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ADVANCES TO NETWORK ANALYSIS THEORIES AND METHODS FOR THE UNDERSTANDING OF FORMAL AND EMERGENT STRUCTURES IN INTERPERSONAL, CORPORATE/ORGANIZATIONAL, AND HAZARDS RESPONSE SETTING

BY

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DISSERTATION

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ABSTRACT

Network analysis provides valuable theoretical and methodological approaches to investigate complex systems of social-technical relations. Network analysis has been applied to many different social science research contexts to understand the mechanisms by which individuals and groups form, sustain, adapt, and dissolve relationships. Furthermore, extant literature finds that networks of social organizing often comprise of structures that are formally specified (i.e., formal) as well as created informally from unplanned interactions (i.e., emergent). This dissertation builds upon prior literature in network science theories and methods to examine formal and emergent structures of organizing in specific social contexts, i.e., (1) interpersonal, (2) corporate/organizational communication, and (3) hazards response settings.

Within the context of interpersonal interactions, we examine the emergent structures of communication in twelve empirical networks based on the tenets of structural balance theory for signed and directed networks. We find evidence in support of structural balance as the overall balance is higher than imbalance, suggesting that individuals and groups prefer minimal tension in their interpersonal connections. Within the context of corporate/organizational communication, we show that emergent communication structures exist alongside formal structures as organizational members interact and maintain balance with others outside of their formally-assigned groups. Studying a scientific organization, which we model as a multilevel network, we find that both an individual's formal role as well as their informal communication network influence the likelihood of them forming interdisciplinary ties with others. Within the context of hazards response, we empirically validate the formalized and informal networks of response collaborations during four major U.S.-

based hurricanes. We find that a number of collaborative relationships take place between organization who are not officially assigned to work together. In the context of biological hazards, i.e., COVID, we examine the structural mechanisms for sharing and communicating information about a hazard on social media. We find differences in the expected diffusion structure based on classic epidemic model versus actual diffusion patterns observed in online social network.

Overall, this dissertation contributes advances to theories, methods and applied analyses of real-world, socio-technical networks, with a focus on discovering emergent network patterns and how they relate to formal (or expected) structures. The research designs and findings documented in this dissertation can provide a framework for network-based studies that aim to examine the mechanisms involved in the formation, quality, and sustenance of ties in different contexts of social interactions.

Dedicated to my beloved family,

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Mr. Bình,

Bách,

Jessica,

for always believing in me.

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CHAPTER 1

INTRODUCTION

1.1 General overview

The field of network analysis has attracted interest from scholars coming from a wide range of disciplines as it provides valuable theoretical and methodological approaches to investigating complex systems of social relations. In congruence with related social science fields that focus on explaining social behavior, network theories and methods continually push for a better understanding of social processes and dimensions that explain different network dynamics. Classical studies in network analysis date back to the 1960s, where scholars examined different types of informal social relationships among pairs of individuals, such as friendship (Newcomb, 1961), affinity (Sampson, 1968), and advice-giving (Krackhardt, 1987). Network analysis, however, is not restricted to just social relationships between individuals that took place in informal settings. Scholars have also examined formal relationships between employees in organizations with respect to who they report to (Krackhardt, 1987), who they work with (Barley, Dinh, Workman, & Fang, 2022), and who they rely on for work-related matters (Barley et al., 2022). Network analysis is also flexible as it can be applied to multiple units of analysis, such as the triads (Cartwright & Harary, 1956; J. Kim & Diesner, 2017) small groups (Katz, Lazer, Arrow, & Contractor, 2004), teams (Poole & Contractor, 2012), and organizations (Krackhardt, 1987; Michalski, Palus, & Kazienko, 2011), as well as entities that are not social agents in social networks (Dabbish, Towne, Diesner, & Herbsleb, 2011; Prill, Iglesias, & Levchenko, 2005). While network analysis requires a defined set of entities (or nodes) and relationships (edges) among them, there are many variations to the

types of nodes and edges that can be included in a network study, as shown in some of the examples above.

Leveraging network science, I examine how specific network theories, methods, and applications can be applied to examine the formal and emergent (informal) structures that are co-present in a number of real-world networks, namely social relationships, corporate/organizational structures, and hazards response (including natural and biological hazards). The comparison between the expected (or estimated) structure and the actual observable network dynamics provides insights to why certain structures exist and persist in the network over time, beyond chance. This process of network analysis and comparison allows us to move from descriptive network analysis to explanatory models that can infer the likelihood of a tie based on known structural characteristics (Börner, Sanyal, Vespignani, et al., 2007; Cranmer & Desmarais, 2011). Additionally, networks are dynamic in that they are constantly changing (Krackhardt & Handcock, 2006; Monge & Contractor, 2001; Scott & Carrington, 2011). The examination of informally emergent dynamics that arise out of the expected formal network structure (or vice versa) becomes crucial to capture all the properties that may explain why networks are created, maintained, and even dissolved in certain ways (H. Aldrich, 1976; Krackhardt, 1994; Monge & Contractor, 2001, 2003).

On the theory front, I focus on the expansion of structural balance theory to signed directed networks. Structural balance is a fundamental theory that explains the formation and maintenance of positive or negative relations in networks that are undirected (Doreian & Mrvar, 2015). The central motivation of structural balance theory is to explain how network structures emerge with respect to the need of individuals or groups to maintain cognitive consistency in their relationships with others (Heider, 1946; Krackhardt, 1994). The theory assumes that emergence of a balanced network configuration begins at the local level (triad) and then ripples through to the higher levels (subgroup, the whole network). The evaluation of how the network structure emerges based on local dynamics is a basis for comparison of balanced dynamics in structures that are formally organized versus emergent in informal

interactions (Sytch & Tatarynowicz, 2014; Van de Rijt, 2011). Consistent with structural balance framework for analyzing emergent and formal dynamics, I focus on the development and empirical analysis of balance for signed and directed networks in chapter 2, and part of chapter 3.

In chapters 3 and 4, I focus on network dynamics that are present in formal structures of organizing where individuals and groups are expected to work together within specified structural configuration (Weber, 1947). Chapter 4 focuses on communication and coordination dynamics in two distinct corporate contexts: one large energy company (Enron), and one large IT company (Avocado-IT). These two empirical contexts are defined as corporations because they are real-world financial entities that are (or were) legally owned by one group (Hessen, 1979). Corporations are a valuable context of study because there are assigned roles and responsibilities for every member of the network, such that coordination patterns between members are often governed by such structure and functions (McPhee & Poole, 2001). Thus, the examination of observed relational structures (based on work email communication) may reveal insights into the communication structures that reflects the formal arrangement and structures that are informally organized irregardless of formal roles. In addition to two large corporations, I also examine a virtual decision-making team where members are assigned clear goals and a set of common objectives to accomplish a mission. The decision-making team case study is intended as a comparison point with the larger formal arrangements to determine if there are differences in communication structures depending on the size of an organization, given that prior literature has found mixed results for the relationship between corporation size and informal communication structures (Pandey & Garnett, 2006; Smeltzer & Fann, 1989). In chapter 5, I focus on another type of formalized arrangement to understanding how formal and informal structures of relationships emerge in another workplace context. Specifically, we examine structures of communication and coordination between research and staff in a medium-sized scientific organization (Computational Research Center, a pseudonym). Based on a framework of interdisciplinary

collaboration (H. Collins, Evans, & Gorman, 2007), we empirically examine the likelihood of two individuals forming an "interdisciplinary" tie, meaning that they are of different expertise (measure: similarity of expertise) but share a common understanding of each other's expertise (measure: linguistic familiarity). We include measures that gauge each individual's formal role in the scientific organization, as well as their informal networks of support, to understand the impact that formal and informal communication has on the formation of interdisciplinary ties.

In chapters 5 and 6, I leverage theories used in emergency management to understand the dynamics of emergent and formalized network structures present in hazards response. Network emergence is a salient phenomenon in hazard response because the nature of hazards is unpredictable (Fritz, 1961), with unique requirements for response that deviates from the normal, routine operations of organization(s) (Dynes, 1970; Sarol, Dinh, & Diesner, 2021; Stallings & Quarantelli, 1985). The non-routine nature of hazard response easily lends to the presence of informally emergent ties that are not observed in formal response networks. Therefore, hazard response is a suitable context to examine structural emergence. In chapter 4, I apply Dynes (1970)'s typology of organizational behavior during disasters to theoretically guide my analyze on the institutionalized and emergent collaboration patterns during response to four major natural hazards. In chapter 5, I leverage Goffman and Newill (1964)'s generalized epidemic theory that connects the spreading of infectious diseases to the diffusion of information to empirically validate whether the spread of information online is structurally similar to the (expected) spread of a virus in the COVID-19 context. The generalized theory provides explanations as to why information spread on social networks have similar structures to the spread of a disease that are driven by likelihood of contact and infection (Abdullah & Wu, 2011; Goffman & Newill, 1964). Recent studies, however, found differences in expected structure of information diffusion (based on virus spread dynamics) and the actual diffusion structure (Lerman, 2016; Ma, Feng, & Lai, 2018), largely because the expected diffusion structure did not account for online user's limited attention (amount

of information a user can be exposed to). In light of evidence in support (and in opposition) to the generalized epidemic theory, we empirically validate the theory in the context of a biological hazard such as COVID-19 pandemic with the goal to understand the dynamics of information spread on social media about a hazard. Ultimately, capturing the structural dynamics of online information sharing during a hazard can be helpful to responders who wish to leverage social media for situational awareness (Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013; Olteanu, Vieweg, & Castillo, 2015; Sarol et al., 2021).

On the methods front, we measure structural balance for signed directed networks using both a classical approach (a triad must be either balanced or imbalanced) and a generalized approach (a triad can have a degree of balance). We present analyses on real-world social networks using the classical balance approach in chapter 2, and analyses using the generalized balance approach on two real-world organizational networks and one empirical network of decision-team trust collected from self-reported surveys are presented in chapter 3. In chapter 4, I discuss an application of multilevel network modeling for egocentric networks to study the presence of interdisciplinary ties among members of a scientific research organization. In chapter 5, we present a framework for reliable text-based network construction and comparison to examine emergent and formal collaboration structures during natural hazard responses. In chapter 6, we empirically compare the network properties based on the information cascades model observed from Twitter data about COVID-19 pandemic with the theoretical diffusion model based on the generalized epidemic (SIR) model.

On the applications front, I focus on three main contexts, namely interpersonal interactions (Chapter 2), corporate/organizational dynamics that includes both corporate arrangements (Chapter 3) and team-based dynamics in a scientific organization (Chapter 4), and hazards response that includes both natural hazards (i.e. hurricanes, Chapter 5) and biological hazards (COVID-19 pandemic, Chapter 6).

Overall, in this dissertation, I demonstrate the utility of network theories and methods in advancing our knowledge about complex structures of formal and emergent relationships

across different domains, with applications in the contexts of interpersonal relationships, corporate and organizational arrangements, and hazards response with respect to interorganizational collaboration patterns and information diffusion patterns during a natural/biological hazard.

1.2 Background on network analysis theories and methods

1.2.1 Basic network properties

The core of network analysis is to examine structural relations among a defined set of entities, which are also known as edges and nodes, respectively (Wasserman & Faust, 1994). The concepts of nodes and edges are derived from graph theory, which enables quantitative examination of networks. A number of fundamental properties of a network are discussed below, with regards to whether they are *directed or undirected*, *valued or non-valued*, *signed or unsigned*, *informal or formal*, and *one-mode or multi-mode*. These properties are important to help researchers in the network data collection stage, as well as determining appropriate metrics and methods for network analysis that are suitable for the theoretical framework(s) and research question(s) proposed.

1.2.1.1 Directed versus undirected network

A basic feature of a network is that it can either be undirected or directed. An undirected network consists of edges that have no direction, because either the edges are reciprocated ($A \rightarrow B$ and $B \rightarrow A$), or that there is no information about the direction of the edges, meaning that which node initiates the connection and which node receives the connection are not known. On the other hand, a directed network consists of edges with directional information in terms of which node is the origin and which node is the destination. In a directed network, there may exist edges that that are not reciprocated ($A \rightarrow B$, but not

$B \rightarrow A$). Communication networks often are directed (Diesner & Carley, 2005; Gupte, Shankar, Li, Muthukrishnan, & Iftode, 2011; Harary, Norman, & Cartwright, 1965). A reciprocal relationship can be represented in a directed network as well, but would contain two edges where $A \rightarrow B$ and $B \rightarrow A$. In special cases, a network can contain both undirected and directed edges, which categorizes a network as mixed. Analysis of mixed networks must be handled with care given that a number of existing network metrics can only be computed for either undirected or directed networks.

1.2.1.2 Weighted versus unweighted network

In addition to directionality, edges can also be weighted or unweighted. For instance, a network of frequency of communication can contain edge weights from 1 to 4, where 1 represents communication on a "daily" basis, and 4 represents communication "less than once a month" (Barley et al., 2022). A network on frequency of communication can also be unweighted if the primary question of interest is whether two individuals communicate or not communicate. Weighted edges are useful for analyses that focus on the quality of ties as a structural property. For instance, Granovetter's strength of weak ties hypothesis (M. S. Granovetter, 1977) is proven based on his empirical assessment of tie strength (measured by the frequency of communication, intimacy level, emotional intensity level, reciprocity of communication (p.1361)): he found that individuals connected by lower values of tie strength are more beneficial for career development as they have access to new information. Individuals connected by higher strength of tie, on the other hand, are useful for providing social and emotional support, but not for sharing new and unique information.

1.2.1.3 Signed versus unsigned network

Signed networks basically mean that edges have properties other than frequencies. Prior empirical assessments of networks have often focused on positive relationships, such as

friendship, advice-giving, or information sharing. Real-world relationships, however, are not restricted to positive relationships, and thus signed networks are useful for modeling relationships as either positive, negative, or neutral (Scott & Carrington, 2011). Positive edges (often represented as "+") are those that connect two nodes based on some positive affinity (e.g. both rating each other as 'friends'), while negative edges (represented as "-") between two nodes indicate negative affinity or an antagonistic relationship (e.g. both rating each other as 'enemies'). This network modeling paradigm is useful for examining the sources of tension in the network based on the fraction of positive and negative edges. Well-known frameworks that have been used to explain the dynamics between signed connections are structural balance theory (Heider, 1946) and status theory (Leskovec, Huttenlocher, & Kleinberg, 2010a). Empirically assessments using these theories often involve triadic analyses of balance (Dinh, Rezapour, Jiang, & Diesner, 2020), network-level analyses of frustration (Aref, Dinh, Rezapour, & Diesner, 2020), as well as blockmodeling that partition the network into "positive" and "negative" blocks (Doreian & Mrvar, 1996).

1.2.1.4 One-dimensional or multi-dimensional network

Two nodes in a network may also be connected by nodes and edges of different types (Aref et al., 2020; Berlingerio, Coscia, Giannotti, Monreale, & Pedreschi, 2013; Genkin, HARRIGAN, Kanagavel, & Yap, 2022; Van Holt, Johnson, Carley, Brinkley, & Diesner, 2013). An example for a network with different node types would be that A is an individual, and B is an event, and A is connected to B because A attended B event. This type of network would be called a *multi-mode* network if there are multiple types of nodes involved in the same type of edge, which in this case, is event attendance. Another type of network is a multi-layer (or multiplex) network, where there are multiple types of edges between the same sets of nodes. An example of a multi-layer network is that A and B are connected both as friends and colleagues. Often, multiple relations are represented as multiple graphs for analysis. There are more complex combinations of multi-mode and multi-layer network, such as a certain

sets of nodes are connected by one type of edge in one layer, but connected by another type of edge in another layer. With all possibilities of different network dimensions, researchers are free to test different structural variables that can either be at the node-level, edge-level, or both (Wasserman & Faust, 1994).

1.2.1.5 Formal versus emergent (informal) network structure

The earliest network analysis study was conducted by Jacob Levy Moreno in the 1930s (Moreno, 1934, 1943), who collected sociometric network data where each individual rates every other individual in a group on whether they "accept", "reject", or are "indifferent" towards that individual. Moreno collected network data in various formal settings such as organizations (i.e. U.S. Navy, (Moreno, 1951)) and small groups (i.e. classrooms, (Moreno, 1951)) and found distinct structural patterns in "institutional/formal" and "informal" groupings (Moreno, 1943), p. 326). Thus, the assertion that a social system contains multiple types of groupings is fundamental to the understanding of formal and informal mechanisms that produce network structures. A number of theoretical mechanisms that explain the co-existence of formal and informal structures come from organizational research traditions such as cognitive social theories (Heider, 1946; Krackhardt, 1987), structuration theory (DeSanctis & Poole, 1994; Giddens, 1984; Pilny, Proulx, Dinh, & Bryan, 2017), and activity foci (Feld, 1981; Homans, 1950) (other theoretical traditions are discussed in Monge and Contractor (2001)'s chapter). The cognitive social tradition focuses on understanding the behavioral of organizational members with respect to how they perceive relationships with others with respect to advice-giving and friendship (Krackhardt, 1987), as well as the level of congruence between the perceived relationships and their attitudes about others (Heider, 1946; Newcomb, 1968). The structurational approach to understanding informal (or emergent network) structures focus on the co-existence of systems and structures, where systems are represented by observed patterns of interactions (Pilny et al., 2017) and the structure is represented by formalized rules for interactions (e.g. formal hierarchy). The recursive

nature between systems and structures suggests a cyclic relationship where formal and informal structures are mutually influencing one another (DeSanctis & Poole, 1994). The activity-based framework (Feld, 1981; Homans, 1950) identifies the linkage between formal and informal structures through the focused activities (e.g. crisis response (Poole & Contractor, 2012)), where formal structure influences the foci through organization of activities, and emergent behaviors that arise from participation in activities are integrated into the formal structure (Feld, 1981).

Altogether, these theoretical frameworks show the co-existence of formal and informal structures when individuals and groups organize themselves. Similar to other network properties discussed above, the operationalization of formal and informal ties depend on the study design and research questions. The primary distinction of formal and informal relationship is that a tie between two nodes is specifically defined (formal), or that a tie is formed organically (informal). As outlined in the next section, there are a number of existing network metrics and methods for comparing formal and informal network structures (also discussed in Chapter 5).

1.2.2 Units of analysis

Mitchell (Mitchell, 1974) asserts that though it is not feasible to capture and study the "total network", scholars can conceptualize social relations through two forms of networks; egocentric networks and global networks. Egocentric networks can be of all types of relations "anchored around" a focal individual, whereas global networks represent the overall structure of a specific type of social relation, ranging from friendship, to advice, to trust. Each type of network has different properties, and can be analyzed at various levels of analysis, ranging from the ego, dyad, triad, subgroup, to the global level (Aref et al., 2020; Monge & Contractor, 2003). It is important to note that while global networks can be analyzed at multiple levels of analysis, egocentric networks are limited to the ego and dyadic level as

only the information about each focal ego's immediate ties are collected. In order to infer global network properties, snowball sampling of egocentric data with a large sample size is needed (Hanneman & Riddle, 2005). Though there are three levels of properties available to egocentric network scholars, a majority of studies choose to focus on either ego-level or global-level analysis, while those who do choose to analyze at the dyad-level do so in terms of presence or absence of a tie (Mizruchi & Marquis, 2006; Robins, Pattison, Kalish, & Lusher, 2007).

1.2.3 Statistical approaches to network analysis

The formation of social networks is not a random process, but rather driven by processes of selection, influence, and environmental factors (analyzed in Q3) which result in network dependencies among individuals. Recognizing that network data is composed of interdependent observations, traditional statistical methods that rely on the assumption of independent and identically distributed (IDD) cannot be applied to examining and modeling network ties. Thus, research scholars have developed two main state-of-the-art approaches to overcome the impact of network autocorrelation; (1) develop new statistical tests that can control for dependencies in the data (Block, Stadtfeld, & Snijders, 2019; Hunter, Handcock, Butts, Goodreau, & Morris, 2008), or (2) explicitly modeling the autocorrelation present in the data (Crossley et al., 2015; Krackhardt, 1988; **?**). In other words, some approaches aim to separate the confounding effects from the main cause-and-effect (Hunter et al., 2008; Krackardt, 1987), while other approaches model these effects directly as network outcomes, along with other outcomes of interest that the model wants to estimate for (Crossley et al., 2015). In the section below, I discuss three classes of techniques that model network ties while taking into account the autocorrelation in the data, specifically for egocentric network analysis; (1) permutation-based methods such as quadratic assignment procedure (QAP) and multiple regression version (MRQAP) which control for dependence between dyads;

(2) random graph models which assess dependencies as network structures; (3) multi-level methods that include dependencies as separate level of analysis to examine their variations with individual-level variables. Each class of model will be assessed with regards to their assumptions, strengths and drawbacks in terms of how they cope with missing data, and how they handle nested structure specifically of egocentric network data.

1.2.3.1 Permutation-based models

Several models such as quadratic assignment procedure (QAP) (Hubert & Schultz, 1976) and multiple regression quadratic assignment procedure (MRQAP) (Krackardt, 1987; van Duijn & Huisman, 2011) have been developed on the basis of permutations, or re-sorting of egos and alters in a network dataset in order to estimate the standard errors. It is an extension to a regression analysis but can preserve the dependence between ego-alter ties through multiple repeated permutations of the dependent variable (often in matrix form). This results in multiple random datasets that together form a sampling distribution with new correlation coefficient generated, and then compared with observed correlations to determine whether the difference between the observed and randomly-generated estimates are due to chance alone (p-value). Permutation methods has advantages over traditional regression in that it moves beyond the ego-level and uses the dyad as its basic unit of analysis, thus considers the correlation and dependence among egos and alters. QAP is also flexible for various types of data, from categorical to ordinal data, that do not need to have a normal distribution (T. A. Snijders, Borgatti, et al., 1999).

The main drawback of QAP and MRQAP is that the relationship between dependent and independent variables are removed as they are merged together into one matrix during permutations, therefore makes hypothesis testing between variables very difficult. In this way, QAP is simply seen as a testing of correlations between the observed and expected networks under the null hypothesis of no correlations between the two networks (Hanneman & Riddle, 2005). Additionally, missing data can have significant effects on the validity

of QAP results. If the observed data matrix already contains many missing cells, this may produce highly problematic permuted data and may inflate type I error rates as the observed and randomly-generated networks are likely to be very different. Thus, the high sensitivity to missing data may make QAP and MRQAP less applicable to a majority of egocentric datasets that often contain some missing data.

1.2.3.2 Random graph models

Recognizing that permutation-based models are only restricted to significance testing methods, random graph models (or ERGM) enable researchers to estimate the likelihood of certain observed structures through probability distributions (Butts et al., 2014; Hunter et al., 2008). These models function by generate a series of random networks that are constructed from the distributions of the parameters (i.e. centralization, density, betweenness) measured from the original network. These random networks are then compared with the actual observed network to assess the model's goodness of fit; the best models are those that use less parameters but produce random networks that are structurally similar to the observed network. ERGM is designed for binary-valued outcome variables in that it can predict the likelihood of a tie between any ego-alter pairs when they share certain attributes. Random graph models are flexible in that they only need a single observed network to estimate model parameters, and can include parameters at various levels of analysis such as reciprocity (dyadic) and transitivity (triadic) to be structural properties of the observed network. For instance, an ERGM can model for reciprocal dyadic relationships where the probability of a tie from A to B is higher when there is an existing tie between B to A and thus the tie from A to B is a reciprocated tie. In addition to modeling structural, or endogenous effects, ERGMs can also make parameter estimates for actor attribute-based, or exogenous effects that can affect the likelihood of a certain tie formation. The important assumption that random graph models make is also one of dependence of observations, or Markov dependence (Holland & Leinhardt, 1981). Markov dependence contains an assumption that if two ties share a com-

mon ego (i.e. if both A⟷C and A⟷B ties contain A), they are likely to be related to each other in some ways. To consider for complex dependencies at multiple levels ranging from dyads to global network, a number of dependence models such as dyadic dependence model (Frank & Strauss, 1986), p* model (Wasserman & Pattison, 1996) and higher-order dependence models (Robins, 2011) have been developed in recent years.

Though with many advantages over permutation-based methods, ERGMs are also very sensitive to missing data (Krause, Huisman, Steglich, & Snijders, 2020; Smith, Morgan, & Moody, 2022). As both classes of statistical techniques consider network interdependencies, incomplete data may substantially under-represent the actual network structures and omit important dynamics among egos and ties. King, Honaker, Joseph, and Scheve (2001) found that even with small portion of missing ties, structural parameters and centrality measures of the network are inaccurately estimated due to the main issue of model degeneracy (Robins, Pattison, & Woolcock, 2004). Models are considered degenerate when they produce a skewed distribution of only a few random graphs out of all possible configurations; these graphs are often either full or empty graphs (Carrington, Scott, & Wasserman, 2005) and do not provide any useful information about network structure. Especially in the case of ERGM, it is even more difficult to measure the extent of degeneracy effects because no two estimation output is the same, as ERGM simulates a different set of random graphs every time. Thus, issues of missing nodes, attributes of nodes, and edges are magnified in estimation techniques such as ERGMs.

1.2.3.3 Multilevel models

Multilevel models are often referred to as random-effects models as they examine the share of variation between both fixed and random effects, allowing researchers to make parameter estimates at multiple levels of analysis (Crossley et al., 2015; Tranmer, Steel, & Browne, 2014). Another strength of these multilevel models is that they are robust to missing data (Baayen, Davidson, & Bates, 2008; Quené & Van den Bergh, 2008) in that they consider

all available data as is, rather than automatically perform a listwise deletion (ego removed from dataset if missing data on any variable). Additionally, these models are able to preserve more statistical power compared to permutation-based methods in the context of incomplete data, thus reduce instances of underestimated parameters and Type I errors (Leckie, 2013; Leckie & Bell, 2013). Thus, the primary advantage of multi-level network models is the ability to handle missing data without questionable imputation methods, allowing researchers to analyze the raw data and correctly infer parameter estimates within the scope of the collected ego-nets. On the conceptual level, multilevel models are most advanced as they can analyze networks at multiple levels of analysis, with a autocorrelation assumption of social ties by which individuals are nested in dyads, triads, and groups (Crossley et al., 2015; T. Snijders, Spreen, Zwaagstra, et al., 1995). The following section examines a specific class of multilevel model often used in egocentric network analysis called multiple membership (MM) models. Multiple membership models (MM) consider cross-level nested structures, with error terms separated to consider variances at the ego and tie-levels (Crossley et al., 2015; Goldstein & Browne, n.d.; Tranmer et al., 2014). MMs are suitable for dependency situations in which individuals, we call 'alters', are members of more than one group (i.e. schools, neighborhoods, hospitals) or ego-network (i.e. friends with multiple egos). In the case of egocentric networks, alters are at the lower level and nested within the egos at the higher level, connected by a tie between them. Having two levels of analysis at both ego- and alter-level with random effects evaluated separately for each level, scholars can compare and analyze what proportion of the variances is due to properties of either ego, alter, or both (ego-alter interaction). Furthermore, similarities in attributes of the ego and alter as mechanisms of selection, influence, or other environmental factors (autocorrelation factors), can also be included in the model as a separate level of ego-alter interaction effect and test whether some homophily effects are strong in one ego-network than others.

1.2.4 Research claims in network analysis

In congruence with other sciences that focus on explicating the causes and effects of human and social behavior, network theories and methods continually push for better understanding of causal processes and dimensions that drive different network dynamics (An, 2011; Doreian, 2001). As shown in the section above on the statistical approaches to network analysis, inferring causality in terms of predictors for tie formation is the foundation for most network models. The section below highlights the requirements for causal claims to be made in a network analytic study:

1.2.4.1 Correlation

Most empirical studies in network analysis are often done outside of the experimental, laboratory settings, which presents challenges for making valid causal inferences from the data (An, 2011; Cipollone & Rosolia, 2007). Network data is usually obtained from primary sources such as observations, self-reported surveys and interviews (Diesner, Kumaraguru, & Carley, 2005; Lemann & Solomon, 1952; Zachary, 1977), as well as from secondary source such as archival datasets (Diesner & Carley, 2010b; Padgett & Ansell, 1993; Pak, 2013). Therefore, network data from these sources may be sufficient to statistically test for correlations among the variables of interest, but the lack of randomized and controlled trials from experiments means that the data is susceptible to biases and confounds. Such 'noise' may interfere with the cause-and-effect relationship between two variables, and thus causality is more difficult to identify. However, with rigorous network surveys and observational study designs, researchers are still able to determine correlations with reasonable confidence, validity, and reliability. For instance, M. S. Granovetter (1977)'s Strength of Weak Ties study came into being through repeated correlational analyses between various network compositions and individuals' job performance outcomes (i.e. average wage). With the appropriate statistical procedures employed and a reasonable sample size, correlations can be established

among network variables of interest. It is important to note, however, that a larger sample size does not mean better results; analyses from bigger data may yield more correlations that could happen due to pure chance.

1.2.4.2 Time order

As cause-and-effect relationship posits that a certain effect on the dependent variable that is caused by the independent variable, there is directionality implied between the two variables (An, 2011; Doreian, 2001). The cause must precede the effect (Finkel, 1995); for instance in a study of social support network and health outcomes, Link and Phelan (1995) needed to ensure that the lack of social support (independent variable) is the cause of disease (dependent variable), rather than the other way around. Conley and Udry (2010) in a time-series study of how communication network structure among pineapple farmers in Ghana causally affect the adoption of new agricultural technologies. Both studies, along with many other causal network studies (Burt, 1992; M. Granovetter, 1986) emphasize the need to use longitudinal data to validate that the temporal order of the cause and effect relationship persists over time (Robins, 2013). However, most SNA research are of static and cross-sectional nature, due to challenges in observing and collecting complete network data over multiple periods of time. I emphasize the term 'complete' network data as it is already difficult to collect whole-network data with complete links among all actors in the sample specified at one point in time, and would be more difficult to have all actors' data at later points. Handling missing network data is also another problem area for longitudinal network analysis, as a number of current models are very sensitive to missing data (i.e. quadratic assignment models, random graph models).

