Furthermore, there is little existing research into the effectiveness of one form of visualization over another in the domain of intelligence (discussed in the literature review in Chapter 2). Therefore, an experiment into the effectiveness of different forms of social network visualization is needed to determine the most effective means of transforming the data into information; this is the focus of this thesis research.

1.3 Research Goals

At the most basic form, this thesis demonstrates that there is more than one means to effectively visualize terror networks within the domain of military intelligence. Specifically, the goal of this research is to demonstrate that some visualization methodologies may be more effective at certain tasks and, furthermore, that no single method of terror network visualization is a "one-size-fits-all" solution. The scope of this research limits the comparison to two visualization methods. The first is the node-link visualization, which serves as the control since it is the most ubiquitous method of terror network visualization used within the intelligence domain today. The second is the matrix network visualization, which is a promising method of social network visualization studied commonly within the academic community [6, 12]. However, it is important to note that the goal of this work is not to prove that the matrix is a replacement for the node-link visualization; rather, it is to demonstrate that the matrix may be more effective at certain analytical tasks than the node-link and can serve as a companion to node-link. The objectives and sub-objectives of this goal are as follows:

- **Objective 1: Understand the cognitive tasks associated with exploiting terror network visualizations**
    - Understand the cognitive model of analyzing terror network visualizations
    - Understand if and/or where the cognitive model can be augmented

- **Objective 2: Adapt a matrix visualization that is useable by intelligence analysts**

    - Adapt a visualization that draws from engineering psychology and human performance to offset any limitations identified in the cognitive task analysis

- **Objective 3: Test the efficacy of the matrix visualization against the current domain standard method (node-link) visualizations using domain experts.**
    - On the aggregate, show statistical evidence which differentiates the matrix from the control

- **Objective 4: Discuss the results of the experiment in a manner that is accessible by members within the military intelligence community.**

Since the overarching goal is, "investigate means to effectively visualize terror networks" the results of this work must be understandable by members within the community where the change is targeted. Therefore, maximum effort is placed on creating models and using academic frameworks that will not obfuscate the results for the average military intelligence reader. Even if this work proved the matrix is more effective to a 95% statistical significance, the results are useless if the military analysts who create and analyze the visualizations fail to comprehend the cognitive model, visualizations, or the experiment.

1.4 Thesis Overview

To answer the research objectives outlined above the thesis was organized in the following manner:

- Chapter 1, *Introduction*: identifies the problem and describes the motivation and research objectives of this thesis

- Chapter 2, *Background*: provides a summary and background of node-link and matrix social network visualizations and outlines the past research done in regards to social network visualizations with in the domain of intelligence.

- Chapter 3, *Cognitive Task Analysis*: outlines the cognitive task analysis used to satisfy the goals of this research, which includes scenario task overviews of visualization exploitation and cognitive flow-charts of visualization exploitation. An information processing model for exploitation terror network visualizations is introduced and described with respect to the cognitive task analysis.

- Chapter 4, *Terror Network Visualizations:* identifies and explains the characteristics of the visualizations that will be used in the human performance experiment described in Chapter 5.

- Chapter 5, *Human Performance Experiment:* discusses the experimental hypotheses and outlines details about the variables, participants, and procedures employed in the human experimentation.

- Chapter 6, *Results:* presents the analysis of variations between the visualizations and the statistical results of the experiment described in Chapter 5

- Chapter 7, *Discussion and Conclusion:* describes the overall findings of this research respective to the hypotheses and discusses the applicability of the results to future exploitation of terror networks. This chapter concludes by summarizing the problem, motivation, and objectives of this research and proposes potential areas of research to extend the work done in this thesis.

Chapter 2

Background

This chapter begins by providing a historical perspective on visualizing social networks and a literature review on social network analysis within the domain of intelligence. After which, the chapter covers fundamental concepts of social network analysis and defines terms which will be used throughout the thesis. The chapter then provides a detailed description of node-link and matrix visualizations and concludes with identifying gaps in current social network visualization research for consideration when developing the human experimentation.

2.1 Historical Perspective on Visualizations

In social sciences, the field of social network analysis aims to comprehend how groups of individuals function and consequentially, how they behave. It is, "a methodological form of analysis that fuses mathematics, anthropology, psychology, and sociology" [13]. In the domain of criminology and terrorism research, social network analysis is an effective model for capturing the structure of a nefarious organization, because it permits an analyst to understand the structural relevance of individual actors and better understand the relationship of one actor to another, or to the group at large. Specifically within the context of terror networks, social network analysis offers three key advantages over traditional forms of intelligence analysis: 1) the ability to detect clusters, 2) identification of important actors and their roles, and 3) discovery of patterns of interaction [14]. These are critical factors, because correctly exploiting networks can assist an analyst, "in predicting behavior and decision-making within the network . . . [and] to evaluate specific courses of action that will influence the members of a social network in a desirable manner" [15].

Social network analysts at large, use graphical representations or visualizations to study the patterning of the social interactions among actors. For the most part, they seek to discover two types of patterns: 1) social groups, defined as collections of actors who are tightly linked to one another; or 2) social positions, defined as actors who are linked into a total social system in a defining way [16]. Since the beginning of social network analysis, researchers have used graphical representations to identify one or both of these two types of patterning. Some visualizations methods are constructed explicitly to identify social groups and, conversely, other methods were designed to reveal social positions. The two most common forms of visual representation are historically known as points and lines, (referred to herein as node-link) and matrices [16]. However, the first form of visualization is far more ubiquitous and commonly used as the primary technique for representing social network data [16, 17, 18], which some scholarly authors argue is because of its naturalness and ability to make detailed connections explicit [17].

To understand the prominence of node-link visualizations, as well as the rise and fall of the matrix, it is important to trace the roots of social network visualization back to the seminal works done during the 1930s. Freeman, in his authoritative work on the history of visualizing social networks, categorizes the evolution of visualizations into five main phases [16]:

- Phase 1: Hand Drawn Images in Social Network Analysis (circa 1930s)
- Phase 2: Point and Line Images Grounded in Computation (circa 1950s)
- Phase 3: Computer Generated Point and Line Images (circa 1970s)
- Phase 4: Screen Oriented Point and Line Images (circa 1980s)
- Phase 5: Network Images in the Era of Web Browsers (mid-1990s to present)

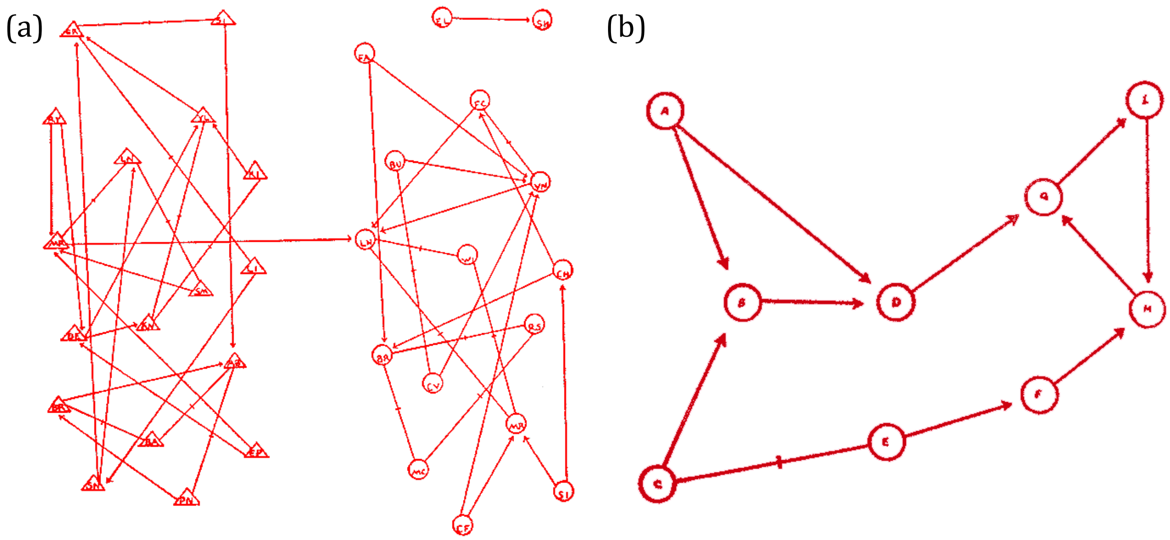

Figure 2-1: (a) Classifying nodes with shapes [17], (b) Moreno's directed graph of a collection of babies [17]

Phase 1: Hand Drawn Images in Social Network Analysis (circa 1930s)

Jacob Moreno, the inventor of sociometry[4], first introduced hand-drawn graphical representations as a fundamental part of social network analysis in the 1930s, where he extensively used node-link visualizations and introduced several innovations that were later adopted by other scholars [19, 20, 21]. His innovations included the development of directed relationships (Figure 2-1(b), where arrows represent the directed links between nodes) and the use of different colors and shapes as categorical schemes for various classes of actors (Figure 2-1(a)). Most notably, Moreno's work also emphasized the idea of placing nodes according to meaningful geographical positions to make the relative power of a specific node more apparent. This theory is the foundation for the many different forms of node-link layout algorithms used today in contemporary social network analysis. Moreno's seminal work is significant because almost all of the techniques he proposed 80 years ago are still in use today and most innovations discussed in later phases can be traced back to one of Moreno's works.

[4] Sociometry is the precursor to social network analysis and much of social psychology. Defined by Mareno himself as, "the mathematical study of psychological properties of populations, the experimental technique of and the results obtained by application of quantitative methods" [20]. Wasserman and Faust offer a more simple definition, "the measurement of interpersonal relations in small groups" [7].

Phase 2: Point and Line Images Grounded in Computation (circa 1950s)

The introduction of computational procedures aided researchers with the problem of determining locations for nodes relative to each other on a plane. During the period from the 1950s through the 1970s the most prominent methods for positioning nodes were: factor analysis [22, 23], multidimensional scaling [24], and correspondence analysis [25]. The introduction of computers offered two key advantages to these methodologies: 1) the opportunity for more elaborate computations and 2) easily replicable results [16]. As such, researchers were now able to take large complex data sets and calculate multiple variables and then analyze the correlations among the variables.

This advancement yielded many significant outcomes, but the one most germane to this thesis is the ease in which researchers could now manipulate matrix data. This increased accessibility of matrices to researchers greatly contributed to the evolution of the matrix as a viable visualization methodology, because the rows and columns of a matrix could now be permutated according to optimization algorithms; so that readily accessible patterns arose on the screen [17]. Figure 2-2 is an example of an early computational matrix manipulation done by Laumann and Guttman using multidimensional scaling to find the best possible arrangement of nodes [24]. Approximately one year after Laumann and

Corporation/Director Choices
for Seven Corporations
and Ten Directors

	Connor, J.T.	Houghton, A.	Jamieson, J.K.	Kappel, F.R.	Lazarus, R.	Learson, T.V.	Mortimer, C.C.	Oelman, R.S.	Williams, A.L.	Wriston, W.B.
	1	2	3	4	5	6	7	8	9	0
1. Gen. Motor:	1								1	
2. Stand. Oil:			1	1		1				
3. Ford Motor:							1	1		
4. Gen. Elect:					1					1
5. Int. Busin:		1				1			1	
6. First Nat.:		1					1	1	1	1
7. Chase Manh:	1		1	1	1					

Figure 2-2: Matrix visualization between corporations and corporate directors [21]

Guttman's work, Jacques Bertin published the seminal works on matrix visualizations [26, 27], which outlined a taxonomy of visualization methodologies and argued the relevance and importance of matrices, which he referred to as "the reorderable matrix," in the domain of network analysis (Figure 2-3).

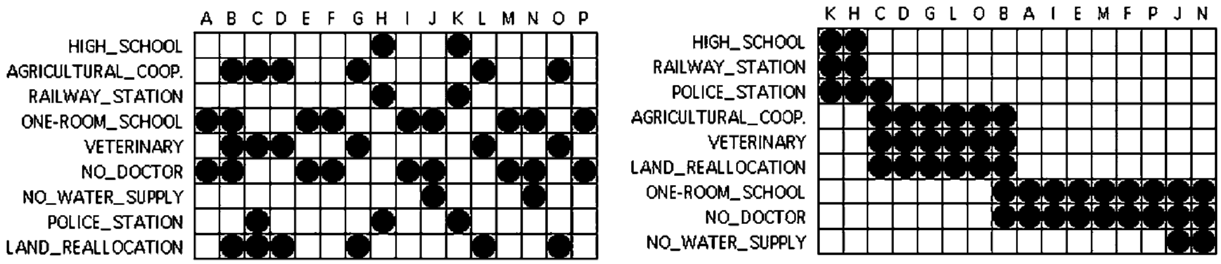

Figure 2-3: Example of a recordable matrix used by Bertin to show groups of nodes with similar characteristics [12]

As the discussion of later phases will reveal, this phase is often characterized as the, "era of graph theory" [7], during which "sociograms waned in importance as sociomatricies became more popular as more mathematical and statistical indices were invented that used sociomatricies" [7]. As such, this era marks the pinnacle of matrix based research with respect to social network analysis, which, from this point forward, takes a secondary role to node-link visualizations.

In addition to the opportunity for more elaborate computations, the other hallmark of this period is the ability to easily produce replicable results. As a result of computational approaches that utilized the same algorithms, different researchers were now capable of producing a near identical visualization for the same data set. While seemingly trivial, this offered a common denominator to the academic community for the comparison and collaboration of social network research data.

Phase 3: Computer Generated Point and Line Images (circa 1970s)

While the computational advancements in Phase 2 offered many benefits, researchers were still drawing the visualizations from their analyses by hand. However, with the introduction of the earliest personal computers in the 1970s two main innovations occurred: 1) the wider availability of computational resources to a larger community and

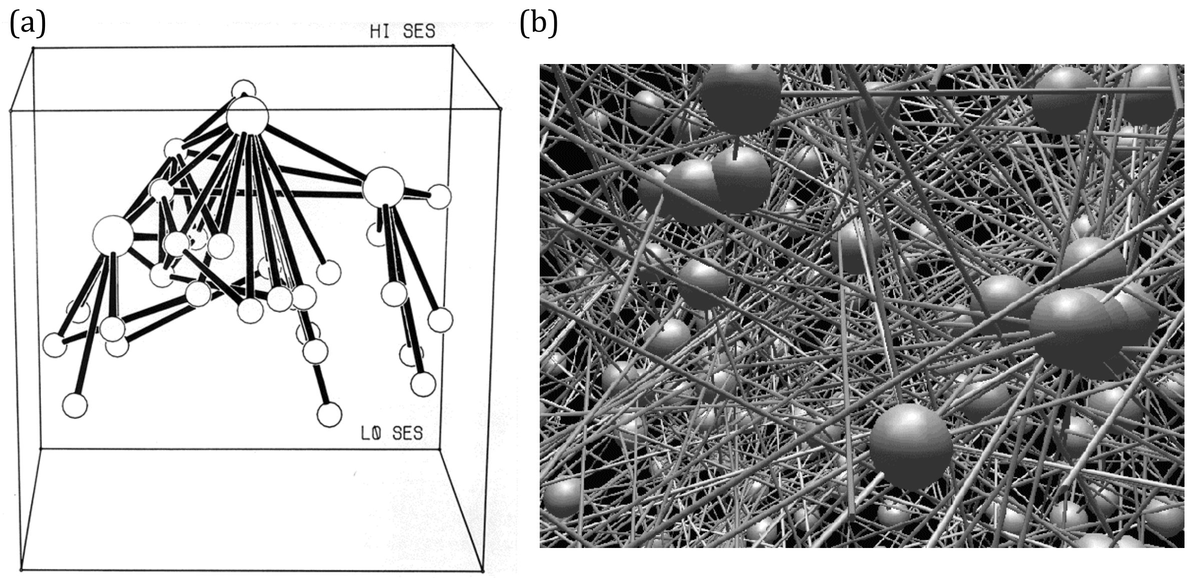

Figure 2-4: (a) Klovdahl's 1982 computer generated visualization [26], (b) Klovdahl's 1988 three-dimensional visualization [27]

2) the possibility of printing images from a computer, as opposed to drawing them by hand [17]. During the first half of this period, most efforts went into the development of applications for analysis of social network data and little attention was devoted to getting computers to draw network graphics [28]. However, in 1978, Lesnaik et al., and Klovdahl separately developed programs which could take outputs from other social network analysis software and produce graphic images [16]. Four years later Klovdahl published a picture produced by an early social analysis tool, ORTEP [29] (Figure 2-4(a)), and seven years later Klovdahl published an early three-dimensional picture using a follow-on visualization tool called View_Net [30] (Figure 2-4(b)) (for a complete history of computer programs in social network analysis see [28]). This period documented many advancements in social network analysis software: specifically, developments in the automated production of node-link visualizations. However, no simular advancements in matricies occurred.

While revolutionary at the time, these early computer generated images were limited because they most commonly produced visualizaitons on black and white plotters. However in the late 1980s, with the widespread use of screen oriented personal computers, a shift occured from paper-based graphics to screen-oreinted visualizations.

This shift to screen images permitted much more flexibility and, for the first time since Moreno's work in the 1930s, facilitated the use of colors in visualizaitons of social networks [16, 17, 28].

Phase 4: Screen Oriented Point and Line Images (circa 1980s)

This phase of social network visualization is defined by the development of many multifaceted analysis tools that included access to various algorithms for locating points, along with various options for moving and editing points and changing their shapes and colors [16]. Four of the most popular tools developed during this phase, which are all node-link focused, were *Krackplot* developed by Krackhardt, Blythe and McGrath (1995), *Pajek* developed by Batagelj and Mrvar (1996), *Netvis* developed by Krempel (1996), and *Multinet* produced by Richards and Seary (1996) [31]. These tools offered researchers an unprecidented amount of customization when analyzing data and the ability to produce visualizations which easily communicated patterns. To illistrate the magnitude the effects this phase had on social network visualization, Freeman built the comparison depicted in Figure 2-5 [16].

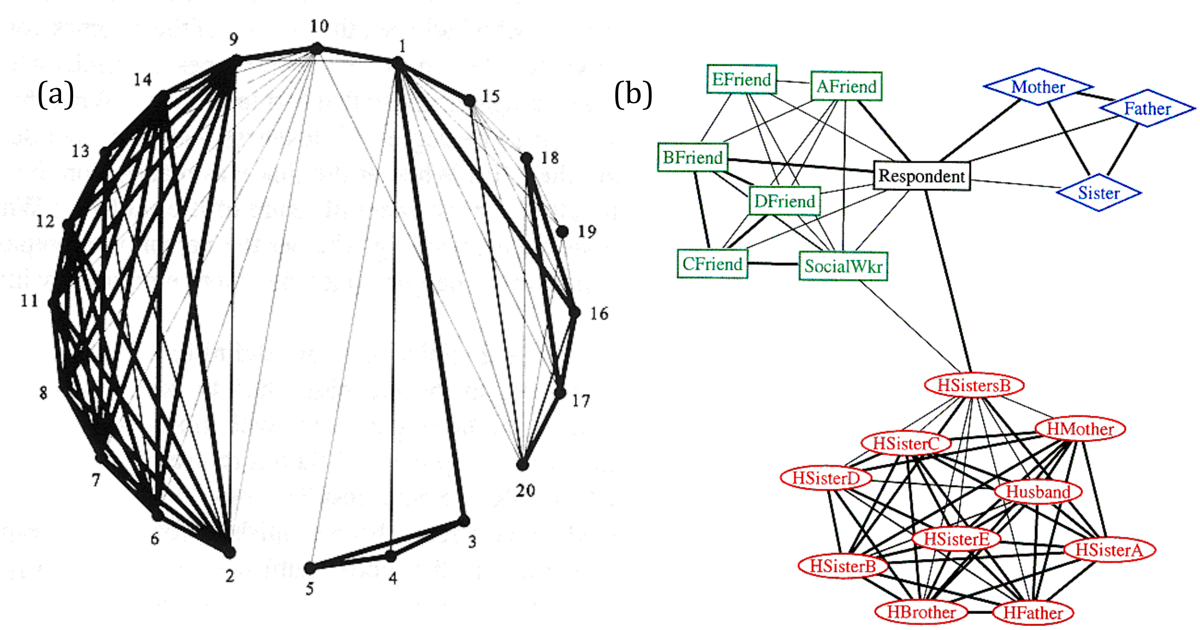

Figure 2-5: (a) Original image from [97] of a homeless woman's social support network; (b) A Krackplot rendition of the data in Figure (a) [15]

Using the new analytical tools, such as Krackplot, a user can now assign shapes and colors for each social group and use the spring embedded layout algorithm within Krackplot to clearly outline the three different social groups within the network. In this regard these tools were a resounding success. However, these programs were still limiting because they each used a specific format that was only accessible by other users with the same program. As a result, many visualizations could be created and distributed for corroboration, but unless the receivers used the same program he or she could only inspect the image. This prohibited further manipulation of the visualizations and thus, the possible discovery of new insights.

Phase 5: Network Images in the Era of Web Browsers (mid-1990s to present)

Finally, in the fifth phase the availability of the Internet allowed for the worldwide proliferation of complex computational algorithms and the rapid exchange of images and results. This phase introduced many new technical formats of visualizations; however, the most important result of this phase is the evolution of visualization standard practices. Freeman argues this evolution started because most early images were constructed by the application of ad hoc rules. As time progressed and as visualization techniques became more replicable, images have increasingly been constructed by applying standardized procedures for placing nodes [16]. Early applications, as discussed in phase 2, used factor analysis, multidimensional scaling, or correspondence analysis. However, more recently these methods have been superseded by various forms of spring embedders, "which is a purely algorithmic technique to find meaningful placements of nodes using the idea of seeing the connections between nodes as springs" [17] to place points in node-link visualizations.

Although the crescendo of matrix research occurred in the late 1960s with Bertin's work, Phase 5 shows the first signs of a resurrection of the matrix. During this period many works have endeavored to add to Burtin's insights [32, 33, 34, 35]. While these works are still relatively few, they show promise and a renewed academic interest using matrix visualizations for social network analysis.

2.2 Literature Review

As discussed in section 2.1, social network analysis as a field of study dates back to the 1930's and contains contributions from notable pioneers, such as Jacob Mareno [19] and Jacques Bertin [27]; however, social network analysis in the context of criminal, covert[5], or terrorism networks is a relatively new field which traces its oldest academically documented roots to the early 1980s.

2.2.1 Social Network Analysis and Terrorism

Over the past thirty years, academic research into the application of social network analysis in crime, intelligence, and covert networks has steadily increased. The catalyst behind the slow evolution of this social network analysis niche is traceable back to a seminal work done by Malcolm Sparrow [36] on the application of network analysis techniques to intelligence analysis, which focused on using social network analysis to identify network vulnerabilities. Sparrow argued that intelligence agencies, "have remained for the most part relatively unsophisticated in their use of analytic tools and concepts" [36]. As an answer to this problem, Sparrow proposed social network analysis, arguing it had a lot to offer intelligence agencies, which could potentially use social network analysis to analyze the structural significance of a network, discover central actors within organizations, and understand roles and positions within a network. However, despite the immense potential for social network analysis within this domain, Sparrow correctly asserted there was little research overlap between the fields of social network analysis and intelligence[6]. Sparrow made three key assertions within his paper to both support his position and start the terrorism social network analysis movement: 1) the relevance of social network analysis to intelligence analysis, 2) the significant potential within the intelligence field for adopting social network analysis, and 3) the mutual rewards obtained from collaboration between both fields [36].

[5] "covert networks" or "dark networks" are often used interchangeably in literature for adversarial subversive human networks – terror networks.

[6] Prior to Sparrow's work there were only three literary sources which tied social network analysis to the criminal or intelligence domains [101] [55] [102]. Those works, while pioneering, offered only 15 pages of combined insight into the field.

Equally important to his efforts to increase the proliferation of social network analysis, Sparrow went on to define the four characteristics of covert or criminal networks that separate them from overt networks:

1. Size – Covert networks can be “huge, with many thousands of nodes” [36].
2. Incompleteness – Covert or criminal network data is, “inevitably incomplete;” some pieces of data are almost always missing or misreported.
3. Fuzzy Boundaries –Borders in covert networks will be unclear and may make it difficult to determine the associations of each actor.
4. Dynamic – New connections are made frequently resulting in a constantly evolving network.

These characteristics, further substantiated in research by Baker and Fulkner [37], are still widely considered to be accurate and remain a key challenge to the adaptation of social network analysis in the domains of intelligence and criminal analysis because these properties produce “computational nightmares, demand algorithmic complexity, and require substantial advances in methods of statistical inference.” [36]

Since Sparrow’s work, published in 1991, several authors have attempted to increase the overlap between the two fields by offering examinations of criminal or covert networks through the use of social network analysis, such as: Baker and Faulkner’s examination of illicit networks within the heavy electrical equipment industry [37], Klerks’ critical analysis of criminal organizations in the Netherlands and the techniques for examining these networks [38], and Deckro and Renfro’s social network analysis of the Iranian Government [15]. While each of these works offered amplifying information on the application of social network analysis to the disciplines of military and criminal analysis, few novel insights or techniques were offered within those works. Furthermore, little research had been undertaken into the application of social network analysis; explicitly towards terrorism. In 2001, recognizing the slow growth within the field of terrorism, Silke [39] and Brennan et al. [40] examined the current state of terrorism research and documented many cases where research in the field of terrorism was lacking empirical, quantitative, and substantive analysis. Silke, quoting Schmid and Jongman [41], offered the following bleak assessment of terrorism research prior to the September 11 attacks, “there are probably few areas in the social science literature in which so much is written on the basis of so little research” [39].

Of the research that existed prior to the September 11 attacks, Arquilla and Ronfeldt’s [42] book titled *Networks and Netwars: The Future of Terror, Crime and Militancy*, synthesized previous research and suggested the concept of “Netwar”[7] and its growing applicability to terrorism. Of particular interest, Arquilla and Ronfeldt discussed the differences in network analysis between social networks and organization networks, arguing, “the field of network analysis, writ large, has been dominated by social network analysis, but organizational network analysis can be even more helpful for understanding the nature of netwar” [42]. Arquilla and Ronfeldt suggest a framework for “organizational network analysis,” which differs primarily from social network analysis in that it does not use empirical methods or mathematics to measure value of networks. Instead, organizational network analysis attempts to understand the strategies, methods, and information exchange systems used within a network to derive intelligence. Although, the organization network analysis framework suggested by Arquilla and Ronfeldt provided a novel way to view network analysis, the authors received criticism for their inability, “to literally apply their theoretical approaches to terrorist or covert groups using any form of sociometric, organizational analysis, or graph theory” [13]. One of the final critical pieces of research, prior to the September 11 attacks, was work done by Carley, Reminga, and Kamneva [43] concerning approaches for destabilization of dynamic terror networks. This particular work is significant, because it acts as a foundation for continued works done by Carley and researchers at the Dynamics Networks project in Computational Analysis of Social and Organizational Systems (CASOS) at Carnegie Mellon University, which include [44, 45, 46, 47].

In the time since the September 11 attacks, many more academic scholars endeavored to research applications between the fields of social network analysis and terrorism. Specifically, works such as: Carley’s [45] research into the emerging field of

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[7] New concept of warfare forces in which adversarial forces organized into, “network forms of organization, often giving them an advantage over hierarchical forms” [42].

dynamic network analysis; Carley et al., [44, 46] continued research into the disruption and destabilization of dynamic covert networks; and work done by Farley [48] and others to adapt and create new mathematical, stochastic, and quantitative social network analysis approaches explicitly for the understanding and analysis of terror networks [49, 50, 51]. Another influential work, similar in nature to Silke's work, is van Meter's [52] thorough chronological examination of the multiple forms of link and network analysis and his illustration of social network analysis application to covert networks using historical examples. Of particular significance, van Meter's work once again reminded academia of the many potential applications of social network analysis to intelligence analysis. However, while the aforementioned works suggest incremental improvements and demonstrate some overlap between social network analysis and the field of terrorism, there was still a lack of substantive application and novel research surrounding the application of social network analysis explicitly for terror networks.

However, 2006 marked the introduction of a seminal academic work where social network analysis was directly applied in the analysis of terrorism. That work, done by Valdis Krebs [53], applied graph theory and network theory in the analysis of the September 11 al-Qaeda cell. In this work, Krebs provided the most illustrative example of the social network analysis of a terrorist organization, specifically because Krebs applied social network analysis to a real terrorist cell, as opposed to previous research, which primarily used notional cells or networks. Krebs work continues to be one of the most referenced works in the application of social network analysis to terror networks and seemingly, provided inspiration for the continued development of social network analysis applications that aim to assist intelligence agencies against the war on terror.

In addition to Krebs' work, and lesser examples in the previously mentioned research, there have been only a small number of other studies that attempt to map terror networks and cells. Specifically, Koschade [13] applied social network analysis to map the 2002 Bali Bombing Cell of Jemaah Islamiyah; Saxena, Santhanam, and Basu [54], used social network analysis to chart the interactions and connection between terror groups in Jammu & Kashmir; and Qin, Xu, Hu, Sageman, and Chen [49], presented a social network analysis case study of the Global Salafi Jihad network.

Despite all the aforementioned works, there still exists little literature in which *substantive* academic advancements have been suggested and proven with any statistical significance. Lacking even further developments in the field of terrorism social network analysis is the actual visualization of these networks as an output of social network analysis. Only three works [13, 38, 50] identified more than one possible technique of visualizing terror networks. However, there were additional works [14, 47, 53, 55, 56] that focused on refining one specific technique of terror social network analysis visualization, but these pieces of literature made few substantive strides towards improving the visualizations.

2.3 Literature Gaps

To help understand where the gaps in literature occur, a literature density map was created (Figure 2-6). This visualization organizes the literature research across two key categories: the social network analysis approach and domain. For social network analysis approach the two sub-categories are quantitative and visualization. The two sub-categories for domain are pedagogy and intelligence. If a piece of literature was primarily aimed at advancing the academic theories of social network analysis or the visualization methods without applicability to any specific domain, then this piece of literature was categorized as pedagogy. The pedagogy domain is further deconstructed into two sub-categories, instructional or proof of concept. The literature categorized in the instructional sub-category were those pieces that made no new assertions about social network analysis, but instead specifically focused on educating the reader on a specific method of social network analysis. All pieces of literature that endeavored to substantiate the effectiveness of a new method within social network analysis were categorized in the proof of concept sub-category.

Conversely, if the pieces of literature were aimed primarily at advancing the applicability of social network analysis within the domain of intelligence, then it was categorized in the intelligence domain. Within this category are two sub-categories: terror/criminal and military. Literature which dealt specifically in the domain of terror or criminal social network analysis was categorized in the terror/criminal sub-category.