1.2.4.3 Non-spuriousness

Both correlation and time-ordering of variables are necessary conditions for establishing causality, but not sufficient without the consideration that there are no alternative explanations for the observed cause-and-effect between two variables. Non-spuriousness indicates a relationship between two variables that is not due to other "extraneous" variables (Wasserman & Faust, 1994) that is also causing the change to the dependent variable. Similar to traditional statistical approaches, network scholars also ensure nonspuriousness by controlling for the effects of other variables, or covariates, that are also correlated with the dependent variable. Common variables often being controlled for in network studies are differences in individual attributes such as age, gender, education, socioeconomic status and more, in order to observe the effect on the dependent variable when only the independent variable changes. Network data, however, is more complex than other data types as networks are naturally composed of confounding mechanisms that drive relationships between network actors, which are selection, influence, and environmental confounds (Manski, 1993; VanderWeele & An, 2013). Before exploring any relationship between pairs of nodes, we should assume that at least one of the actors have influenced the other's state or behavior (influence). Secondly, it is likely that two actors are connected because they have similar characteristics (selection). There can also be other environmental factors shared by two actors that connect them socially, such as going to the same high school or living in the same neighborhood. These three confounding mechanisms brings to light the persistent problems of autocorrelation (discussed in Chapter 3, or causal peer effects (Manski, 1993) in network data. I emphasize that these mechanisms are inherent in every type of network data, in every mode of network research, therefore scholars should take into account these peer effects, and to properly control for them before they can make any causal statements between variables of interest.

1.2.4.4 Causal Unit(s)

Social network analysis is fundamentally different from traditional statistical analysis because the field assumes the main causation mechanisms are inherent in the social structure (Monge & Contractor, 2003; Scott & Carrington, 2011), not within the individuals. Thus, the primary unit of analysis should be the social relation, or the tie, between individuals embedded in a larger social system. Given the previous discussion on autocorrelation and peer effects, explicating causal dynamics only at the individual-level may be problematic as there are interdependencies between individuals outcomes. In fact, individual-level effects may be directly a function of group-level or-network level processes, and therefore it is meaningful to set the network of individuals as the target to examine the effects of different causes. As the network tie exists at multiple levels of analysis (as mentioned above), researchers should specify the level at which a certain causal process occurs.

1.2.4.5 Current methods for examining causality in network analysis

Since most network studies are conducted in cross-sectional, non-experimental settings, establishing causality from such data was difficult. Since then, a number of statistical models (QAP, MRQAP, multilevel analysis) and simulation models (ERGM) have been developed to help scholars make causal inferences from observational network data by identifying structural signatures and detecting structural changes as results of some cause(s) of interest. However, it is still difficult to fully control for all the confounds and autocorrelation issues related to selection, influence, and environmental factors that may give rise to spurious correlations. In the next chapters (i.e. Chapter 3), I discuss in detail the applicability of inferring causal relationships from social network data, specifically egocentric network datasets.

1.3 Research questions

The overarching goal of this thesis is to examine how theories and methods from network analysis can be applied in specific real-world settings. I focus on three contexts, namely interpersonal relationships, organizational/corporate environments, and hazards response. There are unique dynamics in each setting that network theories and methods can be applied to. My first group of research questions (RQ1-1,RQ1-2) is about the application of network analysis to interpersonal settings, with the aim of understanding the 'organic' patterns of relationships in settings where structures of connections are unknown (e.g. not constrained by any organizational boundaries). The second group of research questions (RQ2-1, RQ2-2) asks about the application of network analysis in organizational/corporate settings, with the goal to determine the intricacies unique to organizational network analysis, where formal structures between individuals are known. In the third group of research questions (RQ3-1, RQ3-2, RQ3-3, RQ3-4, RQ3-5), the focus of examination is shifted towards hazards response settings, where network analysis is applied to examine collaboration response dynamics and information spread dynamics surrounding a hazard. Similar to the questions asked in RQ2, questions RQ3-1 and RQ3-2 focus on examining both known structures of collaboration and unknown structures that emerge during actual hazards response. RQ3-3, RQ3-4, and RQ3-5 are also about the comparison between expected information diffusion structures (based on generalized epidemic theory) and diffusion structures observed on social media. Altogether, the answers to these three groups of research questions are needed to understand the advantages and limitations of network theories and methods have in detecting meaningful patterns of relations across different research domains. The research questions are presented below in three main groups:

1.3.1 **Group 1** Network analysis to examine interpersonal dynamics

- $RQ1_1$: How can we evaluate balance for signed directed networks?

- $RQ1_2$: What insights do we gain from balance evaluation of real-world social networks?

The first two research questions are embedded in how a specific network analysis theory and method, structural balance, can be applied to examine networks of social relationships. 'Social' in the context of this thesis means relational ties that are between individuals in an informal setting (e.g. friendship, acquaintanceship). Individuals engaging in these types of ties are not bounded by formalized, pre-existing structures of connection.

To answer these two research questions, I examine 12 different social networks with distinct types of relations, namely friendship, trust, affinity (like or dislike). In this sample, 11 networks are secondary data that have been empirically examined previous, and 1 network is primary data that we collected from self-reported surveys.

1.3.2 **Group 2** Network analysis to examine corporate and organizational dynamics

- $RQ2_1$: What insights do we gain from balance evaluation of real-world corporate communication networks?

- $RQ2_2$: What network analysis theory and method is suitable to address the nested nature of network data in organizations?

These two research questions focus on the examination of formal network ties, where individuals are bounded by pre-existing structures of connection. The theories and methods used to answer these research questions are: Our own theoretical framework for structural balance theory and evaluation with partial balance considered ($RQ2_1$), and egocentric network modeling to capture the formation of interdisciplinary ties in a scientific organization ($RQ2_2$). In the context of corporate communication, I examine two different organizations, namely Enron energy company (Investigation, FERC Western Energy Markets-Enron, 2004), Avocado IT company (Oard, Webber, Kirsch, & Golitsynskiy, 2015), and one virtual decision-making

team. Network datasets for Enron and Avocado are secondary data, containing email communications among employees that the organization. Network data for decision-making team is primary data collected based on the perceived ratings of trust between team members. In the context of organizational communication in a medium-sized scientific organization, I focus on relational dynamics between researchers and staff in Computational Research Center (CRC, a pseudonym, collected in Barley et al. (2022)). Network dataset for the CRC is collected through an egocentric network survey sent to 250 members of the organization in late fall 2015.

1.3.3 **Group 3** Network analysis to examine hazards response dynamics

The first set of research questions focus on the examination of natural hazards response:

- $RQ3_1$: How does the prescribed network's level of response jurisdiction (federal, state, local) relate to the amount of network overlap between the prescribed and observed network?

  $H0_1$= There is no significant amount of congruence in the prescribed and observed network (DV) depending on the prescribed network's level of response jurisdiction (IV1).

- $RQ3_2$: How does the data source (situational reports or tweets) used to construct the observed network relate to the amount of network overlap between the prescribed and observed network?

  $H0_2$= There is no significant amount of congruence in the prescribed and observed network (DV) depending on the data sources used to construct the observed network (IV2).

The second set of research questions focus on the examination of biological hazards response with respect to the expected and observed dynamics of information sharing online

about a real-world biological hazard event (COVID-19):

- $RQ3_3$: What are the simulated and empirical diffusion patterns of COVID-19 virus spread, based on *SIRsim* and *SIRemp*, respectively?
- $RQ3_4$: What are the diffusion patterns of information cascades on Twitter (*INFOcas*), with respect to retweets, quote tweets, and replies?
- $RQ3_5$: What, if any, are the differences in the diffusion patterns between *SIRsim*, *SIRemp*, and *INFOcas*?

These two sets of research questions focus on the networked structures that are unique to hazards response. The first set of research questions focus on the formal and emergent collaboration dynamics between entities responding to a natural hazard. I focus specifically on major U.S.-based hurricane as a natural hazard event type because response to this event requires proactive collaboration between a wide range of governmental and non-governmental organizations. I utilize governmental mandates at the federal, state, local levels to construct the prescribed networks of response collaboration, and situational reports along with tweets to construct the observed networks of collaborations that took place during actual response. In the second set of research questions, I further examine the dynamics of information sharing online (on Twitter) about a hazard to address the affordances (and constraints) that social media has in terms of providing hazard-related information (Palen & Anderson, 2016; Verma et al., 2011). Thus, I empirically test whether information diffusion on Twitter via retweets, quotes, and replies shares the same (rapid) spread dynamics as a biological hazard (i.e. COVID-19), given mixed findings regarding the differences between information and virus propagation in complex networks (Abdullah & Wu, 2011; Lerman, 2016; Mønsted, Sapieżyński, Ferrara, & Lehmann, 2017).

1.4 Dissertation organization

This thesis comprises existing and ongoing publications in which I was a primary contributing author. Below is a list of publications that are included in the chapters of this thesis. Contents have been modified to fit with the thesis's goals and research questions. For each publication listed below, I will outline my specific contributions, as well as the journal's policies on reusing work for thesis. Throughout the thesis, I will use "I" and "we" to appropriately reflect the individual and group-level contributions made in each publication.

[Chapter 2] (Aref et al., 2020) Aref, S.*, Dinh, L.*, Rezapour, R.*, & Diesner, J. (2020). Examination of structural balance at multiple levels of analysis for signed directed social networks (*Equal contribution). Scientific reports, 10(1), 1-12.

My specific contributions: I focused on ensuring that our a multilevel framework comprehensively covers the three fundamental units of network analysis, namely the triad, subgroup, and whole network levels. This involves examining prior networks literature that examine each level separately, or together, and determine the gap that our method can fill. I also collected most of the data, processed the data to edgelists that can be used for balance analysis, and applied our method to evaluate triad-level balance. I also conducted correlational analyses to examine if there are associations at the different levels of balance analysis, and contributed content to the results, discussion, and conclusion sections.

Journal's policy on thesis reuse: Section on *Pre-Publicity*, bullet point 2[1]: Material in a paper submitted to *Scientific Reports* may also have been published as part of a PhD or other academic thesis.

[Chapter 3] (Dinh et al., 2020) Dinh, L.*, Rezapour, R.*, Jiang, L., & Diesner, J. (2020). Assessing balance in signed digraphs using balance and transitivity (*Equal contribution). Under Review at a social networks journal.

My specific contributions: I developed the theoretical framework by introducing the

[1] https://www.nature.com/srep/journal-policies/editorial-policies#confidentiality

concept of semicycles to the calculation of balance for triads, with a special rule to consider transitive semicycles in order to capture the true definition of balance, being both sign consistent and transitive at the same time. In addition, I refined the calculation of balance to allow for partial balance, as opposed to the traditional method where balance is a binary value. In addition, I analyzed the results and contributed content to the results, discussions, and conclusion sections.

Journal's policy on thesis reuse: Section on *Submission declaration and verification*[2]: Submission of an article implies that the work described has not been published previously (except in the form of an abstract, a published lecture or academic thesis).

[Chapter 4] (Barley et al., 2022) Barley, W. C., Dinh, L., Workman, H., & Fang, C. (2020). Exploring the relationship between interdisciplinary ties and linguistic familiarity using multilevel network analysis. Communication Research, 0093650220926001.

My specific contributions: I created and administered an egocentric survey on Qualtrics, transformed the data into nodelists and edgelists for network analysis. I also constructed three multiple membership multiple classifications (MCMC) models based on the network data using MLwIN[3] and interpreted the coefficients for the results section. I also contributed to the writing of the methods section in its entirety, a major part of the results section, and a part of the introduction section.

Journal's policy on thesis reuse: Section on *Dissertation/Thesis Reuse* [4]: You may reuse up to three (3) figures/tables or a total of up to 400 words from a SAGE journal in your dissertation/thesis, provided the work will not be hosted on a commercial platform (such as ProQuest).

[Chapter 5] (Dinh & Parulian, 2020) Dinh, L., & Parulian, N. (2020). COVID-19 pandemic and information diffusion analysis on Twitter. Proceedings of the Association for Information Science and Technology, 57(1), e252.

[2] https://www.elsevier.com/journals/social-networks/0378-8733/guide-for-authors
[3] http://www.bristol.ac.uk/cmm/software/mlwin/
[4] https://us.sagepub.com/en-us/nam/pre-approved-permission-requests-journals

My specific contributions: I developed the experimental framework for the study with respect to how the three diffusion models should be constructed and systematically compared. I collected the data using Twitter API, with the sampling strategy developed in consultation with my co-author. I also conducted structural analyses and empirical comparisons between the three diffusion models using the appropriate statistical procedures. I wrote the manuscript with input from my co-author.

Journal's policy on thesis reuse: Section on *Permissions-AUTHORS*[5]: If you wish to reuse your own article (or an amended version of it) in a new publication of which you are the author, editor or co-editor, prior permission is not required (with the usual acknowledgements).

[5] https://asistdl.onlinelibrary.wiley.com/hub/journal/23739231/homepage/permissions

CHAPTER 2

NETWORK ANALYSIS TO EXAMINE INTERPERSONAL DYNAMICS

Networks can be applied to examine different interpersonal settings, from friendship in a dormitory to preference rankings between monks in a New England monastery. In the sections below, I outline how networks can be applied to examine social networks where relations are directed and signed.

2.1 Measuring balance in signed and directed social networks

Real-world social and communication networks are composed of complex and continually evolving interactions among social agents. Network scholars have examined core principles that explains patterns of social interactions at various levels of analysis, i.e., at the node level (Borgatti & Everett, 2006), dyadic level (Block, 2015), triadic level (Cartwright & Harary, 1956; Johnsen, 1986), subgroup level (Riley & Eckenrode, 1986), and the graph level (Kilduff & Tsai, 2003). Each level of analysis enables different types of hypotheses to be tested, e.g., with respect to structural properties, such as reciprocity at the dyad level, transitivity at the triad level, clusterability at the subgroup level, and centralization at the network level (Monge & Contractor, 2003; Wasserman & Faust, 1994). In this study, we focus on a fundamental unit of analysis, namely triads, given that there are patterns of tie formations between three actors and their associated ties that cannot be explained at any other levels of analysis (Flament, 1963; Simmel et al., 1950; Taylor, 1970). Some of the basic dynamics and theories that drive and explain interactions at the triadic level are structural balance (Heider, 1946) and transitivity (Feld & Elmore, 1982), which both model how stable relationships

emerge in groups of three nodes. Furthermore, extant literature on structural balance has considered signed and undirected triads for analysis (Harary & Kabell, 1980; Krackhardt & Handcock, 2006; Newcomb, 1968); an approach that models relationships between any three individuals as being reciprocated. In real-world networks, however, individual P may perceive individual O as a friend, but O may not have the same perception of P. This simple example highlights the importance of considering directionality for understanding balance in signed networks. Revisiting the central tenet of structural balance theory (Doreian & Krackhardt, 2001; Heider, 1946), we propose that directionality can be understood in terms of the transitive properties within a triad. Therefore, this chapter is based on the assumption that a signed and directed triad is balanced if every transitive semicycle within the triad is positive.

We propose that transitivity is a necessary pre-condition to evaluate balance in signed digraphs. Stemming from the Heiderian (Heider, 1946, 1958) assumption of transitivity is a crucial property that explains how directed and signed ties are oriented in ways that are consistent with balance. Therefore, we incorporate both conditions of transitivity and sign consistency to the assessment of structural balance for triads in a signed digraph. In particular, we leverage the triad census (Holland & Leinhardt, 1978) to extract all transitive semicycles within a particular triad, and calculate overall balance with respect to the proportions of balanced semicycles within the triad. We test this method of calculating structural balance on 11 different signed digraphs representing 11 different types of social interactions, ranging from self-reported trust between team members, to acquaintance ties between college students living in a same dormitory. Analyzing different social networks enables us to determine if balance is consistent within and across different types of relations. On top of the methodological contribution, we also contribute to the social networks literature in terms of how individuals in different contexts maintain balance with respect to who they interact with, and who interacted with them.

2.2 Related work

The central tenet of social network analysis is to understand the structures of relations between sets of objects, such as individuals, groups, or organizations (Wasserman & Faust, 1994). Heider's structural balance theory (Heider, 1946) was one of the earliest formulations of how relationships form between three individuals, or between a pair of indivduals and their perceptions of or attitude towards an common object. Heider initially examined POX triads, where P is a focal individual, O is a second individual, and X is either an individual or a common object. He asserted that the relationship between these three entities is 'balanced' if P liked O, O liked X, and P also liked X. On the other hand, 'imbalance' would occur if P liked O, O liked X, but P did not like X. Heider's primary claim was that balance is a state of equilibrium, and that individuals in networks strive to move towards and maintaining that equilibrium or balance. In a later study, Heider proposed that balance co-exists with symmetry of relations (Heider, 1958), such that P liking O also implies O liking P. Cartwright and Harary (1956) brought balance theory into the context of signed networks, where relationships between pairs of nodes can be represented as either a $(+)$ or $(-)$. They further formalized that a triad within a network is balanced if the product of the signs of its edges is positive. The four possible types of triads in the context of balance assessment are shown in table 2.1, showing the structure of balance and imbalance.

P—O	O—X	P—X	Characteristic
+	+	+	Balanced
+	+	-	Imbalanced
+	-	+	Imbalanced
+	-	-	Balanced
-	+	+	Imbalanced
-	+	-	Balanced
-	-	+	Balanced
-	-	-	Imbalanced

Table 2.1: Patterns of signed relations in POX triad based on balance theory

In addition to symmetry as a prerequisite for balance, in the POX triad as stated above, Heider posited that "three positive relations may be considered psychologically transitive", in that "P tends to like X if $P\mathcal{R}O$ and $O\mathcal{R}X$ are valid at the same time" ($\mathcal{R}$ represents positive relation between two nodes) (Heider, 1946). Transitivity is thus established as a necessary condition for stability (Hallinan & McFarland, 1975) and balance (Holland & Leinhardt, 1978; Krackhardt & Handcock, 2006) in a social network. J. A. Davis (1979) in their study of positive relations in triads found that transitivity is a pervasive property in balanced (all positive) triads. Stix (1974) also asserted that transitivity is an important property of balance, and that "the transitivity of any structure corresponds to its sensitivity to imbalance" (p. 447). In addition to the condition of symmetry, transitivity plays a vital role in explaining the formation of ties within triads.

In real-world networks, however, relations might not be reciprocated (Wasserman & Faust, 1994). For instance, P may regard person O as a friend, but O may not see P as a friend. In such cases, ties are more appropriately represented as directed than undirected edges. In response, scholars have refined the assessment of balance to the level of the semicycles (containing directed ties) embedded each triad (de Nooy, 1999; Feather, 1964; Roberts, 1974), and the extent to which each semicycle is balanced. A semicycle is balanced if the product of its edges is positive (examples of balanced and imbalanced semicycles are shown in figure 2.2). Furthermore, semicycles that are cyclic ($P \rightarrow O$, $O \rightarrow X$, $X \rightarrow P$) are not suitable for balance analysis because they are intransitive (Block, 2015; Roberts, 1974). Another reason to not consider cyclic configuration for balance assessment is because cycles contained limited information on the process of influence among relationships (Rank, Robins, & Pattison, 2010; Veenstra, Dijkstra, Steglich, & Van Zalk, 2013). Another effort to integrate directed edges into triadic analysis stems from Holland and Leinhardt (1978), who developed sixteen classes of MAN (Mutual, Asymmetric, Null) triads, also known as the triad census. These classes represent all possible combination of directed ties between three nodes. Specifically, each configuration contains different combinations of edges, either it be

mutual (P likes O and O likes P), asymmetric (P likes O but O does not like P), or null (P and O do not like each other). The triad census characterizes four triad types that are driven by both transitivity and balance (as show in figure 2.1). As we will show, these four configurations are relevant for our operationalization of balanced triads with transitivity as a precondition of balance.

While a number of theorems has been developed to incorporate directionality into the calculation of balance, studies have ignored the direction of ties and thus analyzed balance for undirected networks as opposed to directed ones. In this study, we revisit the literature on semicycle balance to develop and demonstrate a solution for calculating structural balance for signed and directed networks while considering both transitivity and edge signs.

Figure 2.1: Triad census (include only triads which are transitive and balanced)

Figure 2.2: Balanced and imbalanced semicycles

2.3 Expansion of balance theory using transitivity and direction of edges

In this section, we present our approach to calculating balance in signed directed networks with respect to transitive semicycles.

2.4 Problem definition and notations

Let G be a signed digraph where $G = (D, \sigma)$. D is a digraph underlying G, where $\mathcal{D} = (V, E)$ and sign function $\sigma : E \to \{+, -\}$. A *triad* T in G is a set of three nodes with one directed edge between each two of them (in either direction).

Definition 1: A *semicycle* S in signed directed T is a set of three directed edges that starts from a vertex V, follows the direction of edges, and does not return to the same vertex. In other words, S is *transitive* and *non-cyclic*.

Definition 2: Every *semicycle* S in a signed digraph G must be *transitive* in order to be considered for our balance analysis. For transitivity, we consider four types of triads, i.e., (030T, 120D, 120U, and 300), because they contain only transitive semicycles (030T contains 1 transitive semicycle, 120D and 120U each contains 2 transitive semicycles, 300 contains 6 transitive semicycles). For simplicity of notation, we define $T^{(i)}$ as the set of all transitive triads of type i, where $i = 1, 2, 3, 4$ refers to 030T, 120D, 120U, and 300, respectively.

As an example, consider triad type 300 between (P, O, X), where there are six permutations of P, O, X that are transitive, from the point of view of each node. This also applies to triad types 120D (two permutations), 120U (two permutations), and 030T (1 permutation).

<u>Proposition:</u> We define T a *balanced* triad if and only if every transitive semicycle in T is balanced (positive). A transitive semicycle is positive if it contains an even number of negative directed edges. On the other hand, T is *completely imbalanced* if every transitive semicycle in T is imbalanced (negative).

Algorithm 1 shows our step-by-step computation of balance in a signed directed network.

After calculating balance $B^{j}_{T^{(i)}}$ for each triad j of type i, we compute the balance ratio for the set of all transitive triads of type i ($B_{T^{(i)}}$). Finally, the *overall balance ratio of* G ($B_{Avg(G)}$) is calculated by averaging the balance ratio of all types i across a network. A signed digraph $G = (D, \sigma)$ is balanced if all triads T in G are balanced.

Algorithm 1 Computing Semicycle balance

```
function computeSemicycleBalance(directedSignedNetwork)
    transitiveTriad ← extractTransitiveTriad(directedSignedNetwork)
                                                ▷ extract 030T,120D,120U,300 triads
    listSemiCycles ← extractSemiCycle(transitiveTriad)
    balanceScores ← computeBalance(listSemiCycles)
    aggregateScore ← aggregate(balanceScores)
                                    ▷ get percentage of balance from balanceScores
    return aggregateScore
end function
function computeBalance(listSemiCycles)
    balanceScores ← ARRAYofScore
    for semiCycle ∈ listSemiCycles do
        signProduct ← 1
        for sign ∈ semiCycle do
            signProduct ← signProduct * sign
        end for
        balanceScores[semiCycle] ← signProduct
    end for
    return balanceScores
end function
```

2.5 Network datasets

We evaluate our balance measurement on 9 networks collected in different social settings (e.g. friendships among students, relationships among philosophers), and with different network properties such as temporality and layering. Temporality is the multiplicity of snapshots of the same network over a period of time. The number of snapshots can be either one (static network), or more than one (temporal network). Layering is the number of different relationship types within the same network, which can either be one (single-layer network),

or multiple (multilayer network). We divide our datasets into three categories with respect to the additional dimensions: (a) static single-layer (static for brevity), (b) temporal (multiple snapshots), and (c) multilayer (multiple layers), as labeled in Table 2.2, under *Network type*.

All network datasets we used are from secondary data collection and are publicly available through major network data repositories such as UCINET IV, Stanford Network Analysis Project (SNAP), and Index of Complex Networks (ICON). The exceptions were *Sampson's affect data* (Sampson, 1968), *College Houses A,B,C* (Lemann & Solomon, 1952), and *Philosophers network* which were not in digitized form originally. We digitized Sampson's affect data from Tables in (Doreian & Mrvar, 1996, p. 160-161) considering all the edges. We reconstructed the *College Houses* networks from sociomatrix Tables in (Lemann & Solomon, 1952, p. 18-20) such that all choices and rejections that had a weight of $-4, -3, +3, +4$ were considered as directed signed edges. Collins *Philosophers* network was digitized by Wouter de Nooy[1] and provided to the authors.

Static networks: For four networks (*Reddit*, *Wikipedia election*, *Bitcoin OTC*, *Bitcoin Alpha*) we kept the original datasets with minimal preprocessing, given that the edgelists were directed, and contained signed attributes (-1 or $+1$ in *Reddit* and *Wikipedia*, and -10 to $+10$, excluding 0, in *Bitcoin OTC* and *Bitcoin Alpha*). The strength of the edges are not considered and only the signs were imported for creating the networks. For *College Houses A, B, C*, the sign attribute contained values from -4 to $+4$. We only include edges that contain scores of -3 and -4, which we relabel to -1. and scores of $+3$ and $+4$, which we relabeled to $+1$. Lastly, for the *Highland tribes* network, we combined two edge-lists, *GAMAPOS* ($+1$) and *GAMANEG* (-1), which contains positive and negative relations among tribes, respectively. We then symmetrized the edge-list to convert the network from an undirected to a directed representation.

Temporal networks: For *Sampson's affect*, we use the the data we had digitized from Tables in (Doreian & Mrvar, 1996, p. 160-161) which has weight range from -1 to -3 and

[1] https://www.uva.nl/profiel/n/o/w.denooy/w.denooy.html?cb

from +1 to +3, but we discard the strength of the edges and load the edges only based on their signs.

For *Newcomb's Fraternity*, the original dataset contains 15 matrices on the preference ranking from 17 men. Each person provides a score from 1 to 16 for every other person in the fraternity house, in decreasing order of their preference for friendship with that person. To create a directed signed network, we filter the data to only include the reported top 3 ranks and bottom 3 ranks (which we consider as positive and negative edges respectively). We do not consider different strengths for the edges.

Multilayer network: For *Philosophers network*, we considered edges with weights of -2 and $+2$, representing negative and positive edges between philosophers, respectively. We discarded edges with weight of 1, as they represent "probable ties" according to R. Collins (2009). We then symmetrized all edges of the network in the two layers (master-pupil and acquaintanceship), and combined the two layers to create a flattened representation of the multilayer network.

After all network edge-lists were constructed, we preprocessed the data using *pandas* in Python. This step included calculation of triad-level balance and descriptive metrics such as global clustering coefficient, density, and triad census.

Network	Network type	Nodes	Edges	Clustering coefficient	Balance ratio	Balanced triads	Imbalanced triads
Reddit	Static	18,313	120,792	6.30E-02	0.704	237,148	99,546
Wikipedia election	Static	7,118	103,675	5.30E-02	0.751	426,215	141,380
Bitcoin OTC	Static	5,881	35,592	4.50E-02	0.866	19,447	2,969
Bitcoin Alpha	Static	3,783	24,186	6.40E-02	0.845	11,649	2,141
Highland Tribes	Static	16	116	0.527	0.870	59	9
College - House A	Static	21	94	0.392	0.807	46	11
College - House B	Static	17	83	0.398	0.522	24	22
College - House C	Static	20	81	0.217	0.896	26	3
Sampson's affect - T2	Temporal	18	104	0.349	0.683	41	19
Sampson's affect - T3	Temporal	18	105	0.445	0.684	52	24
Sampson's affect - T4	Temporal	18	103	0.412	0.754	49	16
Newcomb's fraternity - T0	Temporal	17	102	0.376	0.507	38	37
Newcomb's fraternity - T1	Temporal	17	102	0.406	0.603	35	23
Newcomb's fraternity - T2	Temporal	17	102	0.406	0.481	26	28
Newcomb's fraternity - T3	Temporal	17	102	0.376	0.640	32	18
Newcomb's fraternity - T4	Temporal	17	102	0.435	0.566	47	36
Newcomb's fraternity - T5	Temporal	17	102	0.492	0.518	44	41
Newcomb's fraternity - T6	Temporal	17	102	0.484	0.485	50	53
Newcomb's fraternity - T7	Temporal	17	102	0.525	0.505	50	49
Newcomb's fraternity - T8	Temporal	17	102	0.543	0.430	40	53
Newcomb's fraternity - T10	Temporal	17	102	0.461	0.519	40	37
Newcomb's fraternity - T11	Temporal	17	102	0.467	0.507	37	36
Newcomb's fraternity - T12	Temporal	17	102	0.486	0.528	38	34
Newcomb's fraternity - T13	Temporal	17	102	0.516	0.489	44	46
Newcomb's fraternity - T14	Temporal	17	102	0.475	0.537	44	38
Newcomb's fraternity - T15	Temporal	17	102	0.498	0.575	50	37
Master-pupil layer	Multilayer	712	1,354	0.038	0.947	18	1
Acquaintance layer	Multilayer	346	660	0.091	0.917	72	2
Philosophers (2 layers)	Multilayer	855	2010	0.089	0.804	78	19

Table 2.2: Network descriptives and balance ratios

2.6 Results

Table 2.2 shows that triad-level balance values are high across all static networks with an average of 0.78 (Min = 0.52, Max = 0.90, SD = 0.12), except for the *College House B*, where only 52% of triads satisfy the triadic balance property. Our results are consistent with the central tenet of balance theory, which states that networks strive towards triadic balance, which leads to stability and reduced tension (Hummon & Doreian, 2003). Note that a micro-level measurement of balance based on triads is more reliable in networks with a notable number of triads relative to the size of the network, but may fall short in sparse networks where triads are infrequent and clustering coefficient (the fraction of closed triples to all triples) is low.