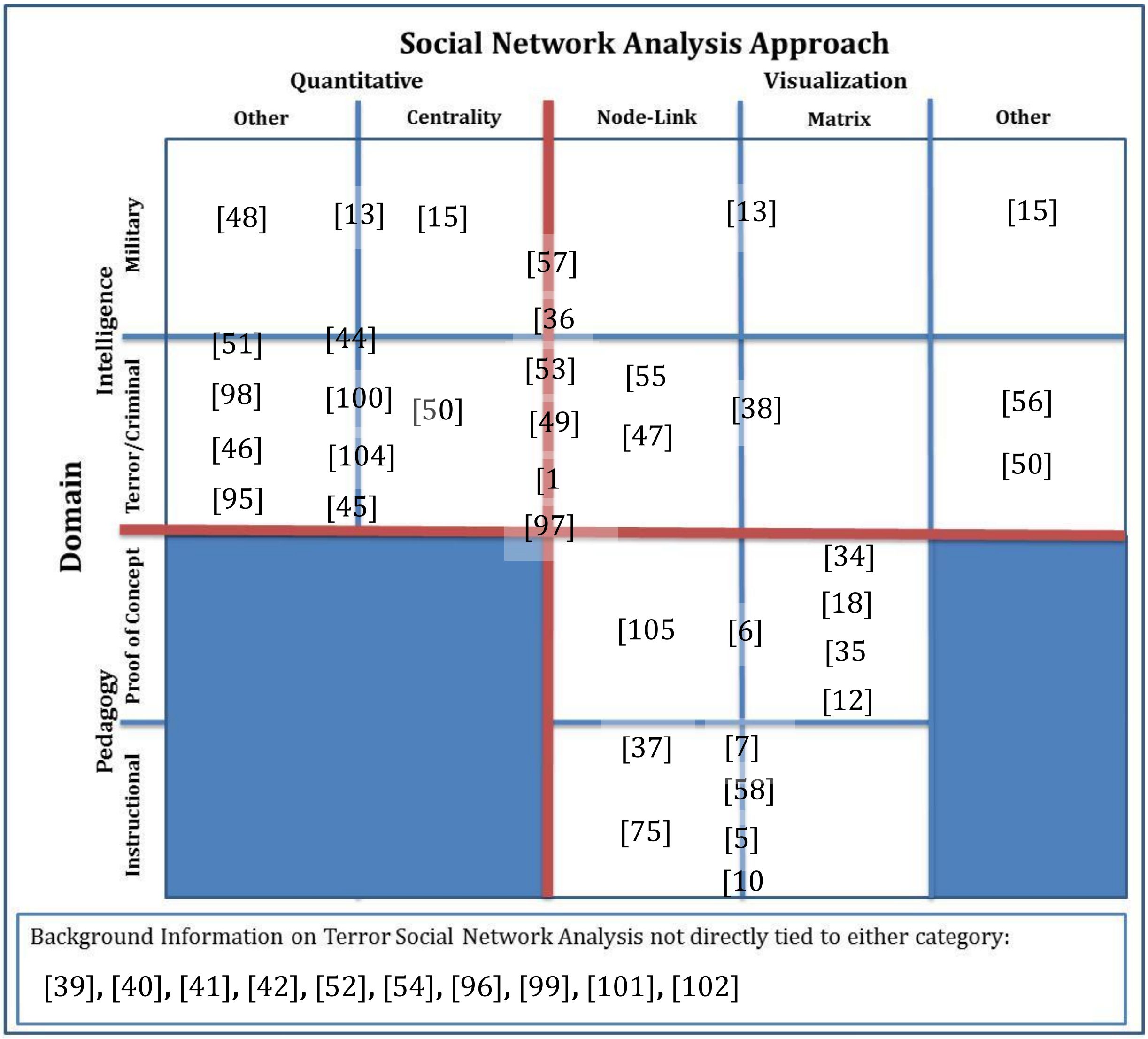

Figure 2-6: Literature Density Matrix

Examples include, analysis of the September 11 terror [53] network and the Global Salafi Jihad network [49]. The military sub-category is different in that it does not deal with any terrorism related analysis. Instead it focuses on more conventional military targets. Examples include: social network analysis of military Command, Control, Communications, Computers, Intelligence, Surveillance and Reconnaissance (C4ISR) architectures [57], and the social network analysis of the Iranian Government [15].

Each piece of literature was placed on the matrix based on the *primary focus* of the research. However, in some cases a piece of literature spanned multiple segments. In this situation the piece of literature was placed on the line between the two or more segments of literature it spanned across (examples include: [58] & [5]). Also of note, the solid blue blocks in Figure 2-6, "Quantitative X Pedagogy" and "Visualization (Other) X Pedagogy," were intentionally not populated because these two cross-sections of research contain potentially hundreds of articles that are not directly applicable to the scope of this literature review. As such, they were purposely omitted to keep the complexity of the visualization manageable.

Additionally, there were ten works that did not fit neatly into any matrix portion of Figure 2-6. Those works are listed below the matrix in a box titled, "Background Information on Terror Social Network Analysis not directly tied to either category." In most cases these documents were excluded from the matrix because they either provided background on terrorism social network analysis or, borrowing from Silke [39], because they were primarily "integrators of previous literature".

From this visualization two key findings become evident. First, the preponderance of social network analysis work done in the domain of intelligence has been primarily focused on developing quantitative approaches to social network analysis. In fact, 18 of the 25 pieces of literature in the Intelligence domain endeavored to develop a quantitative approach or used a primarily quantitative approach to apply social network analysis. While this work is important and shows promise, the complexity of the mathematical models presented makes it almost inaccessible to the average intelligence analyst. Thus, little of this academic work is transferable to the analyst who is charged to apply social network analysis.

The second key finding is the density of literary references in the social network analysis approach of Visualization between the Pedagogy and Intelligence domains. Specifically, there exists a large disparity between the quantities of research done in the domains of Pedagogy compared to Intelligence; 12 works in the domain of pedagogy compared to only 4 in intelligence. However, one could argue that all research originates in the domain of pedagogy and eventually transfers to other domains. Nonetheless, some of the academic research dates back to 2004, but these advancements have not transferred into the intelligence domain. Decomposing the analysis one level further yields a finding of particular importance - the dramatic difference between the pedagogical work done in support of a matrix based social network analysis visualizaiton approach versus the relative absence of any simular work done in the domain of intelligence. This underserved segment of research represents a large gap in literature and research based on the documents reviewed.

The lack of relevant research into intelligence focused social network analysis visualization approaches may help explain why the node-link visualization persists as the most prominent means within the intelligence community. Without data collection and research into other visualization methodologies, little advancements in other areas can be expected.

2.4 Fundamental Concepts in Network Analysis

There are several key concepts at the heart of social network analysis visualization. These concepts are critical to the effective discussion of social network analysis at large and, specifically, social network analysis visualization. These concepts are: social network, actor, group, relational tie, directional versus nondirectional tie, relation, dichotomous relations, social roles, and social positions. Many different definitions exist for these terms [7, 59]; therefore, in an effort to ensure consistency, all of the definitions defined below are extracted from [7]. Additionally, many of the terms defined below are referred to within the intelligence community by domain specific synonyms. Although each term below is defined by its respective social network theory reference, the below definitions will tie the definitions from social network theory to the synonyms of the intelligence community. This is necessary to create a nexus of common terms between the intelligence and academic audience of potential readers.

- *Social Network* – Consists of, “a finite set or sets of actors and the relations defined on them. The presence of relational information is a critical and defining feature of a social network” [7].
- *Actor* – In social network analysis, social entities are referred to as actors. “Actors are discrete, individual, corporate, or collective social units” [7]. Examples of actors

are: people in a group, departments within an organization, or government agencies within a city. While it is possible to represent more than one type of actor in a network, all the actors identified within this thesis are homogeneous; all representing individual people. As such, all further concepts will be defined within the context where actors equate to people. Of particular importance to this thesis, in the lexicon of intelligence, the term node also commonly refers to an actor.

- *Group* – The power of network analysis resides in the ability to model the relationship among groups of actors. For the purposes of this research, a group is, "the collection of all actors on which ties are to be measured. One must be able to argue by theoretical, empirical, or conceptual criteria that the actors in the group belong together in a more or less bounded set" [7]. Of particular note, in the lexicon of intelligence the terms group and cluster are used synonymously.
- *Relational tie* – Actors are linked together by social ties. There are many different types of ties among actors: friendship, business transactions, jointly attending a social event, belonging to the same social club, talking together, or sending messages. However, "the defining feature of a tie is that it establishes a linkage between a pair of actors" [7]. This thesis also uses the term link synonymously with tie, because link is the predominant term used within the domain of intelligence.
- *Relation* – Defined as, "a collection of a specific kind of ties among members of a group" [7]. Examples include the set of friendships among pairs of children in a classroom, or the formal diplomatic ties maintained by pairs of nations in the world. This is an important concept because two actors may have more than one type of relational tie. Therefore, by categorizing the relational ties it is possible to measure several different relations.
- *Directional vs. Nondirectional tie* – In a directional relation, the relational tie between a pair of actors has an origin and a destination; that is, the tie is directed from one actor in the pair to the other actor in a pair" [7]. Examples include: one person gives money to another; the first person is the source of the money, and the second person is the destination. Whereas, in a nondirectional relation, the tie

between a pair of actors does not have a direction. For example, we could define a nondirectional tie as present if two people lived on the same street.

- *Dichotomous relations* – "These relations are either coded as present or absent for each pair of actors" [7]. These relations are analogous to a binary representation, were the tie either exists, (1) or does not exist (0); there is no range of varying states of existence between those values.
- *Social Roles* – Refers to, "the patterns of relations which exist between actors or between positions" [7]. As noted by [60], the theory of "roles" is just a theoretical construct invited by social scientist, but can be expressed in everyday language. Examples include: boss's boss, a brother's friend, or an ally's enemy [7].
- *Social Positions* – Refers to, "a collection of actors who are similarly embedded in networks of relations [or] a collection of actors who are similar in social activity, ties, or interactions, with respect to actors in other positions" [7]. Social positions can be thought of as analogous to, but not strictly defined as, jobs or occupations within a network.

All the concepts outlined in this section will be used in accordance with the above definitions throughout this thesis, unless otherwise noted.

2.5 Visualizations

With an understanding of the basic terms and definitions, it is possible to discuss the two proposed forms of visualization, node-link and matrix, in more explicit detail. Before continuing, it is important to note that there are many different ways to use both node-link and matrix visualizations. The depictions used in this research and the explanations given below are only those that pertain to the visualization of terror networks. It is not meant to be an all-inclusive discussion of every facet or combination of representations possible for either node-link or matrix visualizations (for a complete description see [7]).

Social network visualization, at the most basic form, is a model of a social network data set. The difference between visualizations is the visual encoding used to depict the data set. The next two sections will cover the visual encoding used by node-link and matrix visualizations to depict a notional nondirectional dichotomous data set (derived from [7]).

2.5.1 Node-link Visualizations

Node-link visualizations, also referred to as node-link graphs or sociograms[8], encode data sets by depicting the ties between nodes as lines between objects in a plane. Figure 2-7(b) depicts an example of this configuration from the data in Figure 2-7(a), where the nodes (circles) represent individual people and the lines between the people represent nondirectional dichotomous ties. This simple organization often makes the node-link visualization easy to read and understand. For example, based on the graph in Figure 2-7(b) it is known that Ross has a connection to Sarah, Keith, and Allison because there are lines that connect the different actors. However, it is important to note that in the Figure 2-7(b) the location of nodes on the page is arbitrary, and the length of the links between points in meaningless. The only information in the graph is the set of nodes and presence or absence of lines between pairs of nodes.

However, different algorithms can be applied to place nodes in adjacent positions according to various topological, structural, or node attribute based criteria. Figure 2-7(c) is an example of a free form layout of the same data in Figure 2-7(a) using a spring embedded layout. As discussed in section 2.2 of this chapter, the spring embedder layout is extremely common, "where nodes have repulsive and attractive forces in relation to the number of edges that connect them (attractive force) and the distance that exists between them (repulsive force)" [17]. The result is a graph that forms visually distinct groups, so that an analyst can detect groups of individuals relatively easily. This ability to easily manipulate the relative position of nodes is one of the major strengths of node-link visualizations.

While node-link diagrams are the most familiar representation of graphs in general, and effective at showing the overall structure of a network, Ghoniem et al. [6] showed that

[8] Defined as, "a picture in which people (or more generally, any social units) are represented as points in two-dimensional space, and relationships among pairs of people are represented by lines linking the corresponding points" [7]. This term is a precursor used by Jacob Mareno to what is now referred to as a node-link visualization [21].

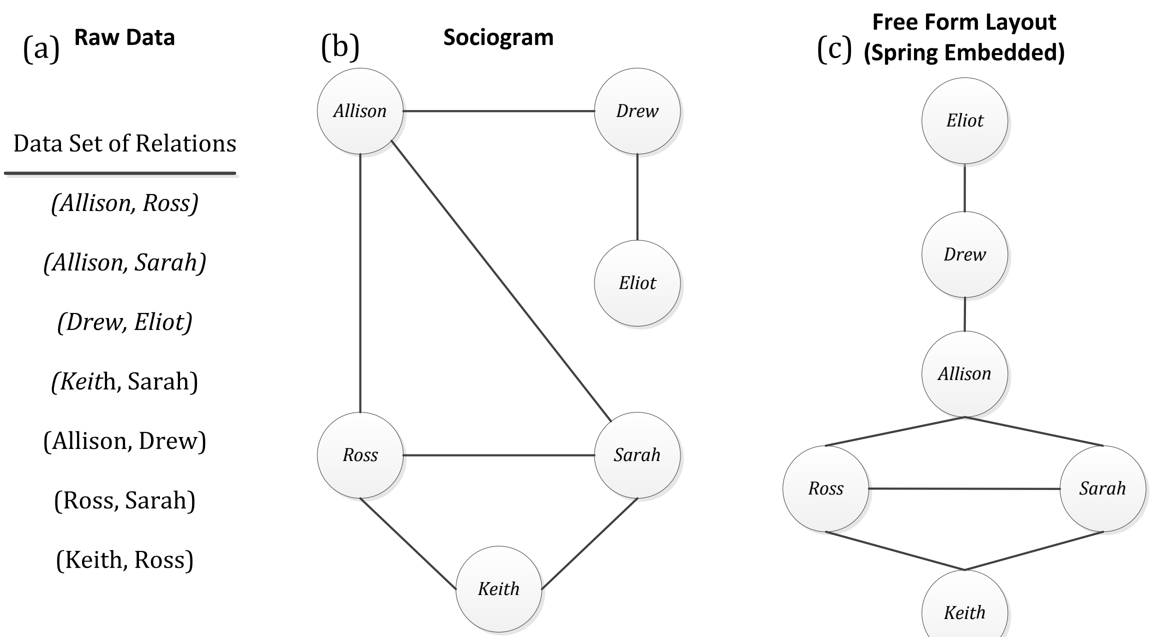

Figure 2-7: (a) Raw data set [7]; (b) Sociogram of data set; (c) Free Form layout of data set

density has a strong impact on readability of these visualizations. Focusing on basic readability tasks, such as finding an actor or determining if two actors are linked, Ghoniem et al., concluded that node-link diagrams perform badly for dense networks, even with few (e.g. 20) nodes. This is the most prominent criticism of node-link visualization; also referred to as the problem of data occlusion [18].

2.5.2 Matrix Visualizations

Matrices visually encode a social network data set by using a two-way matrix, also termed a sociomatrix[9]. In a sociomatrix, once again assuming nondirectional dichotomous relationships, the two dimensions of the matrix are arrayed as an *actors x actors* matrix, which implies the same layout of actors contained on the rows are also contained on the columns. A relationship between actors is communicated by a Boolean value where the rows and columns of specific nodes intersect. Figure 2-8(b) is an example of a basic sociomatrix. Figure 2-8(b) is a symmetrical matrix showing the interconnections between the nodes (Allison, Drew, Eliot, etc.). The matrix is symmetrical because the data set is nondirectional. Meaning the links do not show a relationship from one person to another,

[9] This term is a precursor used by Jacob Mareno to what is now referred to as a matrix visualization [21].

but simply communicates a relationship exists. Furthermore, in this matrix the links between nodes are represented by a “1” at the intersection of nodes; this is a binary value that indicates a connection exists. Likewise a value of “0” indicates no connection exists (note all cells are with a “1” are only highlighted in grey to make the clusters more apparent, there is no social network significance to the coloring).

Since this is a symmetrical matrix it can be read from top down or left to right and yield the exact same results. For example, starting with node “Keith” on the top of Figure 2-8(b), if that column is followed down until the first link it reveals a “1” at the intersection with Ross. This represents a nondirectional link between Keith and Ross. Similarly, if you start Keith on the left side of the visualization and follow the row right it also reveals a “1” at the intersection with Ross. This shows the same relation as using the first method. Additionally, the black diagonals are the intersection of the same node in the matrix and carry no significance. For example, where Keith intersects with himself on the matrix the cell is black because Keith cannot have a relational tie with himself.

In sociomatrices, similarly to sociograms, different algorithms can be applied to place nodes in adjacent positions according to various topological, structural, or node

Raw Data

(a)

Data Set of Relations

(Allison, Ross)

(Allison, Sarah)

(Drew, Eliot)

(Keith, Sarah)

(Allison, Drew)

(Ross, Sarah)

(Keith, Ross)

Sociomatrix

(b)

	Allison	Drew	Eliot	Keith	Ross	Sarah
Allison		0	0	0	1	1
Drew	0		1	0	0	0
Eliot	0	1		0	0	0
Keith	0	0	0		1	1
Ross	1	0	0	1		1
Sarah	1	0	0	1	1	

Ordered Sociomatrix

(c)

	Eliot	Drew	Allison	Sarah	Ross	Keith
Eliot		1	0	0	0	0
Drew	1		1	0	0	0
Allison	0	1		1	1	0
Sarah	0	0	1		1	1
Ross	0	0	1	1		1
Keith	0	0	0	1	1	

Figure 2-8: (a) Raw data set [7]: (b) Sociomatrix from raw data set; (c) Reordered sociomatrix

attribute based criteria. Figure 2-8(c) is an example of a reordered sociomatrix, which contains the same data as Figure 2-8(b). In this case the nodes were manually reordered to reveal the patterning around the Allison, Sarah, Ross, and Keith subgroup.

As mentioned in the previous section, one of the most common criticisms of node-link analysis is its inability to display large and/or dense networks. As node-link visualizations grow in size they have a tendency to occlude data. Some scholarly authors advocate the use of matrices to solve this problem [6], because in matrix visualizations objects cannot overlap; thus resolving the data occlusion and improving readability [17]. Furthermore, the "global" patterns that occur as a result of the layout algorithms applied to matrices, can reveal clusters and show characteristics of the data that are not readily discernible from node-link visualizations due to occlusion.

2.6 Social Network Measures

Although the focus of this paper is not on quantitative analysis methods, a certain number of these measures are required to identify curiosities within social network data. There are many different quantitative analysis algorithms available (see [7]: pp 167-215 for an overview). However, this research will focus specifically on two measures: betweenness centrality and closeness centrality. These two measures were chosen because most intelligence analysts receive preliminary training on them and because they can assist in the analysis of social network roles and positions.

2.6.1 Betweenness Centrality

Betweenness centrality is, "the idea that a node is central when it is able to connect relevant clusters that would otherwise be disconnected" [17]. Extremum betweenness centrality measures reveal actors who have a high degree of control over the information that travels between disparate actors, which indicates a specific node may act as a "broker" of information [49]. Within the context of terrorism, this specific social network characteristic may indicate the network structural properties of a leader. While this measure is unable to solely identify a leader within a network, it can be used to cue an analyst's attention on a specific actor for further study or analysis with other social network measures of centrality or ego.

For example, if the geodesic[10] between actors n_1 and n_4 is: $n_1 \rightarrow n_2 \rightarrow n_3 \rightarrow n_4$, the shortest path between actors n_1 and n_4 has to go through two other actors, n_2 and n_3. This implies that, "the two actors contained in the geodesic might have control over the interaction between [n_1 and n_4]" [7]. Defined mathematically (Equation 2-1), actor betweenness centrality is the sum of the proportions, for all pairs of actors, in which a specific actor is involved in a pair's geodesic(s):

$$C_B\,(n_i) = \sum_{j<k} \frac{g_{jk}(n_i)}{g_{jk}}$$

Equation 2-1: Betweenness Centrality [7]

2.6.2 Closeness Centrality

Closeness centrality is, "how close an actor is to all the other actors in the set of actors. Extremum closeness centrality measures reveal actors who have a high degree of access to the entire network and the information with flows throughout the network, which may indicate a specific actor has the network structural properties of a potential leader. Similar to betweenness centrality, this measure cannot solely determine the presence of a leader. Instead, it is used to cue an analyst's attention on a specific actor for further study or corroboration with other quantitative measures.

The idea is, "that the actor is central if it can quickly interact with all others" [7]. Defined mathematically (Equation 2-2), actor closeness centrality is the inverse of the sum of geodesic distances from actor *i* to all other actors [7].

$$C_C\,(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$$

Equation 2-2: Closeness Centrality [7]

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[10] Defined by [7] as: "A shortest path between two nodes"

These quantitative methods will be used primarily to organize the data within a visualization. Other quantitative measures may be introduced later in the research, but their role will simply be to validate or support the two aforementioned measures.

2.7 Conclusion

This Chapter started by presenting historical perspective on the history of social network visualizations and a review of current terror social network analysis literature. After which, the gaps in literature were discussed, which revealed several gaps within the current academic research; the most prominent of which was the large disparity between the quantities of research done on visualizations of social network analysis in the domain of pedagogy compared to intelligence. Followed by, defining key concepts within social network analysis and providing a detailed explanation of the node-link and matrix forms of visualization.

Chapter 3

Cognitive Processes for Exploitation of Terror Network Visualizations

This chapter provides a description and analysis of the cognitive tasks employed by military intelligence analysts to interpret and exploit terror network visualizations. First, a cognitive task analysis is used to understand the specific tasks and challenges an analyst may encounter. From the cognitive task analysis, both a scenario task overview and event flow diagrams were constructed to support the development of an information processing model. The chapter concludes with a synopsis of the insights from both the cognitive task analysis and the information processing model and a brief discussion on how these help inform the adaptation of social network visualizations for terror network analysis.

3.1 Cognitive Task Analysis

The basic goal of the military intelligence analyst is to construct one or more hypotheses about the future state of the specific topic or situation being analyzed; however, this task is challenging because an analyst must sort through enormous volumes of data while combining pieces of unstructured information to eventually create an accurate understanding of the situation. The nature of the data, the complex cognition and logic required, and an environment characterized by time pressure, task saturation, and significant repercussions for errors, combine to create a challenging and complex environment in which an analyst must operate [61].

To understand the challenges and complexities, a cognitive task analysis was performed to help identify the specific cognitive processes, challenges, and constraints an analyst faces while exploiting terror network visualizations. A cognitive task analysis, as defined by Chipman et al, is, "the extension of traditional task analysis techniques to yield information about the knowledge, thought processes, and goal structures that underlie observable task performance" [62]. The cognitive task analysis conducted herein corresponds to this definition. It utilizes a combination of ecological [63], bootstrap [64], and hybrid [65] approaches including:

- *Literature Review:* Past cognitive task analyses conducted in the domain of intelligence analysis were reviewed [61, 66, 67, 68, 69, 70] along with all the documents outlined in the literature review in section 2.4. Although some the previous cognitive task analyses focused primarily on the tasks associated with generic intelligence analysis, most schemas, methods, and processes used correlate directly to those used in the exploitation of intelligence visualizations.
- *Table-top Analysis*: Defined by Flach as, "review of published literature that describes the nature of the work" [63]. Reviewed works include: military intelligence analyst training curriculum for various courses offered by US Air Force, US Army, US Navy, and Defense Intelligence Agency; Air Force Doctrine Document 2-0*: Global Integrated Intelligence, Surveillance, & Reconnaissance Operations* [10]; Joint Publication 2-0 *Joint Intelligence* [9]; and Joint Publication 2-01, *Joint and National Intelligence Support to Military Operations* [71].
- *Knowledge Elicitation*: Semi-structured interviews were conducted with multiple intelligence analysts with varying levels of experience. Open-ended questions were used to guide the interviews and specific questions were used to clarify inconsistencies between interview responses and information gleaned from other sources. All interviews were conducted either in person or over the telephone and lasted approximately 30 minutes.

- *Naturalistic Observations*: Prior to beginning this thesis research the author spent 4.5 years as an Air Force Intelligence Analyst, which offered the opportunity to observe analyst interactions with varying types of terror network visualizations.

The results of the cognitive task were organized along the procedures described by Nehme et al, for generating requirements for future systems [65]. Specifically, a scenario task overview (Table 3-1), event flow diagrams (Figure 3-2 through Figure 3-5), and an information processing model (Figure 3-6) were created to capture and convey the results of the task analysis. Each of these cognitive task analysis artifacts will be discussed in further detail below.

However, before continuing it is important to understand the process by which an analyst is tasked. This process (outlined in Figure 3-1) is critical because it determines an analyst's goals when exploiting any form of intelligence. Generally (there are minor differences between military services), a commander creates a set of priority intelligence

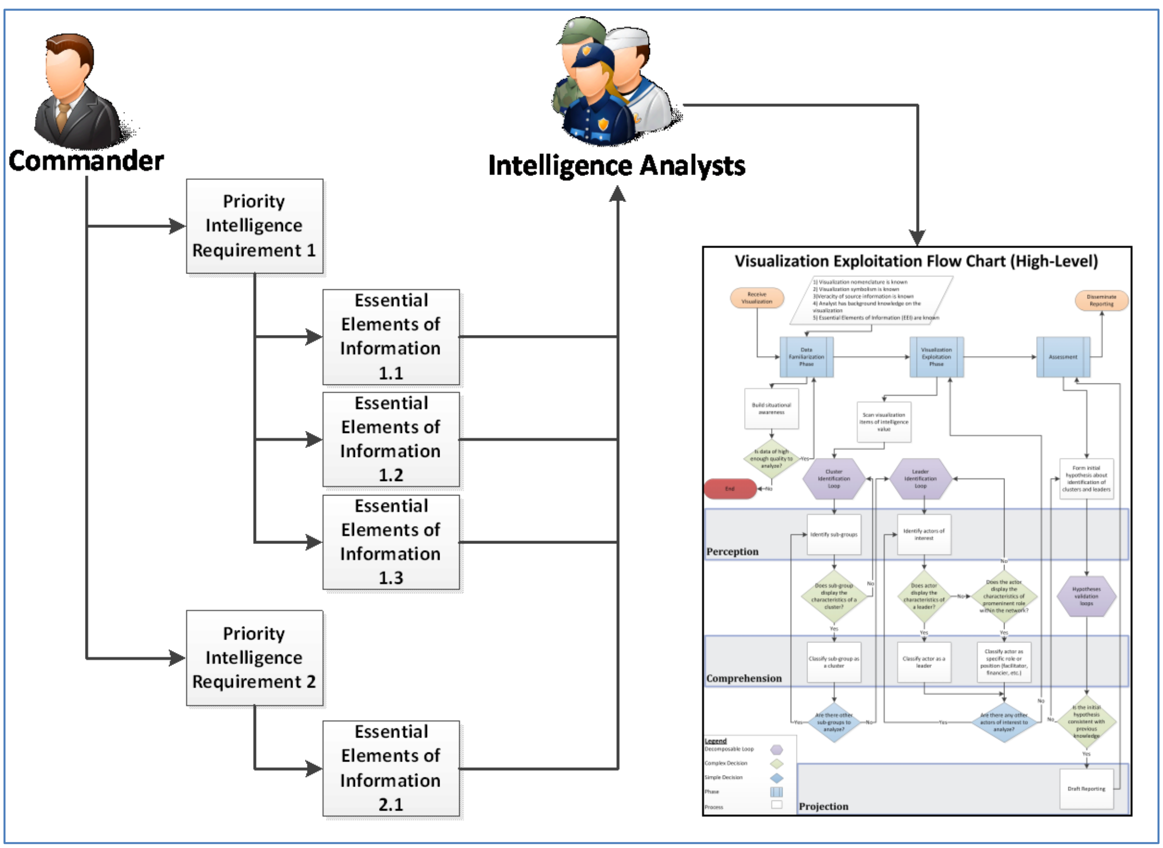

Figure 3-1: Analyst Tasking Process

requirements (PIRs). A PIR is, "an intelligence requirement stated as a priority for intelligence support, that the commander and staff need to understand the adversary or other aspects of the operational environment" [11]. An example of a PIR is, "Who are the leaders of the XXX terrorist network?" These PIRs are then decomposed into essential elements of information (EEI's), which are defined as, "the most critical information requirements regarding the adversary and the environment needed by the commander by a particular time to relate with other available information and intelligence in order to assist in reaching a logical decision" [11]. An example of an EEI based of the PIR used in the previous example is, "Who is the network facilitator?" or "Who is the network financer?" The analyst will then use these EEI's to create a cognitive task flow (depicted in Figure 3-1 as smaller version of Figure 3-2, which is discussed in section 3.1.2).

Understanding this process is important because as the PIRs and EEIs change, the cognitive tasks required to satisfy the PIRs and EEIs change as well; therefore, the cognitive task analysis outlined below was created using two PIRs: 1) the identification of leaders and 2) identification of clusters. These two tasks were chosen because the historical perspective and literature review in Chapter 2, as well as the knowledge elicitation discussed in this chapter revealed they were the two most common tasks conducted by an analyst. All task information from this point forward is a direct result of these inputs.

3.1.1 Scenario Task Overview

Using these two PIRs, a scenario task overview was created for an analyst who is charged with both identifying leaders and identifying clusters with in a terror network. That scenario task overview is outlined below in Table 3-1.

Data Familiarization	It is assumed that the following is known or provided prior to entering this phase: 1) Desired essential elements of information are understood by the analyst. 2) Visualization symbolism is known. 3) Veracity of information communicated in the visualization is known. 4) Context of visualization is known.	During this phase the analyst acquaints himself/herself with the essential elements of information, which determine what information an analyst should extract from the visualization. For example, an essential element of information could be, "Identify the leader of the network." The analyst would then take the information outlined in the assumptions and begins to analyze the visualization and eventually create a projection on which actor is the leader of the network. Depending on the essential element of information the task goals will change slightly to adapt. For the task goals below the essential elements of information are assumed to be: 1) Identify any leaders or actors of interest within the network and 2) Identify any clusters within the network.

Phase Transition	***The essential elements of information provided during the data analysis phase determine what intelligence information the analyst is tasked to extract from the visualization. The analyst uses these "intelligence goals" to search the visualization.***			
Visualization Exploitation	**Phase Goals**	**Phase Task Decomposition**		
		#	**Subtask**	**Description / Explanation (if necessary)**
	1. Understanding Visualization	1.1	Scan visualization	Scan visualization in order to perceive information required for comprehension of the situation.
		1.1.2	Perceive anomalies in the visualization	Perceive topographical anomalies (items which may communicate an error in the data or visualization)
		1.1.2.1	Rectify anomalies to determine validity of visualization	Draw schemas from pre-acquired knowledge and compare against anomalies to determine if visualization is valid; thus, worth further analysis
		1.1.3	Perceive curiosities in the visualization	Perceive topographical curiosities (items of potential intelligence value)
		1.1.3.1	Rectify curiosities to determine future analytical priorities	Draw from pre-acquired knowledge to determine if curiosities are of potential value and use assumptions to determine analytical priority
	Phase Goal Transition	***Information perceived during the Data Familiarization phase feeds the Analyze Phase by providing a starting point for analysis and a prioritized list of items to analyze.***		
	2. Analyze Visualization	2.1	Revisit curiosities perceived in task 1.1.3	
		2.1.1	Determine which essential element of information the curiosity may satisfy	Once correct essential element of information is determined analyst will recall correct schemas from pre-acquired knowledge.
		2.1.2	Recall from memory characteristics associated with essential elements of information	Recall schemas from pre-acquired memory
		2.2	Leader identification	Analyze curiosities to determine if any identified actors demonstrate the characteristics of a network leader
		2.2.1	Perceive actor's network position relative to the network	Does an actor’s relative position in the network communicate a certain position in a hierarchy
		2.2.1.1	Comprehend whether this position qualifies the actor as a potential leader	
		2.2.2	Perceive quantitative measures of actor's structural prominence	Do quantitative measures communicate an extremum value which may indicate a high structural significance

		2.2.2.1	Comprehend whether these measures qualify the actor as a potential leader	
		2.2.3	Classify actor	After comprehension actor will be classified as a leader or remain unclassified
		2.3	Cluster identification	Analyze curiosities to determine if any sub-groups demonstrate the characteristics of a cluster
		2.3.1	Perceive sub-group's network position relative to the network	Does an actor's relative position in the network communicate a certain position in a hierarchy
		2.3.1.1	Determine boundaries of sub-group	Analyst must determine the boundaries of a sub-group. If boundaries are undefinable, then a cluster does not exist
		2.3.1.2	Determine complete list of actors within sub-group	Actor identification is necessary to feed task 2.3.2
		2.3.1.3	Comprehend whether this position qualifies the actor as a potential leader	
		2.3.2	Perceive quantitative measures of sub-group's structural prominence	Do quantitative measures communicate an extremum value which may indicate a high structural significance
		2.3.2.1	Comprehend whether these measures qualify the sub-group as a potential cluster	
		2.3.3	Classify sub-group	After comprehension sub-group will be classified as a cluster or remain unclassified
Phase Transition		***The leaders and clusters comprehended in the Analyze Visualization Phase feed directly into the Assessment Phase where an analyst will make a projection.***		
Assessment	3. Construct Hypothesis	3.1	Recall leaders classified in task 2.2.3 and clusters classified in task 2.3.3	
		3.2	Project hypothesis about future state of network	Projections are used to satisfy and expand upon the essential elements of information
		3.2.1	Create potential targeting outcome hypothesis	Analyst will make projections about the future state of a network if certain nodes are removed.
		3.2.1.1	Recall from pre-acquired knowledge the background and dynamics of the specific network	
		3.2.1.2	Hypothesize on the impacts if a specific leader is removed	Project the future state of the network if specific leaders are strategically removed
		3.2.1.3	Hypothesize on the impacts if a specific	Project the future state of the network if specific clusters are

			cluster is removed	isolated or removed
		3.2.1.4	Hypothesize on the impact if no actions are taken	Project the future state of the network if no actions are taken
	Phase Goal Transition	***The hypotheses created in the previous phase goal must be evaluated against an analyst's pre-acquired knowledge and the information in the visualization to determine the validity of the hypothesis***		
	4. Test Hypothesis	4.1	Recall hypotheses from tasks 3.2.1.2 - 3.2.1.4	
		4.2	Recall from pre-acquired knowledge the background and dynamics of the specific network	
		4.3	Compare hypotheses pairwise	Hypotheses will be compared side-by-side to determine which course of action is most likely to occur and; therefore, which hypothesis is most likely correct
		4.3.1	Assess the meta-information used to create each hypothesis	
		4.3.1.1	Assess the validity of information	What is the level of uncertainty in the reporting for which each hypothesis is based
		4.3.1.2	Assess the quality of the source	What is the quality of the source for which each hypothesis is based
		4.3.1.3	Assess the recency of information	What is the recency of information for which each hypothesis is based
		4.3.2	Project the likelihood of each hypotheses occurring	From the meta-information and the analyst's pre-acquired knowledge on the specific network he/she can project the likelihood of each hypothesis occurring
		4.3.3	Select the hypothesis with the highest likelihood of occurrence	
	Phase Goal Transition	***After determining which hypothesis is most likely to occur the analyst will compile a report and disseminate it to the information requester to satisfy the essential elements of information***		
	5. Disseminate Reporting	5.1	Recall hypothesis with highest likelihood of occurrence from 4.3.3	
		5.2	Substantiate hypothesis in written form	
		5.3	Disseminate written report to requestor	

Table 3-1: Scenario Task Overview

The scenario task provides a useful organization of the tasks an analyst will encounter while exploiting a visualization for both leaders and clusters. This task overview was used as a starting point for creating the cognitive process flow charts, which take the tabular decomposition of tasks outlined in Table 3-1 and maps them to the flow of information and the decisions an analyst will make during the exploitation of a visualization.

3.1.2 Cognitive Process Flow Charts

The cognitive process flow charts capture the sequence of the tasks outlined in the scenario task overview (Table 3-1) and identify where decisions are made by an analyst. The first flow chart (Figure 3-2) illustrates the high-level process that an analyst must navigate. In this flow chart, and all thereafter, the processes begins with both a visualization and assumptions, which are used by the analyst to satisfy the PIRs and EEIs.

This cognitive task analysis assumes a visualization is given to the analyst for exploitation versus the analyst creating the visualization and then exploiting. The cognitive task analysis revealed this to be a common occurrence, where one analyst would create a visualization then disseminate, potentially through email or hard copy, to other analysts for information purposes or for corroboration on the assessment. Furthermore, the distinction between receiving a visualization and creating a visualization is a key assumption, because the process to create a visualization is fundamentally different from the processes to exploit a visualization. This is because creating a visualization is a much more complex process that involves simultaneous research and exploitation.

Additionally, the assumption of exploitation versus creation yields an additional process end point during the Data Familiarization Phase. In this case, if the analyst exploiting the visualization determines the data to be of insufficient quality, he or she will end the exploitation process. This process termination deviates from the visualization creating process, wherein if the analyst determined the data to be of insufficient quality he or she would conduct more research and update the visualization until the quality of the data was sufficient enough to effectively analyze. However, because an analyst that receives the visualization may not have the background, expertise, or the access (for example: research information may be of a higher classification) to further research a topic it forces an analyst in this situation to end the exploitation process.

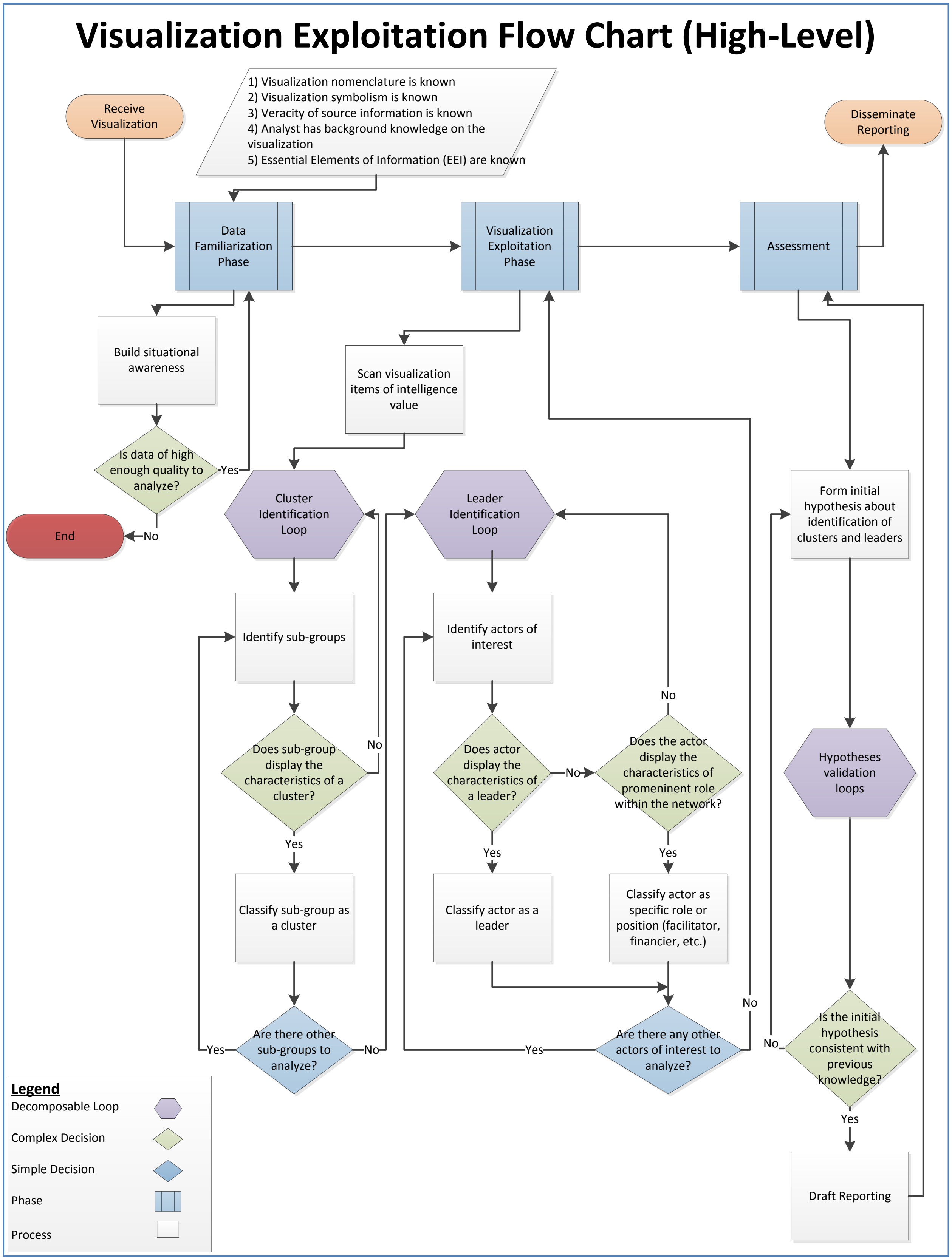

Figure 3-2: Cognitive Process Flow Chart (Overview)

Once an analyst understands the visualization and assumptions, the analyst can begin the data familiarization phase. This phase consists primarily of building an understanding of the visualization and classifying both anomalies and curiosities for later exploitation. Once this phase is complete, an analyst transitions to the visualization exploitation phase, wherein he or she uses identification loops that are designed to yield hypotheses about possible conclusions from the visualization. Once the analyst completes all required identification loops, he or she can then transition to the assessment phase. In this phase the analyst must make an assessment on the information within the visualization. Each of these phases is further decomposed below and shows specifics of each process, loop, and decision.

Data Familiarization Phase

The primary purpose of this phase is for the analyst to build an understanding of the visualization and on the assigned EEIs (Figure 3-3). Thus, the first process in the phase is scanning the visualization. This is done by the analyst to confirm he or she understands all the symbolism and nomenclature prior to analysis. After this, the analyst begins the process of detecting anomalies in the visualization. In this research, anomalies are defined as data that display the potential to be spurious. An example of an anomaly is multiple nodes of the same name. If a visualization has anomalies the analyst must then decide if the visualization is still of sufficient quality to exploit. If it is not, then the process ends (for reasons explained in the beginning of section 3.1.2.). However, if it is of sufficient quality then the analyst begins searching for curiosities within the visualization. In this research, curiosities are defined as data that displays the characteristics of a valuable piece of intelligence. An example of a curiosity would be a single node in a network with an exorbitant quantity of links relative to other nodes. If there are no curiosities in a visualization, then there is no information of intelligence value to be gained by exploiting the visualization and the process ends. However, if the analyst does detect one or more curiosity he or she decides whether they could potentially satisfy an EEI. If they can, then they are classified (i.e. potential leader or potential cluster) for later analysis in the visualization exploitation phase.

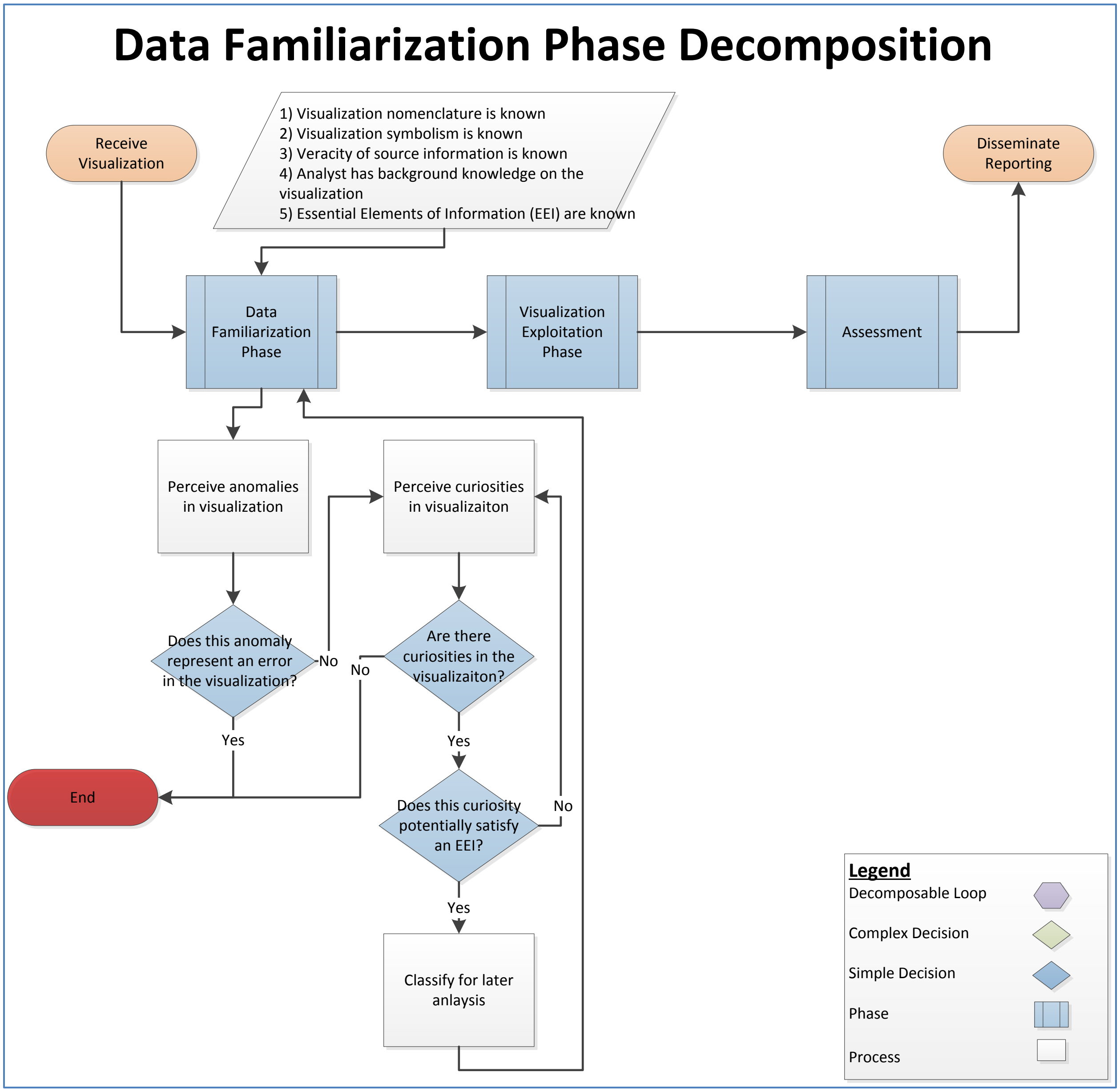

Figure 3-3: Data Familiarization Phase Decomposition

Visualization Exploitation Phase

During this phase (Figure 3-4) an analyst must determine the intelligence value of the curiosities he or she previously classified in the data familiarization phase. This phase starts with the analyst scanning the visualization for the pre-classified curiosities. After identifying the curiosities he or she will enter an EEI specific identification loop. In this loop the analyst must reconcile the data presented in the visualization with previous experience and background knowledge on the subject (referred to in later parts of this

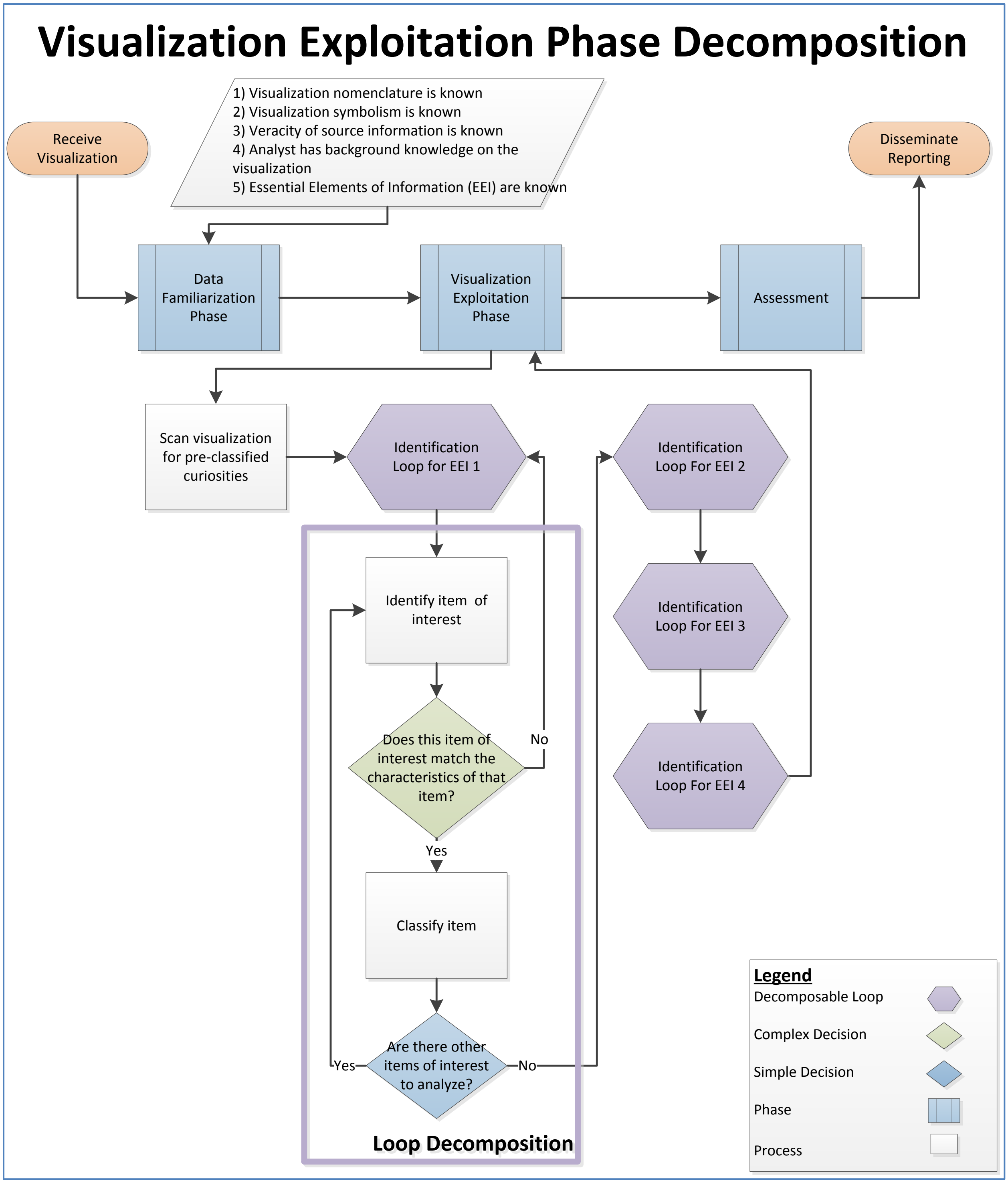

Figure 3-4: Visualization Exploitation Phase Decomposition

chapter as pre-acquired knowledge). If the item of interest matches the analyst's pre-acquired knowledge then he or she will definitively classify the item. The analyst will continue this loop until all items which could potential satisfy the EEI are exhausted. When complete the analyst then moves on to the next EEI identification loop and repeats the same process. This continues until all loops are complete.

Assessment Phase

The final phase in the cognitive flow process is the assessment phase (Figure 3-5). The primary purpose of this phase is for the analyst to construct hypotheses about the network and then select a single one based on the likelihood of that hypothesis occurring. This phase starts with the analyst creating initial hypotheses. These hypotheses are developed from the information the analyst classified in the visualization exploitation phase. For example, if the analyst identified two potential leaders in the visualization exploitation phase, he or she would create a hypothesis about each of those leaders ("Node X is the leader of the XXX network" and "Node Y is the leader of the XXX network") and use the assessment phase to select the most likely hypothesis.

After identifying hypotheses the analyst will use the hypothesis identification loop to determine the validity and project the likelihood of each hypothesis occurring. This is done by reconciling the hypothesis against the analyst's pre-acquired knowledge. The first stage is to determine if the hypothesis is valid. For example, an analyst may hypothesize that, "node X is the leader of the XXX terror network." However, he or she may recall from their pre-acquired knowledge that "node X" died 7 months ago; thus, this is an invalid hypothesis. If the hypothesis is determined to be invalid, the analyst will discard it and move onto the next hypothesis. If the hypothesis is determined to be valid, then the analyst begins the process of predicting the likelihood of the hypothesis occurring. This is done primarily through a sequence of two decisions. The first is the quality of the information source. In most cases the analyst will know the veracity of the information provided by the data source. From this he or she will determine if the hypothesis is of high enough quality. For example, if a data source is identified as "low probability", then the analyst will factor this into the projection of likelihood. If the hypothesis is of sufficient quality the analyst will then assess the recency of the information. If the information is recent enough the analyst will exit the hypothesis validation loop.

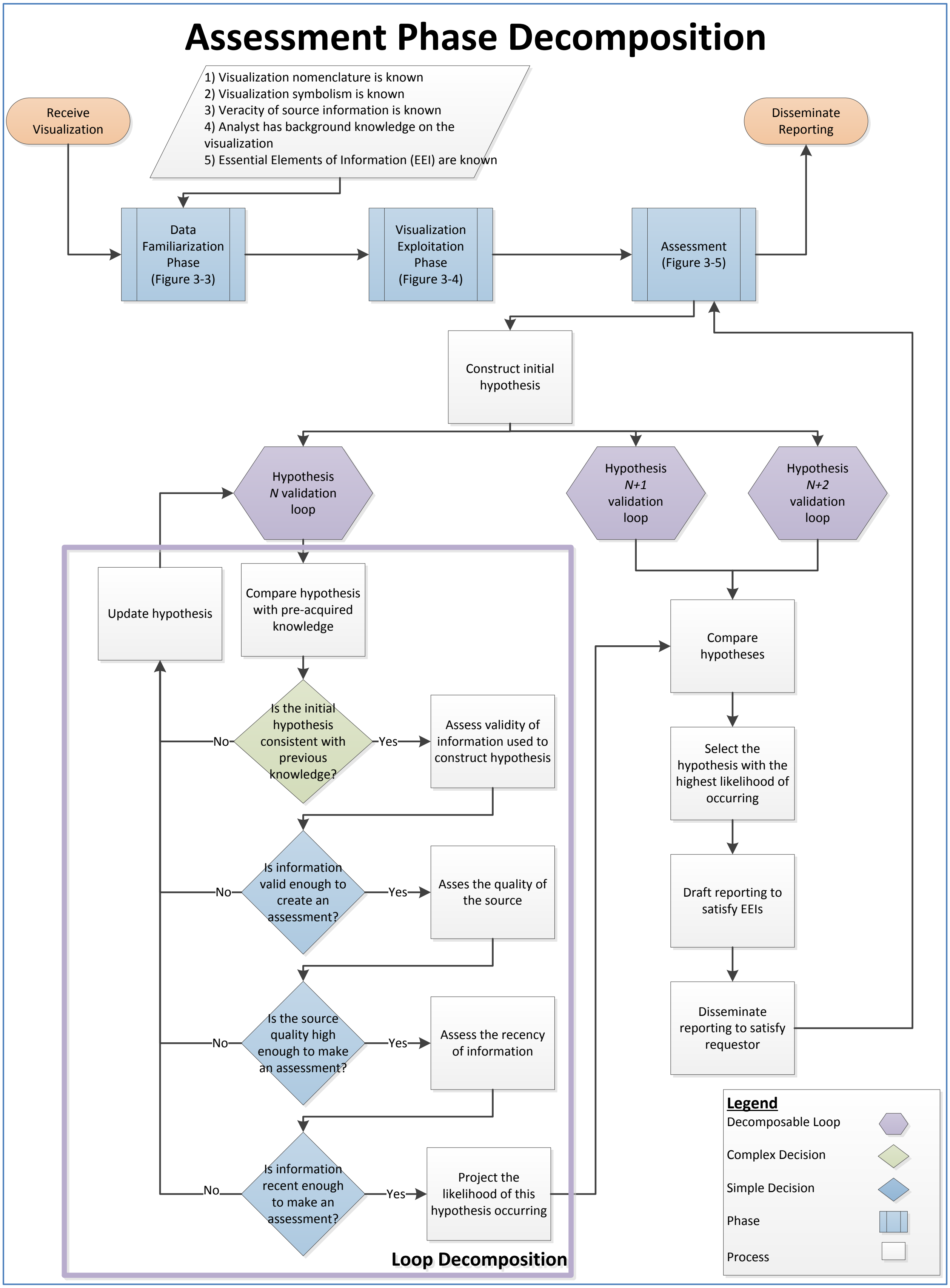

Figure 3-5: Assessment Phase Decomposition

Each loop is evaluated sequentially until all are complete; at which time the analyst will compare the projected likelihood of occurrence for each hypothesis and typically select the hypothesis with the highest likelihood of occurrence. From this, he or she will draft reporting and disseminate it to other analysts, who will continue to develop and refine the hypothesis. Upon completing this phase, the cognitive flow process is complete.

3.2 Information Processing Model for Terror Visualizations

From the cognitive task analysis described in section 3.1 an information processing model was adapted from [72, 73, 74] to illustrate the cognitive processes used by an analyst both within and between phases. The model illustrated in Figure 3-6, outlines a basic information processing model for analyzing visualizations, which resulted from the information gleaned during the cognitive task analysis. In this model the blue squares represent cognitive processes that make up the substantive steps of the information processing function of the model. This model deviates from traditional information processing models in that the action step results in a prediction by an analyst about the future state of the data being analyzed [72]. This is because exploiting terror network

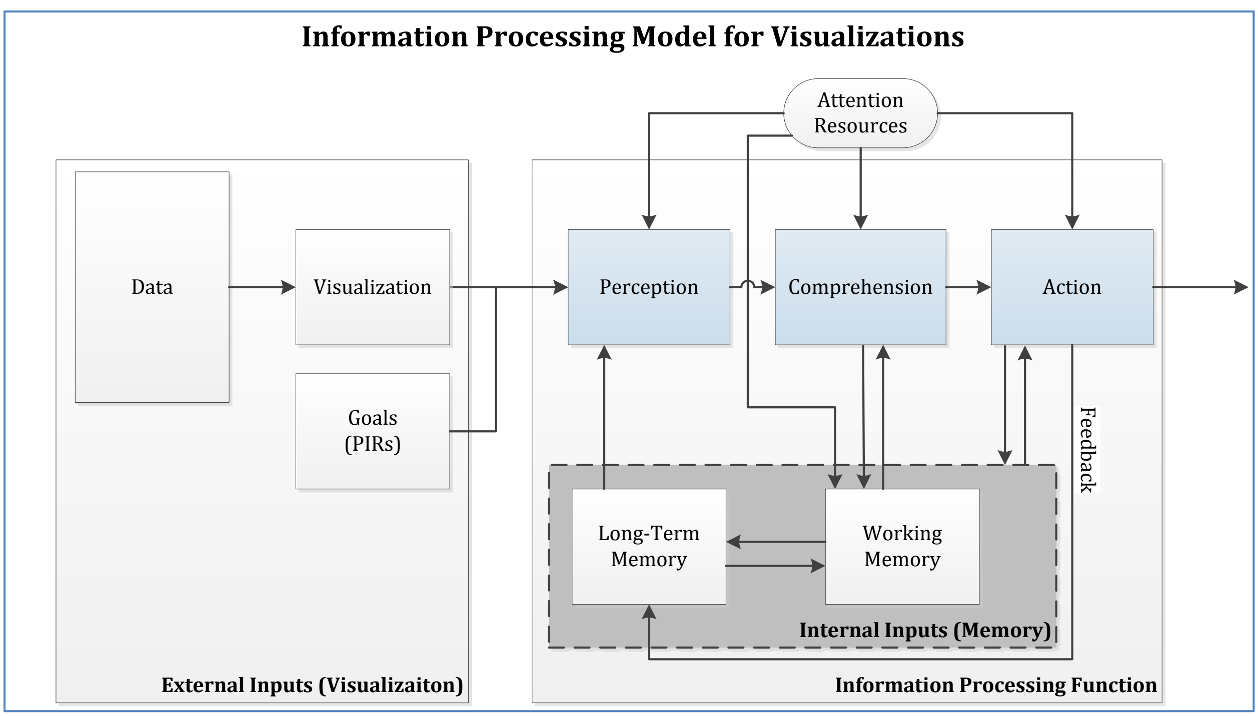

Figure 3-6: Information Processing Model

visualizations does not result in any direct physical action from perceived information. Alternatively, the information perceived while exploiting visualizations must be temporarily stored in the working memory while perceived information is synthesized into an understanding of the situation that is capable of supporting hypotheses on the future state of the external inputs. This prediction process, which involves hypothesis validation, is considered the action process in the model.

There are two primary inputs to the information processing function, information exogenous to the process (visualizations of data) and information endogenous to the process (memory). Each of these inputs and cognitive processes will be explained in more detail in subsequent sections of this chapter.

3.2.1 External Inputs

The cognitive model for exploitation of terror networks starts (from left to right) with external inputs into the information processing function. However, an important nuance when dealing with visualizations is the transformation from data to visualization. This is an entirely separate process from the information processing model outlined above. The specifics of this process were discussed generically in section 1.2, but it is nonetheless important to note that visualizations are abstractions of the data and thus introduce a certain amount of uncertainty. Keim et al. described this phenomenon in the context of creating effective visualizations, "The challenge is to try to come up with a representation that is as faithful as possible to avoid introducing uncertainty. We must not fall into the naïve assumption that visualization can offer a virgin view on the data" [75]. As such, every step in the information processing model outlined above both recognizes and accounts for the imperfect data displayed by visualizations. This key challenge of the external inputs will be discussed in further detail in each of the cognitive process steps.

The input sources in the model are representative of the information gleaned during knowledge elicitation, naturalistic observation, and literature on task taxonomy for graph visualization [76]. They are as follows:

- *Symbolic*: Information provided by the two primitive elements of network visualizations - nodes and links.
- *Magnitude*: Information provided by the two primitive elements (node/links) of network visualizations on the aggregate.
- *Spatial*: Information provided by the relationship of one or more primitive element (node/link) to another.

Symbolic information is characterized as the information provided purely by the nodes and links. Specifically for nodes, this information can include the size, color, shape, or iconic representation of a specific node; all of which are used in terror visualizations to convey specific meaning or context. These nodal symbolic representations, while relatively simplistic, are capable of conveying many additional dimensions of data to an analyst. For example, in a node-link visualization instead of using a generic node form (such as: ❶) an analyst may encounter an icon that commutates specific characteristics about the represented node (such as: ). These same symbolic representations are also possible in matrix visualizations; nodes can be replaced with icons to communicate the same characteristics as outlined above in node-link visualizations; however, this practice is less common in matrix visualizations. While node icons are an effective way to communicate additional information in a relatively small amount of space, if poorly labeled they can also be easily misunderstood.

Similar to nodes, links can also be represented using a variety of methods (color, size, labels); however, links can also communicate directionality within a network. As discussed in Chapter 2, directionality is defined as, "ties oriented from one actor to another" [7], whereby the direction of the link communicates a specific relationship. For example, in a node-link visualization if node X made a phone call to node Y this relationship would be visualized by a directional link (X→Y). This same information is displayed in a matrix visualization by using a nonsymmetrical matrix to communicate the directionality of communication from one note to another. While subtle, this additional dimension of network data can provide key information on the relationships between specific nodes. Perceiving the significance of these relationships and all node and link symbolic representations is absolutely critical to understanding the overall situation and context of the visualized network.

Magnitude information, meaning the emergent abstract characteristics of the network on whole, is important to an analyst because it determines the overall link density[11] of a network and directly contributes a network's perceived complexity [6]. Recognizing the size and complexity of a network is critical to efficient analysis. As such, it is incumbent upon an analyst to understand the limits of readability using specific visualizations and either: 1) break a network down into two or more sub networks, or 2) employ an alternate means (possibly different visualizations) to examine a specific network.

Spatial information includes the effects of any topographic or temporal layouts used to organize or communicate the relationship among the nodes in a network. There are a variety of possible layouts (spring embedder, force directed, hierarchical, attribute based, k-means, etc.), each of which offers a different perspective of the network. An analyst must understand the implications of certain layouts and comprehend the benefits and drawbacks of each. For example, if an analyst is exploiting a network visualization that uses a hierarchical layout the analyst must understand the positions and roles within that network topography. A failure to do so would reduce the amount of information that could be perceived from the hierarchical visualization. Furthermore, spatial information is used in conjunction with symbolic information to interpret and examine the terror network on a whole.

Another external input to the information processing function is goals. Goals both provide context and drive the cognitive processes of an analyst. As discussed in section 3.1, an analyst's goals are set forth based on the PIRs and EEIs. This is significant input, because the goals will drive what information is perceived and processed through the information processing function.

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[11] Link density is defined by Goenhiem et al., as: $d = \sqrt{\frac{l}{n^2}}$; where l is the number of links and n is the number of nodes [6].

3.2.2 Internal Inputs

While external inputs play a large role in an analyst's ability to process information from a terror network, internal inputs play an equally critical role because the ability of any given analyst to reach accurate projections depends on the internal inputs (long-term or working memory). This is because each analyst has a set of pre-acquired knowledge, which is gained through training or past experiences executing cognitively congruent tasks, which is stored in long-term memory. In processing information, the analyst will draw from this pre-acquired knowledge to recall mental models, situational models, and schemata developed in past to help organize or marshal information in a current task [77]. Although all analysts have a baseline of heuristics as a result of formal training (some variation exists based on the source and quantity of training), most analysts will not have the same set of mental models or schemata to draw from. For example, an experienced analyst will have much more developed mental models and schemata than a new analyst. This wide range of experiences is the reason why two analysts exploiting the same visualization can reach two different assessments. Furthermore, these cognitive structures offer a key advantage when attempting to process information, because an analyst can draw from these long-term memory structures (schemata or scripts) to act on current situations with the benefit of not overloading working memory [77].

Working memory, which is "a vulnerable, temporary store of activated information" [72], plays a critical role in the processing of information by linking the long-term memory structures with elements from the current situation. This section of the cognitive model is largely responsible for rectifying the information disparities between what is available and what is required. However, the role played by working memory is highly vulnerable to disruption when "attentional" resources are diverted to other mental activities [72]. Endsley frequently refers to the working memory as the main "bottleneck" and elaborates on the constraints of working memory, "a heavy load is imposed on working memory, as it is taxed with simultaneously achieving the higher levels of SA [situational awareness], formulating and selecting responses, and carrying out subsequent actions" [77]. As such, working memory can become easily overburdened if managed improperly.