2.6.1 Temporal and multilayer networks

For *Sampson's monastery* network, triadic balance has an average value of 0.71. For Newcomb's fraternity, triadic balance values are at an average of 0.53 (Min = 0.43, Max = 0.64, SD = 0.05).

Measurements of balance for the *Philosophers* multilayer network (shown in Figure 2.8 shows changes in values of balance when the two layers of the network are analyzed separately or together. This suggests that most sources of tension operate across layers. Specifically for this network, two layers of acquaintanceship and master-pupil are interdependent in that three actors may be connected through a mixture of acquaintance ties and master-pupil ties. If we were to analyze the two layers independently, we would have observed triadic balance values of 0.92 for acquaintance network, and 0.95 for master-pupil network, which indicate almost no tension among acquaintances and almost no tension among the masters and pupils. When the two layers are combined into one multilayer network, the triadic balance value decreases to 0.80.

A closer look into the unbalanced profiles of individuals in the multilayer network reveals

Figure 2.3: Sampson's temporal network at three time points

Newcomb Fraternity – Time 1

Newcomb Fraternity – Time 2

Newcomb Fraternity – Time 3

Newcomb Fraternity – Time 4

Figure 2.4: Newcomb Fraternity (NewFrat)'s temporal network at fifteen time points-1

Newcomb Fraternity – Time 5

Newcomb Fraternity – Time 6

Newcomb Fraternity – Time 7

Newcomb Fraternity – Time 8

Figure 2.5: Newcomb Fraternity (NewFrat)'s temporal network at fifteen time points-2

Newcomb Fraternity – Time 9

Newcomb Fraternity – Time 10

Newcomb Fraternity – Time 11

Newcomb Fraternity – Time 12

Figure 2.6: Newcomb Fraternity (NewFrat)'s temporal network at fifteen time points-3

Newcomb Fraternity – Time 13

Newcomb Fraternity – Time 14

Newcomb Fraternity – Time 15

Figure 2.7: Newcomb Fraternity (NewFrat)'s temporal network at fifteen time points-4

Philosopher's Network: Master-Pupil relations only

Philosopher's Network: Acquaintance relations only

Philosopher's Network: Multilayered (Master-Pupil and Acquaintance

Figure 2.8: Philosopher's Network as a single-layered vs. multi-layered representations

that sources of tension involve groups of philosophers who were connected by a mixture of acquaintance and master-pupil relations. In fact, Everton (2018) in their analysis of the conflicts within this network observed that there were relations such as "positive ties to two individuals who are at loggerheads with one another", or "three philosophers to consistently attack one another" (p.269 in (Everton, 2018)). Collins himself also discussed that while master-pupil relationship may seem tension-free, in reality how "ideas are created has always been a discussion among oppositions" (p.1 in (R. Collins, 2009)). These assertions reveal the complex co-existence of master-pupil and acquaintance relations which impacts structural balance at multiple levels, from triads of philosophers to the entire network.

2.7 Chapter summary

This chapter provides answers to RQ1-1 and RQ1-2, which ask for the evaluation of balance for signed directed networks (RQ1-1), and the application of balance evaluation for real-world social networks (RQ1-2). The findings to RQ1-1 show that the calculation of balance can be extended to networks with directed ties using the transitive property between three nodes. As an extension, RQ1-2's findings show how our extended evaluation of structural balance can be applied to understand dynamics of social networks with different properties, such as temporality and layering. The primary limitation of the study design in this chapter is that we only examine multilayered networks with no temporal dimension. There is a scarcity of readily-available network data that are timestamped consistently across layers of relations. The next step in this dissertation would be reach out to authors of studies that used temporal and multilayered network and obtained permission to use their datasets for our study.

CHAPTER 3

NETWORK ANALYSIS TO EXAMINE CORPORATE OR COMPANY DYNAMICS

Networks can also be applied to examine structural dynamics in organizational and formal settings such as workplace communication among organizational members, information exchange between departments, or joint ventures between companies. In this chapter, I discuss how network analysis methods can be used to examine how balance analysis of workplace email communication and thereby reveal to what degree there are tension among individuals in the corporate arrangement.

3.1 Network analysis of corporate email communication using partial balance measure

I demonstrate another study that applies network analysis to examine organizational dynamics through workplace email communication. In collaboration with Rezvaneh Rezapour, Lan Jiang, and Jana Diesner, we examine the amount of tension present in an organization by examining the balance dynamics in email exchanges between organizational members. We construct signed and directed networks from two different organizational contexts; business organizations (Enron email dataset[1] and Avocado email collection[2]), and decision-making teams in a virtual simulation. For the two business organizations, we label an edge in terms of whether an email is exchanged, and edge sign in terms of the average sentiment of that email content. For the decision-making teams, we label the edges in terms of whether there is a self-reported trust score towards another team member, and edge sign in terms of the

[1] https://www.cs.cmu.edu/~./enron/

[2] https://catalog.ldc.upenn.edu/LDC2015T03

trust score, where a positive (+) sign represents reported trust towards another member with a rating of 3 or above. Otherwise, an edge was given a negative (-) sign. This work is distinctive from prior balance study presented in Chapter 2 in that the prior balance study adopts a classical balance approach where a balance index is computed by considering triads that contain only positive semicycles. In this study, we adopt a generalized (partial) balance approach to capture the extent to which a network is balanced. We integrate the measure of *partial* balance, Our formulation of the measure is shown below.

3.2 Problem definition and notations

Proposition: We define T a *completely balanced* triad if and only if every transitive semicycle in T is balanced (positive). A transitive semicycle is positive if it contains an even number of negative directed edges. Furthermore, we define T a *partially balanced* triad if it contains at least one negative semicyle. Finally, T is *completely imbalanced* if every transitive semicycle in T is imbalanced (negative).

Algorithm 2 shows our step-by-step computation of balance in a signed directed network. After calculating balance $B^j_{T^{(i)}}$ for each triad j of type i, we compute the balance ratio for the set of all transitive triads of type i ($B_{T^{(i)}}$). Finally, the *overall balance ratio of* G ($B_{Avg(G)}$) is calculated by averaging the balance ratio of all types i across a network. A signed digraph $G = (D, \sigma)$ is balanced if all triads T in G are balanced.

3.3 Results

Table 3.1 presents balance result for the Enron network. The sentiment network has an overall balance ratio of 67.50%, with triad 300 having the highest balance ratio (69.94%) and triad 120U having the lowest balance ratio (64.36%). The prevalence of balanced triad 300s shows that balance is present in situations where individuals initiate and reciprocate

Algorithm 2 Computing triadic balance for a signed directed network. Algorithm adapted from Dinh et al. (2020)

for $i = 1, 2, 3, 4$ **do**
  Consider set $T^{(i)}$
  $\triangleright$ Take element j of $T^{(i)}$, for $j = 1, \cdots, N_j$:
    Find the Semicycles and calculate: $B_k^{sign} := \prod_r$ sign of edge r
    Consider $S_{T^{(i)}}^{+,j} = \{$semicycle k, B_k^{sign} is $+\}$
    Consider $S_{T^{(i)}}^{-,j} = \{$semicycle k, B_k^{sign} is $-\}$
    Let $S_{T^{(i)}}^{j} = S_{T^{(i)}}^{+,j} \cup S_{T^{(i)}}^{-,j}$
  $\triangleright$ Define:

$$B_{T^{(i)}}^{j} := \frac{|S_{T^{(i)}}^{+,j}|}{|S_{T^{(i)}}^{-,j}|}, \quad \big(\text{Note: } B_{T^{(i)}}^{j} \in [0,1]\big)$$

  Let $\tilde{N}_{T^{(i)}} := \{T_j^{(i)} : B_{T^{(i)}}^{j} \neq 0\}$, $\tilde{Z}_{T^{(i)}} := \{T_j^{(i)} : B_{T^{(i)}}^{j} = 0\}$, where, $T^{(i)} = \tilde{N}_{T^{(i)}} \cup \tilde{Z}_{T^{(i)}}$
  Define:

$$B_{T^{(i)}} := \frac{|\tilde{N}_{T^{(i)}}|}{|T^{(i)}|}$$

end for

$$B_{Avg(G)} = \frac{1}{4} \sum_{i=1}^{4} B_{T^{(i)}}$$

[1]

.

email communication.

In terms of triadic profiles, 030T occurs most frequently and is often balanced (67.46%). In the context of this dataset, the 030T triad represents triples of individuals who are bounded by a certain "local hierarchy" - P sends an email to O, who then sends an email to X, then followed by P sending an email to X as well. Such behavior implies a hierarchy, where both P and O initiate communication with X, and X may be at a higher level of influence (consistent with the assumptions of Ranked Clusters model, see de Nooy (1999)). High counts of balanced triads of type 030T also indicates a strong correlation between transitivity and balance at the triad level of the network. Triad 300 represents complete and reciprocated interaction among three individuals, and these communications are carried out with less tension. High triad 030T counts also means that there is lower reciprocity

at the triad level. This insight has implications for professional email communication and practices for companies in crisis as we observe more instances of initiating emails to other individuals and less reciprocity (i.e., replying) in exchanging emails. In addition, we also observe high counts of triads of type 120U, which indicate information reporting (120U, P and O reporting up to X), but not of type 120D, which indicate the act of passing down information. This finding suggests hierarchical information flow at Enron, where email communication is initiated by employees and sent to personnel at different levels in the organization.

Enron_ Sentiment	Type	Count	Completely Balanced	Partially Balanced	Completely Imbalanced	Balance Ratio ($B_{T^{(i)}}$)
Transitive Triads	030T	4238	2859	0	1379	67.46%
	120D	2384	1333	588	463	68.24%
	120U	3513	1775	972	766	64.36%
	300	3056	1312	1605	139	69.94%
Total		13191	7279	3165	2747	$B_{Avg(G)}$ = 67.50%

Table 3.1: Balance counts with respect to **sentiment** in Enron network

Table 3.2 shows balance results for the Avocado network. The overall balance ratio for sentiment is 82.47%, with triad 030T having the lowest balance ratio (76.22%), and triad 300 having the highest balance ratio (90.28%). In addition, triad 300 is the most frequently-occurring.

Similar to the Enron networks, the Avocado networks contains substantially more counts of 120U than 120D. Recurring prominence of 120U triads in email communication networks may indicate the prevalence of information reporting. The primary difference is that Avocado's sentiment network has higher balance ratio (82.47%) than Enron's sentiment network (67.50%), indicating that there may be less tension in the emails exchanged between Avocado

employees compared to Enron. Another difference between Avocado and Enron network is that Avocado network contains higher proportions of 300s triads (74%). In contrast to Enron network, which contain mostly 030T triads, Avocado network is more tightly-connected with frequent and reciprocated communications.

Avocado_ Sentiment	Type	Count	Completely Balanced	Partially Balanced	Completely Imbalanced	Balance Ratio ($B_{T^{(i)}}$)
Transitive Triads	030T	8577	6538	0	2039	76.22%
	120D	14276	10816	1408	2052	80.69%
	120U	28615	22802	1725	4088	82.69%
	300	144865	118673	23870	2322	90.28%
Total		196333	158829	27003	10501	$B_{Avg(G)}$ = 82.47%

Table 3.2: Balance counts with respect to **sentiment** in Avocado network

Table 3.3 shows balance counts of the 18 decision-making teams. Given the experimental condition, all teams' networks are completely connected, resulting in 432 semicycles, all of which are embedded within 72 triads of type 300s. The overall balance in this network is 72.69%. Specifically, 60% of triads (43 out of 72) are partially balanced, 40% (29 out of 72) are completely balanced, and 1% (1 out of 72) is completely imbalanced. This shows that many triads contain some amount of tension, but not significant enough that they become completely imbalanced.

Trust	Type	Count	Completely Balanced	Partially Balanced	Completely Imbalanced	Balance Ratio ($B_{T^{(i)}}$)
Transitive Triads	030T	0	0	0	0	0%
	120D	0	0	0	0	0%
	120U	0	0	0	0	0%
	300	72	29	43	1	72.69%
Total		72	29	43	1	$B_{Avg(G)}$ = 72.69%

Table 3.3: Balance counts with respect to **trust** in Decision-Teams network

We also conduct a sign analysis of semicycles to examine the proportions of positive and negative ties in each semicycle type. The semicycle sign counts are shown in Table 3.4. All three networks contain higher proportions of positive than negative edges. Equivalently, higher proportions of positive semicycles are observed, which explains higher occurrences of both $+++$ and $++-$ semicycles than semicycles that contain higher counts of negative ties. Our findings are consistent with prior work by Doreian and Krackhardt (2001) and J. A. Davis (1979), who all found transitive to be a pre-condition for balance when both $P \rightarrow O$ and $O \rightarrow X$ are positive. Leskovec, Huttenlocher, and Kleinberg (2010b) also empirically observed a majority of all-positive semicycles in three real-world social networks; with the proportion of positive semicycles ranging from 70% to 87%.

Different from Avocado and decision-teams network (as shown in Figure 3.1), Enron network contains a significant proportion of $++-$ semicycles. This particular semicycle type represents a unique type of tension that we frequently observed in the Enron data; e.g., when *"Jeff Skilling"* sent a positive email to *"Rebecca Mark"* (Head of Enron International), *"Rebecca"* sent a positive email to *"Kenneth Lay"* (CEO and Chairman of Enron), but *"Kenneth Lay"* in turn sent a negative email to *"Jeff Skilling"*. This case exemplifies a violation of transitivity and structural balance, such that the link between *"Kenneth Lay"* and *"Jeff*

Skilling" is a source of tension between within a triad. Another interpretation could be that organizational emailing etiquette is generally more positive, with the occasional presence of negative emails within dyads. In fact, all-negative semicycles are rare (about 1% in Enron network, 0.04% in Avocado network), suggesting that it is not common to engage in chains of negative emails.

	Enron		Avocado		Decision-Teams	
Semicycle type	Counts	Ratio-Total	Counts	Ratio-Total	Counts	Ratio-Total
+ + +	19830	0.58	851297	0.89	196	0.45
+ + -	10419	0.30	92938	0.10	91	0.21
+ - -	3630	0.11	10340	0.01	118	0.27
- - -	489	0.01	409	0.0004	27	0.06
Total	34368	1	954984	1	432	1

Table 3.4: Types of signed semicycles for Enron, Avocado, and Decision-Teams

Similar to the Enron and Avocado email networks, decision-teams trust network also has the highest proportion of $+++$ semicycle. As seen in Figure 3.1, there is only a small portion of small groups with more negative edges than positive edges, and they are often unbalanced (due to even number of negative edges). The primary difference with this particular network is that $+--$ semicycles are more prevalent than $++-$ semicycles. The prevalence of two balanced semicycle types in this network is evidence for the tendency to maintain balance; team members may orient their perceptions of trust towards other team members in ways that potentially reduce tensions within their immediate teams. Specifically with the experimental setup where individuals are split into two teams, we observe a number of cases where team member P of team "phantom" trusts (+) member O of the same team, but member O does not trust (-) member X of the "stinger team", therefore team member P does not trust (-) member X, maintaining a strong sense of trust within the team and low trust outside of the team. This finding is consistent with previous literature on trust

in organizations that has shown how trust rather emerges within teams than across teams (Ashleigh & Stanton, 2001; De Jong & Elfring, 2010) as members who actively and frequently work together develop a higher sense of team identity (Hogg, 2012).

3.4 Chapter summary

This chapter provides answers to RQ2-1, which asks about the application of balance theory to evaluate real-world corporate communication networks. Our results show that tension exists in certain triadic configurations within the corporate communication network. The findings also contribute to a methodological understanding that structural balance is not a discrete value (balance or no balance), but rather a continuous value that ranges from completely balanced to completely imbalanced. The primary limitation, however, is that we only examine static networks and thus are not able to capture changes in balance value over time. In the next step, we will convert our three datasets (Enron, Avocado, Decision-Teams) into time-stamped data for temporal analyses of balance and determine whether networks naturally gravitate towards balance over time (Diesner & Evans, 2015; Uddin, Hossain, & Rasmussen, 2013). The substantive findings also show how corporate settings, with specified roles and communication channels, may influence the flow of communication as well as balance dynamics within a network. In turn, the emergent communication patterns, as seen in balance configurations (e.g. more 120D-type triads seen in Avocado and more 030T-type triads seen in Enron), also influence the formal configuration in that corporate members interacted with others outside of their immediate groupings. Ultimately, we are able to observe the co-existence of emergent and formal communication structures from the lens of structural balance, specifically with respect to the who each individual communicates with, and the manner in which they communicate that is correlated with structural balance.

Figure 3.1: Network visualizations of Enron with respect to morality and sentiment, Avocado with respect to morality and sentiment, decision-teams network with respect to trust. Edge color green=positive, and red=negative

CHAPTER 4

NETWORK ANALYSIS TO EXAMINE ORGANIZATIONAL DYNAMICS

In addition to corporate arrangements, I also examine another workplace context with clear formal structure and practices, namely a medium-sized scientific organization where researchers, staff, and administrators work together on computational problems that span multiple disciplines. Along with my collaborators, we choose this particular organization because of its core values in interdisciplinary research, and thus the investigation of interdisciplinary tie formation that is facilitated through either emergent or formal connection is appropriate. In this chapter, I examine how factors relating to individual's (1) formal roles and responsibilities and (2) informal social network influence the likelihood of forming interdisciplinary ties. I also demonstrate the usefulness of multilevel modeling in determining the effects that the aforementioned factors have on tie formation dynamics in a collaboration network.

4.1 Multilevel network analysis of organizational collaboration using egocentric survey data

4.1.1 Introduction and background

Social network scholars are becoming increasingly aware of the nested nature of sampled network data, where individuals may belong to groups, and groups may belong to different networks. In addition, sampled network data contains dependencies in which individuals may be connected by more than one type of relationship (e.g., two students in the same

school are also siblings). Recent developments on multilevel analysis such as permutation-based tests (Dekker, Krackhardt, & Snijders, 2007) and random graph models (Robins et al., 2007; T. A. Snijders, Pattison, Robins, & Handcock, 2006) enabled scholars to collect and analyze network data with both assumptions of nested structure and dependencies taken into account. Multilevel models enable scholars to examine networks at multiple levels of analysis ranging from egos, dyads, to the global network. As these methods are mainly based on maximum likelihood procedures and simulations to determine statistically significant network structures, they require substantial sample sizes and minimal loss of data. Network scholars often rely on egocentric survey methods to collect and collate network data, and recognize that it is very difficult to collect whole-network data with complete links among all actors in the sample specified in order to effectively do a multilevel analysis. Additionally, egocentric survey data is also limited in its ability to capture the whole network because we rely on the 'representative' set of focal egos to infer about our population of interest. Recognizing these limitations with sample size and egocentric survey techniques, a number of researchers resort to traditional statistical techniques such as linear regressions that collapses the multiple layers of the network to a single level of analysis surrounding the egos. This approach introduces certain kinds of errors that may over- or underestimate the effect sizes, and also it does not sufficiently explain where and how certain network effects are occurring. As for studies that have nearly-complete samples, they implement imputation techniques (Huisman, 2009) of missing data on the basis of the existing observed data in order to complete the network structure, thus allowing researchers to apply necessary multilevel techniques. Along with advantages of the technique, imputation may also introduce biases and errors that negatively impact the validity of network results (Borgatti, Carley, & Krackhardt, 2006). With an aim to find multilevel methods that allows network researchers to effectively analyze only the observed network data without the need for imputation, I propose an application of multiple membership multiple classification (MMMC) model that considers the network to consist of two layers, the egos and the ties between them. While

still preserving the nested structure of the network, MMMC is more tolerant of missing data problems as analysis is at the level of the ego-network, not at the whole-network.

Inherent in egocentric survey methods is the problem of measurement and boundary specification (Marsden, 2011). Though it is desirable to observe the whole networks with a 'top-down' approach, it is time-consuming and resource-intensive to collect and process whole-network data as it requires a complete listing of the study population. Thus, egocentric survey allows for a 'bottom-up' approach in which the whole network is generated through multiple networks of focal actors in the study population. This network sampling method is more efficient to collect data on the relationships among actors in the population, however we must be cautious when attempting to infer the global-level structure from these egocentric subgroups. To avoid issues with inferences across levels of the network, we must first specify the unit(s) of analysis under study. An egocentric network (ego-net) consists of a number of individuals (alters) that are formed around a focal individual (ego) by the ties between them. Based on this definition, there are two basic units of analysis in this network, the individual (ego-level), and the ties between individuals (tie-level). Beyond these two fundamental units, researchers may choose to extend to higher-order levels of analysis such as triads, subgroups, and the global levels, only under the condition that the network is complete with all (or nearly all) possible links among actors within the population. Recognizing the difficulty in obtaining such complete network with all necessary ego-alter and alter-alter ties, we assert that researchers should focus on thorough analysis at the ego- and tie-levels first in order to reliably estimate the effect sizes that is faithful to the egocentric data that they have. Thus, robust network methods that focus on these two fundamental units of analysis are necessary.

This section of Chapter 3 is organized as follows. We begin with reviewing the existing statistical methods to analyzing egocentric survey data in terms of their strengths and also drawbacks in capturing the network structure and dynamics among focal actors of the sample. In capturing the developments of statistic techniques, we emphasize the need for multilevel network analysis as networks are inherently nested, with social relations embed-

ded between people, who are embedded within larger network structures (M. Granovetter, 1985). The first section of the chapter identifies that well-known multilevel models often run into measurement issues associated with data loss and limited sample sizes that may influence validity of results when analyzing at higher levels of analysis. Thus, the second part of the chapter proposes to focus on the two primary levels of the network, the egos, and the ties between them. A class of multilevel methods known as multiple membership (MM) models allow researchers to assess network structures at both ego and tie levels, while controlling for the autocorrelation and overlapping nature of egos that have proven problematic for standard regression methods. I then propose an application of multiple membership multiple classification (MMMC) under the family of MM models that allows actors to be membership of more than one ego-network, in which an ego can also be an alter in another's ego-network. Current research using MM are frequently applied for modeling egos belong to different grouping such as schools and areas (Tranmer et al., 2014), but I suggest that MM can be used to model ties, or dyads, directly as well. I provide an egocentric analysis of collaboration networks in a scientific organization (Barley et al., 2022) to demonstrate how MMMC is used to model both egos and ties at the same time in order to help explain the share of effect sizes in both levels and determine whether one level plays more significant role than another in certain types of networks.

4.2 Related work

At the ego-level, traditional statistical methods such as OLS regressions, or ANOVA, can be used as each ego is treated as an independent, non-overlapping cases. One main critique is that egos of the same network are assumed to be connected to each other by certain qualities, thus violates the assumption of independence. At the tie-level, more advanced statistical methods are required that consider nested data such as Quadratic Assignment Procedure (QAP), Exponential Random Graph Models (ERGM), or multilevel modeling.

The commonality among all these methods is they are based on likelihood models, in which the primary goal is to determine if certain structural characteristics are more, less, or likely to occur by chance among various configurations within the current sample space of networks. Recognizing that egos in a network should not be treated as independent observations, scholars have proposed methods that take into account the nested and clustered nature of network egos and their ties. The following section will examine the various statistical models currently used in egocentric network research.

4.2.0.1 Ego-level network analysis

A number of traditional statistical approaches such as regression analyses (Ordinary Least Squares, Logistic regression), correlation analysis, or cross-group comparisons such as ANOVA or Chi-squared test are available for network analysis at the ego-level. Attributes of the focal ego, ranging from various network centrality measures to personal characteristics such as age and gender can be entered as independent variables in a standard regression. Dependent variables can also be any attributes of the focal ego that is the primary interest of the researcher. A prominent example of an ego-network study that uses standard logistic regression is Podolny and Baron (1997)'s research on a large technology organization. The dependent variable is a binary variable that determines whether each ego earns a promotion, or not. Three independent variables entered in the logistic regression model are size of each ego-network, number of alter-to-alter ties in each network, and duration of each ego-alter tie. It is important to note that Podolny and Baron (1997) assume that both the egos and their ego-networks are independent of each other, and that the 658 egos in the study are randomly sampled from a population of over 25,000 employees. The importance of having independent observations in regression analysis (B. L. Perry, Pescosolido, & Borgatti, 2018) is so that the error terms would be randomly distributed across egos in the sampling distributions. However, we know that independence assumption is often violated in many network studies as egos are often connected on various attributes, that create correlated error terms and in-

fluence the validity of the regression model. There is also problem of repeating observations, which can also make error terms correlated with each other and thus inflate the standard errors. Recognizing this limitation, a number of statistical methods specifically designed for relational data are developed that enables network researchers to explore properties beyond the ego-level. Nevertheless, regression modeling is a foundational statistical form that guides the construction of various relational models such as Quadratic Assignment Procedure (QAP) and random graph models (ERGM). In addition to nonparametric testing, ego-level network analysis often relies on visual examination of networks and descriptive statistics of various centrality metrics in order to make inferences about the structures and positions of focal egos (Shumate & Palazzolo, 2010). Although this analytic approach may be helpful to explore the data, it is limited in the capacity for hypothesis testing and evaluating whether certain network patterns occur beyond just random chance. Therefore, descriptive statistics and basic centrality analysis should be combined with statistical and estimation methods to examine observed structures in a robust manner.

4.2.0.2 Tie-level network analysis

There are three families of models available to scholars who aim to investigate how ties are formed among egos, namely permutation-based models, random graph models, and multiple membership models. Permutation-based models include quadratic assignment procedure (QAP) and multiple regression quadratic assignment procedure (MRQAP) (Krackardt, 1987; van Duijn & Huisman, 2011), which test whether correlations between tie-level variables are due to chance. QAP is an extension to a regression analysis but can preserve the dependence between ego-alter ties through multiple re-ordering, or repeated permutations of the dependent variable. This results in multiple random datasets that together form a sampling distribution with new correlation coefficient generated, and then compared with observed correlations to determine whether the difference between the observed and randomly-generated estimates are due to chance alone (p-value). Permutation methods has

advantages over traditional regression in that it moves beyond the ego-level and uses the dyad as its basic unit of analysis, thus considers the correlation and dependence among egos and alters. QAP is also flexible for various types of data, from categorical to ordinal data, that do not need to have a normal distribution (Dekker et al., 2007). The main drawback of QAP and MRQAP is that the relationship between dependent and independent variables are removed as they are merged together into one matrix during permutations, thus makes hypothesis testing between variables very difficult. In this way, QAP is simply seen as a testing of correlations between the observed and expected networks under the null hypothesis of no correlations between the two networks (Hanneman & Riddle, 2005). Additionally, missing data can have significant effects on the validity of QAP results. If the observed data matrix already contains many missing cells, this may produce highly problematic permuted data and may inflate type I error rates as the observed and randomly-generated networks are likely to be very different. Thus, the high sensitivity to missing data may make QAP and MRQAP less applicable to a majority of egocentric datasets that often contain missing data.

Beyond significance testing, random graph models enable researchers to estimate the likelihood of certain observed structures through probability distributions. Exponential random graph model (ERGM) is different from permutation-based tests in that it can simulate many different structures of the expected global network until they match the observed networks through using both attributes of the egos along with characteristics of the network. ERGM is designed for binary-valued outcome variables in that it can predict the likelihood of a tie between any ego-alter pairs when they share certain attributes. Random graph models are flexible in that they only need a single observed network to estimate model parameters, and can include parameters at various levels of analysis such as reciprocity (dyadic) and transitivity (triadic) to be structural properties of the observed network. For instance, an ERGM can model for reciprocal dyadic relationships where the probability of a tie from A to B is higher when there is an existing tie between B to A and thus the tie from A to B

is a reciprocated tie. In addition to modeling structural, or endogenous effects, ERGMs can also make parameter estimates for actor-oriented, or exogenous effects that can affect the likelihood of a certain tie formation. The important assumption that random graph models make is also one of dependence of observations, or Markov dependence (Holland & Leinhardt, 1981). Markov dependence contains an assumption that if two ties share a common ego (i.e. if both A-C and A-B ties contain A), they are likely to be related to each other in some ways. To consider for complex dependencies at multiple levels ranging from dyads to global network, a number of dependence models such as dyadic dependence model (Frank & Strauss, 1986), p* model (Wasserman & Pattison, 1996) have been developed. Though with many advantages over permutation-based methods such as QAP and MRQAP, random graph models are also very sensitive to missing data. Incomplete data may substantially underrepresent the actual network structures and omit important dynamics among egos and ties. King et al. (2001) found that even with small portion of missing ties, structural parameters and centrality measures of the network are inaccurately estimated due to the main issue of model degeneracy (Robins et al., 2004). Models are considered degenerate when they produce a skewed distribution of only a few random graphs out of all possible configurations, and these graphs are either full or empty graphs. Especially in the case of ERGM, it is even more difficult to measure the extent of degeneracy effects because no two estimation output is the same, as ERGM simulates a different set of random graphs every time. Thus, issues of missing nodes, attributes of nodes, and edges are magnified in estimation techniques such as random graph models.