3.2.3 Perception

The first cognitive process in the information processing function is perception where "information received by our sensory system is perceived, that is, provided with some meaningful interpretation based on memory of past experience" [73]. This is where raw data is received by the brain and transformed into a meaningful form of information. Perceptual processing has two key features: 1) it typically proceeds automatically and rapidly (requiring little attention; thus, not overly burdening working memory) and, 2) it is driven by both external inputs (visualizations and goals) and by internal inputs (long-term and working memory) [72].

For an intelligence analyst this information enters the cognitive process in the form of external inputs, described in Section 3.2.1. While most information is perceived directly from external input sources (nodes, links, size, topography, etc.), some of the external inputs are also combined with internal input sources (examples include: known network structures of a leader) to form a more complete understanding of the situation. This fusion of various inputs results in the perception of characteristics that would not have been discernible by examining any one input alone. These perceptions of inputs form the foundation of the information processing function because this is the first point which meaning is applied to the data emerging from the visualization.

3.2.4 Comprehension

The second cognitive process is comprehension of the current situation. In the comprehension process, disjointed information from the perception process is synthesized with goals to achieve a more holistic picture of the current state of the data and comprehend the significance of objects [77]. To achieve comprehension, an analyst must reconcile the differences between the gaps in information provided during the perception process with the information required to satisfy his or her goals. This is done by temporarily storing information in working memory with the objective of accessing "information that was not sensed and perceived but was generated internally" [73]. The greater the mismatch in the information available from the perception process relative to the information required to satisfy the goals, the greater the cognitive workload required to perform the information-processing. All of the literature reviewed during the cognitive task analysis indicates that this is the single most difficult step for an analyst during the exploitation process.

As discussed in section 3.1, the two goals fed into the information processing model for this thesis are: 1) the identification of leaders, and 2) identification of clusters. These goals, along with the perceived information and pre-acquired knowledge, are fed directly into the working memory. The first goal, identification of leaders, involves cross cueing the information resulting from the perception process against any schemata or scripts in the long-term memory to reach valuable conclusions (examples are: positive identification of any salient actors or normalization of anomalies). For example, an analyst may identify a node with an exponentially higher number of links than adjacent nodes. By itself, this perceived information is inconclusive. This is because the perception of this information is important, but the comprehension of the meaning within the context of the network is more critical to satisfy the goal of exploitation. A single node with many connections could indicate a salient actor (leader of a terror network) or it could represent an innocuous actor with many unimportant connections (network facilitator or the suburban equivalent: a mailman). To comprehend which conclusion is most likely correct, an analyst may recall scripts or heuristics from memory to assist in identifying salient actors. In this case, an analyst may fuse a perceived network structure with heuristics or experiences from past analyzed network topologies where the salient actors were known. From this synthesis an analyst can begin to comprehend the salience of particular actors in the network. However, as discussed in the external inputs section, because visualizations interject uncertainty, there is no way for the analyst to know for certain whether his or her comprehension is correct. This remaining gap between information available and information needed to satisfy a goal is what makes intelligence analysis a cognitively complex and challenging task.

To resolve the uncertainty an analyst uses a sub-process, where possible, within the comprehension process to identify and analyze meta-information revealed from the perception process. All perceived information contains some level of meta-information, which is defined by Pfautz et al., as “characteristics or qualifiers of information that affect the user’s information processing, situational awareness, and decision making” [69]. Examples of meta-information are: the source quality of the information, recency, and uncertainty. Occasionally this meta-information is explicitly stated in visualizations, but sometimes this information is left out of visualizations to reduce visual complexity. In the case of the latter, this sub-process is not viable. However, when this information is available it further complicates an analyst’s job, because to comprehend information an analyst must recognize the meta-information and reason through it using one of the following methods (derived from [61]):

- *Deductive Reasoning:* Where the conclusion, or conclusions, follows from the premises.
- *Inductive Reasoning:* Where the conclusion, or conclusions, though supported by the premises, does not follow from them necessarily. This method is the inverse of deductive reasoning, where an observation is used to infer a larger theory.
- *Abductive Reasoning:* When one attempts to determine the best or most plausible explanation for a given set of evidence.

Through these methods of mentally taxing complex reasoning an analyst can often reach some form of comprehension. In a case where an analyst had access to all information and meta-information (i.e. if he or she created the visualization), he or she could use deductive or inductive reasoning to reach comprehension. However, as a result of the uncertainty within visualizations and the lack of access to the complete set of meta-information, most comprehended information is as a byproduct of the best or most plausible explanation, given the limitations of the meta-information (i.e. abductive reasoning). While effective at reaching collusions in complex uncertain domains, abductive reasoning will not consistently produce accurate results. It is the objective of the analyst to accept some uncertainty in his or her analysis, but ensure that any conclusions factor in inaccuracies and minimize them to the maximum extent possible.

3.2.5 Action

The third and final step of information processing is the ability to predict the future states of elements in the situation. In the case of terror network visualization, predictions are typically achieved through knowledge of the data from which the visualization is built and comprehension of the visualization. Specifically, an analyst will form a prediction that answers the goals: 1) the identification of leaders and 2) identification of clusters. The extent to which an analyst can accurately predict either one of these tasks relies heavily on the quality of the information perceived and more importantly the resulting information comprehended. As discussed in the flow charts in section 3.1.2, an analyst will create multiple competing hypotheses regarding the future state of the situation. Each hypothesis is then evaluated based on the aggregate meta-information, such as level of confidence or probability of occurrence. Typically an analyst will predict the hypothesis, or hypotheses, with the highest accuracy and highest level of confidence.

Unfortunately, if an analyst makes an error in perception, then that error can propagate through all the processes in the information processing model. Once an error is made, it is likely that additional errors will be made based on the previous bad information; thus, creating a cycle of error-on-error analysis. This cycle can go largely uncorrected until the analyst has an opportunity to receive feedback on the quality and accuracy of his or her predictions. If feedback on an analyst's prediction is available the analyst will accumulate lessons learned from that projection and use that data to continuously populate and update their pre-acquired knowledge. This iterative cycle of evaluation of analysis and feedback is how an analyst builds experience.

3.3 Conclusion

This chapter outlined a cognitive task analysis to identify the specific cognitive processes, challenges, and constraints an analyst faces while exploiting terror network visualizations. The results of that analysis were then used to create an information processing model for visualization. The model identified and illustrated the cognitive processes used by an analyst to transition through three main stages of information processing: perception, comprehension, and projection. Of particular significance, the transition from perception to comprehension was noted as one of the primary bottlenecks inhibiting effective information processing.

Chapter 4

Terror Network Visualizations

This chapter provides background and details on the specific terror network visualizations that were used in the human subjects experiment described in Chapter 5. This chapter begins with a discussion of the data set used in the study, then transitions into the specific adaptation of node-link and matrix visualizations, concluding with a discussion on the design principles used.

4.1 Overview

The two visualizations described in this chapter were created for the purposes of the human experiment described in Chapter 5, which is designed to test the efficacy of each visualization at identifying leaders and identifying clusters. The intent of these visualizations is to provide an intuitive interface that leverages design principles (discussed in more detail in section 4.5) to present an integrated set of information to an analyst [72]. The specific description of each visualization is discussed in further detail below.

4.2 Visualization Data Set

For this study it is critical to have a data set that has both truth (i.e. the roles and positions of the nodes which compose the network are known) and characteristics of a real-world terrorist network. Failure to use a network with truth or characteristics of a terror network could jeopardize the experimental testing. With this in mind, three possible courses of action were investigated:

- Actual Terror Data Set – The simplest solution would be to use data from an existing terrorist network. However, this method was excluded because classification constraints do not allow for the use of real-world data on terrorist networks, and to guarantee the impartiality of potential experiment participants an open source terrorist network (ex. 9/11 Hijackers) was avoided.
- Simulated Data Set – A data set could be simulated to mimic the topographic and statistical properties of a known terror network. However, this method was also excluded because the scope of this work is to find a visualization that enhances the exploitation of terror networks. The author felt designing a data set and proving its statistical congruence with a terror data set would be outside the scope of this research and distract from the true purpose.
- Surrogate Data Set – The final option explored was finding a surrogate data set that mimicked the topographic and statistical properties of a terror network. In all, six different data sets were explored: Bernard & Killworth Fraternity [78], Padgett Florentine Families [79], Read Highland Tribes [80], Stokman-Ziegler Corporate Interlocks [81], Thurman Office [82], and the Karate Club [83].

The data set ultimately selected to satisfy all three targeted characteristics is the Karate Club data set [83]. The data set was gathered by Wayne Zachary on a university karate club. Zachary describes the specifics of the club as:

> "The karate club was observed for a period of three years, from 1970 to 1972. In addition to direct observation, the history of the club prior to the period of the study was reconstructed through informants and club records in the university archives. During the period of observation, the club maintained between 50 and 100 members, and its activities included social affairs (parties, dances, banquets, etc.) as well as regularly scheduled karate

lessons. The political organization of the club was informal, and while there was a constitution and four officers, most decisions were made by consensus at club meetings. For its classes, the club employed a part-time karate instructor, who will be referred to as Mr. Hi." [83]

Although the data set is not related to terrorist activities, it has truth, which includes documented roles and positions of the members within the group (to include: leaders, and clusters). Additionally, the karate club data set represents a simple graph[12] with single nondirectional dichotomous relations[13] and offers complex interactions among 34 discrete social actors; these characters of the data set mimicked Sparrow's key characteristics of a terrorist network:

- *Complexity* (encompasses Sparrow's characteristics of size and fuzzy boundaries [36]) – Terror networks have the potential to be hundreds of connections spanning multiple time zones and continents; resulting in networks that are often large and dense.
- *Uncertainty* (encompasses Arrow's characteristic of incompleteness and dynamic [36]) – Most of the data an analyst has on a terrorist network is based on invalidated reporting. The veracity of this information is not always substantiated. Therefore, a significant portion of the data in a terror network has the potential to be wrong or misleading.

4.2.1 Descriptive Statistics of Data Set

A specific interest is the overall link density of the network (see section 3.2.1 for a review of link density), which can be used as an indicator of network complexity (research indicates higher density equates to higher complexity [6]). While the density of this network is low (0.259), it is desirable for this research, because it will allow for the entire network (34 nodes and 78 links) to fit on a single sheet of paper. A density above this level may result in static visualization with many confusing clusters of links, which could result

[12] Defined by [7, p. 95] as: "A graph that has no loops and includes no more than one line between a pair of nodes"

[13] Defined by [7, p. 95] as: A graph of a social network where, "the nodes represent actors, and the lines represent the ties that exist between pairs of actors on the relation"

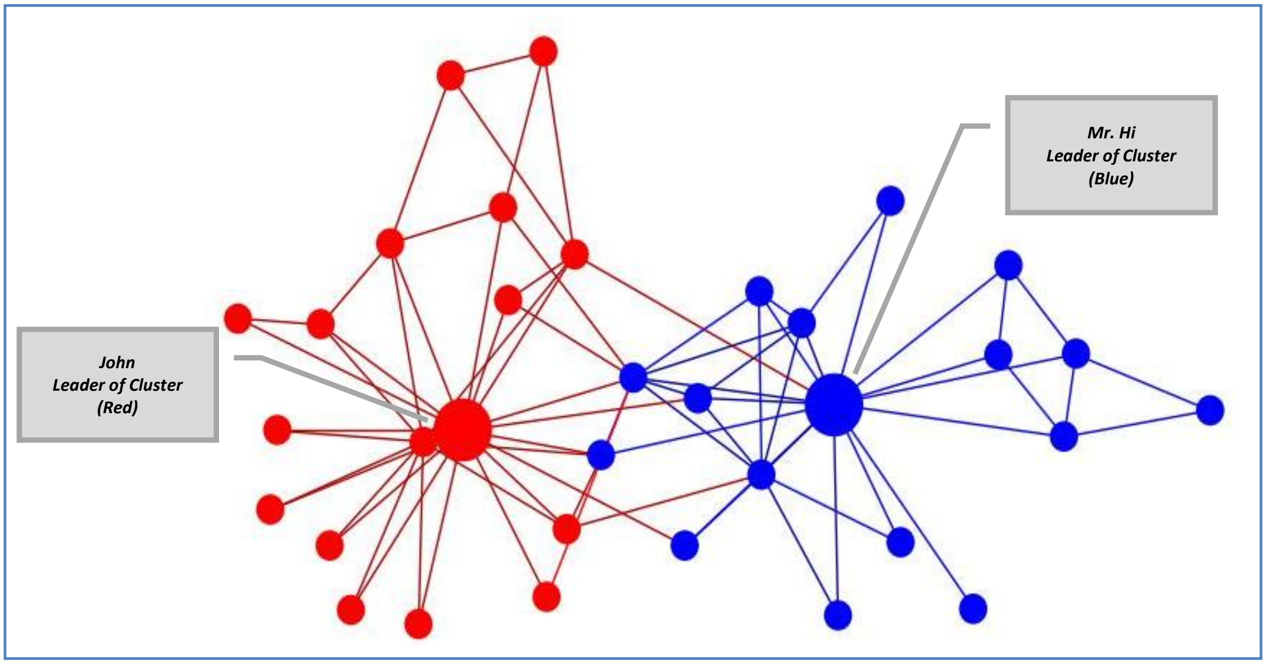

Figure 4-1: Karate Club leaders and clusters

in the occlusion of significant data and subsequently impact an analyst's ability to draw conclusions from the visualization. Although complex networks are common in the domain of intelligence, a network with a density that is too high could make the node-link diagram more complex than the matrix visualization; thus, creating a disparity between the two visualizations and potentially jeopardizing the results of the human experiment.

Regarding the uncertainty of the data set, a cursory analysis yielded two key findings. The network contains two clusters organized around two opposing leaders and six nodes that link the two clusters together (visible in Figure 4-1). To gain an accurate understanding of the network, an analyst will have to walk through the cognitive model outlined in the previous chapter to successfully identify the two clusters, leaders, and normalize the connections between both clusters. Thus the clusters, and the potentially misleading connections between them, display an acceptable level of uncertainty in a network of this density.

4.3 Node-Link Visualizations

The first visualization method this chapter will focus on is node-link. As discussed in

Chapter 2, this form of visualization is by far the most pervasive within the military intelligence enterprise. Academic research indicates that node-link diagrams are one of the most effective ways to visualize relatively low density networks (a link density less than 0.4) [6]. However, when the data density grows larger and more dimensions of data (such as node attributes) are added, node-link visualizations can become very complex and difficult to analyze. Therefore, the challenge when creating a visualization for human experimentation is to create a visualization that will challenge participants, but not confuse or bias participants towards one visualization technique.

Figure 4-2 shows a basic node-link visualization, of the karate club data set, organized using a spring embedded layout (further details on the specific algorithm can be found in [84]). Due to the ease of readability associated with spring embedded layouts, all node-link diagrams depicted herein will use the same spring embedded layout. The primary benefit of node-link visualization is the ability to view the entire network topology. However, at its most rudimentary form, node-link analysis does not show much data; only nodes and links. It is possible, by overlaying additional node attributes, to show multiple dimensions of meta-information using this visualization technique. Figure 4-3

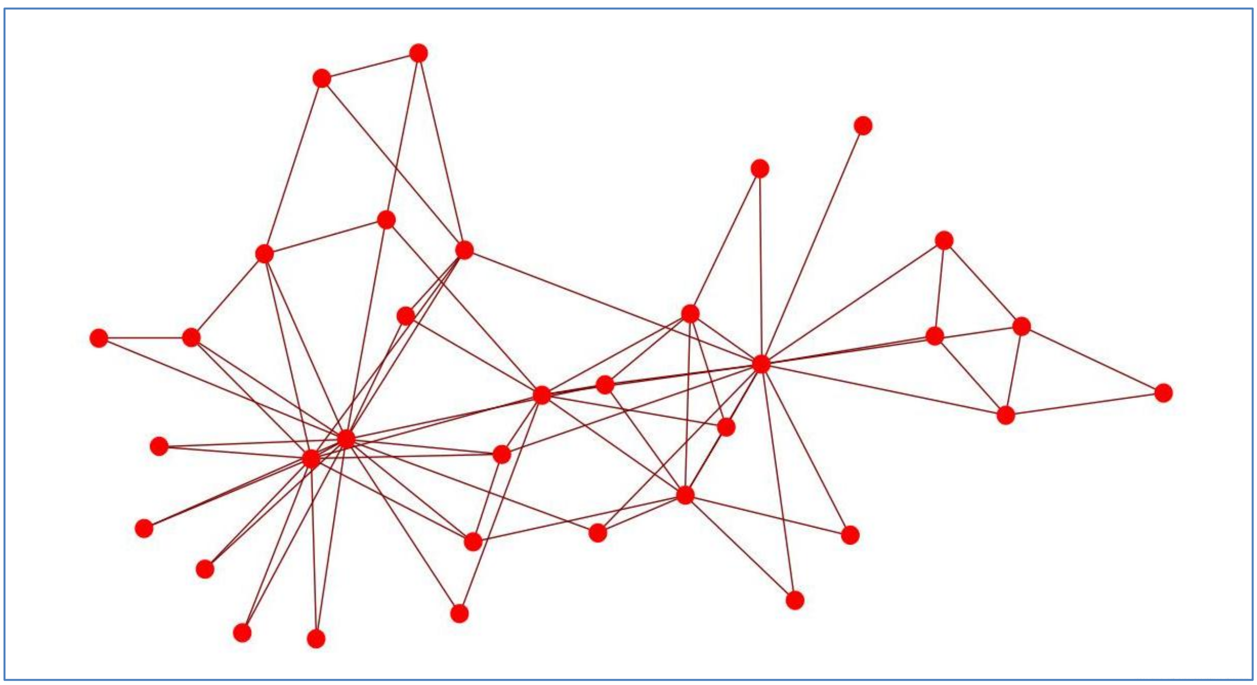

Figure 4-2: Basic node-link visualization of karate club data set

demonstrates one method where meta-information can be incorporated into a node-link visualization. In this example, ordinal values of closeness centrality are depicted by changing node size; where a large node indicates high closeness centrality and a small node indicates low closeness centrality. Additionally, the scalar values are denoted on the left side of the label for each node. By adding the closeness centrality of each node, it overlays an additional dimension of data and communicates emergent meta-information on the network (the concept of emergent features is discussed further in section 4.5).

Another dimension of data can be added by changing the node color. Figure 4-3 illustrates an example of this method. In this case, closeness centrality is still depicted by node size, but betweenness centrality is now illustrated by changing the node color; where blue nodes indicate high betweenness centrality and red nodes indicate low betweenness centrality. The result is a visualization that shows the topology, but also offers quantitative measure of centrality that communicates the relative "importance" of each node.

Many more layers of information may be added on top of this visualization, but each additional layer of information has the potential to complicate analysis and diminish analytical returns by occluding other data. In the case of node-link analysis, it does not necessarily mean that added information and complexity directly correlates to more effective visualizations. Therefore, striking an optimal balance between information and complexity is a primary challenge when creating a node-link visualization.

4.4 Social Network Matrices

As discussed in Chapter 2, this method of visualization currently is not common within the intelligence community. In addition to the reasons mentioned in Chapter 2, the absence of this form of network visualization may also be due to a lack of commercially available intelligence oriented matrix analysis tools, and little to no analyst training on matrix analysis. For example, the matrices created for this thesis were constructed using a combination of UCINET, which is open-source social network analysis program developed by experts in the field of social network analysis [85]and ORA, which is a complex social network analysis tool developed by Carnegie Mellon's Center for Computational Analysis of

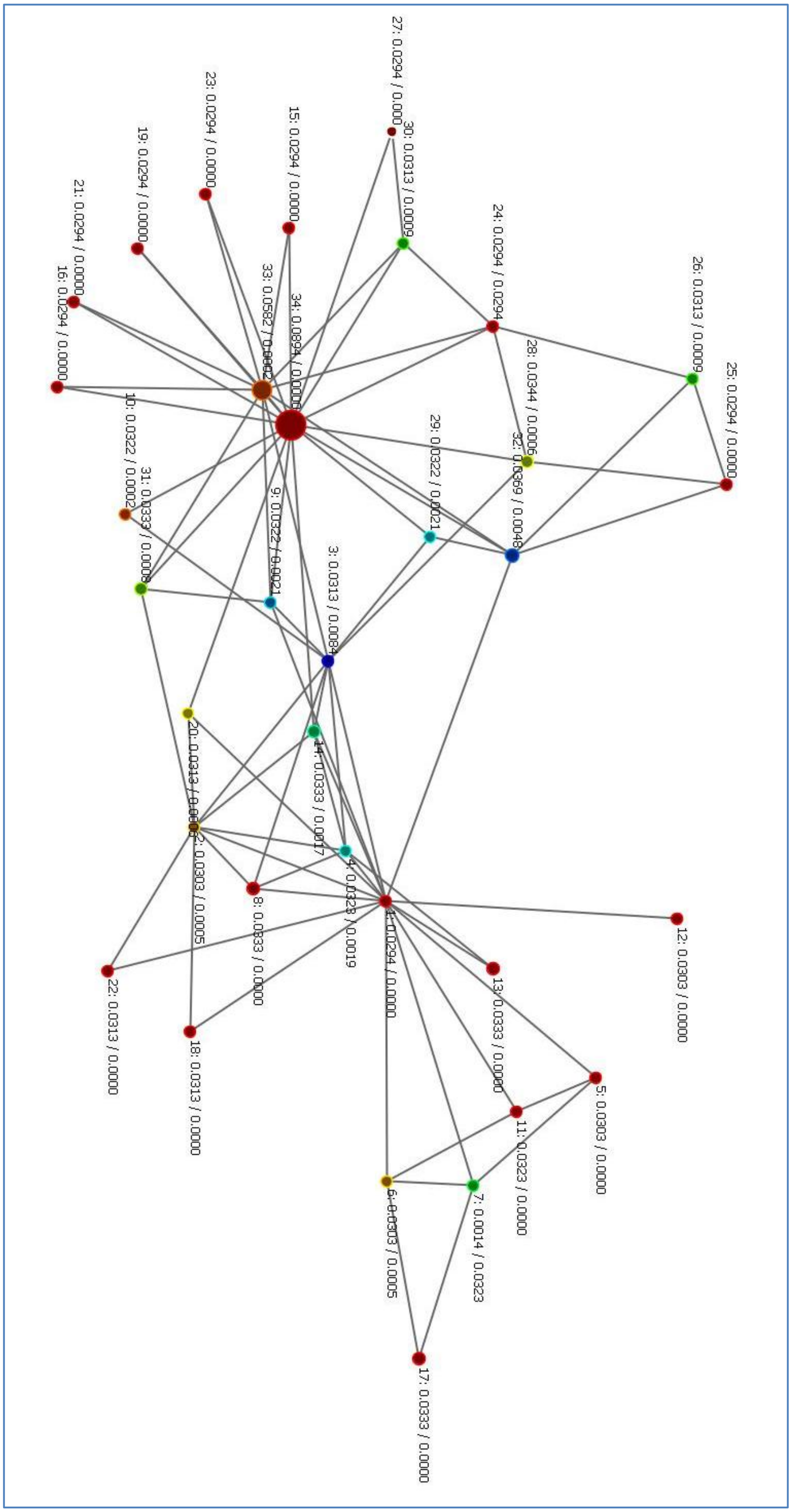

Figure 4-3: Enhanced node-link visualization with multidimensional data

Social and Organizational Systems [86]; and Microsoft Excel. To the author's knowledge there is no single commercially available tool which can accomplish all the tasks necessary to create a visualization similar to the matrices in Figure 4-4 and Figure 4-5. This is supported in research done by Henry et al., who surveyed all the tools in the "International Network for Social Network Analysis" software repository. Their examination revealed that node-link represented the preponderance (54 out of 55) of available tools [18].

Figure 4-4 represents a symmetrical matrix showing the interconnections between the nodes (labeled numerically from 1-34 on the top and left of the matrix). The matrix is symmetrical because the data set is nondirectional. Meaning the links do not show a relationship from one person to another, but simply communicates a relationship exists.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1		1	1	1	1	1	1	1	1		1	1	1	1				1		1		1										1		
2	1		1	1				1						1				1		1		1									1			
3	1	1		1				1	1	1				1														1	1				1	
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32	1																								1	1			1				1	1
33			1						1						1	1			1		1		1	1						1	1	1		1
34									1	1				1	1	1			1	1	1		1	1			1	1	1	1	1	1	1	

Figure 4-4: Unpartitioned symmetrical matrix visualization of data set

Furthermore, in this matrix the links between nodes are represented by a "1" at the intersection of nodes (note all cells are with a "1" are highlighted in grey to make the clusters more apparent).

One of the most common criticisms of nodal-link analysis is its inability to display large and/or dense networks. As nodal-link visualizations grow in size they have a tendency to become cluttered and difficult to analyze. Some scholarly authors advocate the use of matrices to solve this problem [6]. Figure 4-4 is an example of a matrix, which in this case is an un-partitioned[14] symmetric matrix composed from the Karate Club data set. Matrices, such as Figure 4-4, can be used to spot patterns spanning many different nodes or links. These patterns can reveal clusters and show characteristics of the data that are not readily discernible from node-link visualizations due to occlusion.

As with node-link visualizations, basic matrices only depict the basic topology. However, to ensure that each visualization presents similar amounts of data, for purposes of the human experiment described in the next chapter, the same information must be communicated in the matrix as in the node-link diagram. To add additional dimensions of data, the matrix was partitioned using a k-means clustering algorithm (for details on the specific algorithm please see references [87, 88]). Since the number of clusters in this network was already known k was set to 3 (k=3 also returns the lowest r-square for integers $k= x$; $2<x<5$)[15]. This algorithm partitioned the matrix into two large clusters with a third cluster of actors who serve as intermediaries between the two main clusters.

Additionally, both the ordinal and scalar values for betweenness and closeness centrality for each node were overlaid on the diagonal of the matrix, with closeness centrality on the left and betweenness centrality on the right. Similar to the node link visualization, conditional formatting was added to both measures of centrality, where blue nodes indicate high centrality values and red nodes indicate low centrality values;

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[14] Meaning no layout algorithms were been applied to alter the organization of the nodes.

[15] An analyst would not know to employ the k-means algorithm or set k=3. However, this layout selection is relatively insignificant because most layout choices are transparent to an analyst; they are set to a default setting in most social network applications. This also holds true for node-link the layouts, where the data is automatically visualized by most social network applications in a spring-embedded layout.

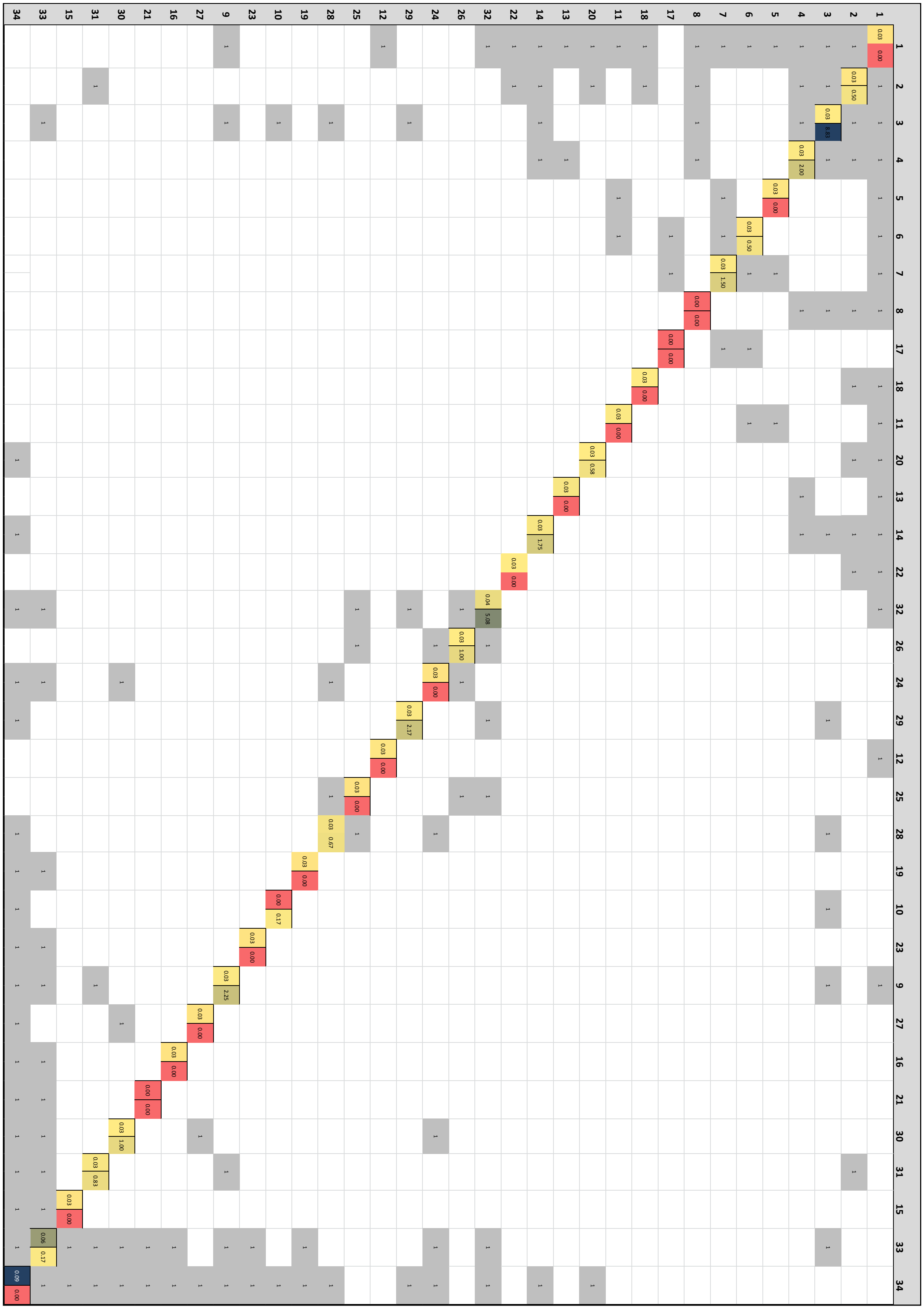


Figure 4-5: Partitioned symmetrical matrix of karate club dataset

used to cue an analyst's attention. The result is a visualization that contains the same amount of information and meta-information as Figure 4-3.

4.5 Visualization performance hypotheses

Academic research [89] has shown that human performance can improve when visualizations promote parallel processing; promoting perception as opposed to the more cognitively demanding process of integrating memory and inference. This research is consistent with the bottleneck identified in the information processing model outlined in Chapter 3. As such, design principles that promote efficient perception can be used to help predict under which tasks each visualization will perform the best. This is because node-link and matrix visualizations promote different design principles, which, hypothetically, should predispose each one to be better at certain tasks. As such, this section will focus on the design principles in each visualization and hypothesize how it will affect performance during the user testing described in the next chapter. However, before identifying design principles within the visualizations, it is important define the design principles.

The first design principle, the proximity compatibility principle (PCP), states that, to "the extent that information sources must be integrated, there will be a benefit to presenting those sources either close together, in an objectlike format, or by configuring them to create emergent features" [72]. The theory behind PCP is based on two principles: display proximity and processing proximity. Display proximity is the physical closeness of two or more display components that display relevant information. Processing proximity is the extent to which two or more information sources are used in the same display oriented task. The level of processing proximity will drive the level of display proximity. Stated more simply, if a display task requires high processing proximity, then high display proximity should follow. The inverse of this relationship also holds true. Therefore, by developing visualizations with certain display components close together, the new visualization creates perceptual similarities and emergent features.

The second design principle, emergent features, can assist in the holistic or global processing of a display. While there is not a widely accepted definition of emergent features, this paper will use the definition provided by Bennett et al., “the high-level, global perceptual features that are produced by the interactions among individual parts or graphical elements of a display (e.g. lines, contours, and shapes)” [90]. These features are the emergent values of a “global property” of a set of stimuli, which are not necessarily evident if each stimulus were viewed in isolation [72]. Bennett et al., along with other researchers, have shown that the use of emergent features is an indicator of improved user performance [90, 91].