Multilevel models are often referred to as random-effects models as they examine the share of variation between both fixed and random effects, allowing researchers to make parameter estimates at multiple levels of analysis. Specifically, in the context of egocentric network analysis where network ties are nested within egos (Wellman, Frank, et al., 2001), multilevel models are relevant to analyze variation dynamics within and between both the ego- and the tie-level. In addition, multilevel models are robust to missing data (Baayen

et al., 2008; Quené & Van den Bergh, 2008) in that they consider all available data as is, rather than automatically perform a listwise deletion (ego removed from dataset if missing data on any variable). Additionally, these models are able to preserve more statistical power compared to permutation-based methods in the context of incomplete data, thus reduce instances of underestimated parameters and high Type I errors. Thus, the primary advantage of multilevel network models is the ability to handle missing data without questionable imputation methods, allowing researchers to analyze the raw data and correctly infer parameter estimates within the scope of the collected ego-nets. There are three main types of multilevel network models, namely network autocorrelation, multiple membership, and multiple membership multiple classification (MMMC) model. Though they operate with different assumptions of the network data structure, three models all account for network dependencies not only within the ego and tie levels but also between the levels. MMMC model is an extension to multiple membership models in that it allows additional grouping of individuals in each ego-net (e.g. same department, same organizational role).

4.3 Application of multiple membership multiple classification model

In a collaborative effort in which I took a lead on network construction and analysis, we adopt MMMC to examine whether interdisciplinary ties are present in ego-networks of 100 employees in a scientific organization. MMMC is appropriate for our research objective in two ways. First, our framework posits that aspects of the ego (e.g. tenure, occupational role) and of relationships (frequency of interaction, similarity of expertise) will both influence the nature of ties. Further, although our data were provided by individuals (egos), our dependent variables are at another level of analysis (i.e. at the tie-level). MMMC separates the influence that tie- and ego-level attributes have on independent variables by modeling each level's effects as a distinct component of variance. MMMC also addresses two unique qualities of

our data that other popular analytic paradigms could not. First, our data are egocentrically sampled, which means each respondent supplied multiple ties for our analysis. Although this is a common structure for network studies, it violates the basic assumption of independence that would allow standard OLS. Second, our effective sample of 40 percent of CRC's 250 employees meant that many whole-network analysis techniques such as ERGM would be inappropriate. Researchers commonly account for missing data by imputing missing ties (Huisman, 2009), but imputation becomes unreliable when the sample is below 70% of the whole network (Smith & Moody, 2013). MMMC has been shown to produce unbiased estimates even with low effective sampling rates of a full network (Paccagnella, 2011).

There are two levels in our multiple membership multiple classification (MMMC) models, as we examine the extent to which similarity of expertise (SimExp) and linguistic familiarity (LingFam) vary between tie-level attributes (level 1) and ego-level attributes (level 2), as shown in Figure 4.1. Tie-level attributes include frequency of interaction, advice-seeking, same team, same project, and alter-indegree. Ego-level attributes include tenure, occupational role, gender, and ego-net size. We constructed two MMMC models, where model 1 examines the extent to which tie-level and ego-level attributes explain the presence of SimExp ties. Model 2 is a variant of model 1, with LingFam as a dependent variable, and SimExp as an independent variable along with other tie-level and ego-level attributes. Outputs of each model includes the fixed effect for each variable, as well as the random effect that accounts for the variance explained by that particular variable at each level of the model (Tranmer et al., 2014).

Model 1 explores factors associated with the level of similarity of expertise (SimExp) for a given relationship within our network. By modeling factors associated with SimExp we are able to test one hypothesis about the tendency of egos to report ties with others of similar expertise. Model 2 explores factors associated with linguistic familiarity (LingFam) for a given tie within our network. Importantly, we added SimExp as an additional independent variable within Model 2 to allow us to test a research question on the relationship between

Figure 4.1: Our multilevel structure of overlapping ego-nets

SimExp and LingFam. In other words, this research question enables us to observe whether an individual who is not familiar with another individual's expertise can still possess high linguistic familiarity with that individual's area of expertise. This is a central tenet of interactional expertise, an important form of expertise for effective interdisciplinary collaboration (H. Collins et al., 2007). Model 1 is expressed as follows:

$$\text{SIMEXP}_{ij} = \text{x}_i\beta + \sum_{j \in ego(i)} \text{w}_{ego} i, j u_i^{(2)} + \sum_{j \in tie(i)} \text{w}_{tie} i, j u_i^{(1)} + \epsilon_i$$

$$i = 1, ..., n, \qquad tie(i) \subset (i, ...J_1), \qquad ego(i) \subset (i, ...J_2)$$

$$u_j^{(2)} \sim N(0, (\sigma^2_{u^{(2)}}), \qquad u_j^{(1)} \sim N(0, (\sigma^2_{u^{(1)}}), \qquad e_i \sim N(0, (\sigma^2_e)$$

In Model 1, SIMEXP_{ij} is a level-1, tie-level response, and we assume it to be a continuous variable. x_i is a vector of fixed variables, and β is the vector of the regression coefficients. We can see two network subgroups defined as $ego(i)$ and $tie(i)$, which represent the two levels that i may be a part of. The term $\sum_{j \in tie(i)} \text{w}_{tie} i, j u_i^{(1)}$ denotes a set of random effects $u_j^{(1)}$ for j_1, in which j_1 is the total number of level-1 nodes. There are 1126 level-1 nodes in our dataset. The term $\sum_{j \in tie(i)} \text{w}_{tie} i, j u_i^{(1)}$ represents a set of random effects $u_j^{(2)}$ for j_2, in which j_2 is the total number of level-2 nodes. There are 100 level-2 nodes in the dataset. Model 1 is an MMMC model, as we can see two levels of classification that are ties and egos.

We formulate Model 2 with Linguistic Familiarity (LingFam) as a dependent variable:

$$\text{LINGFAM}_{ij} = \text{x}_i\beta + \sum_{j \in ego(i)} \text{w}_{ego} i, j u_i^{(2)} + \sum_{j \in tie(i)} \text{w}_{tie} i, j u_i^{(1)} + \epsilon_i$$

$$i = 1, ..., n, \qquad tie(i) \subset (i, ...J_1), \qquad ego(i) \subset (i, ...J_2)$$

$$u_j^{(2)} \sim N(0, (\sigma^2_{u^(2)}), \qquad u_j^{(1)} \sim N(0, (\sigma^2_{u^(1)}), \qquad e_i \sim N(0, (\sigma^2_e)$$

We performed a null-model comparison for each model to assess whether MMMC appropriately fit our data. Both multilevel null models offered improved fit compared to their respective single level null models, as measured by a significant decrease in the deviance information criterion (SimExp: MMMC DIC=3245; Single-level DIC=3784, p<.001; LingFam: MMMC DIC=1907; Single-level DIC=3012, p<.001). The null models indicated tie-level effects explained 65.5% of the variance in SimExp and 62% of the variance in LingFam. Ego-level effects explained 34.5% of the variance in SimExp and 38% of the variance in LingFam. Table 4.1 summarizes the results of models 1 and 2.

Variable	Model 1: SimExp		Model 2: LingFam	
	Estimate	(S.E.)	Estimate	(S.E.)
Fixed effects				
Constant	2.511	(0.208)	3.783	(0.117)
Level-1 (Tie) variables				
Frequency of interaction	0.097*	(0.055)	0.128***	(0.030)
Advice-seeking frequency	0.237***	(0.048)	0.015	(0.026)
Same Team	0.401***	(0.075)	0.027	(0.041)
Same Project	0.362***	(0.087)	0.111**	(0.048)
Alter-indegree	-0.040***	(0.007)	-0.007*	(0.004)
SimExp			0.428***	(0.016)
Level-2 (Ego) variables				
Tenure	0.221	(0.183)	0.187	(0.208)
Manager	-0.020	(0.170)	0.026	(0.093)
Technical staff	-0.078	(0.100)	0.086	(0.054)
Gender	0.485**	(0.206)	0.190	(0.121)
Ego-net size	0.004	(0.015)	-0.018*	(0.009)
Random effects				
Level-2 (Ego) variance	0.553	(0.095)	0.200	(0.036)
Level-1 (Tie) variance	1.014	(0.042)	0.287	(0.013)
DIC	3244.814		1906.945	

***$p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4.1: Results for MMMC models With SimExp and LingFam as DVs

4.4 Results

Model 1 examined SimExp as its dependent variable. A test of difference confirmed that Model 1 fit our data better than the null model ($p < .001$). The addition of ego- and tie-level variables respectively accounted for an additional 3% and 8% of the observed variance

in SimExp. Several significant main effects for variables at the tie-level provided strong support for Hypothesis 1. Individuals at CRC tended to report more similarity with connections who they interacted with frequently (β=0.097, p<.05), worked with on the same team (β=0.401, p<.001) or project (β=0.362, p<.001), and went to for work-related advice (β=0.237, p<.001). At the ego-level, our control variable for gender was the only covariate with a significant estimate (β=.485, p<.01). Men reported higher similarity of expertise with their connections than women. Overall, the coefficients from Model 1 described above suggests a strong tendency toward collaboration with individuals who share similar expertise. In other words, we do not observe a strong culture of interdisciplinary collaboration at this organization.

Results in Model 2 reveal a positive relationship which between similarity of expertise and linguistic familiarity (b=0.428, p<.001). SimExp had the largest effect estimate of any independent variable, followed by three tie-level variables which were frequency of interaction (β=0.128, p<0.001), same project (β=0.111, p<.01), alter-indegree (β=-0.007, p<.05), and one ego-level variable which is ego-net size (β=-0.018, p<.05). Holding all other factors constant, our model predicted that a positive shift by one point on a 5-point Likert scale measuring perceived similarity with a given connection would be associated a consonant .43-point increase in perceived linguistic familiarity. Our results strongly suggest that the presence of ties with low similarity of expertise but high linguistic familiarity was not common in this organization.

4.5 Chapter summary

This chapter provides answers to RQ2-1, which asks about what network analysis theory and method is suitable to address the nested nature of network data in organizations, specifically a medium-sized scientific organization. Findings for RQ2-1 shows the utility of multiple membership models in networks where individuals can belong to multiple ego-networks.

Figure 4.2: Relationship between SimExp and LingFam. Edges with high SimExp is shown on left, and edges with low SimExp are shown on right. Gradient color of edges represent level of LingFam, from low (light green) to high (dark green)

Furthermore, this particular model is suitable to examine the extent to which attributes of an individual's informal social network (individual-level factors) and an individual's formal role in an organizational hierarchy (structural-level factors) explain the likelihood of ties between organizational members. Our multilevel models also reveal that the factors relating to an individual's informal network (i.e. who they go to for advice, who they frequently interact with) are just as important as their formal roles in explaining the mechanisms for forming connections with other organizational members.

CHAPTER 5

NETWORK ANALYSIS TO EXAMINE NATURAL HAZARDS DYNAMICS

5.1 Interorganizational collaboration dynamics during natural hazards response

Managing disasters in a timely and effective manner has always been a challenge to emergency responders and related agencies as they are fundamentally different from routine emergencies where events are predictable and thus within the bounds of planned response actions (Caragea et al., 2011; Dynes, 1970; Palen, Vieweg, Liu, & Hughes, 2009). Given the complex nature of disaster management that requires tremendous amount of planning, resources, and coordination among agencies with different functions, response cannot be handled solely by one organization, but rather a network of organizations (Choi & Brower, 2006; Comfort & Haase, 2006; Kapucu & Garayev, 2016). As exemplified by earlier conversations with captain Deptula (2018) from the United States Coast Guard (USCG), there is an urgent need for a "systematic" and unified way of linking relief efforts between all stakeholders involved in the disaster management process, from search-and-rescue helicopters to volunteer crisis mappers (Meier, 2012). Given the rigid but highly fragmented structure of the current interorganizational response network as outlined by the National Response Framework (FEMA, 2018), fostering collaboration and communication among these stakeholders will be difficult.

Network analysis offers the ability to systematically represent and examine the structural and relational dynamics that take place within and between organizations, whether it be in preparation or response to an immediate crisis. There are a number of studies that examine how agencies connect to each other in emergency situations through commu-

nication (Comfort & Haase, 2006; Kapucu, 2005), coordination (Waugh Jr & Streib, 2006), leadership (Kettl, 2006) and decision-making (Van Borkulo, Scholten, Zlatanova, & van den Brink, 2005). Most studies that have adopted a network-analytic approach to examine the strengths and drawbacks of emergency management networks for specific disasters, such as hurricane Katrina (Kettl, 2006) and the 9/11 attacks (Kapucu, 2005), found that though every disaster is different, there is a persistent need to improve the current interorganizational structure put in place by the National Response Framework (NRF) (U.S. Department of Homeland Security, 2008) to enable more flexible and adaptive communication and coordination flow. A public statement released by the United States Government Accountability Office (Walker, 2006) on hurricanes Katrina and Rita's responses highlights that the NRF is a higher-level planning framework with the expectation that there would be a "proactive national response". Thus, the NRF does not contain specific operational plans compared to state- and local-level plans. Therefore, interorganizational collaboration networks are documented not just at the federal level based on the NRF, but also at state and local levels of the government where response guidelines are continually maintained and implemented (Waugh Jr, 1994). A number of studies have also found that actual response networks include organizations outside of governmental jurisdictions that are crucial to a coordinated response (Boin & Bynander, 2015; Marcelin, Cela, & Shultz, 2016; R. W. Perry & Lindell, 2003). For instance, Marcelin et al. (2016), in their ethnographic study of community-based response during Hurricane Matthew, found that international non-governmental organizations along with private donors were active in providing response assistance and resources for the affected population. In addition, prior literature indicates that information about interorganizational collaboration and relevant situational awareness are also present in situational reports (Sarol et al., 2021, 2020), communication logs (Pilny et al., 2017; Weil, Carley, Diesner, Freeman, & Cooke, 2006; Weil et al., 2008), social media such as Twitter (Olteanu et al., 2015; Verma et al., 2011), and mainstream news (Abel, Gao, Houben, & Tao, 2011; Althaus, 2002; Schmierbach & Oeldorf-Hirsch, 2012). Altogether, the prior work on organi-

zational behavior in a disaster response context reinforces the notion that interorganizational response networks are complex, and may differ in their network structure depending on what level of governmental jurisdiction are examined and what data sources are used to capture situational awareness information (Butts, Acton, & Marcum, 2012; Sarol et al., 2021).

With these findings in mind, our study's objective is to compare interorganizational response networks that are (1) prescribed by governmental guidelines at federal, state, local jurisdictions to those (2) extracted from situational reports (SITREPs) and social media (Twitter) data that reflect collaboration actions that took place during response. We focus on response networks during four major hurricane events of Category 4 and above (i.e. 2016 Hurricane Matthew, 2017 Hurricane Harvey, 2017 Hurricane Irma, 2018 Hurricane Michael) that made landfall in the continental United States. We selected these events as they received considerable attention and involvement from a notable number of governmental, non-governmental, volunteer, and international organizations (Arnold et al., 2021). Consistent with the objectives of this research, we ask the following two research questions:

> $RQ3_1$: How does the prescribed network's level of response jurisdiction (federal, state, local) relate to the amount of network overlap between the prescribed and observed network?
>
> $RQ3_2$: How does the data source (situational reports or tweets) used to construct the observed network relate to the amount of network overlap between the prescribed and the observed network?

Stemming from our research questions as well as evidence from prior literature that found notable differences in the prescribed and observed networks of interorganizational response, we derive the following (null) hypotheses to be statistically tested:

> $H0_1$= There is no significant amount of congruence in the prescribed and observed network (DV) depending on the prescribed network's level of response jurisdiction (IV1).

$H0_2$= There is no significant amount of congruence in the prescribed and observed network (DV) depending on the data sources used to construct the observed network (IV2).

5.2 Related work

Effective responses to crisis events are dynamic; requiring both formal and informal structures of collaboration (Abbasi, Sadeghi-Niaraki, Jalili, & Choi, 2018; Kapucu, 2005) among agencies. Formal collaborations are often guided by official plans from FEMA (FEMA, 2018), including the National Response Framework (NRF), the Incident Command System (ICS), and the National Incident Management System (NIMs). While these national guidelines apply to responses at all levels of the government, the mainstream understanding is that response begins at the local level (as with the saying, "all disasters are local" (Waugh Jr, 1994), then continues to state level, and finally involves the federal level. Support can also be provided by the tribal, territorial, private sector, and international agencies (Bullock, Haddow, & Coppola, 2017). While federal agencies such as FEMA and the Department of Homeland Security (DHS) play important roles in initiating a response as well as funding support (May, 1985), regional agencies at the state- and local-level are primary in response planning and execution to protect individuals within the immediate jurisdiction (FEMA, 2003; Walker, 2006; Waugh Jr, 1994). May and Williams (1985) discussed in their book on "Managing [Response] Programs under Shared Governance" at great length the challenges of an effective response when federal polices are to be enacted while at the same time, local and state agencies have their own response plans. McGuire and Schneck (2010) emphasize that the NRF is created as means to standardize state- and local-level emergency planning plans (p.203), and thus does not contain operational procedures specific to state- or local-level capabilities (Walker, 2006). Schneider (1992) provides evidence for the lack of interorganizational coordination across governmental jurisdictions via the 1989 Hurri-

cane Hugo response, where local and state response authorities struggled with restoration of telecommunication infrastructure (though they did receive assistance from the private sector (Griswold, Lightle, & Lovelady, 1990)), while the federal government did not step in until much later given that they were "unaware" of the conditions in South Carolina (Schneider, 2005). That case study also highlights the necessity of collaboration between the local, state authorities and the private sector (i.e. utility companies (Griswold et al., 1990) and media organizations (Schneider, 2005)) to respond to the hurricane that were helpful but not prescribed in response documents. The continued involvement of organizations not prescribed in government mandates suggests that interorganizational collaborations involve a combination of institutionalized (Dynes, 1970; Stallings & Quarantelli, 1985; 't Hart, Rosenthal, & Kouzmin, 1993) and emergent (Boin & Bynander, 2015; Lanzara, 1983; Petrescu-Prahova & Butts, 2005) connections between organizations within and outside the government.

5.2.1 Institutionalized vs. Emergent Response Collaborations

Given that interorganizational collaboration (or lack thereof) is a critical factor that impacts the success of a crisis response (Boin & Bynander, 2015), governmental guidelines have focused on institutionalizing guidelines that foster "proactive" (Walker, 2006) coordination between federal, state, local, and a limited number of non-governmental and private sector organizations (J. Chen, Chen, Vertinsky, Yumagulova, & Park, 2013). The purpose of institutionalization is so that roles and expectations for response are standardized, along with the specification of which and how organizations should work together to achieve a common set of goals (Boin & Bynander, 2015). Dynes (1970) asserts that institutionalized response collaborations are most effective when the tasks are established (regular tasks & old structure, p.138), meaning that organizations function in crisis situations in the same way as during normal operations. t'Hart, Rosenthal, and Kouzmin (1993) argue that the main advantage with institutionalized structures is the clear hierarchy and unity of com-

mand (p.18), which allows tasks and resources to be delegated effectively and fairly. Boin and Bynander (2015) also discuss the importance of formalized structures that can help to initiate and maintain collaboration. In addition, standardized response plans may provide strategic training and exercises necessary to carry out response plans when a crisis occurs.

Dynes (1970), however, based on their proposed typology of organized behaviors in disasters, finds that institutionalized structures of response may not be effective in crisis situations where tasks are non-routine and not structured similarly to normal operations. Organizations that collaborate and work on these complex tasks are labeled as "emergent" (p.138) organizations, and these connections often arise from informal or personal relationships, combined with existing formal roles. Stallings and Quarantelli (1985) establish that emergency response is an emergent phenomenon, as the nature of crisis is unpredictable and organizations must coordinate on non-regular tasks in a limited time frame. The notion of time is an important factor that gives rise to emergent organizations; two (or more) organizations work on a common task where the perceived needs require "immediate action" (p. 98). Petrescu-Prahova and Butts (2005) also find that individuals and groups who emerged as responders are those nearby the impact area and could immediately provide help. On a related note, Lanzara (1983) shows that emergent collaborations were formed in response to the "[slower] pace of government relief efforts" (p. 74), which is expected of formalized structures with hierarchical constraints. At the same time, Lanzara also finds that an emergent response structure can become disorganized when individuals and organizations arrived to offer help, but did not have the necessary training nor resources to do so (e.g."rescue teams arriving without equipment and event without food for the rescuers themselves").

In summary, prior literature has shown that both institutionalized and emergent collaboration structures have their own affordances and drawbacks, and that their co-existence may result in conflicts between organizations in terms of response jurisdictions and responsibilities (Boin & Bynander, 2015). Recognizing the complex relationship between these two forms of organizing, this study aims to validate the co-existence of institutionalized and

emergent collaboration in response networks of four major U.S. hurricane events, and the types of tensions present in the network structure.

5.2.2 Network analysis of interorganizational collaboration during crisis response

Given the aforementioned complexities of crisis response between organizations that are either institutionalized or emergent groups, a number of research studies have leveraged network analysis as a method to examine the structures of collaborations among agencies (Abbasi et al., 2018; D. P. Aldrich, 2011; Doerfel, Chewning, & Lai, 2013; Kapucu, 2005; Krackhardt & Hanson, 1993). Krackardt and Hanson (1993)'s seminal study on communication patterns in a company reveals that informal advice-giving and friendship relations are equally as important as formal hierarchy in facilitating decision-making and information exchange. Diesner and Carley (2005)'s examination of Enron corporation's communication networks based on email exchanges also reveals that the central players (determined by network-level centrality metrics) in the informal network differ from the formal network. This finding suggests that informal and formal structures reveal that social processes beyond formal roles may also influence information flow in an organization (L. Jiang, Dinh, Rezapour, & Diesner, 2020). In the context of crisis-related networks, Kapucu (2005) constructed a interorganizational network of 41 federal, private, and non-profit agencies that worked together in response to the 9/11 attacks. Using centrality measures and community detection, they identified key players in response coordination (e.g., FEMA, NY mayor, NGOs), as well as organizations that act as "bridges" to connect efforts among other agencies (e.g. FEMA, HHS, DOD). Similar to Kapucu's findings, Aldrich (2011) found social capital to be a notable indicator that speeds up recovery after a crisis (i.e. the Kobe earthquake), where organizations with higher social capital and network connectedness received more financial and logistical support from the government and neighboring organizations. Abbasi and Kapucu (2018) applied network metrics such as density and centralization to examine

collaboration structures among agencies during response to four major Atlantic hurricane events (Charley, Frances, Ivan, Jeanne). They identified the importance of a small group of agencies who has the power to connect agencies together and ensure effective communication flow. Doerfel, Chewning, and Lai's (2013) network analysis of interorganizational relationships during Hurricane Katrina recovery revealed the importance of structural inertia; meaning collaboration is effective when agencies have worked together before. A notable number of studies have also examined the relationship between organizational hierarchy and response network dynamics. Moynihan (2009) as well as Kapucu and Garayev (2016) examined the institutionalized response networks proposed by the ICS system. They found centralized structures of collaborations. These results are consistent with the understanding of institutional structures with a command-and-control structure and a more rigid hierarchy ('t Hart et al., 1993). In contrast, Tierney and Trainor (2004) identified a prominence of decentralization in the September 11 World Trade Center disaster response network, where organizations rapidly adapted to the unforeseen needs and challenges of the crisis. Altogether, these findings show that response networks do not strictly have one organizational structure, but rather a combination of centralized and decentralized configurations (Kapucu & Garayev, 2016) depending on the nature of the response tasks (Dynes, 1970).

Interorganizational networks also vary in their structures based on data sources and methods used to construct the networks and gather information about collaboration response dynamics (Diesner, 2012, 2015a; Sarol et al., 2021). Diesner (2012)'s comparison of metadata-based (keywords and index terms) and text-based networks to determine the key individuals and organizations in Sudan reveals that each data source contains minimal overlap in terms of the key entities detected. Sarol et al. (2021) also finds that situational awareness information about a certain crisis depends on the data source used to extract content. Specifically, the authors examined mainstream news, expert blogs, and social media (i.e. Twitter) surrounding the 2010 Haiti earthquake and found that news data contained the most situational awareness information, whereas blogs and social media contained infor-

mation about needs, donations, and fundraising activities. Furthermore, the authors found that different text mining methods (i.e. topic modeling, text summarization, needs detection) used also influences the type of situational awareness content present in each data source. Diesner (2012) asserted that in addition to the text mining methods used, parameterization of methods used to construct network data from text also influence the network results. Specifically, the author found that conducting reference resolution before relation extraction may be useful to disambiguate entity names, thus increasing the accuracy of nodes in the text-based networks.

As mentioned above, situational awareness information about a crisis event may also depend on the data source(s) used for analysis. Specifically with the advent of social media, information about crisis response has been generated and shared online via platforms such as Twitter (Olteanu et al., 2015; Verma et al., 2011) and Facebook (Birkbak, 2012). Verma and colleagues (2011) examined tweets about four major crisis for the amount of situational awareness information present. They found useful tweets to contain actionable, factual information about the crisis situation with no sentiment-bearing content. Birkbak (2012) showed that public Facebook groups created in response to a Danish blizzard event contained community-generated information about areas of help needed, road conditions, as well as discussions on whether official information about the blizzard is accurate. While social media platforms are effective in terms of providing timely and citizen-based information about a crisis event, the volume (Hiltz & Plotnick, 2013) and trustworthiness (Olteanu et al., 2015; Sarol et al., 2021; Schmierbach & Oeldorf-Hirsch, 2012) of the information can influence the credibility of the source. On the other hand, situational reports (SITREPs, in short) are deemed more credible source of situational awareness information as they are created and validated by organization(s) involved in response (TRACIE, 2021). One drawback of SITREPs is that they are often published on a daily basis, as opposed to social media data, which can be posted continuously. Based on prior literature, this study aims to compare the differences (if any) in the interorganizational network structure based on two primary data

Hurricane Event	Landfall Date	Location	Cat.	Data Sample		Timeframe	
				SITREPs	Twitter	SITREPs	Twitter
Matthew	2016-10-08	McClellanville, South Carolina	4	33	7,623	2016-10-03/ 2016-10-22	2016-09-24/ 2016-10-22
Harvey	2017-08-25	Port Aransas, Texas	4	25	7,955	2017-08-29/ 2017-09-07	2017-08-11/ 2017-09-08
Irma	2017-09-10	Cudjoe Key, Florida	4	30	8,060	2017-09-06/ 2017-09-20	2017-08-27/ 2017-09-24
Michael	2018-10-10	Tyndall Airforce Base, Florida	4	21	4,412	2018-10-11/ 2018-10-19	2018-09-26/ 2018-10-24

Table 5.1: Hurricane events and data samples collected in this study

sources, SITREPs and social media (Twitter). On top of that, we also examine the impact of different relation extraction methods on the resulting network analysis, specifically with respect to the interorganizational collaboration structures present in each method separately, and in combination.

5.3 Data collection

For this study, we focus on four primary hurricane events: 2016 Hurricane Matthew, 2017 Hurricane Harvey, 2017 Hurricane Irma, and 2018 Hurricane Michael. We choose these events because they were all major hurricanes that made landfall in the continental United States and received considerable attention from governmental, non-governmental, and media entities.

5.3.1 Observed Networks

5.3.1.1 Situational Reports (SITREPs)

These documents are means of distributing information about the context of the current situation, including the response actions that are currently taking place, and areas of need to different stakeholders to ensure response actions can be completed (Sarol et al., 2021).

SITREPs are meant to provide an objective or unbiased perspective of emergency responders and associated stakeholders, and can either be distributed internally within an organization or externally across organizations. For the purpose of this study, we collected SITREPs that were distributed externally via the organization's web page with Terms of Use that allow for non-commercial and research-oriented use of the content. Additionally, a SITREP was included into the sample only if it solely focused on a particular hurricane's response efforts and if it was published two weeks before or after a hurricane's landfall date. Our rationale for the timeframe was to ensure all activities related to hurricane preparedness, response, recovery, and mitigation (Alexander, 2002) were captured. The SITREPs contained language of emergency response professionals and situational awareness content that they gathered. Hence, the comparisons between the observed networks based on SITREPs and the perceived networks would provide information on the expected collaboration patterns that were put into practice.

For Hurricane Matthew, we collected 33 SITREPS from four primary sources, namely the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA, n=14), Pan American Health Organization (PAHO, n=17), South Carolina Emergency Management Division (SCEMD, n=1), and National Oceanic and Atmospheric Administration (NOAA, n=1). Documents from UNOCHA and PAHO provided daily situational updates from March 3 to March 22, 2016. Documents from SCEMD and NOAA are after-action reports that contain timeline of events as well as reflections on the successes and areas of improvements for future response.

For Hurricane Harvey, we gathered 25 SITREPs from four sources, namely the Department of Energy (DOE, n=22), Texas Division of Emergency Management (TDEM, n=1), FEMA (n=1), and Humanity Road (n=1). Hurricane Harvey's impacts received national attention and thus SITREPs were produced by organizations at the federal level (DOE, FEMA) and state levels (TDEM) as well as by non-governmental organizations such as the Humanity Road.

For Hurricane Irma, there were 30 SITREPs distributed by the DOE (n=16), UNOCHA (n=8), United Nations Children's Fund (UNICEF, n=3), and PAHO (n=3) that we could find for our sample. Similar to Hurricane Matthew, this particular event also received close attention from non-governmental organizations, suggesting the involvement of organizations that may not be included in governmental response plan.

For Hurricane Michael, we collected SITREPs from three sources, namely the DOE (n=17), Humanity Road (n=3), and FEMA (n=1). FEMA's document is an after-action report with a specific focus on assessment of damages, along with technical guidance to the state of Florida on how to maintain infrastructure resilience for future responses.