The relationship between PCP and emergent features is not discrete. For example, PCP can be used to create emergent features, which should result in improved analyst performance. For example, in the context of the task of identifying clusters, an emergent feature was created by using layout (node-link) and partitioning (matrix) algorithms to promote a high display proximity of certain nodes; which resulted in easily identifiable clusters. Whereas in the task of identifying leaders, an emergent feature was created by increasing the display proximity of the measures of centrality through colocation of this information on the visualization and the use of conditional formatting using colors (also referred to by [92] as color proximity).

With the presence of PCP and emergent features, analysts should realize many cognitive benefits including: reduced visual search costs, increased direct perception, reduced need to retain information, and reduced information access costs or internal division of attention [93]. Therefore, the design principles evident in each visualization should indicate which form of visualization will be most effective, depending on the specific task (identify leaders or identify clusters).

4.5.1 Identifying Clusters

In the specific case of terror network visualizations, clusters emerge as a key global property of the overall network. In both visualizations an emphasis is placed on ordering the nodes, through specific layout or partitioning algorithms, so clusters emerge and cue an analyst’s perception. The clustering algorithms identify those actors in a network that are approximately equivalent in structure [7]. However, clustering algorithms return varying results depending on the inputs of each specific algorithm. Nonetheless, an analyst can still utilize these emergent clusters to cue more localized processing to determine the salience or accuracy of specific clusters. While both node-link and matrix display clusters through the use of algorithms, the boundaries of clusters in node-link visualizations may be difficult to define because of the multiple overlapping links. Comparatively, links do not overlap in the matrix visualization, which may make it easier for an analyst to accurately identify clusters and their boundaries.

4.5.1 Identifying Leaders

Another emergent feature evident in both visualizations is the node salience as a byproduct of the presented measures of centrality. Not only do the colors assist in cuing an analyst's perception, but by stratifying each node based on closeness and betweenness centrality the nodes which are similar in attributes are more easily integrated and compared [72]. This emergent feature can help an analyst more quickly identify which actors in a network are salient and which are innocuous. Once again, this design principle exists in both forms of visualization. Although these attribute based variations make it easier to identify potentially salient nodes, it may be more difficult for an analyst compare the attributes against the over network topology using the matrix. This is because the global topology of the network is not obvious in the matrix visualization.

4.6 Conclusion

This chapter outlined the terror network visualizations that were used for the user experiment outlined in Chapter 5. The result is two visualizations, node-link and matrix, which communicate similar amounts of both information and meta-information to an analyst. These visualizations were then analyzed through a lens visualization design principles, proximity compatibility principle, and emergent features, to formulate hypothesis about the future performance of each visualization during the user experiment. Finally, each of the above hypotheses will be used in the next chapter to formalize higher fidelity experimental hypotheses.

Chapter 5

Human Performance Experiment

5.1 Experiment Objectives

The objectives of this experiment were to test the effectiveness of the node-link visualization compared to the matrix visualization, based on two criteria: 1) effectiveness at identifying leaders within a network, and 2) effectiveness at identifying clusters within a network; two fundamental tasks in terror social network analysis introduced in Chapter 1.

5.2 Experimental Hypotheses

The following experimental hypotheses are a result of academic literature on the subject of comparing the readability of social network graphs [6], on the results of a pilot study conducted by the author pertaining to a sample set of 5 current military intelligence analysts, and on the initial hypothesis outlined in Chapter 5 based on the design principles inherent in each visualization.

5.2.1 Performance at Identifying Leaders

The ability to identify leaders from a node-link or matrix visualization is primarily influenced by the emergent features of the visualization techniques, such as the color proximity presented by conditionally formatting the measures of centrality and node position relative to the network topology. For example, Figure 4-3 and Figure 4-5 clearly identify one of the cluster leaders[16] (node 34) by presenting an extremum closeness centrality using node size or cell color; however, the second cluster leader (node 1) does not have as strong of a color or size cue. As such, successfully identifying this leader would be challenging in both visualization techniques. A node-link visualization may make this task easier by providing information on a node's position relative to the entire network topology. The matrix visualization also provides topological information, but to a lesser degree. As such, the following hypotheses capture the expected performance at identifying leaders:

- *Hypothesis 1: The ability to accurately identify leaders within a network or cluster is expected to be better supported by the node-link visualization as compared to the matrix visualization.*
- *Hypothesis 2: Use of the node-link visualization is expected to require less time to accurately identify leaders as compared to the matrix visualization.*

5.2.2 Performance at Identifying Clusters

Successfully identifying clusters is primarily a function of two sub-tasks: the ability to identify a cluster and to accurately identify where the community stops and where the next community begins. The node-link visualization may make the second sub-task difficult, because there is no clear bifurcation between clusters. The matrix visualization may make this task easier, because it more clearly communicates the boundaries between clusters. However, the accuracy of the clusters within the matrix depends on the quality of the clustering algorithm used to partition the network. This factor and analyst unfamiliarity with this visualization technique may degrade matrix performance; however, matrix

[16] Defined as one of the leaders identified by Zachary in his original description of the data set [83].

training (explained in 5.7) should help offset the second factor. As such, the following hypotheses capture the expected performance at identifying clusters:

- *Hypothesis 3: The ability to accurately identify clusters within a network is expected to be better supported by the use of the matrix visualization as compared to the node-link visualization.*
- *Hypothesis 4: Use of the matrix visualization is expected to require less time to accurately identify leaders as compared to the node-link visualization.*

5.3 Experimental Tasks

As discussed throughout this thesis, two test scenarios were designed for this experiment. The first scenario is focused on identifying leaders within a network, which is referred to in the taxonomy of graph visualization tasks as analyzing roles and positions [6]. The second scenario is focused on identifying clusters within a network; this task is referred to, under the same taxonomy, as identifying communities of interest [6]. All of the below experimental tasks are recognized to be consistent with the primary tasks of social network analysis [7, 8] and were adapted from academic research on task taxonomy for social network graph visualizations [6, 5] (all experimental visualizations and questions discussed below are outlined in Appendix F).

5.3.1 Task 1: Identification of Leaders

Identifying leaders within a social network is among the most important tasks an analyst must perform when exploiting a network. Under normal operational circumstances an analyst would first create a hypothesis regarding which nodes represent the characteristics of a leader and then conduct research to either prove or disprove that hypothesis. For example, an analyst may hypothesize that there are four nodes that display the characteristics of a leader, but research reveals that the network only has two leaders. The analyst must then return to his or her previous hypothesis and update it based on the additional information. To mimic this process, additional information was sequentially incorporated into the questions to mimic these cognitive tasks:

- (Task 1) "Analyze roles and positions - these are higher level tasks relying on the interpretation of groups of actors (positions) and connection patterns (roles)." [6]
    - (Question 1.1) Identify any central actors, which are defined as actors linked to many others or that bridge communities together.
        - *Correct Responses: Any node that acts as a bridge between the two clusters (nodes 1, 3, 9, 14, 20, 31 32, 33, and 34), any node with an extremum measure of centrality (nodes 3 and 34) or a leader from the data set (nodes 1 and 34)*
    - (Question 1.2) Identify any potential leaders within the network.
        - *Correct Responses: Any node with an extremum measure of centrality (nodes 32, 33 and 34) or a leader from the data set (nodes 1 and 34)*
    - (Question 1.3) Assuming there are only two leaders, identify those leaders.
        - *Correct Responses: Leaders from the data set (nodes 1 and 34)*

The correct answers defined above are from one of two sources: 1) the data set truth identified by Zachary [83], or 2) an emergent feature which resulted from the design of Figure 4-3 and Figure 4-5. The answers that resulted from an emergent feature are acceptable responses for questions 1.1 and 1.2 because they display the structural properties of a leader. However, they are unacceptable for question 1.3 because this question attempts to assess the accuracy of identifying the leaders as defined in the data set [83]. Table 5-1 below outlines the source for each correct answer.

Table 5-1: Source of Correct Task Question Answers

Question	*Correct Responses*	*Source of Correct Response*	
		Data Set Truth	*Emergent Feature*
(Question 1.1)			
	Nodes: 1, 3, 9, 14, 20, 31 32, 33, 34	*X*	
	Node: 3		*X*
(Question 1.2)			
	Nodes: 1, 32, 33 ,34	*X*	
	Node: 3		*X*
(Question 1.3)			
	Nodes: 1,34	*X*	

The above outlined sequence of questions mimics the normal process an analyst engages in when he or she tries to satisfy the overall task of analyzing roles and positions.

By increasing the specificity of each sequential question, with the ultimate goal of identifying a leader, it will help identify potential limitations in visualizations.

5.3.2 Task 2: Identification of Clusters

The sequence for identifying clusters is similar to that outlined above for identifying leaders. An analyst will first create a hypothesis and then conduct research to either prove or disprove the hypothesis. The primary difference between identifying clusters and identifying leaders is that the identification of clusters requires one fewer steps, or questions, than identifying leaders. This does not imply that the task is easier than identifying leaders; given the information in the visualizations there is only enough data to support one question, as opposed to three. As such, this experimental scenario will follow an identical construct as the identification of leaders scenario, but will have only one question.

- (Task 2) "Identify all communities, i.e. cohesive groups of actors that are strongly connected to each other." [6]
    - (Question 2.1) Assuming there are only two clusters, identify those clusters.
        - Correct Answer: *Cluster 1, defined by the data set as Mr. Hi's cluster; cluster 2, defined by the data set as John's cluster.* [83]

However, different than Task 1, the correct answers defined above for Task 2 are also from only one source: 1) the data set truth identified by Zachary [83]. Question 2.1 attempts to assess the accuracy of identifying the clusters as defined in the data set [83]. As such, only the true answers from the data set are acceptable responses. Table 5-2 below outlines the source for each correct answer.

Table 5-2: Source of Correct Task Question Answers

Question	*Correct Responses*	*Source of Correct Response*	
		Data Set Truth	*Emergent Feature*
(Question 2.2)	*Clusters: 1, 2*	*X*	

5.4 Experimental Design

This experiment is a 2 (Visualization Technique) x 2 (Visualization Task) mixed design study within-subjects on the visualization task factor and between-subjects on the visualization technique factor.

5.4.1 Independent Variables

Two independent variables were of interest in this experiment: 1) visualization technique and 2) visualization task. Visualization technique refers to specific visualization (node-link or matrix) a participant will use to answer the task questions. In this experiment participants saw either the node-link (Figure 4-3) or the matrix (Figure 4-5) visualization. Therefore, this two level factor was a between-subjects variable. The visualization task factor includes both identifying leaders and clusters. This factor is a within-subjects variable, because every participant was asked to perform both the task of identifying leaders and clusters.

5.4.2 Dependent Variables

Two dependent variables were used in the experiment: 1) accuracy of analyst assessment and 2) time to reach assessment. Each of those variables is described in detail below.

Assessment Accuracy

Assessment accuracy addresses the participant's ability to correctly answer the subordinate questions to each of the task scenarios and is the primary factor supporting all the hypotheses outlined in section 5.2. Accuracy of assessment is a critical task an analyst will perform and is directly correlated to the effectiveness of an analyst at exploiting terror network visualization. In this experiment, assessment accuracy will be measured using the four possible outcomes of signal detection theory (see 2 x 2 matrix in Figure 5-1): *hit, miss, false alarm,* or *correct rejection*. A *hit* indicates the participant provided one of the correct responses outlined in sections 5.4.1 and 5.4.2, which will be recorded by awarding the participant a score of "1" in the signal column for the question. Conversely, a *miss* indicates

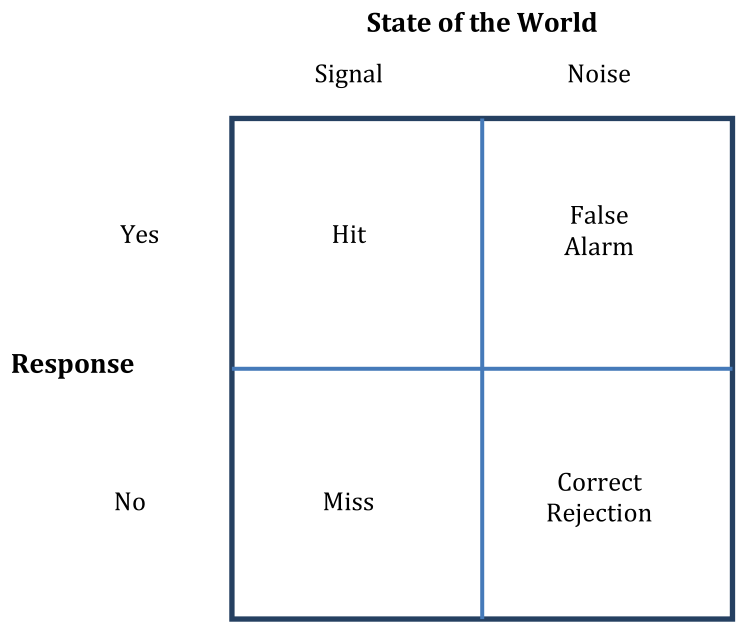


Figure 5-1: The four outcomes of signal detection theory [6]

the participant failed to provide one of the correct responses outlined in sections 5.4.1 and 5.4.2, which will be recorded by awarding the participant a score of “0” in the signal column for the question. A *false alarm* indicates the participant provided a response that was not outlined in sections 5.4.1 or 5.4.2, which will be recorded as a “1” in the noise column for the question. Finally, once the number of false alarms is known the number of correct rejections can be directly computed. [72]

Organizing the collected participant data in this manner will not only allow for the direct comparison of correct answers between visualizations, but also will permit more in-depth analysis on other factors; such as probability of false alarm for each visualization. For this variable, a higher percentage of hits, relative to misses, is desirable and a lower percentage of false alarms, to correct rejections, is desirable.

For questions 1.1 through 1.3 participants were scored primarily on the percentage of hits to the total number of hits possible. This method of evaluation results in an overall percentage correct for each task. For question 2.1, the process used to evaluate the answers and score each participants assessment accuracy is slightly different to the process for questions 1.1 through 1.3. This is because identifying a cluster is a more complex task than simply identifying presence or absence. The difficulty when identifying clusters is determining where one cluster stops and another begins or, said differently, accurately identifying the borders. Therefore, each participant was given two scores. One for each of the two clusters. Then an aggregated percentage based on the number of nodes they correctly identified for each of the two clusters was created for each participant. For example, if a participant was able to correctly identify 16 of the possible 18 nodes in cluster one and only 5 of the possible 16 nodes in cluster two. Those scores aggregated these scores to create an overall percentage correct for question 2.1, which in this example would result in an agregatted score 62%. This method of scoring provided a better indication of which visualization would be better at not only identifying the presence of the cluster, but also which was better at identifying how much of the cluster the participants were able to correctly identify.

Time to Reach Assessment

Time to reach assessment supports hypotheses 1 through 4. This variable provides a measure of how long it took each analyst to answer the task scenarios for a specific visualization. In this experiment, time to reach assessment was used to support the data gathered in the accuracy of assessment variable of the experiment to determine if one visualization took relatively longer to analyze than the other. However, because time to complete the task is not critical on the order of minutes or seconds, this variable is only slightly related to the research goals. As such, it was used as quantitative support to substantiate any qualitative information gathered in the post experiment survey. For this variable, a low time to assessment is desired; this indicates an analyst was able to quickly analyze the visualization and reach an assessment. However, rushing through the tasks to reach conclusions was not encouraged.

5.5 Procedure

The experimental procedure, outlined below, closely follows John Goodall's suggested format for both comparative evaluation of visualizations and for evaluating exploratory tasks [94]. Participants each adhered to the following basic format: 1) a brief introduction by the author to the study and each of the visualizations, 2) refresher training on the definitions and importance of centrality measures, 3) a series of timed experimental tasks using a specific visualization, and 4) a post experiment questionnaire. Further details on the procedure are provided below.

Each participant performed the experiment individually. Upon arriving at the testing site, the participants were first welcomed by the experimenter and given a brief introduction to the experiment. Participants then completed a signed consent form (Appendix A), followed by a demographic survey[17], which gathered information on participants previous experiences with intelligence analysis and exploitation of social network visualizations (Appendix B). After finishing the demographic survey, participants were given a self-paced tutorial on a set of PowerPoint slides that detailed the purpose of the experiment and explained the visualization. Tutorials (Appendix C & D) were created for each visualization. The experimental tutorials took approximately ten minutes to complete. Participants were not offered any incentives for performance.

Included in the tutorials were a series of training lessons on the measures of centrality (closeness and betweenness) used in the visualizations. These lessons involved instruction on the definitions of the measures of centrality with examples of networks and the resulting measures. Participants were then given examples with the measures of centrality and asked to assess which nodes displayed the highest measure for both closeness and betweenness centrality. Only after a participant was able to correctly identify each measure of centrality, thus demonstrating proficiency with measures of centrality, was he or she allowed to proceed to the actual experiment. If a participant failed the training he or she received additional instruction until able to successfully demonstrate proficiency with the measures of centrality.

Following the training and demonstration of proficiency, participants completed the two test scenarios described in the previous sections for the visualization; lasting approximately 10 minutes. Visualizations were individually printed on an 11x17 inch piece of plain white copy paper and given to the participant. In an effort to prevent a possible

[17] Primary intent of demographic survey was to identify those participants who were color blind. None of the participants reported being color blind.

order effect, the order in which visualizations and task scenarios were presented was randomized. Prior to beginning the tests, participants were informed that their accuracy of assessment was recorded and that the time to reach assessment was being recorded. This was done to ensure participants understood the variables by which they would be assessed. Once the experiment was completed, feedback was solicited about each visualization and the experience through a post-experiment questionnaire (Appendix E). In total, the two test scenarios followed by the questionnaire took a total of fifteen minutes on average. The entire experiment took approximately thirty minutes per participant.

5.6 Data Collection

During the experiment, participant's responses to each of the task scenario questions were documented as well as the time required to answer. The experimenter also took notes during the experiment to record any emerging patterns or other matters of interest, which included difficulty focusing or comments made throughout or during a specific task. No audio or video recording was captured at any point during the experiment.

5.7 Conclusion

This chapter outlined the design of the human performance experiment used to judge the efficacy of visualization techniques. Specifically, the experiment consisted of four experimental hypotheses on the subjects of accuracy of assessment and time to reach assessment. These hypotheses were tested using two experimental tasks and two independent variables; the details of which were explained in the experimental design.

Chapter 6

Results

This chapter presents the statistical results of the experiment described in Chapter 5. There were two independent variables: visualization (node-link or matrix) and task (identifying leaders and identifying clusters). Two dependent variables were captured to measure performance: accuracy (quantified in percent correct) and time to complete (quantified in terms of seconds) each task. A thorough analysis of each of these variables is presented within this chapter.

6.1 Overview

The results presented in this chapter are organized by independent variable. The first section (6.2) begins with an analysis of the dependent variables by the visualization independent variable, and then section (6.3) offers an analysis of the dependent variables using the task independent variable. For all reported results, $\alpha = 0.05$ unless otherwise stated. Additionally, any results which represent statistical significance are denoted in the captions with an asterisk, "*".

6.2 Participants

In total, 60 participants took part in the experiment; 30 participants per visualization condition. The 60 participants were all Air Force Airmen, with an average age of 32.92 (σ = 9.59), and who all hold the Air Force Specialty Code of Intelligence Analyst (1NX or 14NX). The average amount of participant intelligence experience was 4.25 years (σ = 2.89). Figure 6-1 shows the age and skill distribution of all sampled participants (some points on the graph represent more than one participant). Since, the earliest age a person can join the military is 18 years old, this is also the earliest age at which a person can begin to accrue intelligence experience. As such, the area shaded in red, on Figure 6-1, reflects a segment of population that is not possible within the military intelligence community.

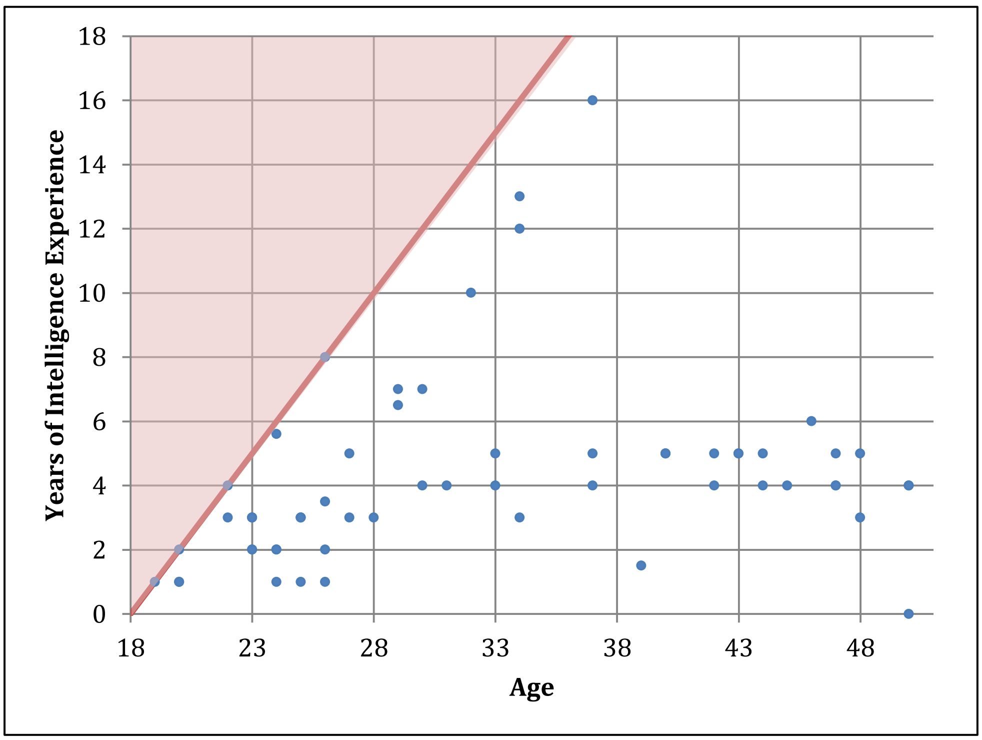


Figure 6-1: Distribution of Sample Set

The wide range of intelligence experience (min = 1 years, max = 16 years) is attributable to the scarcity of intelligence analysts available for testing in the Boston metropolitan area. Additionally, the large concentration of samples at the lower ranges of intelligence experience reflects a common post-September 11 trend within the military intelligence community; many individuals were retrained into the intelligence career field to satisfy the growing demand for intelligence assets to support operations in Afghanistan and Iraq.

6.3 Results by Visualization

6.3.1 Identification of Leaders Performance

As outlined in section 5.4.1, three experimental questions were used to determine the participants' ability to accurately identify leaders within a network. In the first question (Q1.1) participants were asked to: *Identify central actors, which are defined as actors linked to many others or that bridge communities together*. Three participants who were given the matrix misread this question and responded as if they were answering question 2.1, which was: *Assuming there are only two clusters, identify those clusters*. As such, those three responses were removed from the data set; resulting in an uneven number of responses for each condition (matrix = 27, node-link = 30).

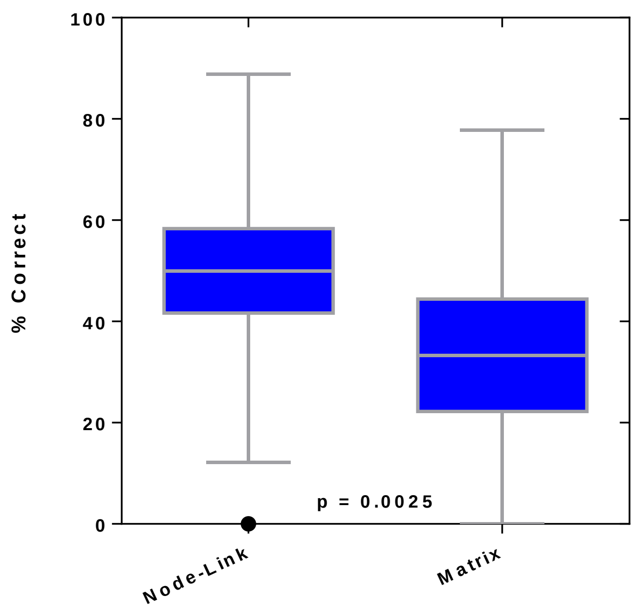


Figure 6-2: Percentage correct for question 1.1: *Identify central actors, which are defined as actors linked to many others or that bridge communities together.* Node-link showed significantly higher percentage of correctly identifying central actors than matrix.

Table 6-1: Question 1.1 Percentage Correct Summary*

	Mean	Median	Std Dev
Node-Link	51.11	50.00	20.76
Matrix	33.33	33.33	21.57

An unpaired two-tailed t-test indicates that there is a statistically significant difference in accuracy of identifying central actors between visualizations ($F(26,29) = 1.080$, $p = 0.0025$). A data transformation was not conducted on the data gathered for question 1.1, because both distributions passed a D'Agostino & Pearson normality test (Matrix $p = 0.2691$, Node-Link $p = 0.6863$). The boxplot in Figure 6-2 shows the median percentage correct, quartiles and extreme values (outside the whiskers, which show 5-95 percentiles) for each visualization, and Table 6-1 summarizes the key statistics.

To understand whether a correlation exists between completion time and percentage correct, a nonparametric Spearman correlation analysis was conducted for both independent variables (Matrix $r = 0.08754$, $p = 0.6642$; Node-Link $r = 0.2154$, $p = 0.2530$). The Spearman correlation was necessitated because the time to complete for this question was not a normal distribution. The results indicate there is a positive correlation; although not statistically significant, between time to complete and percentage correct for both visualizations. The scatterplot in Figure 6-3 shows the distribution of values for both visualization as well as nonlinear semilog curve ($\mathrm{Y} = \mathrm{Slope} * \log(\mathrm{X}) + \mathrm{Y}_{\mathrm{intercept}}$) of the values.

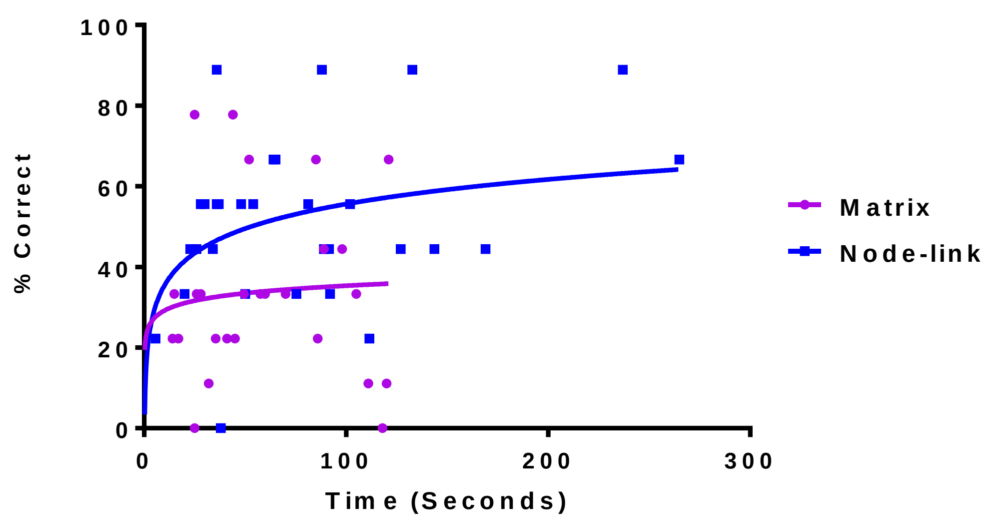


Figure 6-3: Scatterplot of time vs. percent correct for Q1.1 question 1.1: ***Identify central actors, which are defined as actors linked to many others or that bridge communities together.*** **Node-link and matrix both showed a positive correlation that is not statistically significant**

In the second question (Q1.2) participants were asked: *to identify any potential leaders within the network*. An unpaired two-tailed t-test was used to understand the difference in results. This test indicated that the node-link visualization returned a statistically significant higher average percentage correct than matrix when identifying potential leaders between visualizations ($F(29,29) = 1.107$, $p = 0.0044$). Since there were no normality violations and both distributions passed a D'Agostino & Pearson normality test (Matrix p=0.2281, Node-Link p=0.1041), a data transformation was not conducted. The boxplot in Figure 6-4 shows the median percent correct as well as the quartiles and any extreme values (outside the whiskers, which show the 5-95 percentiles) for each visualization; Table 6-2 summarizes the key statistics.

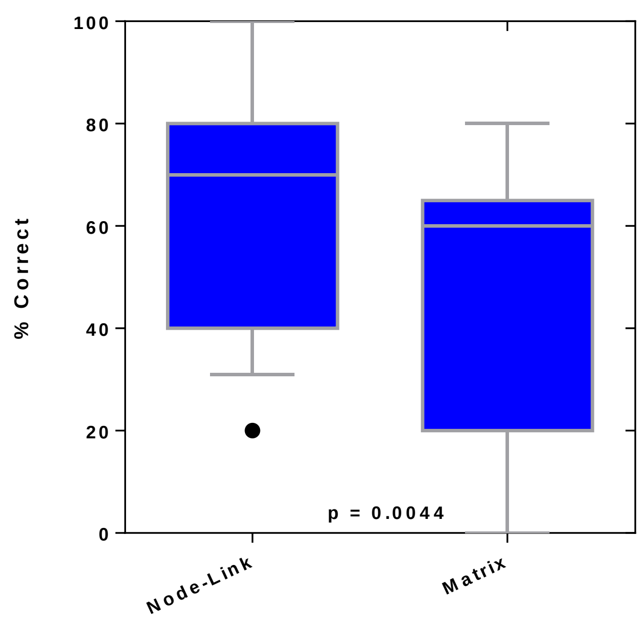


Figure 6-4: Percentage correct for question 1.2: *identify any potential leaders within the network.* Node-link showed significantly higher percentage of correctly identifying potential leaders than the matrix.

Table 6-2: Question 1.2 Percentage Correct Summary*

	Mean	Median	Std Dev
Node-Link	67.33	70.00	23.77
Matrix	48.67	60.00	25.01

An identical correlation analysis to that described for question 1.1 was conducted for question 1.2 to understand whether there exists a correlation between time to complete and percentage correct (Matrix r = -0.1569, p = 0.4076; Node-Link r = 0.3684, p = 0.0452). The results indicate there is a negative correlation; although not statistically significant, between time to complete and percentage correct for the matrix visualization. Indicating that as participants spent more time responding to question 1.2, using the matrix visualization, their percentage correct scores decreased. However, the analysis also indicates there is a statistically significant positive correlation between time to complete and percentage correct for the node-link visualization. The scatterplot in Figure 6-5 shows the distribution of values for both visualization as well as nonlinear semilog curve ($Y = \text{Slope} * \log(X) + Y_{\text{intercept}}$) of the values.

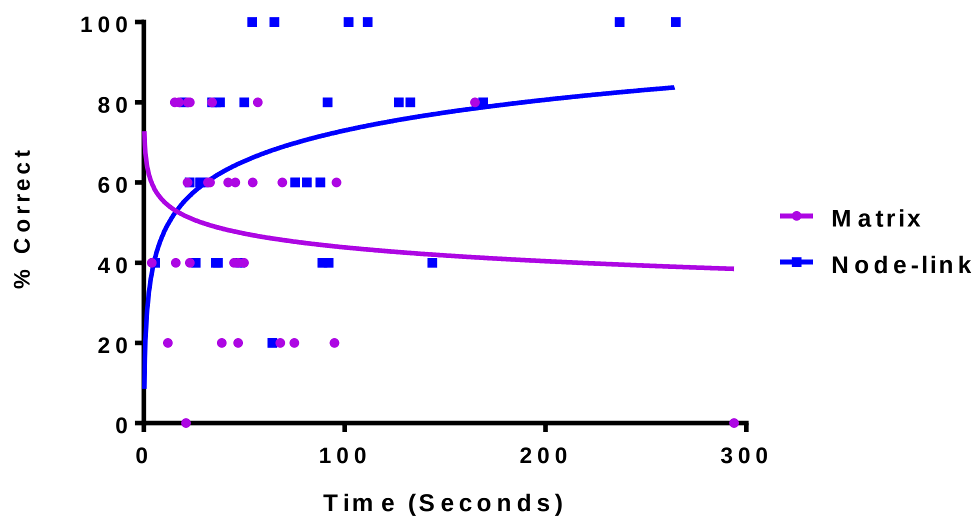
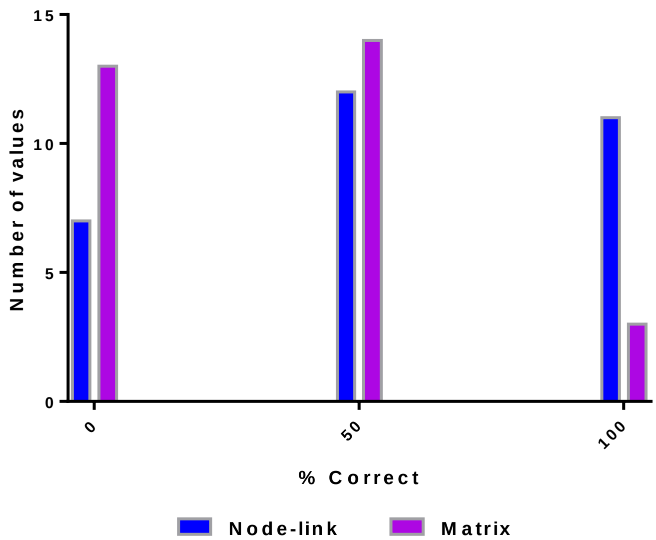


Figure 6-5: Scatterplot of time vs. percent correct for question 1.2: *identify any potential leaders within the network.* Node-link showed a statistically significant positive correlation and matrix showed a negative correlation that is not statistically significant

In the third, and final, question (Q1.3) participants were asked: *Assuming there are only two leaders, identify those leaders.* However, as there were only three possible outcomes for this question (0%, 50%, or 100%), the resulting data is noncontinuous and far from Gaussian. However, the data distributions were far enough apart (visible in Figure 6-6) to yield a statistically significant difference under nonparametric measures of significance. A Mann-Whitney U test confirmed the statistically significant difference ($p = 0.0231$). Figure 6-6 shows both a histogram, which displays the distribution of values for each visualization, and a boxplot, which shows the median percent correct, upper and lower quartiles and any extreme values (outside the whiskers, which show the 5-95 percentiles) for each visualization; Table 6-3 summarizes the key statistics.