5.3.1.2 Tweets

Social media data from sources such as Twitter (Castillo, Mendoza, & Poblete, 2011; Olteanu et al., 2015; Verma et al., 2011) have shown to be useful for situational awareness assessment as they contain actionable information for responders in-real-time. For this study, we collected tweets from the Crimson Hexagon [1] platform, which provides samples from the Twitter firehose. Our inclusion criteria were tweets that contain either "Hurricane [event name]" or "Tropical Storm [event name]", and posted within the date range of two weeks before to two weeks after the hurricane landfall date. Additionally, the tweets' language was limited to English, and the location metadata is limited to continental U.S.. These two inclusion criteria allow us to capture content about collaboration activities that took place only within the U.S. and that were in direct response to the hurricane that made landfall within the U.S.. This distinction is particularly important because the same hurricane name could refer to the same hurricane that made landfall outside of the U.S. (e.g. Hurricane Matthew made landfall in Haiti first before it made landfall in the U.S.). As shown in Table 5.1, we collected a total of 28,050 tweets across four hurricane events. We removed all URLs (i.e. tokens starting with 'http://', 'https://', and 'www.') as well as specific user mentions

[1] https://forsight.crimsonhexagon.com/ch/

Figure 5.1: NER and RE Pipeline

(e.g. @user) from the tweets.

5.4 Methods

5.4.1 Prescribed networks

5.4.1.1 Federal-level

As outlined in FEMA's National Response Framework (NRF), there are 38 official federal agencies potentially expected to collaborate during a crisis response. In particular, the NRF categorizes each federal agency's responsibilities into at least one of 15 Emergency Support Functions [ESF, (FEMA, 2018)]. All agencies are assigned to at least one ESF, with the role of either (1) coordinating agency, (2) primary agency, or (3) supporting agency. There are a number of cases where an agency serves in all three roles within an ESF. For instance, DHS/FEMA is assigned to be primary agency, coordinating agency, and supporting agency at the same time for ESF 2 (Mass Care, Emergency Assistance, Housing, and Human Services). To prepare for network construction, we collected all policy plan on ESF from the NRF, and identified all agencies involved across the 15 ESFs. Based on the formal structure of the ESF, we constructed a one-mode matrix between agencies, where an edge between two agencies represents the fact that both agencies are members of the same group in an ESF. For instance, there is a link between USDA/FS and DHS because they are both supporting

organizations within ESF 3 (Public Works and Engineering).

5.4.1.2 State-level

According to the United States Government Accountability Office (GAO)'s statement on Hurricanes Katrina and Rita responses (Walker, 2006), the federal-level response structure works under the assumption of a "proactive national response" (p.4), and does not contain "detailed plans" that would specify clear operational plans for state- and local-level jurisdictions. Thus, it is expected that state- and local-level authorities develop their own response plans (Kapucu, 2009) as well as the necessary training exercises to ensure coordinated response. In line with this statement, we construct state-level response network for each hurricane event based on the emergency operations plan created by the state where the hurricane made landfall. The state-level response network represents the actual operations that are expected to take place when a disaster event such as hurricane occurs, and the plans used are listed in 5.2.

Hurricane Event	State	Response Plan Name
Matthew	South Carolina	South Carolina Emergency Operations Plan (SCEOP)
Harvey	Texas	Texas Division of Emergency Management Plan (TEDM)
Irma	Florida	State of Florida Comprehensive Emergency Management Plan (FCEMP)
Michael	Florida	State of Florida Comprehensive Emergency Management Plan (FCEMP)

Table 5.2: State response plans used to construct state-level prescribed networks

5.4.1.3 Local-level

Consistent with the GAO's statement, local-level officials are expected to develop detailed implementation plans in compliance with the state-level and federal ESF structure. Thus, the local-level response plans contain specific delegation of responsibilities and resources to be mobilized by the agencies involved in response. Table 5.3 lists each response plan

that correspond to the county where each hurricane made landfall. The assumption is that the local government where a hurricane made landfall would be the first line of emergency response (Reinhardt & Drennan, 2019), and may seek state and federal assistance if needed.

Hurricane Event	County	Response Plan Name
Matthew	Charleston	Charleston County Government 2016 Emergency Operations Plan
Harvey	Aransas	Emergency Management Plan for Aransas County, City of Rockport, Town of Fulton
Irma	Monroe	Monroe County Emergency Management Plan (CEMP)
Michael	Bay	Bay County, Florida Comprehensive Emergency Management Plan

Table 5.3: Local response plans used to construct local-level prescribed networks

5.4.2 Observed network of interactions

The overall purpose of collecting and constructing observed networks of interactions from situational reports is to obtain an objective (with respect to the source) perspective of response from emergency responders. These responders primarily include people on-the-ground and high-ranking military officers. The situational reports were written by emergency response professionals and contain situational awareness content that was gathered on-site. Hence, the comparison between the prescribed networks and the interaction constructed from the situational reports allows us to determine which response efforts that actually took place were aligned with the mandated response guidelines.

Text-based network construction involves two tasks: (1) named entity detection (NER) of social entities that are mentioned in unstructured text, and (2) relation extraction (RE) between pairs of social entities mentioned in texts (Bhattacharya & Getoor, 2007; Bunescu & Mooney, 2005; Diesner & Carley, 2010a, 2011; Sarawagi, 2008). For this project, we define named social entities as individuals (tag: PER) and collectives such as organizations (tag: ORG), geopolitical entities (GPE), nationalities or religious or political groups (NORP), or locations where individuals/groups are present (tag: LOC). Our decision to select these entities is so that we can capture meaningful coordination dynamics between stakeholders

involved in response, as well as being able to justifiably compare the observed networks to the prescribed networks, which comprise of only social entities.

5.4.2.1 Named entity recognition (NER)

We used two open-source tools, namely FlairNLP (Akbik et al., 2019) and SpaCy (Honnibal & Montani, 2017), to detect and label the social entities of interest to us. the models in both tools we use are trained based on the OntoNotes 5.0 corpus[2] with 18 entity types tagged, 5 of which are relevant to our definition of social relation. These 5 types are PER, ORG, GPE, NORP, LOC. The corpus contains a number of text genres that come from professional sources such as broadcast news and newswires from the Wall Street Journal, in which the professional language use may mirror that of SITREPs. Furthermore, text data from weblogs and telephone conversations may contain informal language that's likely to be present in social media tweets (Imran, Mitra, & Castillo, 2016).

We evaluate the performance of Flair and SpaCy NER when applied to our data in terms of precision, recall, and F1. The ground truth consists of hand-annotated data based on a random sample of SITREPs and tweets from our collected data. The SITREPs sample consists of: 1 full SITREP (authored by South Carolina EMD) from hurricane Matthew response, one-third of full SITREP (authored by DOE) from hurricane Harvey, one-third of full SITREP (authored by UNICEF) from hurricane Irma, and one-third of full SITREP (authored by DOE) from hurricane Michael. The rationale for this sampling technique is that the annotated document would contain the response language that is representative across the different hurricane events. We trained two coders based on an annotation scheme (in section 5.7.0.1) that described the types of entities to be coded, examples for each entity type, and the possible relations between each entity pair. Each coder coded every sentence in the document based on entity 1 (if any), entity 2 (if any), entity 1 type, entity 2 type, and relation between them (relation or no relation). A pair of entities is coded as having a

[2] https://catalog.ldc.upenn.edu/LDC2013T19

relation when there is a noun (or noun phrase), verb (or verb phrase) connecting them. After an iteration of coding, discussion of disagreements, and recoding of 50 randomly-sampled sentences, two coders ranged an interrater agreement of 89.8%. Agreement is based on the amount of relations coded with the same entity pairs and entity types labeled. Our tweets sample contains 1000 randomly sampled tweets equally divided across the four hurricane events (250 tweets each). Similar to the task above, the annotation involves coding every tweet sentence with the entity 1 (if any), entity 2 (if any), entity 1 type, entity 2 type, and relation (relation or no relation). Three coders are assessed for pairwise interrater agreement based on 50 randomly-sampled tweets, and achieved an average of 86.95% agreement (89.9% agreement between coder 1 and 2; 92% agreement between coder 1 and 3). Agreement is also based on how many relations are identified with the same entities and entity types.

The overall performance of each NER method is shown in Table 5.4. Performance (F1 measure) is calculated based on whether two entities have a perfect match in entity name, boundary, and entity type. We only consider exact boundary matches as a match (i.e. all words in common), any partial match (one word or more in common) is not considered a match. Overall, NER performance is highest when using an intersection of both Flair and SpaCy for the SITREPs data (F1=0.8045). On the tweets data, performance is the highest when using only SpaCy (F1=0.6440). Thus, for SITREPs data, we will use intersection of entities detected in both Flair and Spacy. For tweets data, we will use entities detected in SpaCy only.

5.4.2.2 Relation extraction

After conducting NER, we established an edge between pairs of entities based on a combination of features: (1) entity co-occurrence, (2) shallow, and (3) deep syntax structures based on constituency trees and dependency trees, respectively. Our rationale for using multiple mechanisms for relation extraction is to increase the accuracy of relation extraction results on unlabeled label with respect to both precision and recall. We identify the

Model	SITREPs			Tweets		
	Precision	Recall	F1	Precision	Recall	F1
Flair (OntoNotes)	0.8402	0.7179	0.7742	0.8380	0.3371	0.4807
SpaCy (OntoNotes)	0.7718	**0.7988**	0.6779	0.7300	**0.5760**	**0.6440**
Flair + SpaCy	**0.9085**	0.7219	**0.8045**	**0.8951**	0.3936	0.5468
Flair or SpaCy	0.7770	0.5701	0.6577	0.7508	0.4444	0.5584

Table 5.4: Performance of NER methods

optimal parameter settings these three approaches by examining the most frequent window sizes for co-occurring entities, and most frequent constituency and dependency patterns in the identified relations and non-relations in the ground truth dataset (described in section above). The comparison between relations and non-relations allow us to determine patterns that distinguish entity pairs that are actually related based on a response-related activity from pairs that do not contain such information.

The resulting observed networks thus are based on a combination of the three types of relationships in the underlying text data (settings discussed in section 5.4.2.3):

(1) Co-occurrence based relations: Within this relationship construction method, two entities get connected if they are both mentioned within a user-defined, length-based window of words in a sentence. Window size is determined by the number of words between two entities, not including the entities themselves. The assumption with this approach is that two entities are likely to have a semantic relationship with each other because they are mentioned together within a sentence. This approach is widely used for extracting relational information from semi- and un-structured text data (K. Carley, 1993; K. M. Carley, 1997; Danowski, 1993), but is also prone to high error rates, especially due to high recall rates, i.e., picking up false positives (Diesner, 2015b; Diesner & Carley, 2010a). Specifically in the context of crisis response plans, prior studies that examined communication patterns

during crises (Nerghes & Lee, 2018; Park, Kim, & Rim, 2020) found that entities are often co-mentioned together if there is shared meaning between them. These studies, however, only considered co-occurrence with respect to whether two entities are mentioned together within the same sentence. The large context window may influence the accuracy of the relations extracted as it may capture more noise (Rohde, Gonnerman, & Plaut, 2006), and thus smaller window sizes are preferred especially with larger text corpora (Bullinaria & Levy, 2012; Rohde et al., 2006) (examples of relations extracted for small window sizes are shown in Figure 5.2. To determine the appropriate window sizes for our analysis, we analyze the co-occurrence window sizes present in our ground truth data, and select the top three windows as features for learning. Table 5.5 shows the top window sizes found in the ground truth data, where the windows of 1,2,3 are most frequent in the SITREP-based ground truth, and windows of 1,3,4 are most frequent in tweet-based ground truth.

Figure 5.2: Example of two sentences with co-occurrence relations identified in tweets about hurricane Michael and Matthew, respectively

	Number of relations with window size in ground truth of:	
Window size	SITREPs	Tweets
0	10 (1.414%)	1 (0.124%)
1	**134 (18.953%)**	**127 (15.796%)**
2	**102 (15.134%)**	93 (11.567%)
3	**97 (13.72%)**	**126 (15.7%)**
4	85 (12.022%)	**113 (14.054%)**
5	71 (10.042%)	102 (12.687%)
6	57 (8.062%)	78 (9.701%)
7	55 (7.779%)	68 (8.458%)
8	48 (6.789%)	55 (6.841%)
9	43 6.082%)	41 (5.099%)

Table 5.5: Top cooccurrence-based window sizes of relations present SITREP-based and tweet-based ground truth data

(2) Constituency-based relations: This relationship type establishes a connection between two entities based on the parts-of-speech patterns of the words in between the entities. This approach divides the sentences into smaller syntactic components, specifically information about part-of-speech patterns in between any two entities (which are nouns or pronouns) (M. Jiang & Diesner, 2019). An example of constituency parsing is shown in Figure 5.3. We determine the top three constituency patterns present in the SITREP-based and tweet-based ground truth data by (1) extracting the top 30 patterns found between two entities in a relation, and (2) determine top three recurring patterns present. We initially started with the top 50 patterns with ten patterns identified, then narrowed those down to top 30 patterns with top three patterns that are representative of the prominent patterns in the dataset. Table 5.6 shows the top three part-of-speech patterns between two entities in the ground truth data.

Figure 5.3: Example of a constituency tree parsed from a sentence in ground truth SITREPs data

Constituency pattern	# of relations in **SITREPs** ground truth	Constituency pattern	# of relations in **tweets** ground truth
1-8 PROPNs	29.8%	1-3 PROPNs	34.415%
CCONJ	3.9%	VERB-ADP	12.553%
ADP	1.6%	NOUN-ADP	6.488%

Table 5.6: Top three part-of-speech patterns identified between two entities in SITREP-based and tweet-based ground truth

(3) Dependency-based relations: Similar to constituency-based relations, dependency-based relation extraction leverages the syntactic structure of a sentence to establish a relation between entity pairs. While constituency parsing focuses on the syntactic ordering of words and phrases (i.e. constituents), it does not provide information on how words/phrases are related to each other to express a certain meaning. Dependency parsing, on the other hand, extracts the relationships between pairs of words/phrases in a sentence and how they are connected with respect to various syntactic dependencies such as predicate-argument relations (e.g. "who did what to whom") (Bunescu & Mooney, 2005; Gerner, Schrodt, Francisco, &

Figure 5.4: Example of two dependency trees parsed from sentences in hurricane Harvey and Matthew SITREPs

Weddle, 1994; Ivanova, Oepen, Øvrelid, & Flickinger, 2012; Schrodt & Gerner, 1994). Given that a dependency path between two entities is not constrained to their respective word positions within a sentence, we can connect two entities based on the shortest dependency path between them. Bunescu and Mooney (2005) found that two entities are most likely to be meaningfully related to each other if there is a shortest path between them in a dependency tree. The rationale is that if two entities belong to the same predicate-argument structure where they are connected to the same predicate, then there must be a shortest path between them. For instance, with the sentence "*DOE supported TDEM in efforts*" (shown in Figure 5.4), the shortest path between two entities *DOE* and *TDEM* passes through the predicate *supported* (verb). The authors demonstrated the reliability of the shortest path hypothesis to detect *located (at)* relation type between two entities. Latter studies (Fundel, Küffner, & Zimmer, 2007; Xu et al., 2015) have also found that shortest dependency paths are efficient for extracting meaningful relations in terms of reducing noise from other mentioned entities that are not directly related to the entity pair. Stemming from prior literature, we utilize the shortest dependency path to establish a relation between two entities. Example of a dependency parse tree is shown in Figure 5.4.

	Number of relations with window size in ground truth of:	
Window size	SITREPs	Tweets
0	62 (8.769%)	4 (0.498%)
1	**170 (24.045%)**	67 (8.333%)
2	70 (9.9%)	99 (12.313%)
3	**86 (12.164%)**	**145 (18%))**
4	**72 (10.183%)**	**158 (19.652%)**
5	62 (8.769%)	**104 (12.935%)**
6	47 (6.648%)	69 (8.582%)
7	46 (6.506%)	34 (4.229%)
8	32 (4.526%)	26 (3.234%)
9	23 (3.253%)	3 (0.373%)

Table 5.7: Top dependency-based window sizes of relations present SITREP-based and tweet-based ground truth data

Dependency pattern	# of relations in **SITREPs** ground truth	Dependency pattern	# of relations in **tweets** ground truth
2-16 PROPNs	48.949%	VERB-ADP	22.003%
VERB-ADP-PROPN	3.704%	2-4 PROPNs	14.81%
VERB-NOUN	1.401%	NOUN-ADP	6.347%

Table 5.8: Top three dependency patterns identified between two entities in SITREP-based and tweet-based ground truth

5.4.2.3 Feature selection and machine learning

Based on the analyses presented above, we derive eight unique rules each for SITREPs and tweets based on word co-occurrence distance (one rule), dependency-based distance (one rule), constituency patterns (three rules), and dependency patterns (three rules). We then propose a majority decision rule in which a relation between two entities exists if it meets five rules or more out of eight possible rules. As shown in Figure 5.5, however, the

(a) Number of correctly-identified relations

(b) Number of incorrectly-identified relations

(c) Number of correctly-identified relations

(d) Number of incorrectly-identified relations

Figure 5.5: Distribution of correctly-identified and incorrectly-identified relations based on SITREPs (a and b) and tweets (c and d) ground truth data

majority rule is not feasible as most correctly-identified relations only meet one to two rules. Alternatively, we leverage Support Vector Machine (SVM) and Random Forest (RF) classification algorithms through Python Scikit-learn package (Pedregosa et al., 2011). We use a 80%-20% split for training (n=1033) and testing (n=259) with the ground truth data, and 10-fold cross-validation to evaluate the performance of each algorithm. The performance metrics with respect to precision, recall, and F-1 measure is shown in Table 5.9. Based on the results, we choose to use SVM classifier to identify relations in the unseen SITREPs and tweet datasets.

	SITREPs		Tweets	
	SVM	RF	SVM	RF
Precision	0.928	0.927	0.928	0.928
Recall	0.913	0.908	0.820	0.816
F-1	**0.920**	0.917	**0.870**	0.868

Table 5.9: Classification results of predicting relations with SVM and RF for SITREP-based and tweet-based ground truth data

In summary, we constructed eight networks that consist of entities and relations extracted from each data source (SITREPs or tweets), for each hurricane event. The networks are undirected and weighted, in which weight represents the number of times a relation is found between the same two entities. Before network construction, we preprocess the edgelist data by removing special characters, non-ASCII characters, and URLs. We also detect abbreviated words in the dataset (list of abbreviations and their full names created from documents used to construct prescribed networks) and convert them to non-abbreviated version. For example, abbreviation "FDEM" is renamed as "Florida Division of Emergency Management".

5.4.2.4 Network analysis

We analyze each network, i.e., entities and relations extracted from text data, with network level measures, namely degree centralization, density, global clustering, average path length, community detection using Clauset-Newman-Moore (CNM) greedy modularity maximization (Clauset, Newman, & Moore, 2004), and number of components. These measures provide higher-level information about the relative connectedness between (groups of) nodes and edges. The networks in this study are all defined and analyzed as multigraphs (multiple edges between the same sets of nodes are permitted), given the original prescribed and observed interaction data contains repeated interactions between the same node pairs.

An example of a multigraph edge in our prescribed interaction data with South Carolina State-level documentation, *South Carolina Emergency Management Division-South Carolina National Guard* edge is repeated twice as they are both expected to collaborate within ESF-5 (Emergency Management) and ESF-15 (Public Information).

We also examine topological characteristics of the networks with respect to its goodness-of-fit to either the small-world or power-law properties. Topological analysis reveals underlying patterns that may explain how nodes and edges organize themselves in ways that are above and beyond random chance. Extant literature has found that real-world social networks often follow a small-world topology (high clustering, low average path length) (Watts & Strogatz, 1998), or power-law degree distribution (Barabási & Albert, 1999) (although there is recent empirical evidence that this topological feature is not as common in real-world networks, see Broido and Clauset (2019). The small-world topology is based on the social assumption that an individual has many local connections and a few distant connections (Milgram, 1963). Consequently, a few distant connections from each individual provide *shortcuts* within the network that lowers the average distance between any two individuals. Alternatively, power-law degree distribution is an outcome of the preferential attachment process (Barabási & Albert, 1999), whereby individuals who are well-connected continue to make more connections than those who have less connections. Thus, a network with power-law degree distribution has a hubs-and-spokes structure, with a few hubs containing most of the connections.

To test whether the actual networks follow a small-world topology, we compute the small-world coefficient ($\omega = Lr/L - C/Cl$) where C is the clustering coefficient and L is the average path length of the actual network, Lr is the average path length of the simulated random graph and Cl is the clustering coefficient of the simulated lattice graph [parameter settings: ten iterations for rewiring per edge (niter=10) and ten random graphs generated to compute simulated statistics (nrand=10)]. The resulting ω statistic ranges from $-\infty$ to positive ∞ depending on the network size, where ω close to zero reflects a small-world topology, where

$L \approx Lr$ and $C \approx Cl$. A positive ω reflects a random topology, while a negative ω reflects a lattice topology.

We also examine the networks' degree distribution to assess whether the networks follow a power-law topology. A network with this typology often has a hubs-and-spokes structure, where there is small subset of nodes with many connections, and a larger proportion of nodes with few connections (Barabási & Albert, 1999). For each network, we generate an optimal (α) value of power-law fit for a given degree distribution. The resulting (α) value is 1 and above, and the value range between 2 and 3 indicates that the power-law distribution is a good fit (Newman, 2005).

Each network is also examined with respect to its hierarchical (or lack thereof) structure using Krackhardt's four graph-theoretic dimensions (Krackhardt, 1994). The first dimension, Hierarchy, ranges from 0 to 1, where a value of 1 indicates complete hierarchy where there is no reciprocated edges present between nodes. The second dimension, Connectedness, ranges from 0 to 1, where a value of 1 indicates that all nodes can reach any other node, hence completely connected. The third dimension, Efficiency, ranges from 0 to 1, where a value of 1 indicates a pure out-tree structure where each node has one and only one distinct path to another node. The fourth dimension, Least Upper Boundedness (LUB), ranges from 0 to 1, where a value of 1 indicates perfect unity-of-command where all node pairs have at least one shared node that they received connection from (i.e. an upper bound). Altogether, these four dimensions assess the extent to which the network has an out-tree structure, resembling a typical hierarchy in an organization (Krackhardt, 1994).

5.4.3 Experimental design

		IV2: Data Source	
		SITREPs	Twitter
IV1: Response Jurisdiction	Federal	Federal + SITREPs	Federal + Twitter
	State	State + SITREPs	State + Twitter
	Local	Local + SITREPs	Local + Twitter
DV: Network Overlap in prescribed and observed response networks (node-level, edge-level, network-level)			

Table 5.10: 3X2 factorial design for this study

As shown in Table 5.10, we follow a 3x2 factorial design to investigate the effects of data sources and governmental response jurisdiction on the amount of network overlap between the observed and prescribed networks. The first independent variable is the response jurisdiction of the prescribed networks, which contains three levels corresponding to three levels of the government (federal, state, local). The second independent variable is the data source used to construct the observed networks, which contains two levels corresponding to two sources used (SITREPs & tweets). The primary dependent variable is the amount of network overlap between the prescribed and the observed networks, which are assessed at three levels of analysis: (1) node-level, (2) edge-level, and (3) network-level. Node- and edge-levels of network overlap are categorized as comparisons made at the local scale (Tantardini, Ieva, Tajoli, & Piccardi, 2019), while network-level overlap refers to comparisons to be made at the global scale (Tantardini et al., 2019; Wasserman & Faust, 1994). Extant literature in complex social networks have established methods for comparing networks at multiple levels of the network, namely the local and global scales (M. S. Granovetter, 1977; Kossinets & Watts, 2006; Robins, Pattison, & Woolcock, 2005; Tantardini et al., 2019). Given that global properties can be explained by the local-level processes that occur at the node and edge levels (Robins et al., 2004), it is important to examine how two networks are structurally similar (or different) at these levels.

At the local level, existing methods have focused on comparing node overlap (whether two networks contain the same set of nodes) (Tantardini et al., 2019), and edge overlap (whether two networks contain the same edge between two same nodes) (Papadimitriou, Dasdan, & Garcia-Molina, 2010). To compute the node overlap for every two networks (G_1,G_2), we determine the node set N that is found in both G_1 and G_2. The process of creating N involves fuzzy matching every node pair i, j where i is in G_1 and j is in G_2 (using FuzzyWuzzy[3] Python module), determining if i, j matches with 88% similarity and above, then choosing one un-abbreviated and correctly-spelled node label (e.g. {USCG; Coast Guard}=U.S. Coast Guard) representing i, j that would go into N. Then, the amount of node overlap is measured using pairwise Jaccard index (Szell, Lambiotte, & Thurner, 2010-08-03), a well-known distance-based similarity measure that calculates the portion of shared nodes between two networks (G_1 and G_2) relative to the total number of nodes in both networks. The formula for Jaccard similarity index for node overlap between G_1 and G_2, is:

$$JacNodeSim(G_1, G_2) = \frac{N_{G1G2}}{N_{G1} + N_{G2} - N_{G1G2}}, \tag{5.1}$$

where N_{G1G2} is the intersection of nodes that appear in both G_1 and G_2; N_{G1} is the number of nodes in G_1; and N_{G2} is the number of nodes in G_2.

To compute the edge overlap for any two networks G_1,G_2, we also use the Jaccard index (Szell et al., 2010-08-03) to find the similarity between the adjacency matrices of G_1 and G_2. Jaccard similarity has often been used to measure overlap at both the node- and edge-levels (Coscia, Rossetti, Giannotti, & Pedreschi, 2014; S. Liu et al., 2018; Narayanan & Shmatikov, 2009), where the Jaccard index for edge overlap represents the amount of edges overlapped in two networks divided by the union of edges in two networks. The formula for Jaccard similarity index for G_1 and G_2 in terms of edge overlap is:

[3] https://pypi.org/project/fuzzywuzzy/

$$JacEdgeSim(G_1, G_2) = \frac{E_{G1G2}}{E_{G1} + E_{G2} - E_{G1G2}}, \tag{5.2}$$

where E_{G1G2} is the intersection of edges that appear in both G_1 and G_2; E_{G1} is the number of edges in G_1; and E_{G2} is the number of edges in G_2. Computation of Jaccard index for edge overlap requires that the two networks must have some overlapping nodes (Tantardini et al., 2019), and thus the prerequisite for this calculation is that the number of node overlap must not be zero.

Global-level comparisons are different from local-level comparison methods in that they do not require any two networks to have a shared number of nodes and edges, otherwise known as node-correspondence (Tantardini et al., 2019). Global-level comparisons focus on the structural properties of the networks, specifically with respect to topological features (Szell et al., 2010-08-03), degree distributions (Broido & Clauset, 2019; Clauset et al., 2004), and network statistics such as clustering coefficient (Yang & Counts, 2010), average path length (Myers, Sharma, Gupta, & Lin, 2014), and centralization (Y. Kim, Choi, Yan, & Dooley, 2011). While global-level network comparisons are useful to see if two networks share similar patterns of connectivity and community structures as a whole (Donnat & Holmes, 2018), comparing only network statistics may not be sufficient to establish structural similarities between two networks (Pržulj, 2007; Tantardini et al., 2019). To address this shortcoming, we compare networks based on four network statistics (degree centralization, density, global clustering, average path length), two measures of community structure (Clauset-Newman-Moore community detection, number of components), along with two measures of topology (small-worldiness ω and power-law exponent α). Details about these measures are outlined in the *Network Analysis* section above. The comparisons will be conducted using Kendall's Tau-b (τ_b) non-parametric measure of correlation between two networks. The calculation of (τ_b) is based on identifying the number of concordant pairs (ordered in same way) and discordant pairs (ordered differently) of structural features in G_1

and G_2. The formula is:

$$\tau_b(G_1, G_2) = \frac{C - D}{\sqrt{(C + D + G_{1_0})(C + D + G_{2_0})}}, \tag{5.3}$$

where C is the number of concordant pairs, D is the number of discordant pairs, G_{1_0} is the number of pairs within G_1 only, and G_{2_0} is the number of pairs within G_2 only. The resulting τ_b coefficient ranges between -1 to 1, where -1 indicates a perfect negative correlation where two networks have all discordant pairs, and 1 indicates a perfect positive correlation where two networks have all concordant pairs. This method of paired comparison allow us to examine the rank-based similarity between every pair of network feature without a requirement for a normal distribution of values (Simon, 1977). Consistent with Tantardini et al. (2019)'s definition of global-level network comparison, we compare the networks based on their structural features, regardless of whether the nodes and/or edges match.

With a 3x2 design, there are six conditions based on the two independent variables (corresponding to six cells in 5.10). The main effects are captured at the column and row levels: the column main effect, obtained by column means averaged across three rows, would capture if the level of response jurisdiction of the prescribed network [IV1] has an association to the amount of network overlap [DV]; the row main effect, obtained by row means averaged across two columns (SITREPs & tweets) would capture if the data source of the observed network [IV2] is associated with the amount of network overlap [DV]. Additionally, the interaction effects between the two independent variables can also be captured if the main effect plot lines intersect. On the other hand, parallel lines indicate there is no interaction effect. A two-way analysis of variance (ANOVA) is conducted to compute the main effects and interaction effects across the two IVs and one DV. The statistically procedure is carried out only if the data meets the assumptions of independence, normality, and equality of variance. A non-parametric equivalent of an ANOVA will be used, namely the Scheirer-Ray-Hare test (Scheirer, Ray, & Hare, 1976), if the data does not meet either of the three

assumptions above. As a non-parametric method, Scheirer-Ray-Hare test focuses on the differences in ranks of all observations across both IVs, as opposed to the observations themselves. The rank-based method allows fair comparisons in a factorial design where the distributions of the data are not normally distributed.