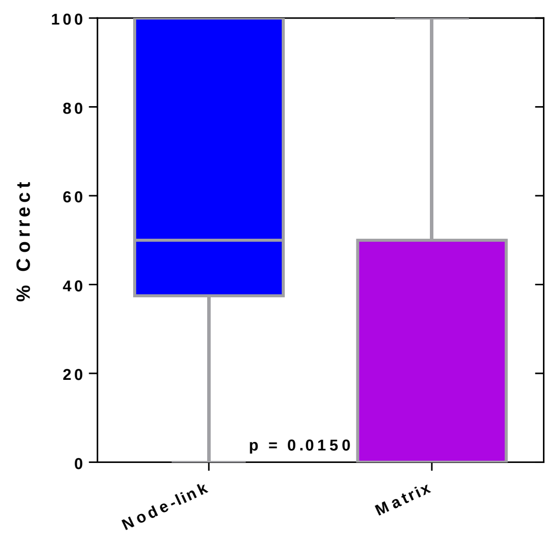


Figure 6-6: a) Histogram of percentage correct for question 1.3: *Assuming there are only two leaders, identify those leaders.*; b) Boxplot of percentage correct for question 1.3: *Assuming there are only two leaders, identify those leaders.* Node-link showed significantly higher percentage of correctly identifying leaders than the matrix.

Table 6-3: Question 1.3 Percentage Correct Summary*

	Mean	Median	Std Dev
Node-Link	56.67	50.00	38.80
Matrix	33.33	50.00	33.04

Because the responses for question 1.3 were noncontinuous, a nonparametric Spearman correlation analysis was conducted for both independent variables to only understand whether there was a positive or negative correlation, versus understanding the specific quantifiable level of correlation (Matrix $r = 0.004801$, $p = 0.9799$; Node-Link $r = 0.06294$, $p = 0.7411$). The results indicate there is a very small positive correlation;

although not statistically significant, between time to complete and percentage correct for both visualizations. The scatterplot in Figure 6-7 shows the distribution of values for both visualization and a nonlinear semilog curve ($Y = Slope * \log(X) + Y_{intercept}$) of the values.

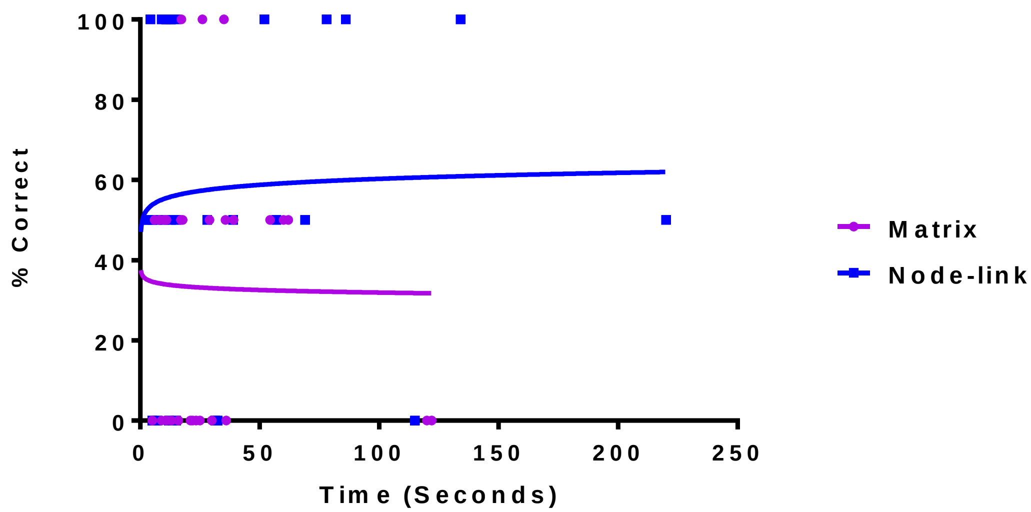


Figure 6-7: Scatterplot of time vs. percent correct for question 1.3 *Assuming there are only two leaders, identify those leaders.* Node-link showed a positive correlation that is not statistically significant and matrix showed a negative correlation that is not statistically significant

6.3.2 Identification of Clusters Performance

As outlined in section 5.4.1, one experimental question was used to determine the participants' ability to accurately identify clusters within a network. Participants were asked: *Assuming there are only two clusters, identify those clusters*. An unpaired two-tailed t-test indicates that there was not a statistically significant difference in accuracy of identifying clusters between visualizations ($F(29,29) = 1.480$, $p = 0.0948$). As there were normality violations, a log transformation of the data was required to meet homogeneity and normality assumptions. After transformation, both categories of data passed a D'Agostino & Pearson normality test (Matrix $p = 0.7258$, Node-Link $p = 0.0639$). The boxplot in Figure 6-8 shows the median % correct as well as the quartiles and any extreme values (outside the whiskers, which show the 5-95 percentiles) for each visualization; Table 6-4 summarizes the key statistics.

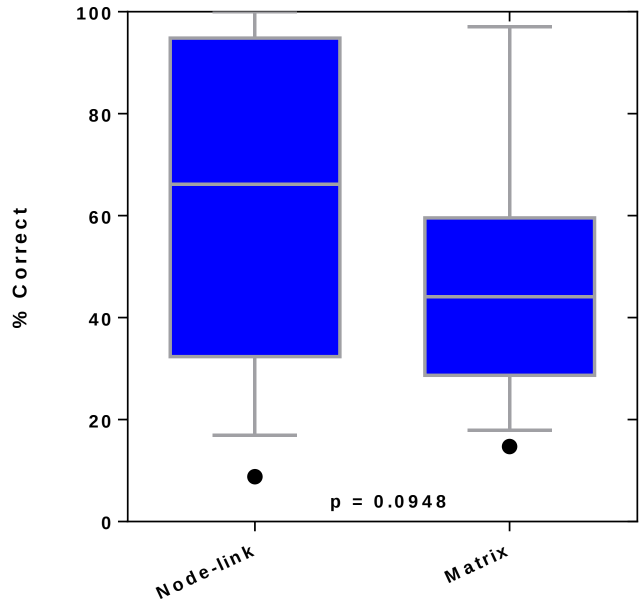


Figure 6-8: Percentage correct for question 2.1: ***Assuming there are only two clusters, identify those clusters.*** **Node-link showed a higher percentage of correctly identifying clusters than the matrix, although not statistically significant**

Table 6-4: Question 2.1 Percent Correct Summary

	Mean	Median	Std Dev
Node-Link	53.64	66.02	26.65
Matrix	41.93	44.11	21.91

Similar to the correlation results for question 1.2, Spearman correlation analysis (Matrix r = 0.4326, p = 0.0170; Node-Link r = -0.1502, p = 0.4281) results indicate there is a negative correlation; although not statistically significant, between time to complete and percentage correct for the node-link visualization. Indicating that as participants spent more time responding to question 2.1, using the node-link visualization, their percentage correct scores decreased. However, the analysis also indicates there is a statistically significant positive correlation between time to complete and percentage correct for the matrix visualization for question 2.1. The scatterplot in Figure 6-9(a) shows the distribution of values for both visualization as well as nonlinear semilog curve ($Y = \text{Slope} * \log(X) + Y_{\text{intercept}}$) of the values.

Although there is a statistically significant positive correlation between time to complete versus percentage correct for the matrix visualization, there is also a statistically significant correlation between time to complete and frequency of false alarms for the matrix (Matrix r = 0.4287, p = 0.0181; Node-Link r = -0.2458, p = 0.1904). Indicating that while additional time to complete results in a higher percentage complete, it also results in a higher quantity of false alarms. The scatterplot in Figure 6-9(b) shows the distribution of values for both visualization and a nonlinear semilog curve ($Y = \text{Slope} * \log(X) + Y_{\text{intercept}}$) of the values.

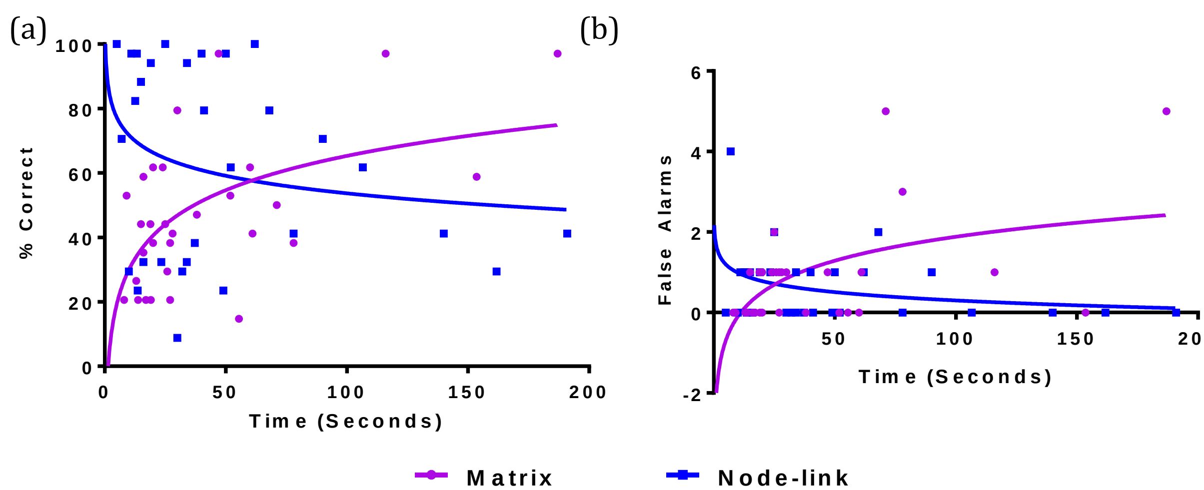


Figure 6-9: (a) Scatterplot of time vs. percent correct for question 2.1: *Assuming there are only two clusters, identify those clusters.* Matrix showed a statistically significant positive correlation and node-link showed a negative correlation that is not statistically significant; (b) Scatterplot of time vs. false alarms for question 2.1: *Assuming there are only two clusters, identify those clusters.* Matrix showed a statistically significant positive correlation and node-link showed a negative correlation that is not statistically significant

The percentage correct results for all participants, from all questions, were averaged in to a composite average percent correct. A Pearson correlation analysis was conducted for both independent variables to only understand whether there was a positive or negative correlation, between age and average percent correct (Matrix r = 0.03729, p = 0.8449; Node-Link r = 0.06378, p = 0.7377). The results indicate there is a very small positive correlation; although not statistically significant, between age and average percentage correct for both visualizations. The same correlation analysis was conducted for years of experience versus average percent correct as well. The results (Matrix r = 0.02272, p = 0.9052; Node-Link r = 0.03176, p = 0.8677) indicate there is a very small positive correlation; although not statistically significant, between years of experience and average percentage correct for both visualizations. The scatterplot in Figure 6-10 shows the distribution of values for both visualization as well as linear regression curve with 95% confidence bands ($Y = \text{Slope} * X + Y_{\text{intercept}}$) of the values.

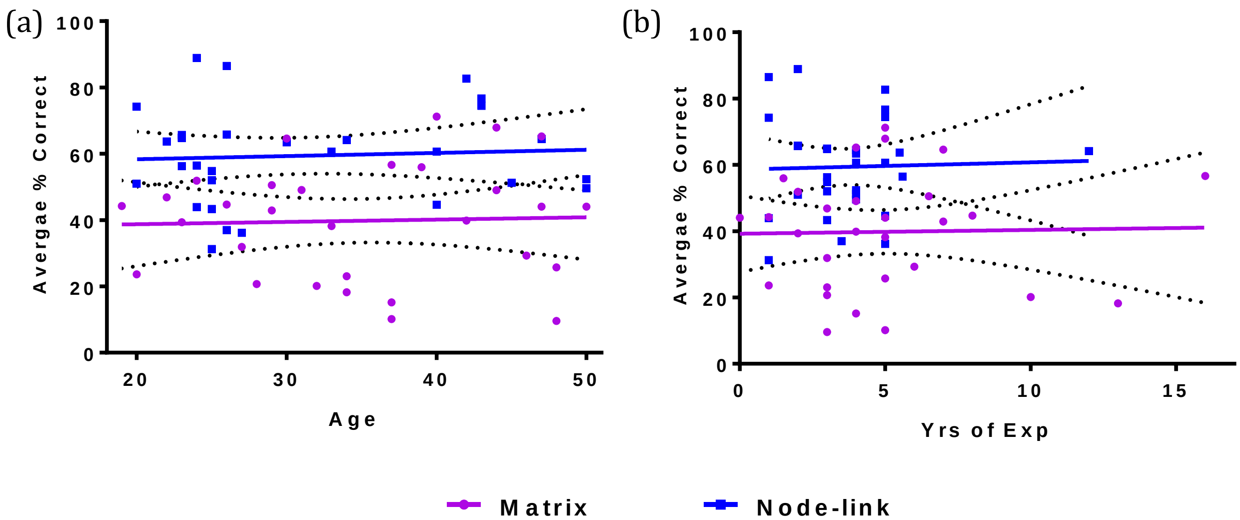


Figure 6-10 (a) Scatterplot of average percentage correct vs. age for questions 1.1, 1.2, 1.3, and 2.1. The results of a correlation analysis indicate a slightly positive correlation that is not statistically significant (b) Scatterplot of average percentage correct vs. years of experience for 1.1, 1.2, 1.3, and 2.1. The results indicate a slightly positive correlation that is not statistically significant

6.3.3 Time to Complete Performance

As outlined in section 5.4.1, time to complete was recorded for all previously discussed questions. An unpaired two-tailed t-test was performed on the time to complete each question to determine if there was a statistically significant difference in the time required to complete for a given visualization. The results of the t-test indicates that there was not a statistically significant difference in time to complete for any of the questions (Q 1.1: F = 1.352, p = 0.2456 / Q 1.2: F = 1.088, p = 0.8085 / Q 1.3: F = 2.079, p = 0.6373 / Q 2.1: F = 1.369, p = 0.7743). As there were normality violations for all the time distributions, a log transformation of the data was required to meet homogeneity and normality assumptions.

After transformation all the data passed a D'Agostino & Pearson normality test. Figure 6-11 shows the boxplots of median time, as well as the quartiles and any extreme values (outside the whiskers, which shows 5-95 percentiles) for questions 1.1, 1.2, 1.3, and 2.1; Table 6-5 summarizes the key statistics.

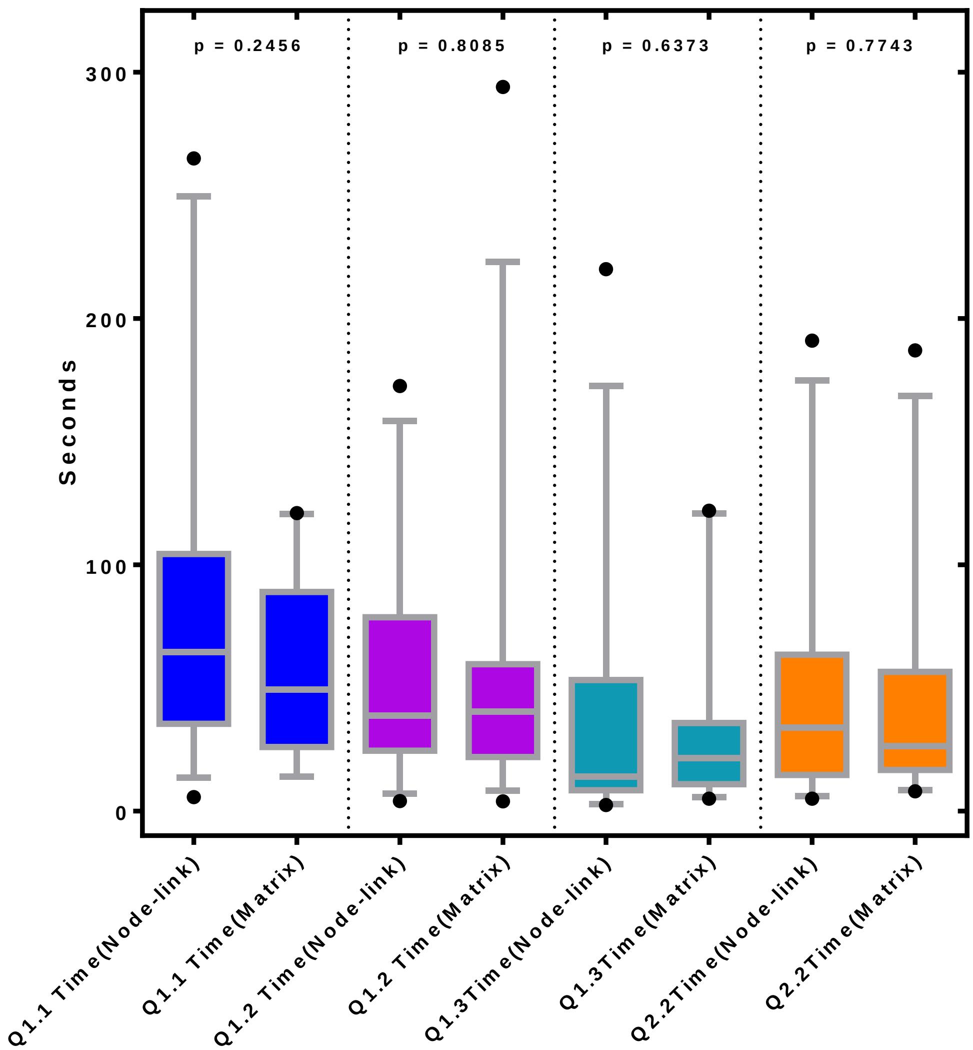


Figure 6-11: Time to Complete for Questions 1.1, 1.2, 1.3, and 2.1

Table 6-5: Time to Complete for Questions 1.1, 1.2, 1.3, and 2.1 Summary

	Q 1.1 (Seconds)		Q 1.2 (Seconds)		Q 1.3 (Seconds)		Q 2.1 (Seconds)	
	Node-Link	Matrix	Node-Link	Matrix	Node-Link	Matrix	Node-Link	Matrix
Mean	59.98	47.31	39.99	37.93	18.88	21.33	32.73	30.69
Median	64.56	49.43	38.90	40.46	13.96	21.48	33.88	26.42
Std Dev	2.267	2.022	2.369	2.286	3.244	2.262	2.538	2.217

6.4 Conclusion

The data collected as a result of the human experiment proposed in Chapter 5, revealed that node-link visualizations produce better accuracy for questions 1.1, 1.2, and 1.3. Thus, indicating that the node-link visualization performed superiorly in all studied scenarios where the objective was identifying leaders. However, there was not enough of a difference in between the performance of the node-link visualization and the matrix visualization for identifying clusters (question 2.1) to indicate which is more suited. The same holds true for the time to complete dependent variable. In all cases, there was not enough difference between the times produced by the node-link and matrix to determine if either offers a statistically significant decrease in the time it takes to complete tasks using either visualization.

Chapter 7

Discussion and Conclusion

This chapter discusses the quantitative results presented in Chapter 6 and compares them to the experimental hypotheses outlined in Chapter 5. Where possible, an explanation is offered if experimental results deviated from the experimental hypotheses. Finally the chapter concludes with a discussion of experimental observations documented by the investigator during and after the experiment, and subjective responses gathered from participants in the post-experiment questionnaire.

7.1 Identification of Leaders Performance

Identification of leaders was classified by the percent correct responses for questions 1.1, 1.2, and 1.3. As outlined in section 5.2.1 and 5.5.2, identification of leaders addresses an analyst's ability to correctly analyze a visualization and identify central actors, potential leaders, and the true leaders. The results indicate that for each of the identification of leaders questions, the node-link showed a statistically significant higher average percent correct than the matrix. Furthermore, the node-link also showed a positive correlation between time spent analyzing the visualization and the percentage correct for all identification of leaders tasks; however, the correlation was only statistically significant for question 1.2. These results are consistent with hypothesis 1, which postulated; *the ability to* *accurately identify leaders within a network or cluster is expected to be better supported by the node-link visualization as compared to the matrix visualization.*

However, the results also indicate that for questions 1.1 and 1.2 the node-link took longer on average, although not statistically significant, to analyze than the matrix. These results are inconsistent with hypothesis 2, which theorized; *use of the node-link visualization is expected to require less time to accurately identify leaders as compared to the matrix visualization.*

7.2 Identification of Clusters Performance

The results for the identification of clusters, classified by the percent correct response for question 2.1, were not as straightforward as those from the identification of leaders task. As outlined in section 5.2.1 and 5.5.2, identification of clusters addresses an analyst's ability to correctly identify the two true clusters within the presented visualizations. Node-link showed a higher average percentage of correctly identifying clusters than the matrix, although not statistically significant. These results are not consistent with hypothesis 3, which theorized that; *the ability to accurately identify clusters within a network is expected to be better supported by the use of the matrix visualization as compared to the node-link visualization.* However, there was a higher amount of variability in the responses for the node-link than the matrix. These results possibly indicate that although the matrix lacked in accuracy over the node-link, it showed improved precision over the node-link. Nonetheless, the matrix showed the highest statistically significant positive correlation between the time to complete and the percent correct for any of the visualization or task combinations experimented. Whereas the node-link showed a negative correlation, not statistically significant, between time to complete and percentage correct.

Although the percentage correct favored the node-link, the matrix showed a shorter average time to complete, although not statistically significant, than the node-link. This result is consistent with hypothesis 4, which postulated that the; *use of the matrix visualization is expected to require less time to accurately identify leaders as compared to the node-link visualization.* However, when considered in parallel with the relatively high positive correlation between time to complete and percent correct for identifying clusters on the matrix, it raises the curiosity that if participants had spent more time, could the overall percent complete have been higher.

7.3 Subjective Responses

After the experiment each participant was given the opportunity to fill out a questionnaire about his or her experience. The specific questions asked of each participant are outlined in Appendix E. In total, about 60 percent of the participants filled out the post-experiment questionnaire. Both their responses regarding the effectiveness of the visualizations, as well as general feedback on the overall experiment and observations made by the investigator during the experiment, are discussed below.

7.3.1 Matrix Subjective Responses

The participants who used the matrix often cited many obstacles that stemmed from unfamiliarity with the visualization. A frequent participant comment when asked, what he or she like least about the visualization, was "it's not [a] totally natural look or feel, so it did take some getting used to." However, a few participants were quick to point out that the matrix was easy to use once the basics were understood. One participant commented, "it took a little bit to understand the flow, but once you did you could move around pretty fast, understanding who knew who without it being convoluted when the groups get bigger". In all, the majority of responses about the matrix indicated that the analysts were interested in the new form of visualization, but struggled to learn how to analyze the matrix in such a short period of time. One participant explicitly stated, "I need more time to understand it". Coincidentally, that participant was the second highest performer for the matrix.

When asked what each analyst liked best about the matrix visualization, some participants made comments in support of the experimental hypothesis concerning the performance of the matrix. Commenting, "this visualization is another good tool for id'ing [identifying] relationships, leadership, and clusters." This comment, and others like it, may be indicative of the promise analysts see in the matrix as a complement to other well established forms of visualization. Additionally, these comments and discussions with participants, after the experiment, also suggested that analysts acknowledge the limitations of the current forms of visualization and were intrigued by the new form of visualization presented in this experiment.

Although no participants explicitly stated that any part of the visualization precluded them from accomplishing either task, four participants recommended that the numbers should be bigger in the diagonal of the matrix. The investigator followed-up on these responses with a discussion to confirm what, if any, the small size of these numbers had on the experiment. In all cases, the analysts indicated that the numbers were not used at all to reach the conclusions for either task and that even if they were larger that they would not have factored into their specific responses.

7.3.2 Node-link Subjective Responses

Much of the feedback on the node-link diagram is consistent with the experimental hypotheses. Specifically, when asked what he or she liked about the node-link, analysts often replied, "the visualization allowed you to see the big picture easier". This comment refers to the global perspective provided in the node-link diagram. However, many participants found the node-link diagram to be overly complex and difficult to analyze. This was a resounding topic of feedback, "very distracting visualizations, a lot of graphics condensed in [a] small area", "sometimes lines were hard to see to identify connections in some areas do [to] there being so many", or "a lot of intersecting nodes made it confusing". As discussed in Chapter 4, one of the most common criticisms of the node-link visualization is the overlapping of many links, which results in the occlusion of data. The feedback from this experiment confirms that criticism.

In all, less feedback was received on the questionnaires that followed node-link visualizations. Although there is no obvious reason for this lack of feedback, one explanation may be that the analysts, who have in most cases received instruction on this form of visualization at some point in their career, had less trouble understanding and utilizing the node-link visualization as a result of the previous instruction. This is a known risk anytime an experimental control is tested against a domain standard.

7.3.3 Universal Subjective Responses

Universally, many participants had difficulty understanding the numbers associated with the betweenness and closeness centrality. Roughly ten participants asked the investigator about the relative significance of the numbers and indicated the presence of the numbers complicated their analysis. The participants' questionnaire responses supported this experimental observation and indicated they knew the significance of both measures, but were unsure of the purpose of the quantitative representations. A common comment when the participants were asked, was there anything negative or distracting about the visualization, was, "I didn't really understand the numbers . . . so I just used the colors and amount of links". This same sentiment was conveyed by roughly half of those participants who commented on the betweenness or closeness centrality measures. Although seemingly negative, the quick adjustment away from the numbers to the colors indicates that this section of the tutorial was effective and that the analysts, on the whole, generally understood how the measures of centrality could help them answer the tasks and employed gestalt-based reasoning.

Some participants felt recording the time forced them to rush through the experiment. Five participants even cited this as the component of the experiment they liked least, often indicating that it forced quick conclusions over thorough analysis. The utility offered by the collection of this dependent variable may not be worth the impact on the overall experiment. This is a consideration which must be factored into future experiments of a similar nature.

Regardless of the visualization, the preponderance of participants recognized the importance and necessity of this type of research. Many either left feedback on the questionnaire similar to, "this is something we do not do enough of", or explicitly communicated this sentiment to the investigator after the experiment. While unsupported by any quantitative data, this resounding feedback indicates that analysts recognize that they may not be using the most effective means available to analyze terror networks. This conclusion does not support either visualization, but supports the need for continued research along the lines of this thesis.

7.4 Recommendations

7.4.1 Visualization Experiment Recommendations

Based on the quantitative assessment of the data collected and the comments elicited at the completion of the experiment, the following recommendations should be taken into consideration for future experiments into the effectiveness of visualizations for terror network analysis.

- *Continue to use intelligence analysts to test the effectiveness of intelligence visualizations*. This demographic responded differently to the visualizations than hypothesized, in part because the hypotheses were based on research in academic literature where the participants were not intelligence analysts [6]. Although more research is required, initial conclusions supported by the work in this thesis indicate that the results of academic work on the effectiveness of different forms of social network visualizations may not be wholly extensible to the domain of intelligence.
- *Time to complete each task should not be an explicit component of the experiment.* Either this variable should be captured passively by an investigator or not at all. Although analysts often work under time pressure, the time pressure is not on the order of seconds or minutes. Furthermore, they were unaccustomed to having their analysis timed on a stopwatch. Removing this factor should help eliminate the affects which result from analysts rushing through the analysis and subsequently reaching premature conclusions as documented in the post experiment comments.
- *Remove quantitative measures from visualizations or identify a better way to integrate this information.* Many analysts appeared intimidated by numbers and immediately disregarded them in favor of a color scale. Although this could be a byproduct of the tutorial, the experimental observations coupled with the post experiment feedback indicated that the numbers were only a distraction to the analysts and offered little to no assistance in answering the tasks.

7.5 Conclusions

There is an increasing requirement for more advanced analytical methodologies to help intelligence analysts cope with the growing amount of data they are saturated with on a daily basis. This trend will only be further exasperated in the future if the means for acquiring data continue to advance and the tools for making sense of the data remain static. Specifically, within the context of terror network analysis, one of the largest problems is the transformation of raw tabular data into a visualization that is easily and effectively exploited by intelligence analysts. To be effective, a visualization must allow analysts to readily identify both leaders and clusters within a network. The current method within the intelligence domain is the node-link visualization, which encodes data sets by depicting the ties between nodes as lines between objects in a plane. This method, although useful, has limitations when the size and complexity of data grows. Therefore, this research was motivated by the desire to evaluate the matrix visualization with intelligence analysts to assess the efficacy of this form of visualization and potential identify an alternate means of visualizing terror network data.

The matrix offers an alternate perspective because the two dimensions of the matrix are arrayed as an *actors x actors* matrix, which implies the same layout of actors contained on the rows is also contained on the columns. A relationship between actors is communicated by a Boolean value where the rows and columns of specific nodes intersect. This form of visualization may offer benefits over the node-link, because as node-link visualizations grow in size, they have a tendency to occlude data. Matrices offer a solution to his problem, because in matrix visualizations objects cannot overlap; thus resolving the data occlusion and improving readability.

7.5.1 Research Objectives and Findings

The objectives of this research, outlined in Chapter 1, were to understand the cognitive processes associated with exploiting terror network visualizations, adapt a matrix visualization that is useable by intelligence analysts, and assess its efficacy as compared to the current domain standard (node-link). These objectives were addressed throughout the thesis in the following manner.

- Objective 1: Understand the cognitive tasks associated with exploiting terror network visualizations (see Chapter 3).
- Objective 2: Adapt a matrix visualization that is useable by intelligence analysts (see Chapter 4)
- Objective 3: Test the efficacy of the matrix visualization against the current domain standard method (node-link) visualizations using domain experts (see Chapters 5-6).
- Objective 4: Discuss the results of the experiment in a manner that is accessible by members within the military intelligence community (see Chapter 7).

Chapter 3 outlined a cognitive task analysis to identify the specific cognitive processes, challenges, and constraints an analyst faces while exploiting terror network visualizations. The results of that analysis were then used to create an information processing model for visualization. The model identified and illustrated the cognitive processes used by an analyst to transition through three main stages of information processing: perception, comprehension, and projection. Of particular significance, the transition from perception to comprehension was noted as one of the primary bottlenecks inhibiting effective information processing.

Chapter 4 built upon the analysis in Chapter 3 and outlined the adaptation of a matrix visualization and node-link visualization which were used for the user experiment outlined in Chapter 5. The resulting human performance testing revealed that node-link visualizations produce statistically significant better average accuracy for questions 1.1, 1.2, and 1.3. Thus, indicating that the node-link visualization performed superiorly, in terms of percentage correct, in all studied scenarios where the objective was identifying leaders. The node-link visualization also performed better on the task of identifying clusters, returning higher average percent correct, although not statistically significant, than the matrix.

Although the matrix visualization did not perform as well as hypothesized in this thesis, some subjective feedback from participants in the experiment suggests that matrix performance may improve as participants become more familiar with the matrix.

7.5.2 Recommendations and Future Work

Although the results of this thesis indicate that the node-link supported both investigated tasks better than the matrix, more investigation is needed to determine if this conclusion is universal across all intelligence tasks and populations. The following are recommendations for future follow-on experiments based on the research presented in this thesis.

- To gain a more detailed understanding of the potential of matrices. A longitudinal study should be conducted using only the matrix, where a static group of analysts are tasked to exploit multiple terror networks at different times over a predetermined period of time; perhaps a month. This type of experiment would provide detailed data on learning that may occur as analysts become more familiar with the matrix.
- A similar experiment to the one outlined in this thesis should be conducted with other data sets of varying size and complexity. While the node-link proved superior in the research outlined herein, this may be a byproduct of the specific data set chosen, not the visualization. To understand the extent of these affects, more experiments are needed using a variety of data sets.
- An experiment similar to the one described in this thesis should also be run for both the node-link and matrix on a computer. This form of experimentation is required to understand the effectiveness of each visualization in a more realistic setting.
- The participant responses outlined in section 7.3 should be addressed and further investigated in future experiments; specifically the effects of collecting time of the conclusions reached by participants

At this time, the matrix should not be universally integrated into the current methodologies used by analysts to exploit terror network visualizations until more research is conducted into the respective strengths and weaknesses within the intelligence domain. However, analysts should be independently encouraged to explore and adapt new methods of visualization into their current practices and identify new or improved versions of the visualizations identified within this thesis for future testing.

Appendix A

Consent to Participate

The following consent to participate was signed by all participants prior to taking part in the experiment

CONSENT TO PARTICIPATE IN

NON-BIOMEDICAL RESEARCH

Design and Exploitation of Terrorist Networks Visualizations Protocol

You are asked to participate in a research study conducted by Christopher Berardi from the Systems Design and Management Program in the Engineering Systems Division at the Massachusetts Institute of Technology (M.I.T.). The results of this work will support Chris' thesis work into the Design and Exploitation of Terrorist Networks Visualizations. You were selected as a possible participant in this study because you are a formally trained military intelligence analyst. You should read the information below, and ask questions about anything you do not understand, before deciding whether or not to participate.

- **PARTICIPATION AND WITHDRAWAL**

Your participation in this study is completely voluntary and you are free to choose whether to be in it or not. If you choose to be in this study, you may subsequently withdraw from it at any time without penalty or consequences of any kind. The investigator may withdraw you from this research if circumstances arise which warrant doing so.

- **PURPOSE OF THE STUDY**

The Design and Exploitation of Terrorist Networks Visualizations project investigates assisting users in exploiting complex visualizations of terrorist networks through the employment of multi-mode visualizations. The objective of this experiment is to ascertain the efficacy of varying visualization techniques in the context of military intelligence analysis. The primary interest is relative performance of users while executing exploratory task on multiple modes of visualizations.

- **PROCEDURES**

If you volunteer to participate in this study, we would ask you to do the following things:

Each participant will perform the experiment individually. Upon arriving at the testing site, they will be greeted and given a brief introduction to the experiment. Participants will then be asked to sign in- formed consent forms and complete a background questionnaire gathering demographic information and their previous experiences with intelligence analysis. After finishing the demographic survey, the experiment and visualizations will be explained in detail to the participant. The experiment administrator will provide training on any quantitative social network analysis measures used in the visualizations. Once the participant has received instructions on the execution of the experiment and completed the social network analysis measures training, they will begin the experiment. At this point the experimenter will present the participant a randomly selected visualization and asked to respond to each exploratory task. After which the participant will be asked to answer the same exploratory tasks for a second visualization. It is expected that the tasks for each set of visualizations will take approximately 10 minutes. Participants will conclude the experiment by taking the NASA TLX workload survey and interview on the interface with the experimenter. Participants will then be debriefed about the experiment, and thanked for their participation.

- **POTENTIAL RISKS AND DISCOMFORTS**

Participants will be given a clear explanation of the study tasks and study tasks are commensurate with the tasks performed by analysts during routine performance of their job. Thus, there are no anticipated physical or psychological risks

- **POTENTIAL BENEFITS**

There are no potential benefits a subject may receive from participating in this study. However, the results of the study will be used to improve the design of future terror network visualizations.

- **PAYMENT FOR PARTICIPATION**

There is no compensation offered for participation in this study.

- **CONFIDENTIALITY**

Any information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission or as required by law.

Participant's responses to each of the exploratory tasks will be documented as well as the time required to answer. Field notes will be taken during the experiment to record any emerging patterns or other matters of interest. Usability, mission performance, demographic and experience data will be collected by questionnaire.

Each subject will randomly be assigned a number which will identify data related to their experiment. At no point will personally identifiable information be associated with a subject's experimental data.

Data will be stored electronically in a locked room on campus and will be destroyed 90 days after the analysis of the experiment is complete.

- **IDENTIFICATION OF INVESTIGATORS**

If you have any questions or concerns about the research, please feel free to contact Christopher Berardi (email: cberardi@mit.edu / phone: (719) 930-8907) or alternately Professor Mary Cummings (email: missyc@mit.edu / phone: (617) 252-1512)

- **EMERGENCY CARE AND COMPENSATION FOR INJURY**

If you feel you have suffered an injury, which may include emotional trauma, as a result of participating in this study, please contact the person in charge of the study as soon as possible.

In the event you suffer such an injury, M.I.T. may provide itself, or arrange for the provision of, emergency transport or medical treatment, including emergency treatment and follow-up care, as needed, or reimbursement for such medical services. M.I.T. does not provide any other form of compensation for injury. In any case, neither the offer to provide medical assistance, nor the actual provision of medical services shall be considered an admission of fault or acceptance of liability. Questions regarding this policy may be directed to MIT's Insurance Office, (617) 253-2823. Your insurance carrier may be billed for the cost of emergency transport or medical treatment, if such services are determined not to be directly related to your participation in this study.

- **RIGHTS OF RESEARCH SUBJECTS**

You are not waiving any legal claims, rights or remedies because of your participation in this research study. If you feel you have been treated unfairly, or you have questions regarding your rights as a research subject, you may contact the Chairman of the Committee on the Use of Humans as Experimental Subjects, M.I.T., Room E25-143B, 77 Massachusetts Ave, Cambridge, MA 02139, phone 1-617-253 6787.

SIGNATURE OF RESEARCH SUBJECT OR LEGAL REPRESENTATIVE

I understand the procedures described above. My questions have been answered to my satisfaction, and I agree to participate in this study. I have been given a copy of this form.

____

Name of Subject

____

Name of Legal Representative (if applicable)

____________________________________ ____________

Signature of Subject or Legal Representative Date

SIGNATURE OF INVESTIGATOR

In my judgment the subject is voluntarily and knowingly giving informed consent and possesses the legal capacity to give informed consent to participate in this research study.

____________________________________ ____________

Signature of Investigator Date

Appendix B

Demographic Survey

The following survey was completed by all participants prior to starting the experiment.

Visualization Demographic Survey

SUBJECT: __________
DATE: __________
TIME: __________

Age: __________________

1. Gender:

□ Male

□ Female

2. If currently or formerly part of armed forces:

a. *Country/State*: __________________

b. *Status*: □ Active Duty □ Reserve □ Guard □ Retired

c. *Service*: □ Army □ Navy □ Air Force □ Other __________________

d. *Rank*: __________________

e. *Years of Service*: __________________

f. *Military occupation*: ______________

g. Years of experience in occupation: ________________

3. Do you have experience exploiting terrorist network visualizations?

□ Yes

□ No

If yes:

Number of years: __________________

4. Are you color blind?

□ Yes

□ No

5. Is your vision correctable to 20/20?

□ Yes

□ No

Appendix C

Matrix Experiment PowerPoint Tutorial

The following experiment tutorial was seen by all participants prior to starting the experiment.

Experimental Tutorial

Experiment Explanation

Thank you very much for participating in this experiment. Today you will be tasked with analyzing a terrorist network visualization. Specifically, you will be asked to identify leaders and clusters. Your participation in this experiment will help with determine the efficacy of terror network visualizations.

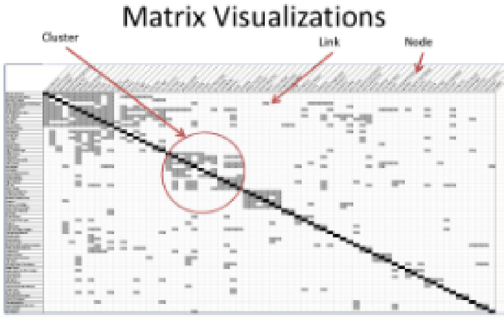
Before beginning the experiment you will be given a tutorial on measures of centrality, the visualization and an explanation of the tasks which will be asked of you. Please use this opportunity to ask questions and ensure you understand the content, because once the experiment begins no questions will be answered. After the tutorial, you will be given the visualizations on a piece of 11x17 copy paper and asked to answer 3 questions for each visualization.

The following slides cover some basics about the visualization technique and explain the definitions and significance of betweenness centrality and closeness centrality.

Definitions

- For this experiment the following definitions apply:
  - Network = Depiction of the entire data set
  - Node = Actor (a specific individual)
  - Link = A relation or connection between two nodes
  - Cluster = A set of three or more nodes *closely related* nodes

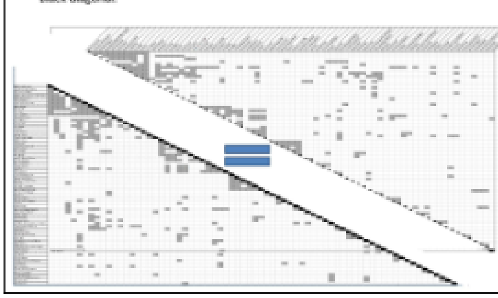
Matrix Visualizations



- Node = Actor (terrorist)
- Link = A relation or connection between two terrorists
- Cluster = A set of three or more nodes *closely related* terrorists

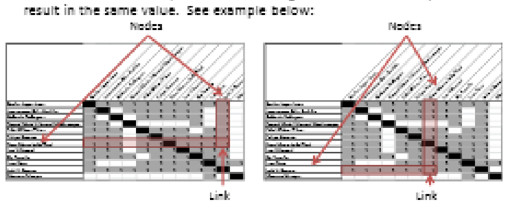
Matrix Visualizations

- All matrices shown during this experiment are symmetrical, which means that the information above the black diagonal is exactly the same as the information below the black diagonal.



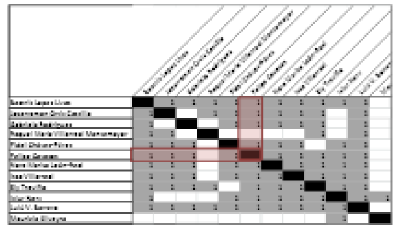
Reading Matrix Visualizations

- Start with the node Lulu V Barrera on matrix below and follow that column down to the row where it intersects Nora Marisa Leon-Real.
- If there is a "1" in this box or it is shaded that indicates a link between those nodes.
  - Any intersection with a number = relationship between terrorists
- Because the matrix is symmetrical, reading it from the left or top will result in the same value. See example below:



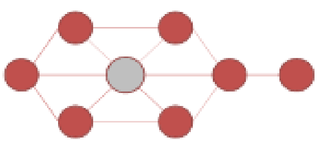
Matrix Visualizations

- The black diagonals are the intersection of the same node (terrorist) in the matrix and carry no significance.
- In the example below, where Felipe Cavazos intersects with himself on the matrix the cell is black because Felipe Cavazos cannot be linked to himself.



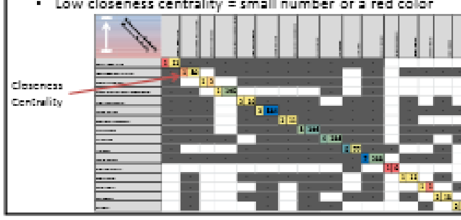
Closeness Centrality

- The idea that if a node is very close to a large number of nodes, it can monitor the overall flow of information and thus it has a high visibility on what happens in the network
- A node with a high closeness centrality will most likely have the best visibility into what is happening in the network.



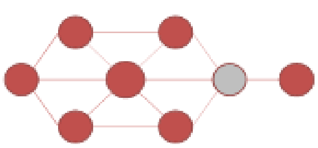
Matrix Closeness Centrality

- Closeness centrality will be displayed on the ***LEFT*** side of the diagonal.
- High closeness centrality = large number or a blue color
- Low closeness centrality = small number or a red color



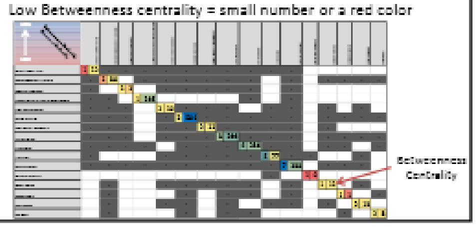
Betweenness Centrality

- The idea that a node is central when it is able to connect relevant clusters that would otherwise be disconnected
- Often referred to as an information broker in a network, because a node with high betweenness has great influence over what flows -- and does not -- in the network.



Matrix Betweenness Centrality

- Betweenness centrality will be displayed on the ***RIGHT*** side of the diagonal.
- High Betweenness centrality = large number or a blue color
- Low Betweenness centrality = small number or a red color



Questions

- Any question about what you have seen thus far?
- This is your last opportunity to ask question prior to the start of the experiment

Great Job! You have successfully passed the training sessions

- Now that you have completed your training, you will participate in 2 short practice scenarios
- At the completion of each practice scenario, you will be asked a series of questions on a paper that will assess your experience exploiting the visualization.

Task Objectives

- The following tasks are the **key goals** of this experiment and should be performed to the best of your ability. They are in no specific order
- Primary Goals:
  1. Identify leaders within a presented visualization
  2. Identify clusters within a presented visualization

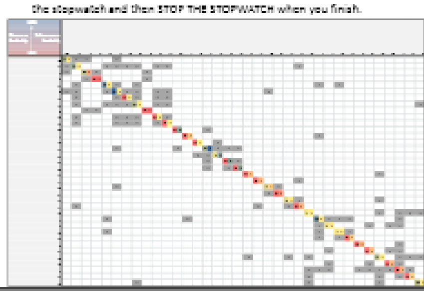
Scenario #1

- In the first scenario you will be asked to perform the following task:
- (Task 1) Analyze roles and positions — these are higher level tasks relying on the interpretation of groups of actors (positions) and connection patterns (roles).
  - This task consists of identifying potential leaders within a network and then subsequently identifying the correct leader

Scenario #1 Example Visualization

(Question 1.1) Identify any central actors, which are defined as actors linked to many others or that bridge communities together.

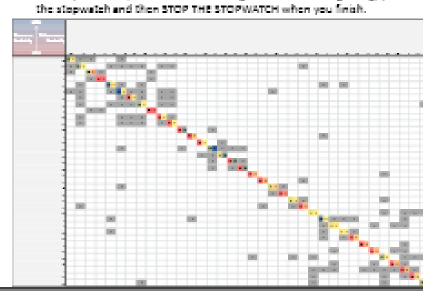
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



Scenario #1 Example Visualization

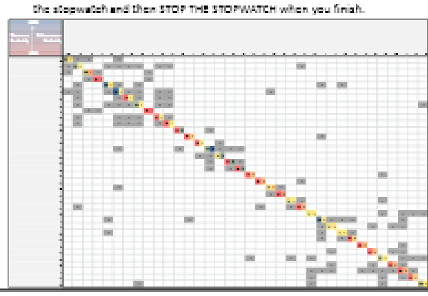
(Question 1.2) Identify any potential leaders within the network.

- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



Scenario #1 Example Visualization

(Question 1.3) Assuming there is only one leader, identify that leader.
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.

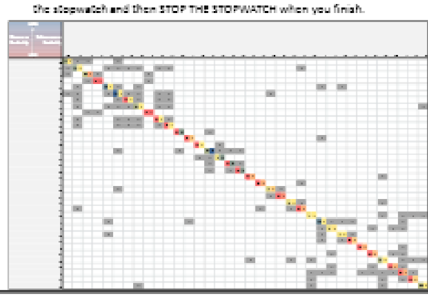


Scenario #2

- In the second scenario you will be asked to perform the following task:
- (Task 2) Identify communities, i.e. cohesive groups of actors that are strongly connected to each other.
  - This task consists of identifying potential clusters within a network and then subsequently identifying the correct number of clusters

Scenario #2 Example Visualization

(Question 2.2) Assuming there are only two clusters, identify these clusters.
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



Final Questions?

Appendix D

Node-Link Experiment PowerPoint Tutorial

The following experiment tutorial was seen by all participants prior to starting the experiment.

Experimental Tutorial

Experiment Explanation

Thank you very much for participating in this experiment. Today you will be tasked with analyzing a terrorist network visualization. Specifically, you will be asked to identify leaders and clusters. Your participation in this experiment will help with determine the efficacy of terror network visualizations.

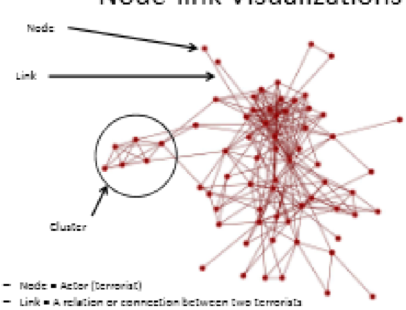
Before beginning the experiment you will be given a tutorial on measures of centrality, the visualization and an explanation of the tasks which will be asked of you. Please use this opportunity to ask questions and ensure you understand the content, because once the experiment begins no questions will be answered. After the tutorial, you will be given the visualization on a piece of 11x17 copy paper and asked to answer 5 questions for each visualization.

The following slides cover some basics about the visualization technique and explain the definitions and significance of betweenness centrality and closeness centrality.

Definitions

- For the experiment the following definitions apply:
  - Network = Depiction of the entire data set
  - Node = Actor (a specific individual)
  - Link = A relation or connection between two nodes
  - Cluster = A set of three or more nodes *closely related* nodes

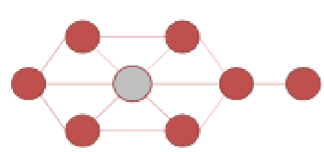
Node-link Visualizations



- Node = Actor (terrorist)
- Link = A relation or connection between two terrorists
- Cluster = A set of three or more nodes *closely related* terrorists

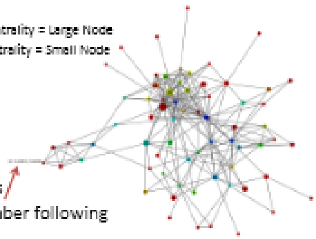
Closeness Centrality

- The idea that if a node is very close to a large number of nodes, it can monitor the overall flow of information and thus it has a high visibility on what happens in the network
- A node with a high closeness centrality will most likely have the best visibility into what is happening in the network.



Node-link Closeness Centrality

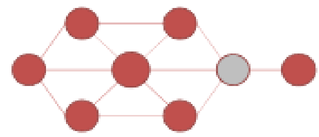
- Closeness centrality will be displayed by changing node size.
  - High Closeness Centrality = Large Node
  - Low Closeness Centrality = Small Node



- Closeness values are the first number following the node label.

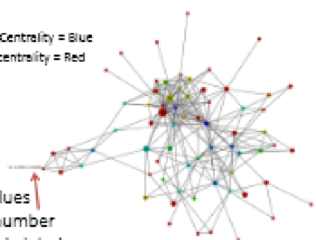
Betweenness Centrality

- The idea that a node is central when it is able to connect relevant clusters that would otherwise be disconnected
- Often referred to as an information broker in a network, because a node with high betweenness has great influence over what flows -- and does not -- in the network.



Node-link Betweenness Centrality

- Betweenness centrality will be displayed by changing node color.
  - High bewteenness Centrality = Blue
  - Low betweenness centrality = Red



- Betweenness values are the second number following the node label.

Questions

- Any question about what you have seen thus far?
- This is your last opportunity to ask question prior to the start of the experiment

Great Job! You have successfully passed the training sessions

- Now that you have completed your training, you will participate in 2 short practice scenarios
- At the completion of each practice scenario, you will be asked a series of questions on a paper that will assess your experience exploiting the visualization.

Task Objectives

- The following tasks are the **key goals** of this experiment and should be performed to the best of your ability. They are in no specific order
- Primary Goals:
  1. Identify leaders within a presented visualization
  2. Identify clusters within a presented visualization

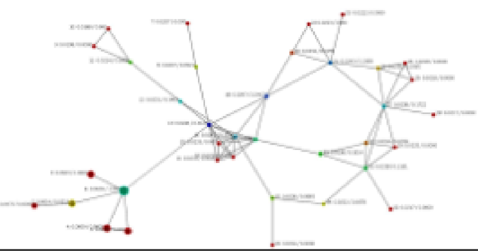
Scenario #1

- In the first scenario you will be asked to perform the following task:
- (Task 1) Analyze roles and positions — these are higher level tasks relying on the interpretation of groups of actors (positions) and connection patterns (roles).
  - This task consists of identifying potential leaders within a network and then subsequently identifying the correct leader

Scenario #1 Example Visualization

(Question 1.1) Identify any central actors, which are defined as actors linked to many others or that bridge communities together.

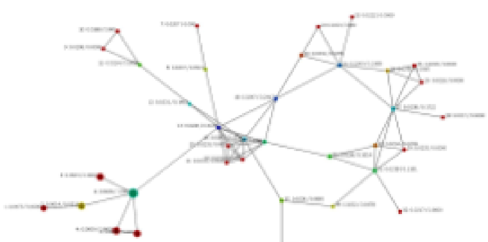
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



Scenario #1 Example Visualization

(Question 1.2) Identify any potential leaders within the network.

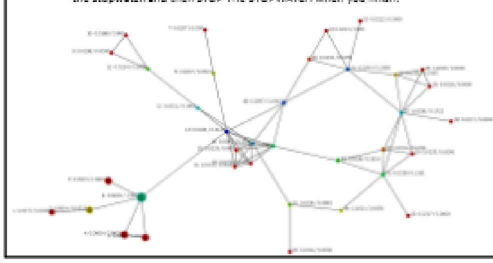
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



Scenario #1 Example Visualization

(Question 1.3) Assuming there is only one leader, identify that leader.

- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



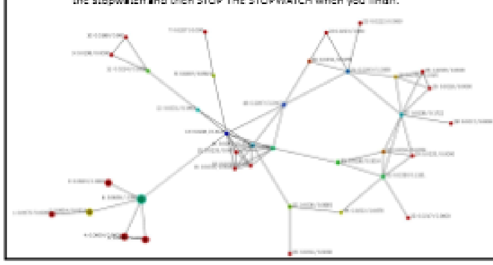
Scenario #2

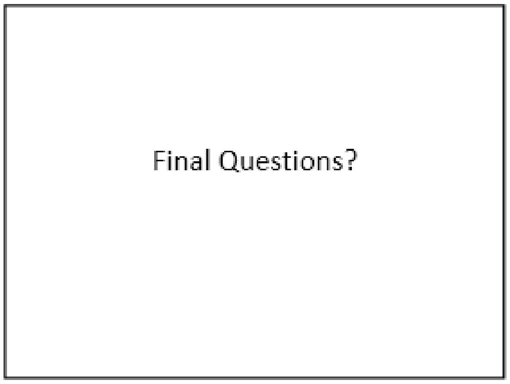
- In the second scenario you will be asked to perform the following task:
- (Task 2) Identify communities, i.e. cohesive groups of actors that are strongly connected to each other.
  - This task consists of identifying potential clusters within a network and then subsequently identifying the correct number of clusters

Scenario #2 Example Visualization

(Question 2.2) Assuming there are only two clusters, identify those clusters.

- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.




Final Questions?

Appendix E

Post Experiment Questionnaire

This appendix outlines the post experiment questionnaire used to solicit feedback from participants on the visualizations.

E.1 Node-link Questions

The following questions were used to guide post-experiment discussion with the participants on the topic of the node-link visualization.

1. How did you use the node-link visualization to satisfy Task 1?

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2. How did you use the node-link visualization to satisfy Task 2?

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3. What did you like best about the visualization? Please explain your answer below.

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4. What did you like least about the visualization? Please explain your answer below.

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5. Was there anything negative or distracting about the node-link visualization? Please explain your answer below.

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6. Is there any additional information that you wished you had, which would have help with your exploitation tasks?

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7. Are you an expert in Microsoft Excel? Please check appropriate box.

Yes ____________ / No ____________

E.2 Matrix Questions

The following questions were used to guide post-experiment discussion with the participants on the topic of the matrix visualization.

1. How did you use the matrix visualization to satisfy Task 1?

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2. How did you use the matrix visualization to satisfy Task 2?

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3. What did you like best about the visualization? Please explain your answer below.

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4. What did you like least about the visualization? Please explain your answer below.

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5. Was there anything negative or distracting about the node-link visualization? Please explain your answer below.

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6. Is there any additional information that you wished you had, which would have help with your exploitation tasks?

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7. Are you an expert in Microsoft Excel? Please check appropriate box.

Yes _______________ / No _______________

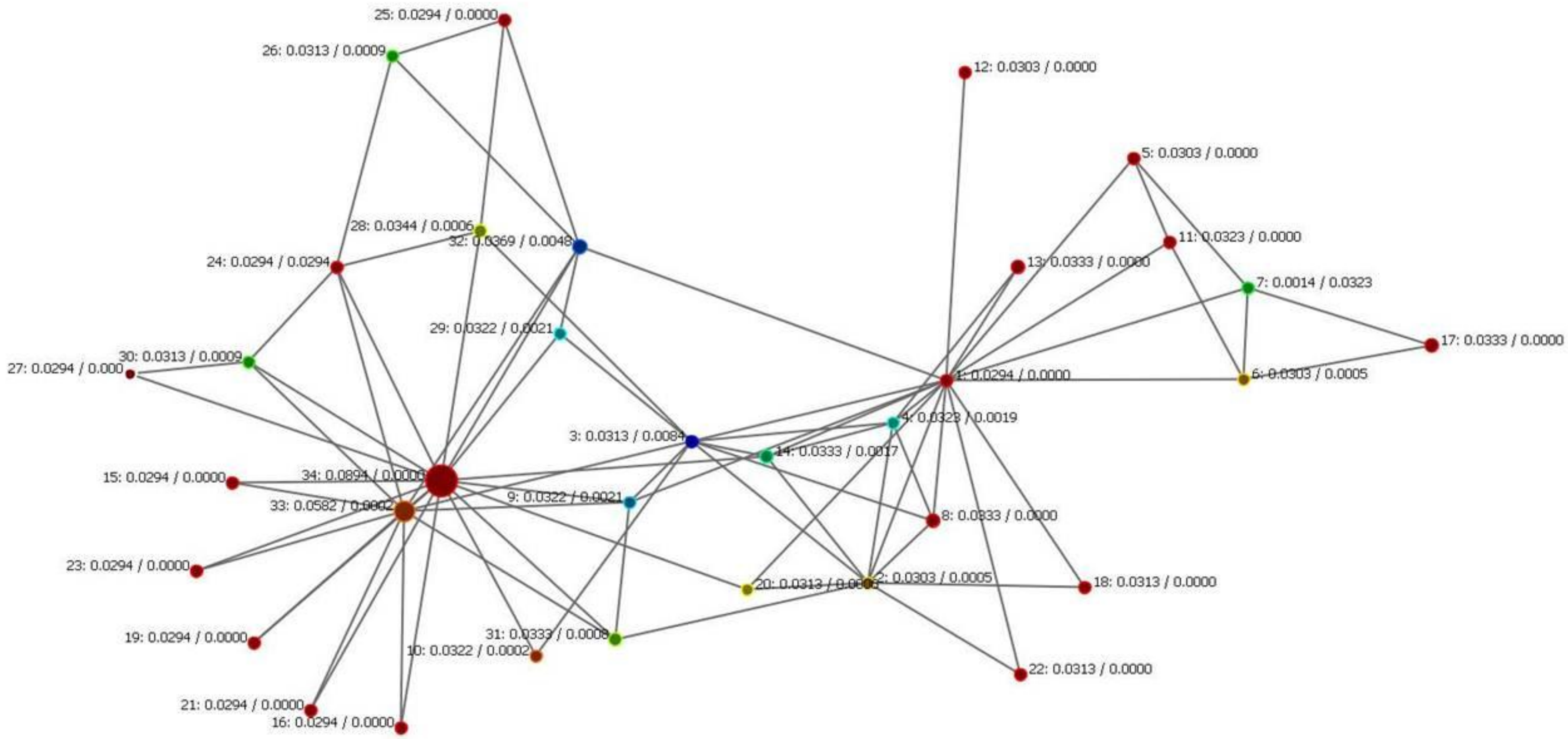
Appendix F

Experiment Visualizations

This appendix outlines the visualizations used during the human experiment..

(Question 1.1) Identify any central actors, which are defined as actors linked to many others or that bridge communities together.

- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.

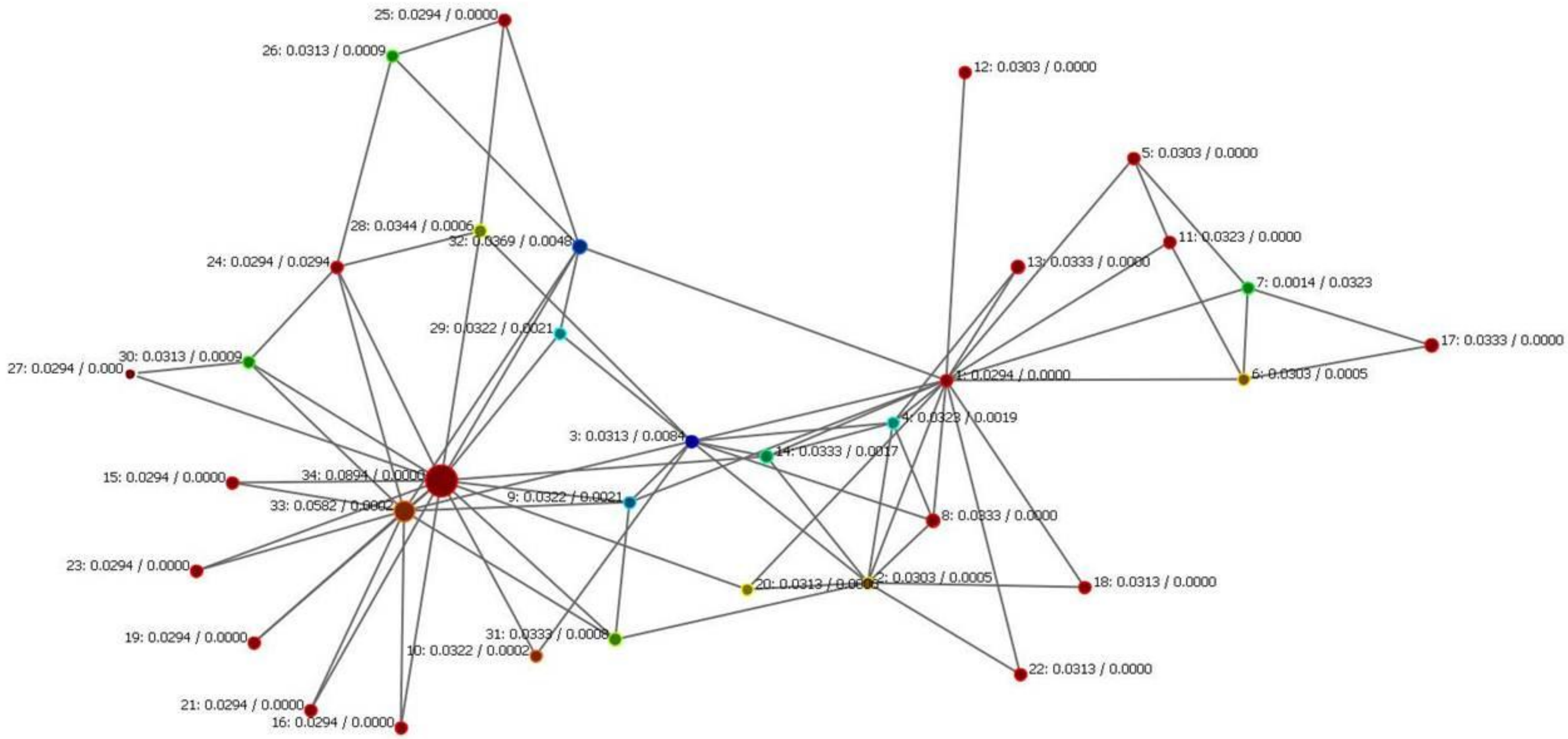


ID: ________

Time: __________

(Question 1.2) Identify any potential leaders within the network .