5.5 Results

5.5.1 Prescribed networks

	Federal	State			Local			
		South Carolina	Texas	Florida	Charleston County	Aransas County	Monroe County	Bay County
# of Nodes	38	86	38	132	139	27	43	58
# of Edges	1,194	1,367	673	2,433	187	229	207	215
Deg. Centralization	62.84	31.79	35.42	35.35	2.691	16.96	9.628	7.414
Density (δ)	1.698	0.374	0.957	0.281	0.20	0.652	0.229	0.13
Global Clustering (C)	0.918	0.841	0.975	0.90	0.029	0.891	0.818	0.89
Average Path Length (L)	1.151	1.762	1.043	1.904	3.878	1.348	1.936	2.57
# of Communities (CNM)	34	5	1	4	11	3	4	6
# of Components	1	1	1	1	1	1	1	3
Size of Largest Component	1,194	1,367	673	2,433	187	229	207	191
Small-Worldliness (ω)	-0.008	-0.253	0.00	-0.715	0.768	-0.025	-0.218	-0.658
Power-law Exponent (α)	9.703	2.465	76.60	4.205	2.985	8.829	2.623	9.158
Krackhardt GTD								
• Hierarchy	0.001	0.755	1.00	0.804	1.00	1.00	1.00	1.00
• Connectedness	0.903	1.00	1.00	1.00	1.00	1.00	1.00	0.697
• Efficiency	0.159	0.71	0.05	0.775	0.995	0.375	0.833	0.854
• LUB	1.00	0.916	0.996	0.987	0.393	1.00	0.923	0.78

Table 5.11: Network descriptives for prescribed networks at federal, state, and local levels (removed self-loops and isolates)

5.5.1.1 Federal level

Table 5.11 provides the structural characteristics of the federal-based collaboration network. Consistent with the National Response Framework, the 38 nodes represent the 38 organizations mentioned are connected with 1,194 edges between them. Measures of density (δ=0.903) and degree centralization ($\approx$33.4) show that the network is densely connected,

with each organization connected to approximately 33 other organizations within the ESF hierarchy. The network also exhibits a small-world topology with high global clustering (C=0.918) and low average path length (L=1.151), and a small-world coefficient (ω) of -0.008 (index ranges between -1 and 1, where value close to 0 indicates small-world characteristic). Consequently, the network's degree distribution does not follow a power-law distribution (α=9.703), suggesting that coordination is not led by subsets of dominant organizations, but rather more evenly distributed across subsets.

Overall, topological and descriptive characteristics of the network are consistent with the goals of the federal-based collaboration network, where organizations from across different support functions are expected to coordinate resources and personnel during crises. Furthermore, the prescribed network is not as hierarchical as expected in a federally-prescribed plan (hierarchy=0.001), but rather highly connected (connectedness=0.903) but with some level of redundancy (efficiency=0.159). Least-upper boundedness (LUB) of 1 signifies that the federal network has a strong unity of command, where every two organizations are connected to a common third organization. High LUB along with high connectedness may suggest that most organizations have several opportunities to direct and lead other organizations across different support functions.

5.5.1.2 State level

While there is a unified plan for response at the federal level, there is not a common structure expected for response at the state level. As shown in Table 5.11, collaboration networks across states are unique in terms of network size, representing different coordination dynamics between different sets of stakeholders. Specifically, the state of Florida has the highest number of nodes and edges, indicating the involvement of more organizations compared to Texas and South Carolina. In fact, Florida's response network includes not only state departments but also a number of nongovernmental and professional associations such as Volunteer Florida, Florida Municipal Electric Association, and Florida Interfaith Network-

ing in Disaster. However, the low density (δ=0.281) signals that organizations are not tightly connected compared to organizations within the Texas response network, but modular in structure with four communities detected. The largest community contains 61 organizations, with most departments being the state-level organizations that follow the ESF structure (e.g. Florida Division of Emergency Management Florida Department of Environmental Protection, Florida National Guard). The smallest community contains 14 organizations that are mainly focused on small businesses and financing associations (e.g. Florida Small Business Development Centers Network, Florida Retail Federation, Florida Housing Finance Corporation).

South Carolina's response network has higher structural similarity to the Florida's network than Texas' network. This network's density is also low (δ=0.374), along with a modular structure containing five distinct communities. The largest community contains 34 organizations, which are primarily state departments (e.g. South Carolina Department of Administration) and a small subset of Clemson University's departments that are active in public service programs and environmental regulations (e.g. Clemson University Department of Pesticide Regulation). The active involvement of Clemson University as a major land-grant institution and a host to the state's regulatory services is an example of partnerships between research institutions and governmental organizations (Richards, Novak, & Davis, 2009). The smallest community contains two organizations under ESF-12 (Energy), which are responsible for monitoring and restoring energy systems during a crisis.

Texas's response network is distinctive from other states' networks, specifically with respect to network size, density, and topological characteristics. Average density (δ=0.957) and global clustering (C=0.975) are the highest among all networks, indicating that organizations are expected to connect with almost all other organizations. High clustering also suggests a small-world effect (ω=0.00), along with the lowest average path length compared to other networks (L=1.043). This topological characteristic indicates that the entities that a node is connected with have connections to each other as well, signifying dense but po-

tentially redundant edges. This feature is reflected in the Krackhardt's GTD dimensions where this network's efficiency value is almost zero (efficiency=0.05). In comparison to other states' response networks, Texas's response network involves almost all organizations working together, which may be necessary given the fewer number of entities involved in Texas state's ESF functions.

There is a common expectation that state governments organize their response collaboration efforts under the federal ESF structure (Kapucu, 2009). Our graph-theoretic analyses, however, reveal that state-level response networks are different from the federal network, especially with respect to structural hierarchy and efficiency. In contrary to the federal network, all three state-level networks exhibit strict hierarchy (hierarchy =0.791-1.00). At the same time, all three state-level networks yield higher levels of connectedness than the federal network (connectedness=0.99-1.00).

5.5.1.3 Local level

Out of the four counties, Charleston county's response network has the highest number of organizations involved in response. Additionally, there are eleven communities detected within the network, with the largest community containing 20 organizations that are primarily hospitals and medical centers within the county (e.g. Charleston County Medical Society, East Cooper Community Hospital, MUSC medical center university hospital). These licensed medical centers recognized within ESF-8 (Health and Medical Services) include those within the county departments, as well as partners from private hospitals and healthcare facilities. The smallest community has four organizations within ESF-7 (Resource Support) that are responsible for logistical support operations such as emergency procurement and delivery of response supplies.

Aransas county's response network has the least number of unique organizations involved in response, but has the highest density out of all local response networks. Thus, organizations are expected to actively work with all other organizations within the network. High

density is also correlated with lower number of communities detected, with only three distinct communities. The largest community consists of twelve organizations that are involved in the "Direction and Control" function (e.g. Mayor, County Attorney's Office, County Road and Bridge Supervisor) in terms of planning and assigning responsibilities to other local, state, and federal stakeholders. The smallest community contains seven organizations that are within the "Human Services" response function; these organizations are local volunteer organizations (e.g. Aransas Count Ministerial Alliance, American Legion) that can provide donated goods such as used clothing, furniture, and kitchen facilities. Out of all the counties response networks, Aransas county's network most closely resembles a small-world topology (ω=-0.025), suggesting that while organizations are clustered into smaller communities, there are still shortcuts available if organizations who are in separate clusters want to collaborate.

Monroe county's response network has four communities detected, with the largest community containing 17 organizations. Within the largest community, there are eleven organizations within the Monroe county government (e.g. Division of Emergency Services, Monroe County Veterans Affairs), and six non-governmental organizations (e.g. Rural Health Network, Habitat for Humanity) expected to actively coordinate during crisis. The smallest community contains four organizations that are all medical facilities such as hospitals and ambulance services. In contrary to Aransas county's network, Monroe county's network exhibits a power-law degree distribution (α=2.623). Indeed, there is a presence of two main hubs, with one hub centralized towards the Division of Emergency Services (degree centrality=0.952), and one hub centralized towards the Division of Public Works (degree centrality=0.833) and Sheriffs Office (degree centrality=0.738). A majority of organizations, on the other hand, are not well-connected to each other.

Bay County's response network is more modular when compared to Aransas county and Monroe county's networks, with six communities detected. The largest community contains 16 organizations that are closely connected across the command, operations, planning, and

logistics function of the response network. These organizations include Bay County Administration, Bay County Purchasing Department, and Bay County Department of Emergency Services. The smallest community contains three organizations that are all under ESF-17 (Animal Protection), and are responsible for animal control and safety services. Unlike other county networks, the Bay County response network do not follow a power-law nor a small-world topology. An examination of this network's degree distribution shows a stark plateau when degree k=19, meaning that the probability of nodes having degrees of 19 or more stays the same with increasing degree values. Thus, the network contains a combination of different topologies, which is expected in real-world networks (Wang & Chen, 2003).

Local-level response networks are structurally more similar to the state-level networks than the federal networks with respect to Krackhardt's GTD dimensions. With the exception of Aransas county's network, all other networks have similarly high values of hierarchy (range: 0.833-1.00), connectedness (range: 0.697-1.00). and efficiency (range: 0.833-0.995). Similar to Texas state's response network which follows a small-world topology, Aransas county's network also exhibits the same topological feature and low level of network efficiency (efficiency = 0.375). Overall, the local-level networks are more similar to their state-level counterparts with respect to all graph-theoretic dimensions than with the federal network. The main distinction between the local- and federal-level networks is that local-level networks are more hierarchical, with more frequent presence of least upper bounds.

Figure 5.6: Bay County degree distribution in log-log scale (blue line), with power-law line of best fit (dashed green line)

5.5.2 Observed networks

	Matthew		Harvey		Irma		Michael	
	SITREPs	Tweets	SITREPs	Tweets	SITREPs	Tweets	SITREPs	Tweets
# of Nodes	951	1,432	622	1,121	937	1,844	332	1,067
# of Edges	4,477	7,721	12,500	3,620	17,848	7,490	2,754	3,460
Deg. Centralization	9.415	10.784	40.193	6.459	38.096	8.124	16.590	6.485
Density (δ)	0.010	0.008	0.065	0.006	0.041	0.004	0.050	0.006
Global Clustering (C)	0.512	0.456	0.544	0.384	0.555	0.458	0.536	0.426
Average Path Length (L)	3.902	2.320	3.382	2.855	3.456	2.392	3.068	2.710
# of Communities (CNM)	93	168	50	134	56	196	60	143
# of Components	74	39	34	76	32	58	45	65
Size of Largest Component	4,303	7,676	12,430	3,518	17,709	7,416	2,638	3,363
Small-Worldliness (ω)	-2.200	-0.101	-0.679	-0.058	-1.123	-0.068	-0.523	0.080
Power-law Exponent (α)	2.029	2.939	1.573	2.510	1.740	2.178	1.839	2.203
Krackhardt GTD								
• Hierarchy	0.724	0.883	0.688	0.890	0.688	0.891	0.679	0.909
• Connectedness	0.631	0.893	0.757	0.724	0.825	0.871	0.402	0.744
• Efficiency	0.994	0.999	0.980	0.998	0.992	0.999	0.980	0.998
• LUB	0.896	0.875	0.890	0.809	0.929	0.834	0.916	0.805

Table 5.12: Observed network descriptives for four hurricane events per source (removed self-loops and isolates)

5.5.2.1 SITREPs

Hurricane Matthew's SITREP-based response network size is the third-largest compared to the other SITREP-based networks (nodes=951, edges=4,477), where on average each entity is connected to nine other entities (deg centralization=9.415) The network has the lowest density (δ=0.010) compared to other networks, indicating low connectedness among a sizable set of entities involved in response. The network has slightly high clustering (C=0.512) and higher average path length (L=3.902) than other networks. With these features, the

network does not follow a small-world topology, and thus is reflected in the small-worldiness coefficient (ω=-2.20). The network structure exhibit a slightly better fit with the power-law topology (α=2.029), indicating the presence of a hub-and-spoke structure. The network contains the second higher number of components (74 components) with 93 communities detected, suggesting that the network is modular with many functional divisions that do not interact with each other. Specifically, the largest community contains 189 entities, most of which are non-governmental organizations such as PAHO, WHO, and United Nations' branches such as UNOCHA, UNICEF, UNFPA (United Nations Population Fund). There are 49 communities that consist of only one pair of relation, signifying that they are only collaborating with each other but not with other entities within the network.

Hurricane Harvey's SITREP-based network is the second-largest network (edges=12,500) with the highest density among the networks (δ=0.065). Thus, the network has the least number of communities detected (50 communities) with 34 components, where approximately 99.4% most of the nodes and the edges are in the largest component. The network does not follow either a small-world (ω=-0.679) or a power-law (α=1.573) topology, given the overall densely-connected structure. The largest community contains 346 entities that consist of major governmental organizations with the highest degree centralities such as Environmental Protection Agency (EPA, degree centrality=0.214), Federal Motor Carrier Safety Administration (degree centrality=0.068), National Weather Service under the Department of Commerce (degree centrality=0.066), and state-level departments such as Texas Commission on Environmental Quality (degree centrality=0.060) and Texas Department of Public Safety (degree centrality=0.027). There are 22 communities that are disjoint from large communities, as they are edges of entities that only coordinate with each other. There is a smaller subset of 23 communities consisting of only triads that coordinate within each other, which may indicate strong dependencies between entities (Dinh et al., 2020). An example is a triadic relationship [HHSC State Operated Facilities Emergency Operations Center $\longleftrightarrow$ State Hospital $\longleftrightarrow$ State Supported Living Centers] where three entities are mentioned only

together, specifically in terms of HHSC "coordinating support" to the hospitals and living centers in Texas.

Hurricane Irma's SITREP-based network contains the most number of relations among entities, where each entity has an average of thirty eight connections (degree centralization = 38.096) to other entities. Similar to other networks, this network also has relatively high clustering (C=0.555) and high average path length (L=3.456), and thus it does not follow small-world (ω=-1.123) nor a power-law (α=1.740) topology. This network has the least number of components (32 components) compared to other networks, with 56 communities detected. The largest community consists of 615 entities which are mainly nonprofit organizations, namely United Nations' organizations such as UNOCHA, UNDP (UN Development Programme), UNFPA, UNICEF, as well as international response organizations such as Caribbean Disaster Emergency Management Agency (CDEMA), Barbados Coast Guard, and European Civil Protection and Humanitarian Aid Operations. There is a small subset of U.S-based organizations in the largest community, namely the NOAA and National Weather Service (both under Department of Commerce), U.S. Coast Guard, Environmental Protection Agency (EPA), and USAID.

Hurricane Michael's SITREP-based network has the smallest size compared to other SITREP-based networks (edges=2,754), but the density is approximately equal to other networks (δ=0.050). Additionally, the network also has a relative better fit to a small-world topology (ω=-0.523) compared to other SITREP-based networks, with a lattice-like structure given the coefficient is negative. Though with a smaller size, this network is highly modular (CNM=60, and 45 components). The largest community contains 76 entities, which are primary governmental organizations at the county-level such as the Bay County Council, Bay District School System, and Panama City Police Department. The next large community (49 entities) contains a number of state-level departments and affiliates such as Florida Department of Emergency Management (FDEM), State Emergency Operation Centers (SEOCs), and Florida Hospital Association. The smallest communities of size two

(34 communities) are pairs of entities that only coordinate with each other, and not with other clusters in the network (e.g. National Institute of Standards and Technology $\longleftrightarrow$ American Institute of Architects; American Architectural Manufacturers Association $\longleftrightarrow$ Designers Social Services).

Krackhardt's GTD analyses for all SITREP-based networks reveal that the networks are all relatively hierarchical (range: 0.688-0.724), efficient (range: 0.980-0.994), with clear unity of command (LUB range: 0.834-0.929). The main variability between the networks is in terms of their connectedness structures. Hurricane Michael's response network has the lowest connectednness (0.402), while Hurricane Irma's network has highest connectedness (0.825). This particular pairwise difference shows that even though the responses to Hurricanes Irma and Michael both took place in the same state (Florida) and both received federal assistance, differences in the first-line response at the local-level may influence the network structure of response (G. L. Davis & Robbin, 2015).

5.5.2.2 Tweets

Compared to the SITREP-based networks for the same hurricane event, almost all tweet-based networks are smaller in size (except for Hurricane Matthew, where the tweet-based network has notably more nodes and edges). Consequently, structural features such as density, global clustering, and average path length are smaller in the tweet-based networks, which may be due to their smaller network sizes. The consistently low densities (δ range:0.004-0.006) across the tweet-based networks, along with notably higher number of communities and components suggests that the tweet-based networks all have more modular structure compared to their SITREP-based counterparts. Interestingly, all the tweet-based networks exhibit better fit for both small-world (ω range:-0.101-0.080) and power-law (α range: 2.178-2.939) topologies than the SITREP-based networks. These topological characteristics are examples of real-world networks that contains a mix of small-world and scale-free features (Wang & Chen, 2003).

Hurricane Matthew's tweet-based network exhibits a good fit with a power-law node degree distribution (α=2.939), with some small-world characteristics (ω=-0.101). There are 168 communities detected, with the largest community contain interactions between 783 entities. Most of the entities in this community are locations of immediate impact at the county level such as Beauford County, Cocoa Beach, Colleton County, and Mount Pleasant. Organizations operating at the federal, state, and local levels do not belong to the largest community, signifying that these organizations are not among the most frequently mentioned in the network. There are 115 communities of size two (68% of the communities), showing that the network contains a notable number of entity pairs that are not connected to the rest of the network.

Hurricane Harvey's tweet-based network most closely resembles a small-world topology (ω=-0.058) compared to other tweet-based networks, and the fit leans towards a lattice graph topology as the coefficient is positive. The graph has relatively low clustering (C=0.384), but with a shorter average path length (L=2.855), entities can connect across different clusters with less distance. There are 134 communities detected, with the largest community containing 368 entities. The largest community contains a prominent number of political figures (i.e. Donald Trump, Ted Cruz, Greg Abbott) and political parties (i.e. Democrats, GOP, Congress, Republicans). A closer examination of the original tweets reveal major discussions about Donald Trump's disaster declaration for Hurricane Harvey and the associated response activities from the White House. In the largest community, a number of prominent federal-level organizations are also frequently mentioned, namely Red Cross (deg. centrality=0.060) and FEMA (deg. centrality=0.046). There are 81 communities of size two, meaning that about two-thirds of the network is pairs of entities that are only connected to each other.

Hurricane Irma's tweet-based network is the second-largest in size compared to tweet-based networks of the other three hurricane events, where each entity is connected to approximately six other entities (degree centralization=8.124). This network also has the high-

est number of communities detected (CNM=196, and 58 components) compared to other tweet-based networks, suggesting that the network is more fragmented across the different components. The largest community contains 932 entities, most of which are governmental (e.g. FEMA, IRS (federal), Salvation Army (state), Florida Power & Light (local)), as well as a notable proportion of locations (e.g. Seminole county, Palm Beach county, Clearwater Beach) that were impacted by the hurricane. The network's degree distribution exhibits both a power-law fit (α=2.178), and small-world topology (ω=-0.068) towards a lattice-like structure. This goodness-of-fit measure is consistent with the community detection results, as the network consists of a small subset of densely-connected "hubs" and a larger subset of smaller communities.

Hurricane Michael's tweet-based network has the smallest network size compared to others (edges=3,460). The network also has the lowest clustering (C=0.426) but with higher average path length (L=2.710), indicating that the network is not a good fit for a small-world topology (ω=0.080). The network has a power-law degree distribution (α=2.303), which is reflected in the size of the largest component where 97.2% of the edges are within one component. There are 143 communities detected, with the largest community community consisting of 364 entities. This community consists of primarily governmental officials (e.g. Donald Trump, Rick Scott, Andrew Gillum, Pam Bondi), federal-level response agencies (e.g. FEMA, Red Cross, DHS, DOD), and counties (e.g. Bay county, Mexico Beach, Calhoun county) that were affected and involved in response. Smaller communities of size two (n=91) and size three (n=32) are present in the network as well, containing small groups of entities that are co-mentioned with each other but not with any other entities (e.g. Nassau County $\longleftrightarrow$ Nassau County Sheriff's Office $\longleftrightarrow$ Volunteer Ham Radio; Florida Disaster Fund $\longleftrightarrow$ Volunteer Florida).

Krackhardt's GTD analyses on the tweet-based networks show that these networks are notably more hierarchical than their SITREP-based counterparts (range: 0.883-0.909). Three tweet networks based on hurricanes Matthew, Irma, and Michael have higher connect-

edness than their SITREP-based counterparts (0.893, 0.871, and 0.744, respectively). The LUB values are slightly lower than the SITREP-based networks, but still considered high (LUB range: 0.805-0.875), suggesting that most pairs of entities receive connections from a common third entity. The efficiency scores of the tweets-based networks are consistently higher than the SITREP-based networks, complementing the more hierarchical structure of these networks.

5.5.3 Network overlaps

5.5.3.1 Node-level overlap

Hurricane Matthew			Hurricane Harvey		
	SITREPs	Tweets		SITREPs	Tweets
Federal	0.006	0.006	Federal	0.041	0.009
State	0.005	0	State	0.015	0
Local	0	0.001	Local	0	0
Hurricane Irma			**Hurricane Michael**		
	SITREPs	Tweets		SITREPs	Tweets
Federal	0.014	0.006	Federal	0.043	0.010
State	0	0	State	0.004	0.002
Local	0.005	0	Local	0.026	0

Table 5.13: Jaccard node-level similarity index ($JacNodeSim$) for every pair of network based on response jurisdiction (prescribed network) and data source (observed network) across different hurricane events

Table 5.13 shows the Jaccard similarity score for every prescribed-observed network pair (following the 3x2 factorial design in *Experimental design*) in terms of node overlap. Overall, the amount of overlap is minimal (range: 0.00-0.043), with the highest overlap found between local-level prescribed network and Hurricane Michael's SITREP-based observed network ($JacNodeSim$=0.043). There are six pairs of networks with no node overlap, where four pairs contain prescribed networks and the tweet-based observed networks with no overlap. The remaining two pairs are those with no overlap between local-level prescribed networks

Factor	Sum of Squares	df	Mean Square	H	p-value	sig?
Response Level (Federal, State, Local)	510.063	2	255.031	10.788	0.005	yes
Data Source (SITREPs, Tweets)	150.0	1	150	3.172	0.075	no
Interaction Effect	8.3125	2	4.156	0.176	0.916	no
Within-Group Variability	419.125	18	23.285			
Total	1087.5	23	47.283			

Table 5.14: Scheirer-Ray-Hare test result on the effects of response jurisdiction and data source on the node-level overlap (measured by $JacNodeSim$) between prescribed and observed networks

and their SITREP-based counterparts (in Hurricanes Matthew & Harvey).

To statistically test whether the prescribed network's level of response jurisdiction (factor 1) and the data source used to construct the observed network (factor 2) have effects on the amount of node overlap between the prescribed and observed networks, we conducted the Scheirer-Ray-Hare non-parametric test. We use a non-parametric test because our data did not meet the requirements of normality, equality of variance, and that our sample size is small (n=24, with 141 observations corresponding to the number of nodes where overlap were found). The Scheirer-Ray-Hare test does require independent samples, which is applicable to this particular analysis as the networks' edges are distinct from each other. Normality and equality of variance were checked using the Shapiro-Wilk test, where the p-value of less than 0.05 suggests that the distribution of our data is significantly different from a normal distribution. Two out of six distributions are not normally distributed (p=0.002; p=0.001), and thus we confirmed that the non-parametric test is needed. The result (shown in Table 5.14) indicates a significant association between the prescribed network's response level and the amount of node overlap (H=10.788, p<0.05). On the other hand, there is no significant relationship between the observed network's data source and the amount of node overlap (H=3.172, p=0.075), though the p-value is close to statistical significance. There is no interaction effect found between the two factors (H=0.176, p>0.05), suggesting that the

association between the prescribed network's level of response jurisdiction and the amount of network overlap is not significant across SITREP-based and tweet-based networks.

Table 5.17 details the number of node overlaps between each observed network and a prescribed network with a specified level of jurisdiction. Visual inspection of the node overlap counts show that across all eight networks, federal-level prescribed networks share the highest number of nodes with the observed networks. Specifically, the highest amount of node overlap at the federal-level is found in Hurricane Harvey's SITREP-based network (n=27, [3.664%]), and also the highest at the state-level (n=10, [1.357%]). In terms of overlap with local-level prescribed network, Hurricane Michael's SITREP-based network is found to have the highest node overlap (n=10, [2.513%]). Cumulatively, however, the percentage of node overlap at the three levels of response jurisdiction is minimal with respect to the node non-overlaps (range: 78.290%-95.755%). This result suggests that for both SITREP-based and tweet-based networks, most nodes in the observed networks are not mentioned in the prescribed networks. Cross-level node overlap considers the nodes mentioned in the prescribed networks that are connected to nodes that are either (1) not in the same response level, or (2) not mentioned in the prescribed networks. For example, Hurricane Irma's SITREP-based network contains a proportion of federal-state node pairs (e.g. Florida State Emergency Operations Center $\longleftrightarrow$ DOE), which counts as a cross-level node pair. Another example would be a local-other node pairs (e.g. Florida Power and Light [local-level] $\longleftrightarrow$ Duke Energy [other]). In all networks, the number of federal-other overlap (F-O) is the highest compared to other types (range: 2.905%-5.834%). In particular, we observe the highest F-O node overlap in Hurricane Harvey's SITREP-based network (43 nodes, [5.834%]), and the lowest node overlap in Hurricane Matthew's tweet-based network (43 nodes, [2.905%]).

5.5.3.2 Edge-level overlap

Table 5.15 shows the Jaccard edge-level similarity score for every prescribed-observed network pair. Similar to the pattern found in node-level overlap results, the amount of edge

Hurricane Matthew			Hurricane Harvey		
	SITREPs	Tweets		SITREPs	Tweets
Federal	0.003	0.001	Federal	0.004	0.002
State	0.002	0	State	0.001	0
Local	0	0.0001	Local	0	0
Hurricane Irma			Hurricane Michael		
	SITREPs	Tweets		SITREPs	Tweets
Federal	0.007	0.001	Federal	0.014	0.003
State	0	0	State	0.0002	0.0002
Local	0.0008	0	Local	0.003	0

Table 5.15: Jaccard edge-level similarity index ($JacEdgeSim$) for every pair of network based on response jurisdiction (prescribed network) and data source (observed network) across different hurricane events

overlap is also minimal (range: 0.00-0.014), with the highest overlap also found between Hurricane Michael's SITREP-based observed network and its local-level (Bay county) prescribed network ($JacEdgeSim$=0.003). The amount of edge overlap is slightly less than the amount of node overlap (based on Jaccard index), suggesting that prescribed entities that were actually mentioned in the observed networks were not as frequently connected to each other as expected in the prescribed networks.

Scheirer-Ray-Hare test (result in Table 5.16) shows a significant association between the prescribed network's response level and the amount of edge overlap (H=12.763, p<0.05). On the other hand, there is no significant impact of observed network's data source on the amount of edge overlap (H=3.395, p=0.065). This result is correlated with the prior test for node overlap, and thus there is also no interaction effect found between the two independent variables (H=0.698, p>0.05).

Table 5.17 shows the counts of edge overlap (column: *# of edges*) for each event based on the prescribed network's level of response and the data sources used for observed network construction. Based on the statistical finding above, we find that federal-level prescribed networks on average, have the highest overlap with the observed networks (range: 0.130%-1.961%) compared to state- (range: 0%-0.503%) and local-level (range: 0%-0.499%)

networks. Altogether, these results show that the amount of edge overlap between the prescribed networks within one level of response jurisdiction (e.g. federal-federal connections only) and the observed networks are minimal, though statistically significant. On the other hand, the amount of overlap between prescribed networks across levels of jurisdiction (e.g. federal-state connections) are more frequently occurring. The amount of non-overlap, though, is most prominent across all networks (range: 93.137%-97.744%), indicating that many entities that are mentioned in the observed networks are not prescribed in governmental guidelines.

Factor	Sum of Squares	df	Mean Square	H	p-value	sig?
Response Level (Federal, State, Local)	602.063	2	301.031	12.763	0.002	yes
Data Source (SITREPs, Tweets)	160.167	1	80.083	3.395	0.065	no
Interaction Effect	1.396	2	0.698	0.030	0.985	no
Within-Group Variability	321.375	18	160.688			
Total	1085.0	23	47.174			

Table 5.16: Scheirer-Ray-Hare test result on the effects of response jurisdiction and data source on the edge-level overlap (measured by $JacEdgeSim$) between prescribed and observed networks

Figures 5.8-5.11 are network visualizations of the edge overlap between prescribed and observed networks across different response jurisdictions and data sources. Within each network, colors of the edges represent edge overlap at the federal, state, and local response jurisdiction. Given the prominence of cross-level edge overlap (as mentioned in the *node-level overlap* section), these edges are represented in green. Visual inspections confirm that cross-level edges are most frequently-occurring across all networks, suggesting meaningful connections between entities that belong to different levels of jurisdiction. Additionally, both Hurricane Harvey's SITREP-based network and Hurricane Michael's SITREP-based network contain most diversified types of edges, with instances of overlap found for every type of response jurisdiction and combinations of cross-level types. Although prior statistical finding

shows no statistically significant relationship between data source and network overlap, this particular result may suggest that SITREPs contain more details into the collaboration dynamics between entities than tweets. Additionally, SITREPs have been found to contain verified information about events and collaboration activities during hurricane response, but the verification process is often why SITREPs are not released in a timely manner (Bennett et al., 2013). Thus, SITREP-based information may be more trustworthy than information extracted from tweets, but tweets are more timely than SITREPs.

5.5.3.3 Network-level comparisons

Structural comparisons of network-level properties are important to capture how any two networks are similar (or different) to each other based on the combination of local-level processes that produce these networks (Robins et al., 2005). We perform a non-parametric test of correlation between every pair of networks according to the corresponding network-level characteristics (i.e. degree centralization, density, clustering coefficient, communities detected using CNM, number of components, small-worldiness coefficient, power-law exponent, and Krackhardt GTD measures). Table 5.7 shows the correlational matrix between two networks based on Kendall's τ_b coefficient, ranging from -1 to 1 where -1 means perfect negative correlation, 0 means no correlation, and 1 means perfect positive correlation. Based on the heatmap, the lower right quadrant contains the pairs of networks with highest correlation (τ_b range: 0.92-1.00), and these pairs consist of only observed networks that are either SITREP- or tweets-based. The upper left quadrant contain pairs of prescribed networks across all three jurisdictional levels, and the heatmap indicates the correlation overall (τ_b range:0.64-0.98) is not as high as the lower right quadrant. As for the lower left quadrant, the correlational values are notably lower (τ_b range: 0.59-0.84), with the lowest correlation between federal-level prescribed network and Hurricane Irma's tweet-based observed network (Kendall's τ=0.59). The highest correlation is found between the local-level prescribed networks from Monroe county and Bay county and Hurricane Matthew's tweet-based observed

network (τ_b=0.84). This finding is interesting because Monroe and Bay counties are local-level jurisdictions responsible for Hurricanes Irma and Michael's responses, not Matthew's response. Further examination of the structural features show that the two networks are similar with respect to the lower degree centralization (9.628 for local-Monroe and 10.784 for Matthew-tweets) and density compared to other networks (0.229 and 0.08 respectively), which relatedly explains the similar hierarchical structures between these networks with high efficiency (0.833 and 0.999 respectively) and moderately high LUB (0.923 and 0.896 respectively). Across all three prescribed network types, federal-level network on average, as the lowest correlation with all the observed networks (range: 0.59-0.66) when compared to the state- (range: 0.63-0.78) and local-level (range: 0.71-0.84) prescribed networks. The main reason is that federal-level network is the least hierarchical (hierarchy=0.001) and least efficient (efficiency=0.159) compared to the observed networks which all have some level of hierarchy and efficiency in them. The reason for the federal-level network to have this structure is because the network is highly-connected (degree centralization=62.84; δ=1.698) where an organization is likely connected to every other organization in the network via a direct path. This is consistent with the goal of the NRF-based federal response network where organizations are expected to be actively collaborating (Walker, 2006). In reality, as reflected in the observed networks' structural features, some hierarchy and command structure may be needed to ensure resources and organizational responsibilities are distributed with minimal redundancy (Nowell, Steelman, Velez, & Yang, 2018).

Figure 5.7: Correlation (Kendall's τ_b) between prescribed and observed networks

(a) SITREP-based network

(b) Tweet-based network

Figure 5.8: Hurricane Matthew's observed networks based on SITREPs (left) and tweets (right). Entity names abbreviated for visualization purpose.

5.6 Discussion

In this study, we constructed and analyzed prescribed and observed interorganizational response networks. The prescribed networks were constructed from governmental guidelines, and the observed networks were constructed based on situational reports and tweets that report on collaborations that took place during response. Using a 3x2 factorial design, we compared the networks with respect to response jurisdictions (federal, state, local) and source (SITREPs, tweets). The networks were also structurally compared at the node, edge, and network-level to identify local and global processes that make the networks similar (or different) (Robins et al., 2004; Tantardini et al., 2019). Consistent with the study's objectives and experimental design, we investigated two main research questions and three

(a) SITREP-based network (b) Tweet-based network

Figure 5.9: Hurricane Harvey's observed networks based on SITREPs (left) and tweets (right). Entity names abbreviated for visualization purpose.

(a) SITREP-based network (b) Tweet-based network

Figure 5.10: Hurricane Irma's observed networks based on SITREPs (left) and tweets (right). Entity names abbreviated for visualization purpose.

Hurricane		Federal	State	Local	Other	Cross-Level					
						Federal-State	Federal-Local	Federal-Other	State-Local	State-Other	Local-Other
Matthew-SITREPS	nodes	6 (0.595%)	5 (0.496%)	0 (0%)	930 (92.262%)	2 (0.198%)	0 (0%)	56 (5.556%)	0 (0%)	9 (0.893%)	0 (0%)
	edges	16 (0.537%)	10 (0.223%)	0 (0%)	4207 (93.969%)	2 (0.045%)	0 (0%)	231 (5.160%)	0 (0%)	11 (0.246%)	0 (0%)
Matthew-Tweets	nodes	9 (0.608%)	0 (0%)	2 (0.135%)	1415 (95.608%)	0 (0%)	0 (0%)	43 (2.905%)	0 (0%)	5 (0.338%)	6 (0.405%)
	edges	10 (0.130%)	0 (0%)	1 (0.013%)	7569 (98.031%)	0 (0%)	0 (0%)	129 (1.671%)	0 (0%)	6 (0.078%)	6 (0.078%)
Harvey-SITREPS	nodes	27 (3.664%)	10 (1.357%)	0 (0%)	577 (78.290%)	24 (3.256%)	0 (0%)	43 (5.834%)	0 (0%)	56 (7.598%)	0 (0%)
	edges	53 (0.424%)	8 (0.064%)	0 (0%)	12157 (97.256%)	70 (0.560%)	0 (0%)	139 (1.112%)	0 (0%)	73 (0.584%)	0 (0%)
Harvey-Tweets	nodes	10 (0.853%)	0 (0%)	0 (0%)	1101 (93.862%)	4 (0.341%)	0 (0%)	45 (3.836%)	0 (0%)	10 (0.853%)	3 (0.256%)
	edges	10 (0.276%)	0 (0%)	0 (0%)	3479 (96.105%)	2 (0.055%)	0 (0%)	114 (3.149%)	0 (0%)	13 (0.359%)	2 (0.055%)
Irma-SITREPS	nodes	14 (1.397%)	0 (0%)	5 (0.499%)	918 (91.617%)	6 (0.599%)	0 (0%)	41 (4.092%)	0 (0%)	0 (0%)	18 (1.796%)
	edges	131 (0.734%)	0 (0%)	15 (0.084%)	17250 (96.649%)	37 (0.207%)	0 (0%)	362 (2.028%)	0 (0%)	0 (0%)	53 (0.297%)
Irma-Tweets	nodes	12 (0.629%)	0 (0%)	0 (0%)	1827 (95.755%)	0 (0%)	2 (0.105%)	60 (3.145%)	0 (0%)	4 (0.210%)	3 (0.157%)
	edges	8 (0.107%)	0 (0%)	0 (0%)	7321 (97.744%)	0 (0%)	1 (0.013%)	155 (2.069%)	0 (0%)	3 (0.040%)	2 (0.027%)
Michael -SITREPS	nodes	16 (4.020%)	2 (0.503%)	10 (2.513%)	315 (79.146%)	8 (2.010%)	5 (1.256%)	19 (4.774%)	0 (0%)	13 (3.266%)	10 (2.513%)
	edges	54 (1.961%)	1 (0.036%)	9 (0.327%)	2565 (93.137%)	36 (1.307%)	4 (0.145%)	41 (1.489%)	0 (0%)	36 (1.307%)	8 (0.290%)
Michael -Tweets	nodes	11 (0.989%)	2 (0.180%)	0 (0%)	1045 (93.975%)	0 (0%)	3 (0.270%)	40 (3.597%)	2 (0.180%)	5 (0.450%)	4 (0.360%)
	edges	16 (0.462%)	1 (0.029%)	0 (0%)	3341 (95.561%)	0 (0%)	4 (0.116%)	88 (2.543%)	1 (0.029%)	5 (0.145%)	4 (0.116%)

Table 5.17: Proportions of nodes and edges at the federal, state, and local level across hurricane events and different sources

(a) SITREP-based network (b) Tweet-based network

Figure 5.11: Hurricane Michael's observed networks based on SITREPs (left) and tweets (right). Entity names abbreviated for visualization purpose.

corresponding hypotheses.

Our first research question asked about the association between the prescribed network's level of response jurisdiction and the amount of network overlap between the prescribed and observed networks. The amount of network overlap is an indicator of similarity between the two networks, where overlap can be in terms of the nodes shared (node-level), edges shared (edge-level), structural, and topological features shared (network-level). At the node level, we find that the amount of overlap between the prescribed and observed networks to be minimal. In our work, this is mainly due to false positives, i.e., most entities in the observed networks are not mentioned in the prescribed networks. This finding is consistent with Li and Ji (2021)'s finding that a notable number of organizations actively involved in Hurricane Harvey's response were not specified in the governmental guidelines (p.8). The small subset of nodes that do overlap are mainly between the federal-level prescribed networks and the observed networks (average $JacNodeSim$=0.017, range: 0.006-0.043), followed by a smaller subset of overlapping nodes at the local-level (average $JacNodeSim$= 0.004, range: 0-0.026),

and lastly at the state-level (average *JacNodeSim*=0.003, range: 0-0.015). In fact, Scheirer-Ray-Hare statistical test reveals a significant association between the prescribed network's level of response jurisdiction and the amount of node overlap found in the observed networks (H=10.788, p<0.05). This finding also suggests that if an overlap of nodes are present, it is more likely that the nodes belong to federal organizations. It is important to note that this finding applies to the specific hurricane events considered in the study, and may not apply to other hurricane events that have different state- and local-level response network structures.

At the edge-level, statistical tests also reveal statistically significant relationship between prescribed network's level of response jurisdiction and the amount of edge overlap with the observed networks (H=12.763, p<0.05). Specifically, the collaboration between two federal organizations are more likely to be mentioned in the observed networks compared to organizations at state- or local-levels. The higher node- and edge-level overlap found in federal prescribed network and the observed networks compared to other response jurisdictions indicate that federal organizations received more coverage in SITREPs and tweets. However, further examinations are needed to confirm whether more coverage means that these organizations are more involved in the response. Another possible explanation for the higher overlap at the federal-level is that while there is only 38 primary organizations involved under ESF, each organization contains multiple agencies that report to them (e.g. U.S. Energy Information Administration (EIA) is under the DOE). Hence, the larger number of nodes and edges that exist within the federal prescribed network increases the likelihood of overlap with observed networks. This finding also brings out the resource discrepancy across the levels of jurisdiction where local-level (and sometimes, state-level) are expected to provide immediate response, but with limited resources and capabilities compared to the federal-level (Waugh Jr, 1994). This discrepancy is a reason for the continued efforts (Schneider, 1992; Walker, 2006) from the federal government to help strengthen local and state capacities to prepare and respond to disasters.

At the network-level, however, the structural features of federal-level prescribed networks are the least correlated to the observed networks' features (range: 0.59-0.66). Local-level networks' features, on average, have the highest correlations with observed networks compared to other jurisdictional levels (range: 0.71-0.84), followed by state-level networks (range: 0.63-0.78). These results are in contrast with the findings from the node- and edge-based overlap as they show that networks can be similar at the local level but be different at the global level (Tantardini et al., 2019). In particular, the federal network's densely connected structure with high edge redundancy may explain the increased likelihood of edge level overlap with the observed networks. This highly decentralized collaboration structure, however, is not observed in the actual collaboration networks where some hierarchy is required to minimize the redundancy of tasks and resources (Kapucu & Garayev, 2016; 't Hart et al., 1993).

The second research question asked about the association between the data sources used to construct the observed networks and the amount of network overlap between the prescribed and observed networks. Based on Scheirer-Ray-Hare tests, there is no statistically significant association in the amount of node overlap (H=3.172, p=0.075), edge overlap (H=3.395, p=0.065) with the prescribed networks for both SITREP- and tweet-based networks. This result shows that SITREPs and tweets are not different in terms of amount of nodes and edges that are also found in the prescribed networks. Moreover, the low overlap indicates that the observed networks show collaboration patterns between entities that are not mentioned in government guidelines. Visual inspections of the two network types (as shown in Figures 5.8-5.11) show that tweet-based networks are less likely to contain local-level response information (as indicated by the lack of yellow edges), as opposed to cross-level (in green edges) or federal (in blue edges). This result is consistent with McCormick (2016)'s finding based on 19 interviews with local responders that local authorities did not utilize social media for formalized coordination during response. The informal response organizations at the local level, however, did use Twitter and Facebook (p. 214) to communicate

and coordinate tasks. This insight from the McCormick study provides an incentive for us to further examine the edge non-overlaps in the tweet-based networks with respect to the informal organizations that are not prescribed in the local response network, but were actively collaborating with the local authorities. At the global level, the correlation between SITREP-based networks and the prescribed networks (average τ=0.738) are on average, only slightly higher than with the tweet-based networks (average τ_b=0.737). The structural similarity between the prescribed and the SITREP-based observed networks reveals the nature of SITREPs; these reports are often created by governmental and non-governmental organizations (primary UN-based organizations, (Finn & Oreglia, 2016)) according to their organizational guidelines. Thus, the organizational structure may be reflected in the SITREPs in ways that are consistent with the prescribed networks. On the other hand, the structural similarity between tweet-based networks and the prescribed networks also reveals that the many governmental, non-governmental entities, citizens, and volunteer organizations (Hiltz & Plotnick, 2013; Olteanu et al., 2015) are co-mentioned and connected in ways that are similar to the prescribed networks. Tweets also may contain more information about emergent collaboration structures between individuals and groups that extends beyond formal organizational affiliations (Lanzara, 1983; Petrescu-Prahova & Butts, 2005). Both data sources (SITREPs and tweet), in tandem, provide information on what and how institutionalized and emergent collaborations are present during actual response. Recurring structural patterns in both data sources show that in actual responses to major hurricanes, emergent collaboration patterns were more prominent than institutionalized relationships, consistent with the unpredictable nature of major crises where the tasks and personnel required extend beyond what is anticipated in governmental guidelines (Dynes, 1970; Stallings & Quarantelli, 1985).

5.7 Chapter summary

The findings of this chapter shed light on the similarities and differences between the response collaborations as prescribed by governmental guidelines, and as observed in actual collaborations that took place during responses to major hurricanes. The comparisons are conducted at multiple levels of the network, namely the node level (number of entities mentioned in both prescribed and observed network), edge level (number of entity pairs connected in both networks), and network level (structural and topological features across the two networks). Within the scope of this work, we primarily focused on the extent of network overlap to determine what prescribed collaboration patterns that did occur in practice. In future work, we will examine the non-overlaps with respect to the unique types of capabilities and resources these entities bring to the network that prescribed entities do not. On a methodological level, we will compare our resulting networks with existing state-of-the-art relation extraction methods (i.e. OneIE (Lin, Ji, Huang, & Wu, 2020) and Open Information Extraction-OpenIE (Etzioni, Banko, Soderland, & Weld, 2008)) to examine the differences in the network coverage when different off-the-shelf methods are applied.

5.7.0.1 Annotation procedure used for entity and relation extraction task

The purpose of this annotation task is to label the entities mentioned (Task 1) and the relations (Task 2) between them in a text document in the disaster management domain. In particular, a text document is a situational report produced by a governmental agency to update the public and associated stakeholders of the response activities to a hurricane event OR a social media message about a hurricane event. Your task is to identify the named entities that are mentioned in a sentence, and the relation that links the entities, if any.

1. We define <u>entities</u> as persons *(PER)*, organizations *(ORG)*, nationalities or religious or political groups *(NORP)*, countries, cities, states *(GPE)*, locations *(LOC)*. The following rules are established for identifying entities:

- For ORG entities, identify the full name, if possible (e.g. instead of "UN", identify "United Nations", if stated in the sentence)

- For PER entities, identify only the specific noun, not including any determiners, such as quantifiers (e.g. many, most, some, a few) or numbers (e.g. 50, two hundred, ten thousand of). For instance, with a sentence, “200,000 people need homes”, you would need to only identify “people” (PER).

- For PER entities that belong to higher-order entities (ORG, NORP, GPE), you would code only the higher-order entity. For example, with a sentence, “doctors from Doctors Without Borders”, you would need to only identify “Doctors Without Borders” (ORG).

- LOC entities are names that are non-GPE.

- NORP entities are those that identify groups or organizations that are not affiliated with the government. Examples would be faith-based organizations (e.g. South Baptist Disaster Relief, United Church) or national/political groups (e.g. HaitiOne, USA Citizens Foundation).

2. We define a <u>relation</u> as a verb, or a verb phrase, that connects two or more entities together. The following rules are established for identifying relations:

- 1 to 2 verbs are allowed in one relation. For example, a phrase "agreed to restore" has 2 verbs connected by a preposition “to”, and are permitted to be coded as one relation.

- No adjectives before or after a relation needs to be coded. For example, with a sentence, “UN OCHA is effectively coordinating with Canadian Medical Force”, only "coordinating" needs to be coded.

We will be identifying the entities and relations between them in terms of triples, in the form of “who-with/to-who”.

"who" is defined as the initiator of the action. There should only be one initiating "who" in each triple.

"with/to" is the action what was conducted.

There are 2 types of triples permitted: "who-with-who", "who-to-who"

The "who" in a triple must be one of the following entity types: PER, ORG, NORP, GPE, LOC. In other words, only social entities are permitted to be the "who" in a triple.

The "with/to" in a triple is the same as the relation, and can be one of two types: (1) *relation*, or (2) *no relation*.

- The "with/to" is labeled as *relation* if the term signals two (or more) "who(s)" working together to achieve a certain task. An example:"WFP is coordinating with UNOCHA to deliver food to needed population".

- The "with/to" is labeled as *no relation* if the term signals no direct collaboration or interaction between two entities OR that there is only one entity mentioned in a sentence. Two examples: "Two additional zones were added in Jasper and Colleton counties" (no relation between Jasper and Colleton). "Florida Governor urges 1.5 million to flee" (only one entity present).

Please follow the steps outlined below to complete the coding task for the following five sentences. For each sentence, please identify all triples involved.

The Government has asked humanitarian partners for the rapid provision of humanitarian assistance to affected regions outside of Port-au-Prince, such as Leogane, Petit Goave and Grand Goave.

PAHO/WHO is working with the Dominican Republic to identify places where patients recovering from surgery can be transferred in order to free up hospital beds.

A dedicated safety coordination focal point for NGOs has been provided to ensure liaison with MINUSTAH and other military partners.

In preparation of the conference, the Government has requested humanitarian partners to provide it with a comprehensive overview of the humanitarian needs and assistance requested so far.

CHAPTER 6

NETWORK ANALYSIS METHODS TO EXAMINE BIOLOGICAL HAZARD DYNAMICS

The COVID-19 pandemic has impacted all aspects of our lives, including the information spread on social media. Prior literature has found that information diffusion dynamics on social networks mirror that of a virus, but applying the epidemic Susceptible-Infected-Removed model (SIR) model to examine how information spread is not sufficient to claim that information spreads like a virus. In this chapter, we explore whether there are similarities in the simulated SIR model (*SIRsim*), observed SIR model based on actual COVID-19 cases (*SIRemp*), and observed information cascades on Twitter about the virus (*INFOcas*) by using network analysis and diffusion modeling. We propose three primary research questions: (1) What are the diffusion patterns of COVID-19 virus spread, based on *SIRsim* and *SIRemp*? (2) What are the diffusion patterns of information cascades on Twitter (*INFOcas*), with respect to retweets, quote tweets, and replies? and (3) What are the major differences in diffusion patterns between *SIRsim*, *SIRemp*, and *INFOcas*? Our study makes a contribution to the information sciences community by showing how epidemic modeling of virus and information diffusion analysis of online social media are distinct but interrelated concepts.

6.1 Information diffusion dynamics during a biological hazard: COVID-19 case study

On December 31, 2019, The World Health Organization (WHO) reported the first confirmed case of SARS-CoV-2 virus, frequently known as "COVID-19". To date, the virus has spread to more than 150 countries, with over three million confirmed cases globally. Modeling and

examining diffusion dynamics of COVID-19 pandemic network is critical to provide information that health professionals and associated stakeholders can leverage to make effective decisions (Xie et al., 2020).

Extant literature has found that information diffusion dynamics on social networks mirror that of a virus (Abdullah & Wu, 2011; Lerman, 2016; Seki & Nakamura, 2016; Ver Steeg, Ghosh, & Lerman, 2011). Abdullah and Wu (2011) show that trending topics on Twitter spread in similar patterns with an epidemic Susceptible-Infected-Removed model (SIR), in which I and R both started at 0 but as I began to increase at a certain reproductive rate, S and R would be impacted. Seki and Nakamura (2016) assert that the SIR model can be applied to examine the decline of diffusion activities on Friendster online social network, and found that the decline started when popular users left Friendster (labeled as R in SIR model). However, applying the epidemic SIR model to examine how information spread is not sufficient to claim that information spreads like a virus (Lerman, 2016; F. Wu, Huberman, Adamic, & Tyler, 2004). There are different mechanisms that influences how information spread from one user to another, but does not influence how a virus spread from one person to another, and vice versa (Lerman & Ghosh, 2010; Mønsted et al., 2017).

In this study, we examine in parallel the epidemic and information diffusion, and the mechanisms by which both diffusion processes contribute to COVID-19's spread. Specifically, we compare COVID-19 virus's (1) *SIR*-modeled and (2) empirically observed diffusion patterns with (3) information cascades of retweeting, quote tweeting, and replying behaviors on Twitter social network to understand the relationships between information and virus diffusion. To do this, first, we create an *SIR* simulation (we call this *SIRsim*) of COVID-19's diffusion with respect to empirically validated parameters such as reproductive rate (*R0*), incubation period, and symptom length range. Secondly, we create an SIR model from actual confirmed cases with data gathered from JHU-CSSE (2020) (we call this *SIRemp*). Thirdly, we construct information cascades from on our collected Twitter data (we call this *INFOcas*) based on three dimensions: retweets, quote tweets, same as retweets but with comment

included), and replies to tweets. For the information cascades, we also categorize each piece of information to either *Susceptible* (new tweet about the virus), *Infected* (retweets, quoting of retweets, or replying to tweets), or *Removed* (tweet not shared by others after a period of time). Consistent with the aspects of the study, we propose three primary research questions:

RQ3-3: What are the simulated and empirical diffusion patterns of COVID-19 virus spread, based on *SIRsim* and *SIRemp*, respectively?

RQ3-4: What are the diffusion patterns of information cascades on Twitter (*INFOcas*), with respect to retweets, quote tweets, and replies?

RQ3-5: What, if any, are the differences in the diffusion patterns between *SIRsim*, *SIRemp*, and *INFOcas*?

Our study makes a contribution to the information sciences community by showing how epidemic modeling of virus and information diffusion analysis of online social media are distinct, but interrelated concepts.

6.2 Related work

6.2.1 Information diffusion on social networks

With the advent of social networking sites and online microblogs such as Twitter, individuals can create and exchange information with larger amounts of people in lesser amounts of time. These online social networks are thus instrumental for researchers to examine what types of information diffuses between individuals and what underlying mechanisms facilitate the diffusion. In the context of social networks, information diffusion is formally defined as a process by which a piece of information is passed down from one node to another node through an edge (Gruhl, Guha, Liben-Nowell, & Tomkins, 2004; Guille, Hacid, Favre, & Zighed, 2013). Two seminal models have been widely adopted to examine diffusion dynamics with network structure considered, namely independent cascade models (Goldenberg, Libai,

& Muller, 2001) and linear threshold models (M. Granovetter, 1978). Independent cascade models assume that each node has a certain fixed probability to spread, or "infect" a piece of information to a neighboring node. On the other hand, linear threshold models posit that a node would be "infected" by a piece of information if a certain threshold of neighboring nodes have also been infected by that information. Both models have been widely used to detect influential topics (Gruhl et al., 2004) and influential users (Yang & Leskovec, 2010) in online social networks and the impacts they have on diffusion rate. Gruhl et al. (2004) focus on the spread of topics on blogs based on RSS (rich site summary) feeds and found that topics were either consistently popular (called "chatter") or only popular for a short time (called 'spikes"). The authors also observed that topics with high chatter also contained larger and more frequent spikes. Yang and Leskovec (2010) demonstrate that an influential node can be detected with respect to how many nodes have been influenced by that particular node before.

6.2.2 Epidemic Models for Information Diffusion

In addition to the independent cascade model and linear threshold model, scholars studying information diffusion from a wide range of disciplines have also found the utility of modeling diffusion as an epidemic process. In particular, the SIR model has been frequently used to explain how information in an online social network becomes "infectious" and passes from one node to another. SIR is known as a compartmental model. because it categorizes an individual to be in one of three states at a certain point in time , susceptible (S), infected (I), or removed (R) (Kermack & McKendrick, 1927). An individual may transition their state due to influence from another individual in the same network, in which the transition is linear ($S \rightarrow I$, $I \rightarrow R$). At the first transition point, $S \rightarrow I$ occurs because a susceptible individual was in contact with an infected individual and therefore got the virus. The infection assumed at this transition point is at a constant rate of β per time unit. At second

transition point, $I \rightarrow R$ transition occurs when an infected individual either recovered from the virus and got immunity from it, or has been removed (i.e. has died). At this transition, the model assumes that recovery rate is fixed at γ per time unit. These assumptions are stated in the following set of equations of (S), (I), (R) at time (t):

$$\frac{dS}{dt} = -\beta \cdot S(t)$$

$$\frac{dI}{dt} = \beta S(t) - \gamma \cdot I(t)$$

$$\frac{dR}{dt} = \gamma \cdot I(t)$$

Abdullah and Wu (2011) examine how trending news spread on Twitter by sorting users into three compartments, S for users who saw tweets from an infected user, I for users who tweet about a news topic, and R for users who no longer tweet about a topic after a predefined timeframe of four hours. The authors also assume fixed infection rate β and recovery rate γ in their epidemic simulation and observed model with Twitter data, and found a strong fit between the models. In addition to news, scholars have also examined whether false rumors and disinformation diffuse on social networks in a manner similar to how an infectious disease spread (Jin, Dougherty, Saraf, Cao, & Ramakrishnan, 2013; Nekovee, Moreno, Bianconi, & Marsili, 2007). Research by Nekovee et al. (2007) conceptualizes rumor spreading as a epidemic transition process between ignorants, spreaders, and stiflers. They found that rumor spread rate is higher in scale-free networks than in random graphs. Their finding is consistent with Lerman and Ghosh (2010)'s observation that information cascades on Twitter follow a power-law distribution. Jin et al. (2013) also refine the SIR model to examine rumor diffusion by adding exposed E and skeptical Z individuals, and found that the rate of rumor infection (I) increases as the rate of E decreases, and the susceptible (S) rate decreases as Z increases. Other works have also found SIR models to be useful in explaining diffusion of content on other social networking platforms such as Flickr (Cha, Mislove, Adams, & Gummadi, 2008) and Digg (Ver Steeg et al., 2011).

On the other hand, several studies observe that there are clear differences in SIR epidemic model and information diffusion process. Goel, Munagala, Sharma, and Zhang (2015) do

not find strong correlation between the SIR model and observed retweet cascades as the epidemic model do not take into account users' characteristics. Similarly, C. Liu and Zhang (2014) point out that information diffusion process includes variables not in SIR model such as content of the information, strength of ties among individuals, and other social factors. In light of diverse findings on the extent to which SIR models can explain information diffusion on social networks, we examine whether there are similarities in our simulated SIR model (*SIRsim*), observed SIR model based on actual COVID-19 cases (*SIRemp*), and observed information cascades on Twitter about the virus (*INFOcas*).

6.3 Framework and methodology

We empirically test whether there are similarities between the information diffusion process on Twitter about COVID-19 topics and the diffusion of the virus itself between individuals. To do this, we develop three different networks. The first two networks are created to capture the diffusion of the COVID-19 virus in the entire population, via an SIR simulated model (*SIRsim*) and an observed model based on reported data about infected (*I)*, and removed (*R)* cases (*SIRemp*). The third network is constructed from information cascades on Twitter (we call this *INFOcas*), where infected (*I)* are tweets that interacted with the original tweets about COVID-19 by either retweeting, quoting, or replying, and removed (*R*) include tweets that are no longer interacted with for a defined period. We describe the datasets used and the process of constructing each network in the following sections. All data collected and code used in this work are available on FigShare (Dinh & Parulian, 2020).

6.3.1 SIR simulation model (*SIRsim)*

We implement a SIR simulation model of Covid-19 on NetLogo[1], an open-source environment for agent-based modeling. We extended an existing model[2] on virus spread on Netlogo, and refined model parameters based on official sources' information about COVID-19 spread and shown in Table 6.2. We keep the parameters constant throughout the simulation, and set the duration of the simulation to 88 days. We choose the duration of 88 days to reflect the timeframe between December 17, 2019 to March 14, 2020. We choose December 17, as opposed to December 31, as the first date of COVID-19 to take into account the 14 days (see Table 6.2 for virus symptom length) of symptoms leading up to the confirmation of the infected case. The initial population for our model includes the entire world population, at 7.7 billion people[3].

Figure 6.1 shows the NetLogo interface of our *SIRsim* model, with additional parameters included to simulate the transitions of agents from ($S \rightarrow I$), and $I \rightarrow R$*)*. Adhering to the SIR model, S agents represent the carriers of the virus, I agents are those infected by the carriers, and R are agents who are removed due to death. Due to computational limitations that poses difficulty to represent each individual as an agent, we group 5 million people in each agent (#-people-per-agent setting). Thus, our model contains 1,540 agents interacting with one another. The first agent represents patient zero, and is originated the city of Wuhan in our world map (x-axis: 205, y-axis: -10). We assign agents to move around 36 major cities across the world (e.g. New York City, Paris, Tokyo, Moscow) (See 6.1). All agents initially started in S state, except for patient zero, who then spreads the disease by contacting with agents from other cities through two modes of traveling: driving (parameter *mode* = "human") or flying (parameter *mode* = "plane"). We set these parameters through the use of *patches* (*pixel)* feature, enabling each agent to move certain distances depending on the patch size. The circumference of our simulated "world" is 711 pixels, and with the

[1] http://ccl.northwestern.edu/netlogo
[2] Netlogo model #4286
[3] World population:https://www.worldometers.info/world-population/

given circumference of 24,901 miles[4], each patch covers about 35 miles in our model. To simulate driving, we calculate the average mileage driven per day[5] (36.9 miles), and then derive a movement of 1.05 patches per day for each agent. To simulate flying, each agent has a random chance to create an airplane and fly to any other major cities. While our model accounts for many parameters that are reflective of actual virus spread dynamics, we do not take into account any virus control strategies such as quarantine or social distancing.