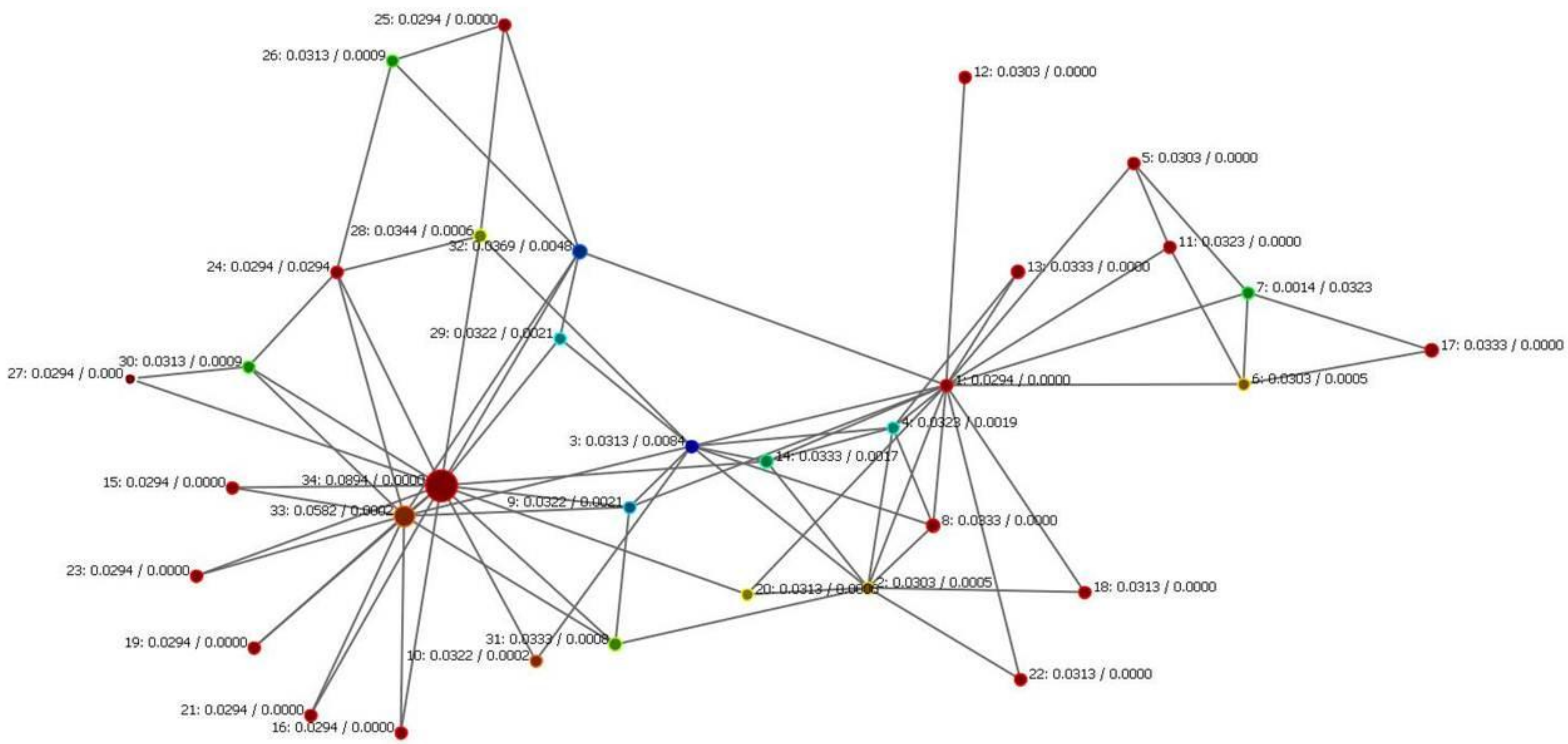
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



ID: ________ Time: __________

(Question 1.3) Assuming there are only two leaders, identify those leaders.

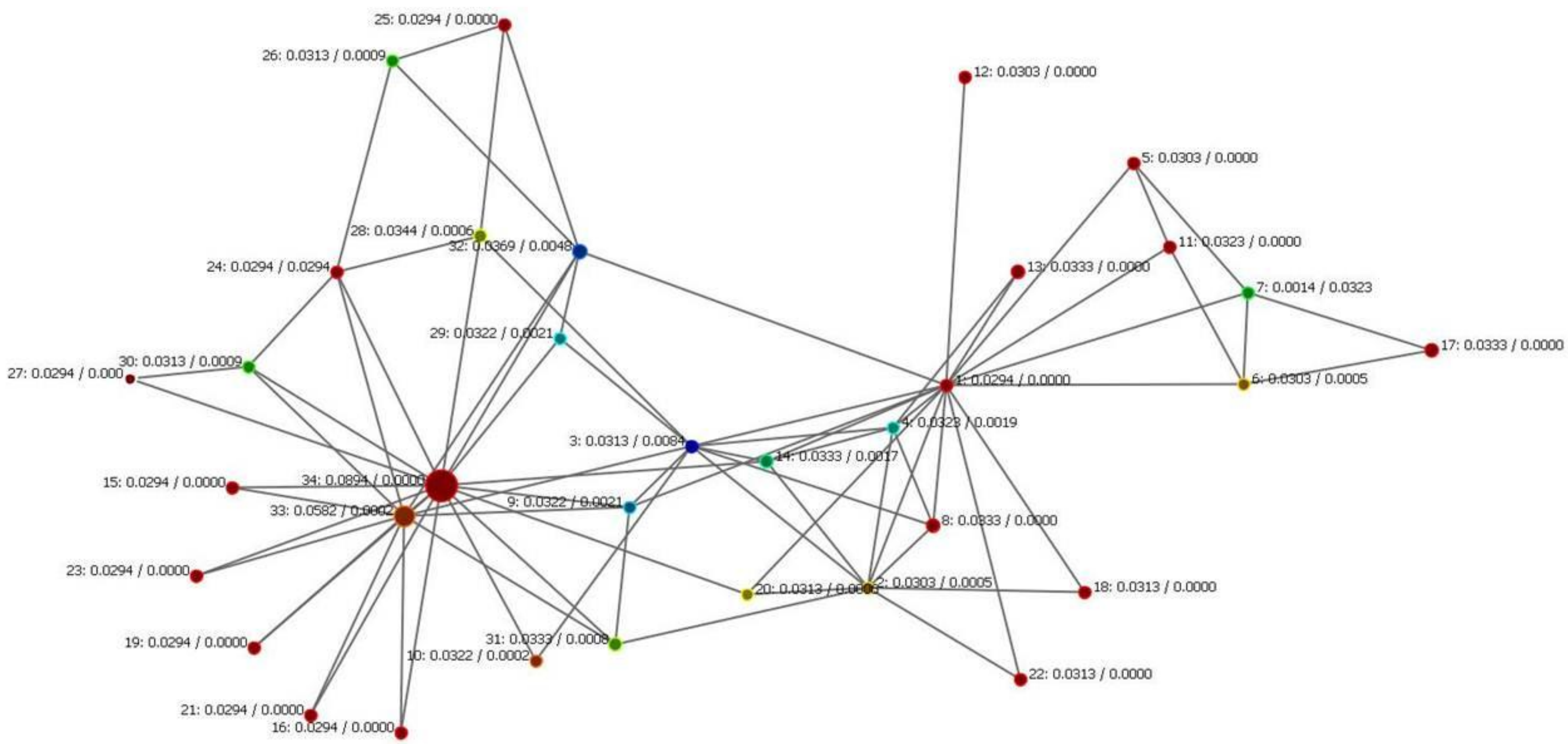
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



ID: ________ Time: __________

(Question 2.1) Assuming there are only two clusters, identify those clusters.

- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.

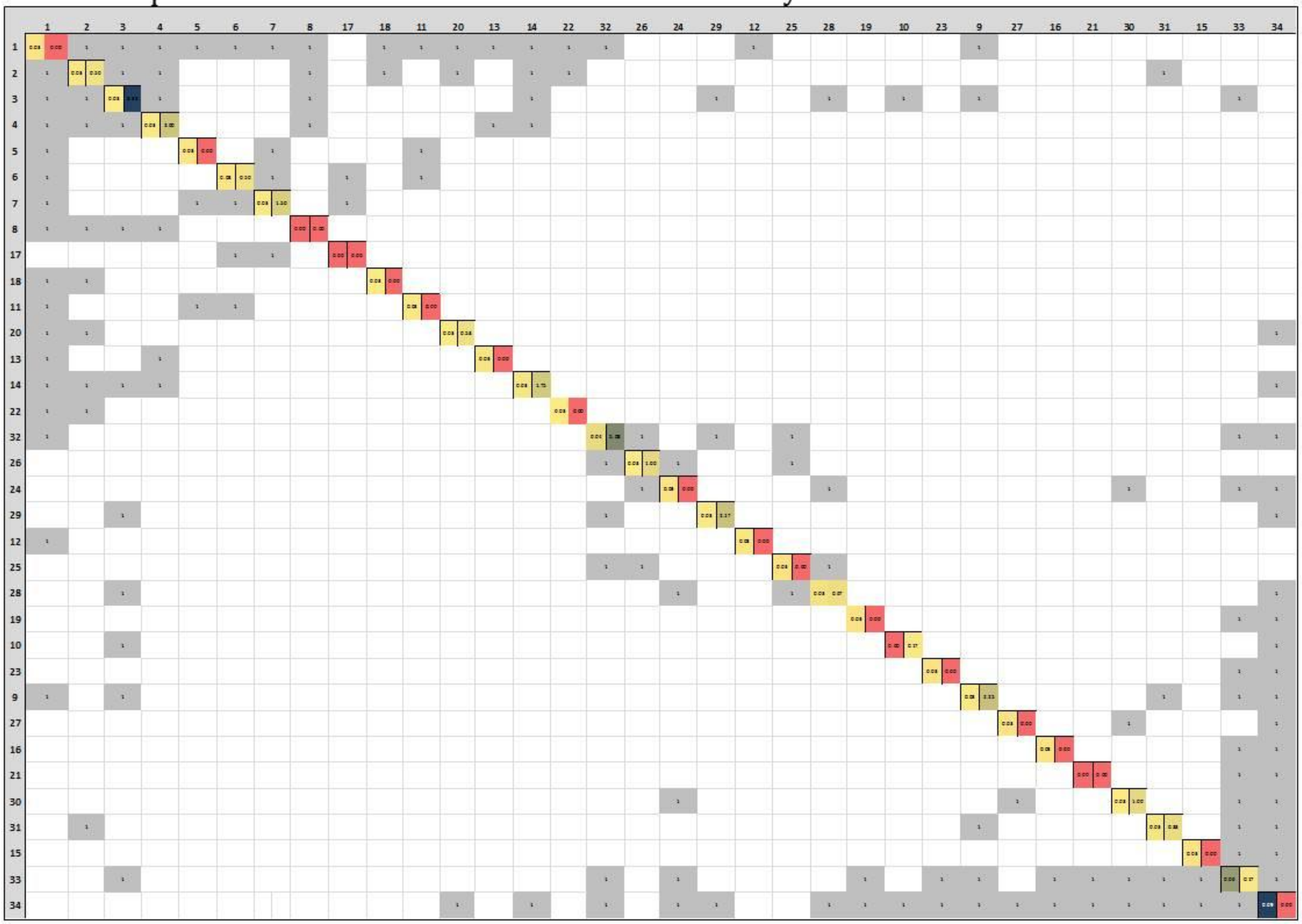


ID: ________

Time: __________

(Question 1.1) Identify any central actors, which are defined as actors linked to many others or that bridge communities together.

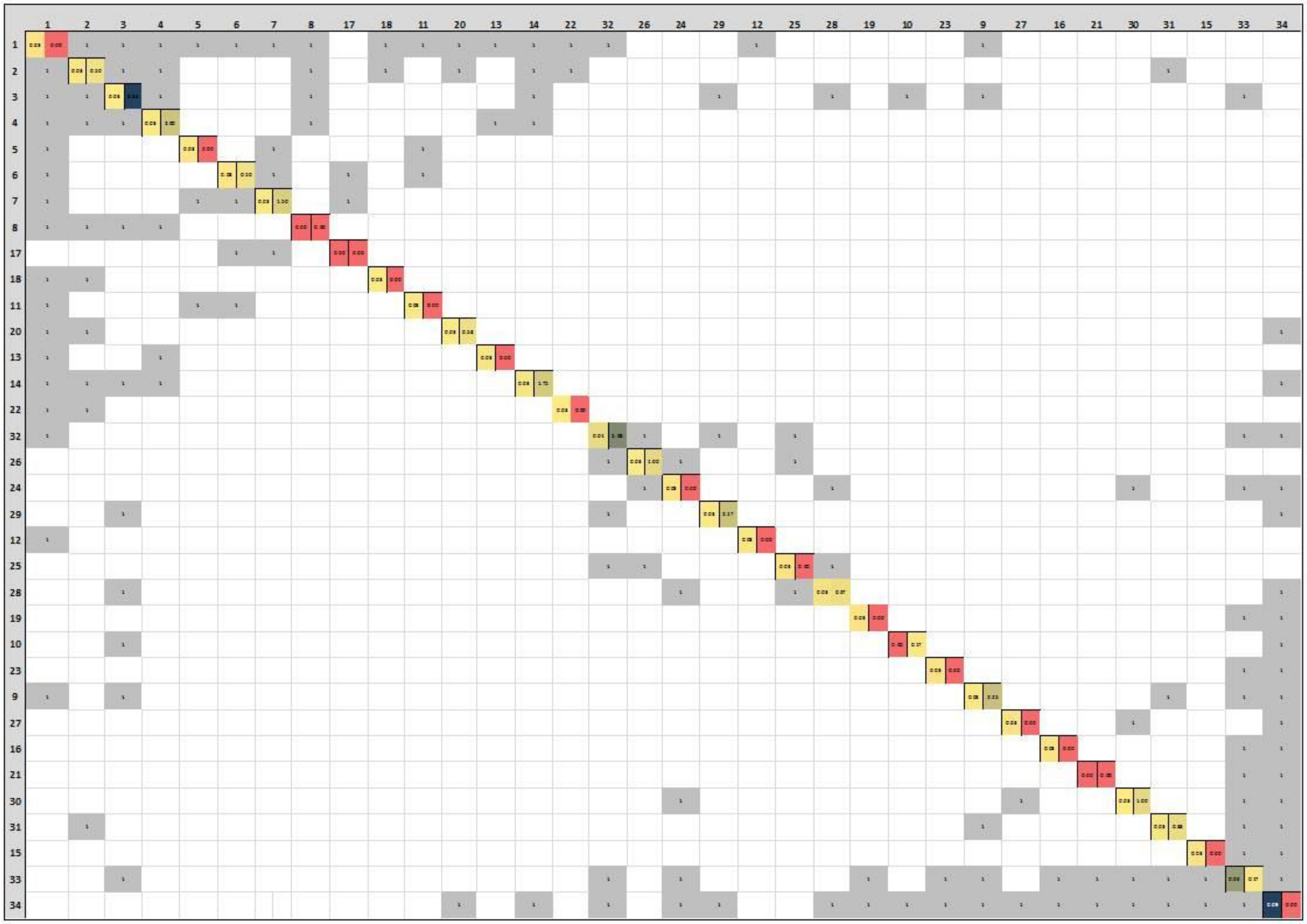
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



ID:________ Time:__________

(Question 1.2) Identify any potential leaders within the network .

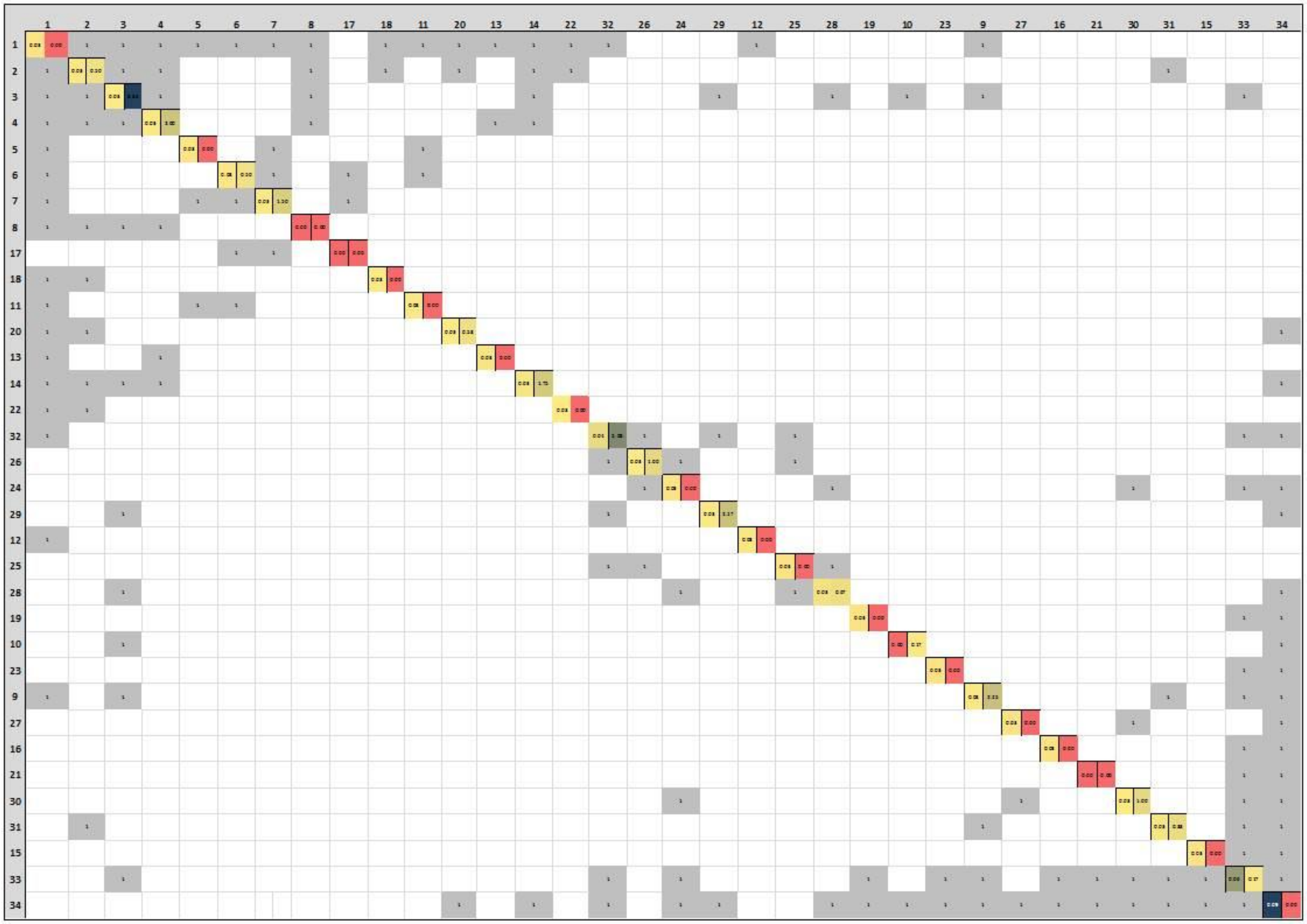
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



ID:________ Time:__________

(Question 1.3) Assuming there are only two leaders, identify those leaders.

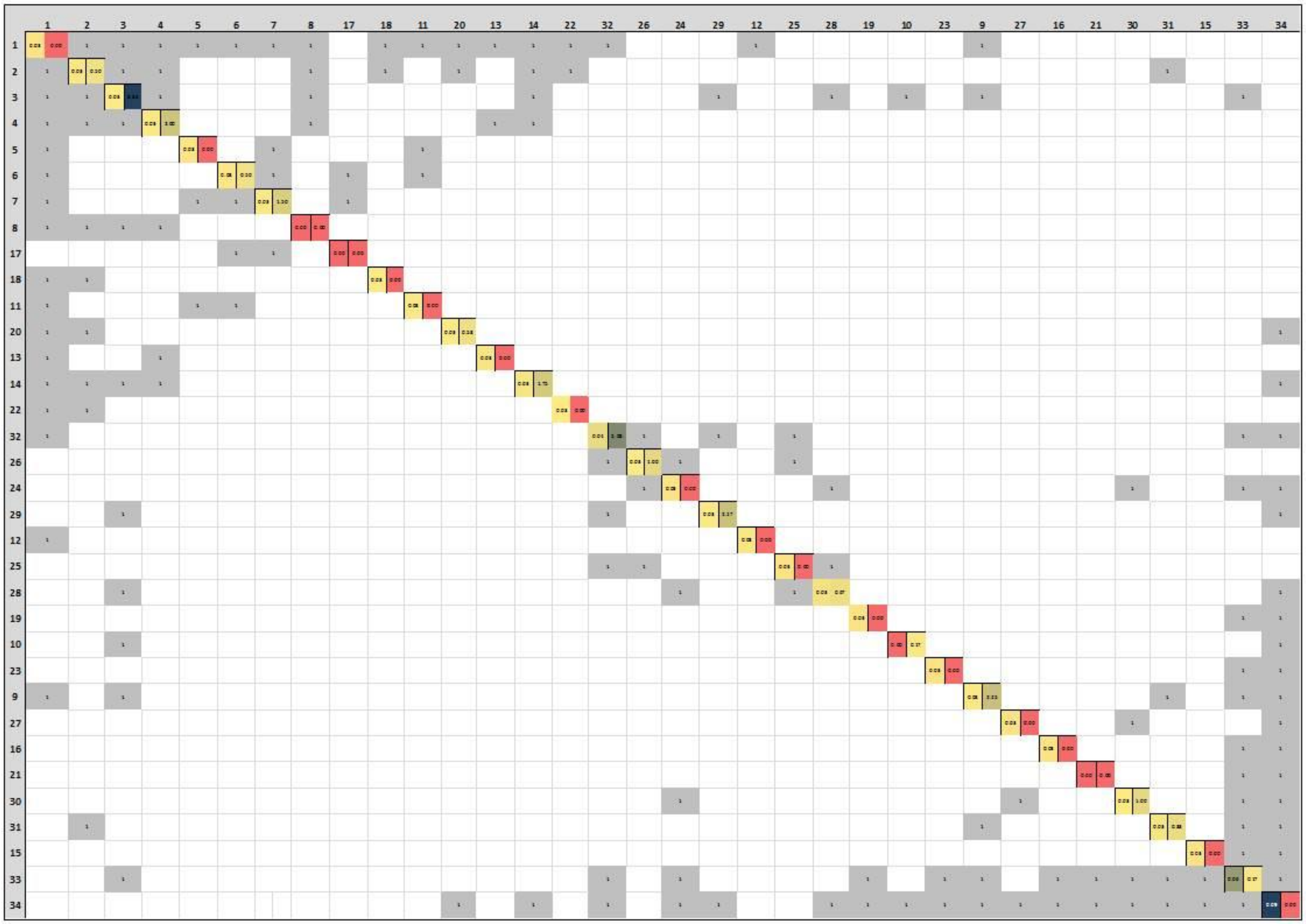
- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



ID:________ Time:__________

(Question 2.1) Assuming there are only two clusters, identify those clusters.

- Be as precise as possible when drawing circles. Before beginning, you must start the stopwatch and then STOP THE STOPWATCH when you finish.



ID: ________ Time: __________

Appendix G

Supporting Statistics

This appendix outlines the supporting statistics for of the results and calculations presented in Chapter 6.

Table G-1: Summary Percentage Correct

Percent Correct	Q1.1 Matrix	Q 1.2 Matrix	Q1.3 Matrix	Q2.1 Matrix	Q 1.1 Node-Link	Q 1.2 Node-Link	Q 1.3 Node-link	Q 2.1 Node-link
Number of values	27	30	30	30	30	30	30	30
Minimum	0.0	0.0	0.0	14.71	0.0	20.00	0.0	8.824
Median	33.33	60.00	50.00	44.12	50.00	70.00	50.00	66.18
Maximum	77.78	80.00	100.0	97.06	88.89	100.0	100.0	100.0
Mean	33.33	48.67	33.33	47.16	51.11	67.33	56.67	62.45
Std. Deviation	21.57	25.01	33.04	22.97	20.76	23.77	38.80	30.31
D'Agostino & Pearson omnibus normality test								
K2	2.626	2.956	1.961	4.035	0.7529	4.524	6.900	19.44
P value	0.2691	0.2281	0.3751	0.1330	0.6863	0.1041	0.0317	<0.0001
Passed normality test (alpha=0.05)?	Yes	Yes	Yes	Yes	Yes	Yes	No	No

Table G-2: Summary Percentage Correct after log transformation for Question 2.1

Percent Correct	Q1.1 Matrix	Q 1.2 Matrix	Q1.3 Matrix	Q2.1 Matrix	Q 1.1 Node-Link	Q 1.2 Node-Link	Q 1.3 Node-link	Q 2.1 Node-link
Number of values				30				30
Minimum				1.167				0.9456
Median				1.645				1.820
Maximum				1.987				2.000
Mean				1.623				1.730
Std. Deviation				0.2191				0.2665
D'Agostino & Pearson omnibus normality test								
K2				0.6409				5.501
P value				0.7258				0.0639
Passed normality test (alpha=0.05)?				Yes				Yes

Table G-3: Summary Time to Complete

Time	Q1.1 Matrix	Q 1.2 Matrix	Q1.3 Matrix	Q2.2 Matrix	Q 1.1 Node-Link	Q 1.2 Node-Link	Q 1.3 Node-link	Q 2.1 Node-link
Number of values	27	30	30	30	30	30	30	30
Minimum	14.00	4.000	5.000	8.000	5.710	4.030	2.460	5.000
Median	49.40	40.47	21.50	26.42	64.53	38.92	14.00	33.92
Maximum	121.0	294.0	122.0	187.0	265.0	172.6	220.0	191.0
Mean	58.64	53.18	30.00	43.04	79.98	54.61	37.06	48.91
Std. Deviation	36.21	55.79	29.10	42.48	61.85	42.68	48.71	46.91
D'Agostino & Pearson omnibus normality test								
K2	5.446	43.86	26.05	25.04	14.30	9.819	29.10	16.61
P value	0.0657	<0.0001	<0.0001	<0.0001	0.0008	0.0074	<0.0001	0.0002
Passed normality test (alpha=0.05)?	Yes	No	No	No	No	No	No	No

Table G-4: Summary Time to Complete After log transformation

Time	Q1.1 Matrix	Q 1.2 Matrix	Q1.3 Matrix	Q2.1 Matrix	Q 1.1 Node-Link	Q 1.2 Node-Link	Q 1.3 Node-link	Q 2.1 Node-link
Number of values	27	30	30	30	30	30	30	30
Minimum	1.146	0.6021	0.6990	0.9031	0.7566	0.6053	0.3909	0.6990
Median	1.694	1.607	1.332	1.422	1.810	1.590	1.145	1.530
Maximum	2.083	2.468	2.086	2.272	2.423	2.237	2.342	2.281
Mean	1.675	1.579	1.329	1.487	1.778	1.602	1.276	1.515
Std. Deviation	0.3057	0.3591	0.3545	0.3458	0.3554	0.3746	0.5111	0.4045
D'Agostino & Pearson omnibus normality test								
K2	3.605	2.682	0.7395	1.952	3.204	2.205	1.492	0.4564
P value	0.1649	0.2615	0.6909	0.3767	0.2015	0.3320	0.4743	0.7959
Passed normality test (alpha=0.05)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table G-5: Summary of Percentage Correct Unpaired t tests

Unpaired t test	Q1.1 Matrix vs Node-Link	Q1.2 Matrix vs Node-Link	Q2.1 Matrix vs. Node-Link
P value	0.0025	0.0044	0.0948
Significantly different? (P < 0.05)	Yes	Yes	No
One- or two-tailed P value?	Two-tailed	Two-tailed	Two-tailed
t, df	t=3.169 df=55	t=2.963 df=58	t=1.698 df=58
F test to compare variances			
F,DFn, Dfd	1.080, 26, 29	1.107, 29, 29	1.480, 29, 29
P value	0.8360	0.7854	0.2971
Significantly different? (P < 0.05)	No	No	No

Table G-6: Summary of Mann Whitney U Test for Question 1.3

Mann Whitney U test	Q1.3 Matrix vs Node-Link
P value	0.0231
Exact or approximate P value?	Exact
Significantly different? (P < 0.05)	Yes
One- or two-tailed P value?	Two-tailed
Sum of ranks in column R,AX	766.0 , 1064
Difference between medians	
Median of column R	50.00
Median of column AX	50.00
Difference: Actual	0.0
Difference: Hodges-Lehmann	50.00

Table G-7: Summary of Percentage Correct Time to Complete Unpaired t tests

Unpaired t test	Q1.1 Time Matrix vs Node-Link	Q1.2 Time Matrix vs Node-Link	Q1.3 Time Matrix vs Node-Link	Q2.1 Time Matrix vs. Node-Link
P value	0.2456	0.8085	0.6373	0.7743
Significantly different? (P < 0.05)	No	No	No	No
One- or two-tailed P value?	Two-tailed	Two-tailed	Two-tailed	Two-tailed
t, df	t=1.174 df=55	t=0.2435 df=58	t=0.4740 df=58	t=0.2881 df=58
F test to compare variances				
F,DFn, Dfd	1.352, 29, 26	1.088,29, 29	2.079, 29, 29	1.369, 29, 29
P value	0.4401	0.8214	0.0532	0.4032
Significantly different? (P < 0.05)	No	No	No	No

Table G-8: Summary Spearman r Correlation for Time vs. Q1.1 Percent Correct

Spearman r	Time (Seconds) vs. Q 1.1 % Correct(Matrix)	Time (Seconds) vs. Q 1.1 % Correct(Node-link)
r	0.08754	0.2154
95% confidence interval	-0.3133 to 0.4619	-0.1680 to 0.5422
P value		
P (two-tailed)	0.6642	0.2530
Exact or approximate P value?	Approximate	Approximate
Significant? (alpha = 0.05)	No	No
Number of XY Pairs	27	30

Table G-9: Summary Spearman r Correlation for Time vs. Q1.2 Percent Correct

Spearman r	Time (Seconds) vs. Q 1.2 % Correct(Matrix)	Time (Seconds) vs. Q 1.2 % Correct(Node-link)
r	-0.1569	0.3684
95% confidence interval	-0.4980 to 0.2262	-0.001876 to 0.6498
P value		
P (two-tailed)	0.4076	0.0452
Exact or approximate P value?	Approximate	Approximate
Significant? (alpha = 0.05)	No	Yes
Number of XY Pairs	30	30

Table G-10: Summary Spearman r Correlation for Time vs. Q1.3 Percent Correct

Spearman r	Time (Seconds) vs. Q 1.3 % Correct(Matrix)	Time (Seconds) vs. Q 1.3 % Correct(Node-link)
r	0.004801	0.06294
95% confidence interval	-0.3659 to 0.3742	-0.3144 to 0.4231
P value		
P (two-tailed)	0.9799	0.7411
Exact or approximate P value?	Approximate	Approximate
Significant? (alpha = 0.05)	No	No
Number of XY Pairs	30	30

Table G-11: Summary Spearman r Correlation for Time vs. Q 2.1 Percent Correct

Spearman r	Time (Seconds) vs. Q 2.1 % Correct(Matrix)	Time (Seconds) vs. Q 2.1 % Correct(Node-link)
r	0.4326	-0.1502
95% confidence interval	0.07453 to 0.6919	-0.4929 to 0.2327
P value		
P (two-tailed)	0.0170	0.4281
Exact or approximate P value?	Approximate	Approximate
Significant? (alpha = 0.05)	Yes	No
Number of XY Pairs	30	30

Table G-12: Summary Pearson r Correlation for Years of Experience vs. Average Percent Correct

Pearson r	Yrs of Exp vs. Avg % Correct(Matrix)	Yrs of Exp vs. Avg % Correct(Node-link)
r	0.02272	0.03176
95% confidence interval	-0.3404 to 0.3800	-0.3324 to 0.3877
R square	0.0005160	0.001009
P value		
P (two-tailed)	0.9052	0.8677
Significant? (alpha = 0.05)	No	No
Number of XY Pairs	30	30

Table G-13: Summary Pearson r Correlation for Age vs. Average Percent Correct

Pearson r	Age vs. Avg % Correct(Matrix)	Age vs. Avg % Correct(Node-link)
r	0.03729	0.06378
95% confidence interval	-0.3275 to 0.3924	-0.3035 to 0.4146
R square	0.001390	0.004068
P value		
P (two-tailed)	0.8449	0.7377
Significant? (alpha = 0.05)	No	No
Number of XY Pairs	30	30

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