Figure 6.1: NetLogo Simulation Interface for our *SIRsim* model

[4] https://www.space.com/17638-how-big-is-earth.html
[5] https://www.fhwa.dot.gov/ohim/onh00/bar8.htm, updated March 29, 2018

Major City	x-coordinate (in pixels)	y-coordinate (in pixels)
Tokyo	257	6
New Delhi	135	-13
Seoul	232	7
Shanghai	216	-7
Mumbai	127	-33
Mexico City	-221	-28
Beijing	208	14
Sao Paulo	-112	-113
Jakarta	194	-85
New York City	-165	20
Karachi	115	-19
Osaka	247	3
Manila	219	-39
Cairo	44	-9
Dhaka	159	-23
Los Angeles	-254	5
Moscow	49	64
Buenos Aires	-137	-143
Kolkata	151	-24
London	-22	50
Bangkok	180	-42
Lagos	-9	-55
Istanbul	40	16
Rio de Janeiro	-104	-112
Tehran	83	4
Guangzhou	205	-21
Kinshasa	15	-78
Shenzhen	202	-23
Lahore	127	-3
Rhine-Ruhr	-4	48
Tianjin	211	9
Bengaluru	133	-44
Paris	-14	38
Chennai	136	-43
Hyderabad	134	-37
Wuhan	205	-10

Table 6.1: List of 36 major cities used in our model, and their associated coordinates (in pixels)

We repeat the simulation over 100 iterations to ensure reliability of experimental results. Each iteration result is presented as a network that contains multiple types of nodes, *susceptible*, *infected*, and *removed*. An edge can form between any two node types, and node type can change over time (e.g. from *susceptible to infected* if there is an edge between the two nodes), except for when a node has been labeled as *removed*.

Parameter	Setting	Source
Fatality Rate	3.4%	WHO Director-General's media briefing on COVID-19 (Ghebreyesus, 2020)
Avg. Reproductive Ratio ($R0$)	1.95%	(Ghebreyesus, 2020)
Avg. $R0$ Range	1.1	(Ghebreyesus, 2020)
Avg. Incubation Period	5.1	(Lauer et al., 2020)
Incubation Period Range	1.3	(Lauer et al., 2020)
Symptom Length (Lowest)	2 days	(CDC, 2020) (Lauer et al., 2020)
Symptom Length (Highest)	14 days	(CDC, 2020) (Lauer et al., 2020)
Duration of Simulation	97 days	Virus started from Dec. 8, 2019 - Mar. 14, 2020 (Z. Wu & McGoogan, 2020)

Table 6.2: Parameter settings for *SIRsim*

6.3.2 SIR model from empirically-validated cases (*SIRemp*)

We gather actual cumulative cases of COVID-19 from Johns Hopkins Center for Systems Science and Engineering (JHU CSSE)'s data repository. This repository contains global confirmed cases, death cases, and recovered cases from January 22 to March 14, 2020, for over 185 countries (JHU-CSSE, 2020). To our knowledge, this data repository is the most comprehensive so far, with triangulation of cases counts from 18 sources (e.g. WHO, China CDC, Italy Ministry of Health, WorldoMeters). We analyze this dataset within the assumptions of SIR model, where S are individuals in the population that are not yet

infected nor immune to the virus, I is equivalent to "confirmed cases" in the dataset, and R is equivalent to "deaths cases". We do not include the "recovered" cases in our model as the data does provide whether these cases are re-entered into the "confirmed cases" in latter time-frames. In the original dataset, there is no inclusion of S, given that susceptible nodes include all members of the world population.

6.3.3 Information diffusion on Twitter (*INFOcas*)

The third dataset we use for this research is Twitter data that contains information about COVID-19. We collect tweets during the period of December 31, 2019 to March 14, 2020 with a maximum of 10,000 samples (limit set by firehose) for each day from Crimson Hexagon firehose[6]. We collect 675,228 tweets that include either or all of the hashtags #coronavirus, #covid19, #ncov. We construct information cascades based on three primary behaviors that occurs between tweets in our dataset: (1) retweet, (2) quote tweet, and (3) reply. We exclude all tweets content originated from European countries, in recognition of General Data Protection Regulation (GDPR)[7]. Based on the *SIR* model, we define the conditions for *infected* nodes, and *removed* nodes below. Our approach does not consider *susceptible* nodes, because intuitively, susceptible nodes in this context are all tweets that exist on Twitter.

New Information: An original tweet that has yet to be retweeted or interacted with is counted in this category. There are 14,139 tweets in this category.

Infected (I): If a tweet interacts with an S tweet through either retweeting, quoting, or replying, the tweet is counted in this category. (1) Retweet is an action of reposting an original tweet, and without changing the original tweet content. Our sample contains 419,739 retweets. (2) Quote tweet is an action to forward the message with additional information related to the original tweet. Quoting is usually used if the user wants to add a new comment

[6]Crimson Hexagon:https://forsight.crimsonhexagon.com/
[7]General Data Protection Regulation (GDPR), https://gdpr-info.eu/

about the related event but still preserving the original content. Our sample contains 17,569 quote tweets. (3) Replying entails commenting on the original tweet, using Twitter's "reply" function. Reply tweets are aggregated into a "thread" of discussions under the original tweet. There are 22,594 tweets that are in the replies category.

Removed (R): If an original tweet has not been retweeted, quoted, or replied to by other tweets in a defined period. We used the average delta time between each activity on the original tweet as our incubation period. Therefore, if there is no user interaction with the tweet between the average time frame from the latest spread, we consider the tweet is removed. Average delta time statistics for each type of cascade (retweet, quote tweet, and reply tweet) can be seen in Table 6.3. There are 69,216 tweets in total that are in this category.

An information cascade is determined by the period other tweets (I) interact with an original tweet (S) on this dataset. Given an original tweet (T_0) on time $t0$ the cascade c on time $t1$ (c_{t1}) is equal to:

$$c_{t1} = t1 - t0 \tag{6.1}$$

For each type of information cascade, we analyze the cascade growth by aggregating the S, I, and R tweet for each day.

	Retweet	Quote tweet	Reply tweet
Count	419,739	17,569	22,594
Avg. delta time	0 day-04:54:29	0 day-14:55:33	0 day-08:42:30
Standard dev.	1 day-00:42:14	2 days-17:55:19	1 day-19:27:15

Table 6.3: *INFOcas* cascade statistics

6.4 Results

6.4.1 *SIRsim* and *SIRemp*

Our first research question asks about the diffusion patterns of COVID-19 based on both a simulated SIR model (*SIRsim)* and actual number of cases from empirically-validated sources (*SIRemp*). For *SIRsim*, across 100 iterations of our simulation, we find the average counts of *susceptible* agents to be 7,299.4 million, average counts of *infected* to be 384.9 million, and average counts of *removed* to be 15.0 million. Thus, the proportion of healthy, but susceptible agents is 94.8% (S) in our model. There are only 5% (I) of agents that are infected by the virus, and only 0.19% (R) are removed due to death. As shown in Figure 6.3, the distribution of *infected* (blue line, left) and *removed* (red line, left) agents per day, non-cumulatively, and find an increasing pattern for both trendlines. The proportions of removed cases is much lower than infected cases (as shown in Figure 6.2).

Figure 6.2: *SIRsim* network. *Blue nodes* = infected cases, *Red nodes* = removed (death) cases

Figure 6.3: Distributions of *Infected* and *Removed* agents for *SIRsim* (left) and *SIRemp* (right) models

We then compare these results to *SIRemp*, which finds that as of March 14, 2019, there were 156,102 *infected* cases, and 5,819 *removed* cases (deaths only). By proportion with the world population, therefore, *infected* cases is 0.002%, and *removed* cases is a minimal percent. By comparison, the empirically-validated results show substantially lower proportions of *infected* and *removed* agents, and in turn, higher proportion of *susceptible* agents. We also analyze the distribution of *infected* (blue line, right) and *removed* cases (red line, right) for *SIRemp*, and finds multiple spikes in the blue line, but flat distribution for the red line. The spikes in *infected* counts are due to inclusion of cases from countries such as the U.S, South Korea, Italy. In comparison to the distributions from *SIRsim*, the distribution of *removed* cases in *SIRemp* is relatively static throughout.

6.4.2 Twitter cascades: *INFOcas*

Table 6.4 shows the sizes of the three network cascades within *INFOcas*, retweet, quote tweet, and reply tweets. We find that retweet cascade is 19 times larger in size than the quote tweet cascades, and 16 times larger than the reply cascades.

Network	# of nodes	# of edges	Density
INFOcas - Retweet	303,486	389,717	4.23e-06
INFOcas - Quote tweet	15,962	15,651	6.14e-06
INFOcas - Replies	19,016	17,712	4.89e-05

Table 6.4: Network descriptives for retweet, quote tweet, and reply tweet cascades

Figure 6.4: Retweet, Quote tweet, and Reply tweet growth for each day during the COVID-19 outbreak period Jan 1, 2020 - March 14, 2020. x axes represents the day, and the y axes represents the number of tweets. New information is the original source of information, infected is representing interaction to the other users, and dead represents the end of the information spread after a period.

Figure 6.4 presents the rapid growth in tweet activities, with stark increase in retweets, quote tweets, and reply tweets during mid-January. We find that the growth distributions for all three tweet types follow a logarithmic curve. In addition, the number of infected users, equivalent to individuals spreading the information, is much higher compared to the new information consistent on the three observations. We also observe that the cascade growth for retweets is substantially higher than growth for quote tweets and reply tweets.

type	intercept (β_0)	coefficient (β_1)	r^2
Retweet			
New Information	-7570.42	2414.83	0.89
Infected	-23000.00	7847.59	0.82
Removed	-3736.46	1176.49	0.87
Quote tweet			
New Information	-660.72	216.79	0.87
Infected	-1533.84	500.18	0.89
Removed	-181.96	56.84	0.85
Reply tweet			
New Information	-537.23	178.34	0.79
Infected	-1513.02	487.25	0.88
Removed	-217.06	68.34	0.79

Table 6.5: Linear-log regression summary for *INFOcas*

Table 6.5 shows the coefficients and parameters for each linear fit of the number of tweets to the day-period. As we can see from the table, the slope of a retweet is the highest, followed by the quote tweet and reply tweet. The slope for *removed* information is the lowest compared to the infected and new information and consistent for all cascade types. This indicates that as the number of *new information* is introduced each day, some portion of the information stops spreading.

6.4.3 Correlations between *SIRsim*, *SIRemp*, and *INFOcas*

We aggregate the data from SIR-simulation over 100 iterations (*SIRsim*) and CSSE's real-infection data (*SIRemp*) and analyze correlation with Twitter's information growth (*INFOcas*) for the same time period. Table 6.6 shows the correlational values, with respect using

Pearson's correlation, for each SIR state.

In terms of cascades for *new information* nodes, we find highest correlation between SIRsim and INFOcas-reply tweets (r=0.67). We also find high correlation between INFOcas-reply tweets and INFOcas-quote tweets (r=0.84). INFOcas-retweets, on the other hand, has a lower correlation with quote tweets (r=0.53, and a slightly higher correlation with reply tweets (r=0.73).

Figure 6.5: Number of retweet count for new information on daily period. Trendline (in red) shows a exponential fit

Figure 6.5 shows the growth of retweet count for new information that presented each day. As we can see, the real retweet counts are following the exponential curve compared to the logarithmic curve we have on the sample data. This also indicates the amplification of new information in social media, with more people retweeting the information, the information will become viral and bring more attention to Twitter users. For the cascades of *infected* nodes, we find the highest correlation between *SIRsim* and *INFOcas*-retweets (r=0.86). The second-highest correlation is between retweets and quote tweets (r=0.83). Another notable

correlation is between *SIRsim* and quote tweets (r=0.76). *SIRemp* has low correlations with all other types of cascades, with correlations ranging from 0.31 to 0.47.

In terms of the *removed* nodes cascades, there is also high correlation observed between *INFOcas*-retweets and quote tweets (r=0.83). Retweets also have high correlation with reply tweets (r=0.74). These two correlations show that retweet cascades are most correlated to quote tweets and reply tweets with respect to tweets that are no longer interacted with, and thus can no longer spread that particular tweet content in the network. Correlation between *INFOcas* and *SIRsim* is relatively lower (r=0.58-0.69), showing that there is a weaker relationship between the simulated and observed Twitter's *removed* cascades. Similarly, there is a weak relationship between *SIRemp* and all *INFOcas* cascades, especially with reply tweets (r=0.28).

	Infected nodes						**Removed nodes**				
	Retweet	Quote tweet	Reply tweet	*SIRsim*	*SIRemp*		Retweet	Quote tweet	Reply tweet	*SIRsim*	*SIRemp*
Retweet	1	0.83	0.75	0.86	0.41	Retweet	1	0.83	0.79	0.66	0.53
Quote tweet	0.83	1	0.65	0.76	0.39	Quote tweet	0.83	1	0.74	0.69	0.51
Reply tweet	0.75	0.65	1	0.58	0.31	Reply tweet	0.79	0.74	1	0.58	0.28
SIRsim	0.86	0.76	0.58	1	0.47	*SIRsim*	0.66	0.69	0.58	1	0.57
SIRemp	0.41	0.39	0.31	0.47	1	*SIRemp*	0.53	0.51	0.28	0.57	1

Table 6.6: Correlations between *INFOcas*, *SIRsim*, *SIRemp* in terms of *Infected* and *Removed* nodes

6.5 Discussion

Our study focuses on the diffusion patterns of COVID-19 virus itself and the information shared online about the virus. To capture the diffusion patterns of the virus, we create an SIR model (*SIRsim*) based on empirically-validated transmission dynamics of COVID-19 (e.g. reproductive ratio, incubation period), and then compare with actual confirmed cases

of COVID-19 from January 22 to March 14, 2020 (*SIRemp*). To examine diffusion patterns of information discussed online about COVID-19, we construct three cascades (*INFOcas*) based on retweets, quote tweets, and reply tweets on Twitter that mentioned COVID-19 from the period of December 31st to March 14, 2020.

Our first research question asks about the diffusion patterns of COVID-19 virus, based on epidemiological assumptions of SIR. From our *SIRsim* model, we find the proportions of infected cases to be only 5% of the entire world population, and the proportions of removed (dead) cases is only 0.19% of the population. Our model accounts for 88 days since the first case of the virus, and the upward trajectory beyond linear growth suggests to us that rate of infection and deaths may increase logarithmically. This is consistent to current findings on COVID-19 that finds the distributions of infected cases follow a logarithmic distribution (Cao et al., 2020; Maier & Brockmann, 2020). Cao et al. (2020) finds the logarithmic growth rate is suitable considering that COVID-19 is relatively in the early stage, and thus growth is slowly increasing. We also find notable differences in the simulated model and the actual confirmed cases of COVID-19 (from *SIRemp*). In fact, the distribution of *removed* cases in *SIRemp* is flat, as opposed to the increasing distribution observed in *SIRsim*. There are two reasons for the mismatch in simulated and actual distributions of *SIR* cases. The first is that our model does not take into account preventive measures such as social distancing, self-quarantine, and shelter-in-place which are found to be effective in "flattening the curve" (Lewnard & Lo, 2020; Parmet & Sinha, 2020). The second reason may be that the quantification of infection and death rates need further modifications, specifically because there is still limited testing Ioannidis (2020), and reporting delays (Gardner, Zlojutro, & Rey, 2020).

The second research question asks about the diffusion patterns of information cascades on Twitter about COVID-19. We construct retweet cascade, quote tweet cascade, and reply cascade (we call these *INFOcas*) to fully capture the different types of interactions between users on Twitter. All three cascades shows strong fit with linear-log distribution, suggesting a power-law decay in the diffusion of new information about COVID-19 over time. With

this finding along with the cascade length of each tweet type, we expect that retweet cascade decays at the fastest rate, given that its cascade length is only approximately 4 hours. On the other hand, we find quote tweets' average cascade length to be about 3 days, which means that each original tweet that has been interacted with via quotes has longer duration in terms of activity. This is also observed for reply tweets, where the average cascade length is about 2 days.

The third research question focuses on the correlation in diffusion patterns between *SIRsim*, *SIRemp*, and *INFOcas* to address the connection between epidemic and information diffusion dynamics. Based on the examination of *infected* cascades, we find the stronger positive correlation between *SIRsim* and *INFOcas*-retweets (r=0.86), and quote tweets (r=0.76). On the other hand, we observe low correlations between *SIRemp* and all three *INFOcas* types (r=0.31-0.41). This shows that the distribution of infected agents are more correlated between *INFOcas* and *SIRsim*, and not so much with *SIRemp*. With the rapid spread dynamics seen in *SIRsim*, this correlation shows that tweets about COVID-19 gets retweeted most quickly, then followed by quote tweets, and reply tweets. The correlation between *SIRsim* and *SIRemp* is relatively low (r=0.47), which may indicate that either the simulated model potentially overestimates the *infection* rate, or that the actual reported cases may underestimate the *infection* rate. For the *removed* cascades, we find strongest correlations between *INFOcas* cascades, specifically between retweets and quote tweets (r=0.83), retweets and reply tweets (r=0.79), and quote tweets and reply tweets (r=0.74). We find weaker correlations between *INFOcas* and *SIRsim* (r=0.58-0.69), and weakest correlations between *INFOcas* and *SIRemp* (r=0.28-0.53). This result is consistent with our observation that the *removed* distribution on *SIRemp* is more uniform and flat compared to other distributions. It is also expected that the *removed* distribution for *INFOcas* would be different from *SIRsim*, given that the likelihood of tweets to transition from *infected* to *removed* is substantially higher.

6.6 Chapter summary

In this chapter, we find complex relationships between diffusion dynamics about COVID-19 from the simulated virus spread model, the actual reported cases of the virus spread, and the information shared and discussed online. In congruent with recent empirical literature (Z. Chen, 2016; Lerman, 2016; Mønsted et al., 2017), we find that information spread on social media is not similar to epidemic *SIR* model as human's likelihood of *infection* is bounded by our cognitive and time limits for each new information, while the virus does not have the same constraints. In future work, we hope to expand our data collection to more recent dates, given the constantly-changing nature of the pandemic. Additionally, we aim to improve our simulated epidemic model (*SIRsim*) to include additional control variables that reflects actual prevention strategies, namely social distancing, self-quarantine, and shelter-in-place.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Summary of main findings

This thesis contributes advances in network theories and methods to examine the emergent and formal network dynamics present in the contexts of interpersonal relationships, corporate/organizational arrangements, and hazards response. More specifically, this thesis draws from prior work on computational communication with specific focus on organizational communication dynamics and crisis informatics (Barley et al., 2022; Dinh et al., 2020; Sarol et al., 2021, 2020) using large-scale data that capture the real-world interactions between individuals and groups. In chapter 1, three groups of questions are proposed, representing three main camps of contribution for the thesis. The section below summarizes the three camps of research questions, as well as the main findings:

7.1.1 **Group 1** Network analysis methods to examine interpersonal dynamics

RQ1-1 and RQ1-2 in chapter 2 aim to examine how network analysis theories and methods can be applied to interpersonal contexts. RQ1-1 asks about how we can evaluate balance for sign directed networks. RQ-1-2 asks about the insights we gain from balance evaluation of real-world social networks. Chapter 2 is dedicated to answer these questions, and I find that balance theory is effective in determining if the structural configurations of the network is stable. A part of chapter 3 also provides an extension to balance evaluation where I show that we can determine the extent to which a network is balanced, and the identify the triadic

configurations where sources of imbalance are present. The rationale for structural balance as a primary theoretical framework for understanding interpersonal relations stems from the cognitive social tradition (Heider, 1946, 1958; Krackhardt, 1987) which focuses on how individuals interact with others in ways that are consistent with their perceptions of others. Thus, the framework is suitable to explain social/interpersonal interactions that arise out of each individual's need to minimize relational tension in their connections.

7.1.2 **Group 2** Network analysis methods to examine corporate/organizational dynamics

RQ2-1 in chapter 3 focuses on the application of network analysis theories and methods to corporate and organizational contexts. Chapter 3 contains network examinations of three organizations, namely two corporate organizations, one team-based group. In this chapter, I show that balance evaluation can pinpoint the sources of tension that is present in an organization based on the communication network among organizational members. Balance evaluation in the corporate context is also meaningful as it reveals whether the sources of tension present in the interpersonal network (based on email communication) is reflective of the formal organizational structure. Indeed, the differences in balance and triadic profiles seen in Enron and Avocado, where Enron network contains frequent 030T triads while Avocado contains frequent 120D and 300 triads, show that formal structure has an impact on communication and balance dynamics.

RQ2-2 in chapter 4 asks about the structural dynamics in a medium-sized scientific organization that values interdisciplinary research. I show that an individual's informal network of connections (via frequent interaction, advice-receiving, etc), in combination with their formal roles in the organization (via job position, tenure at organization) are also indicative of them likely to form ties with similar other (high SimExp), as well as those who are familiar with the expertise language of that individual (high LingFam). Based on the multilevel modeling results, I also find that likelihood of two researchers who come from

different expertise (low SimExp) to form a tie and possess high familiarity with each other's expertise language (high LingFam) is low, meaning that the types of interdisciplinary ties in the scientific organization is rare. On the methodological front, I demonstrate that multilevel models (i.e. multiple membership multiple classification model is suitable to analyze nested egocentric data where alters can be in multiple ego-networks, and an ego can also be an alter in another ego-network.

7.1.3 **Group 3** Network analysis methods to examine hazards response dynamics

RQ3-1 and RQ3-2 presented in chapter 4 ask for the factors that influence the amount of structural overlap between the formally prescribed and empirically observed (emergent) networks of collaboration during responses to natural hazards. I find that the level of response jurisdiction (on which the prescribed networks are based on) influences the amount of overlap detected between prescribed and observed network. This finding suggests that the perspective of which governmental level we take changes the structure of the prescribed network. Federal-level prescribed interactions are most frequently present in the observed networks, suggesting that either (1) federal organizations are highly involved in response, or (2) observed response documentation contain language most congruent with federal-level documentation. There is no effect of data source on the amount of network overlap between the prescribed and observed networks, meaning that both SITREPs-based and tweet-based networks yielded comparable amount of overlap (low) with the prescribed networks. This finding also suggests that social media data (i.e. tweets), along with situational reports, may contribute crisis-related information for situational awareness (Hiltz & Plotnick, 2013; Olteanu et al., 2015; Sarol et al., 2021; Verma et al., 2011).

RQ3-3, RQ3-4, and RQ3-5 in chapter 5 focus on the network differences between the expected diffusion structure based on virus spread and the observed diffusion structure based on information sharing online (via tweets) to empirically test the hypothesis that diffusion

of information is similar to virus diffusion (Abdullah & Wu, 2011; Goffman & Newill, 1964). I find that the diffusion patterns between the two networks are similar only based on certain types of sharing (i.e. retweets and quote tweets), given that some types of sharing such as replies and quotes with replies require more cognitive effort to produce and thus may delay the diffusion rate compared to retweets. Chapters 4 and 5, altogether, focus on the application of network science for the natural and biological hazards response context, where the comparisons between emergent (from social media data, situational reports) and formalized (prescribed in governmental documentation; simulated based on theoretical epidemic models) network structures bring out how hazards-related collaboration dynamics (Chapter 4) and hazards-related situational awareness (Chapter 5) are discussed in various platforms.

7.2 Contributions

Figure 7.1: Dissertation's contributions in terms of advancing network science theories, methods, and applications

With the aforementioned research questions and the main findings that are obtained, this dissertation demonstrates a theory-driven pipeline for network analysis research. Network science as a field is interdisciplinary in nature; its theoretical, methodological, and conceptual foundations are produced by the efforts of a number of core disciplines, ranging from sociology, mathematics, to political science, communication, information sciences, and many more. This also means that the process of conducting network analysis differs depending on the discipline; an inductive network study may focus on making empirical observations that contribute to theory building, and a deductive study may have a clear theoretical framework that it aims to empirically validate. This dissertation is created under the assumption that inductive and deductive research is not a dichotomy, but rather can be a combination (Paul, 1993; Walton, 2014), where we engage in a cycle of theorizing and making observations that helps generate and regenerate research questions/hypotheses. In the works presented in this dissertation, we engage in the iterative process of empirical evaluation of a theoretical framework that in turn informs the theoretical refinements needed. This connection between theory and empirical observations, or what Charles Peirce calls abductive reasoning 1992, is especially relevant to network science as theories about social dynamics can be applied and refined to real-world relational contexts.

As shown in Figure 7.1, the overarching structure of the works in this dissertation is a tight interconnection between, theory, method, and application to (1) interpersonal, (2) organizational/corporate, and (3) hazards response contexts. The three application areas are constructed in chronology, in which network analysis for interpersonal and social contexts is a building block for many theoretical frameworks that explain the formation of relationships (M. S. Granovetter, 1977; Heider, 1946; Krackhardt, 1987; Monge & Contractor, 2003). Based on a foundation theory of structural balance that explains how individuals organize their social connections, we show that in all networks of different interpersonal relationships types and different sizes, balance is preferred over imbalance. We also find that balance is a local process that takes place between individuals in a triadic configuration (size of

three), then the effect ripples through the network which then influence the global dynamics of structural balance. These two findings both empirically verify the tenets of structural balance, and further confirms latter generalizations of the theory (Cartwright & Harary, 1956; Doreian & Mrvar, 2009) that balance is at multiple levels of the network.

Relatedly, we also find that balance is preferred in corporate settings between workplace members. Theories about how corporate and organizational structures form, sustain, and dissolve over time (Feld & Elmore, 1982; Giddens, 1984; Homans, 1950; Monge & Contractor, 2001) is also a major area of interest in network science research. As shown in our work on interdisciplinary collaboration in a scientific organization, empirically-observed mechanisms that explain the formation of a tie between two organizational members are both at the attributes of the individual (i.e. their formal roles, tenure, age, gender) and the attributes of their interpersonal/social networks (i.e. friendship, advice-receiving). Similarly, balance dynamics between corporate members also show that while a formal structure of communication is present, individuals exchange information that spans across sub-units and organizational boundaries. These findings also has implications for network modeling as network dynamics can be observed at the level of the node and the edges between nodes; multilevel models are suitable to account for variance at these two levels of the network. Additionally, the studies discuss in this context also contributes to the computational communication literature (Hilbert et al., 2019) in terms of how network methods are applied to uncover the communication dynamics that take place between individuals (dyad), groups (triads and cliques), and the whole network overall.

In the last section of the dissertation, I argue that hazards response is a type of complex interorganizational system, which can be explained by theories about organizational dynamics. I demonstrate that formal and emergent response dynamics are present in hurricane response networks, where both prescribed collaboration relationships and informal connections between response organizations co-exist. In the context of biological hazard such as COVID-19, I empirically show that the theoretical model of epidemic spreading is partially

similar to information diffusion online depending on the feature of sharing (i.e. retweets is most similar to fast-spreading virus, but quote tweets and replies are not). In combination, these two works show that hazards response is complex and information about response as well as about the hazard itself is different across data sources (i.e. situational reports versus social media).

7.3 Future directions

7.3.1 **Group 1** Network analysis methods to examine interpersonal dynamics

Chapters 2 and 3 have begun to show that structural balance is a dynamic process that can change over time, with a preference to increase overall balance. However, as we see in the Newcomb's fraternity network, balance does not increase consistently over time, and there is still a substantial amount of imbalance in the network towards the end. Interestingly, the network still remains with no indicators of dissolution. With this observation in mind, I aim to empirically determine a level of "imbalance" that keeps the network maintained without dissolving or breaking apart into separate networks. Specifically, I ask for the configurations of imbalance with respect how many negative ties are frequently detected in each imbalanced triad, subgroup, and why they do not turn positive over time. Capturing these patterns of negative relationships may reveal if there are certain configurations that may be harder to change over time, and the reasons for the resistance towards balance.

7.3.2 **Group 2** Network analysis methods to examine corporate/organizational dynamics

Chapter 3 shows that interdisciplinary collaboration dynamics are complex, and the performance benefits associated with high interdisciplinary in a scientific organization is still a developing area of research. In collaboration with researchers in the Department of Commu-

nication and the School of Integrative Biology, I aim to capture whether interdisciplinarity relate to positive performance in a scientific organization. Specifically, we ask: Does participation in a interdisciplinary science center affect researchers' careers? In asking this question, we aim to capture the dynamics of how interdisciplinary scientific teams form, as well as the impact of working together before and after interdisciplinary team formation for their research productivity. Given that the focus is on scientific collaboration, network data will consist of bibliometric data and author-specific attribute data that will be used to explain mechanisms for forming a collaborative tie.

7.3.3 **Group 3** Network analysis methods to examine hazards response dynamics

Chapters 5 and 6 highlight hazards response as a complex system of organizing where multiple processes of communication and coordination occur to ensure shared situational awareness. Such processes can be captured through a network-analytic perspective. The differences in network structures across different levels of response jurisdictions (federal, state, local, non-governmental), data sources (situational reports, social media), and hazards events show that there is no one-size-fits-all response guideline. The case-specific nature of crisis response warrants an in-depth case study where situational awareness gained from secondary data can be complemented with crisis responders' perspectives to understand aspects of response guidelines that can be improved. In collaboration with Aransas County's emergency operations officer, I will further examine collaboration dynamics that took place during 2017 Hurricane Harvey with respect to crisis responder's perception of an effective response, and actual response dynamics that took place during the hurricane event.

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