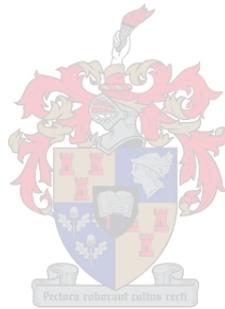# Cognitive Structural Accuracy

by

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Thesis presented in fulfilment of the requirements for the degree of Master of Arts (Socio-Informatics) in the Faculty of Arts and Social Sciences at Stellenbosch University

Supervisor: Mr. L.A. Cornellissen

April 2019

Declaration

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Abstract

Cognitive Structural Accuracy

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An understanding of how individuals view their social network and the implications thereof is a prominent theme in social network analysis. An individual is considered to have an accurate cognition about their social network when their perception of the relations between other actors in the social network is similar to the actual relations in the social network.

Current social network accuracy measures are limited to measuring similarity between specific actors in the social network, however, it is plausible that individuals perceive their social network in terms of higher-order network structures. This research project addresses this gap in social network cognitive accuracy measures by proposing three network structural accuracy measures for determining an individual's structural accuracy.

The three structural accuracy measures were demonstrated on four social networks of two small entrepreneurial firms and compared to interpersonal accuracy. The triadic accuracy measures only showed substantial difference with

regards to interpersonal accuracy in two of the four social networks. The inconclusive comparison for the two other networks may have been due to the limited number of social networks investigated.

The triadic accuracy measures present the opportunity for future research to revisit previous examinations of the effects of cognitive accuracy in social networks. Further research is needed to determine how well the triadic accuracy measures provide a distinct approach to measuring structural accuracy.

Uittreksel

Kognitiewe Strukturele Akkuraatheid

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'n Begrip van hoe individue hul sosiale netwerk beskou en die implikasies hiervan is 'n prominente tema in sosiale netwerkanalise. 'n Individu word beskou om 'n akkurate kognisie van hul sosiale netwerk te hê wanneer hul persepsie van die verhoudings tussen ander akteurs in die sosiale netwerk soortgelyk is aan die werklike verhoudings in die sosiale netwerk.

Huidige sosiale netwerk akkuraatheid mates is beperk tot mates van ooreenkomste tussen spesifieke akteurs in die sosiale netwerk, maar dit is moontlik dat individue hul sosiale netwerk waarneem in terme van hoër-orde netwerkstruktuur. Hierdie navorsingsprojek spreek hierdie gaping in sosiale kognitiewe netwerk akkuraatheidsmates aan deur drie netwerkstruktuur akkuraatheidsmates voor te stel om die strukturele akkuraatheid van 'n individu te bepaal.

Die drie strukturele akkuraatheidsmates is gedemonstreer op vier sosiale netwerke van twee klein entrepreneursfirmas en vergelyk teen interpersoonlike akkuraatheid. Die triadiese akkuraatheidsmates het slegs merkwaardige verskille ten opsigte van interpersoonlike akkuraatheid in twee van die vier sosiale

netwerke getoon. Die onbesliste vergelyking van die twee ander netwerke mag as gevolg wees van die beperkte hoeveelheid sosiale netwerke wat ondersoek was.

Die triadiese akkuraatheidsmates bied die geleentheid aan vir toekomstige navorsing om vorige ondersoeke van die effekte van kognitiewe akkuraatheid in sosiale netwerke te herondersoek. Verdere navorsing is nodig om te bepaal hoe geskik die triadiese akkuraatheidsmates is om strukturele akkuraatheid te meet.

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Chapter 1

Introduction

1.1 Background

In an increasingly connected world, studying the effects of our social connections has become a prominent theme in the social and behavioural sciences (Borgatti et al., 2009). One area of interest is how individuals conceptualise their social networks—their perception of the social connections in their social environment.

Understanding how individuals perceive their social networks is a substantive area of research: much of an individual's behaviour is influenced by their perception of their social network—for example, whom they consider to be their friends or whom they would go to for advice.

However, one individual's perception of the social connections may well differ from another individual's perceptions about the same social connections in the same environment. For example, a manager may consider himself or herself to be friends with his or her employees, but if the employees do not share this view the manager has an inaccurate perception of the actual relationships in his or her social network.

Krackhardt (1990) found that individuals who are more accurate in their perceptions of the social ties in their network are also considered to be more powerful. Other research has also focused on the antecedents of cognitive accuracy including personality traits (Casciaro et al., 1999; Ouellette, 2008), gender (Brashears et al., 2016), and network position (Bondonio, 1998; Simp-

son and Borch, 2005).

Determining an individual's (network perception) accuracy involves measuring and comparing the perception which the individual has about the social connections in their social environment to the actual[1] social connections in the social environment. Social network analysis (SNA) provides the framework for analysing the effects of an individual's perceptions about the social connections in their social environment as it focuses on the connections between social entities rather than the entities themselves (Wasserman and Faust, 1994:21).

Most studies involving accuracy measure interpersonal accuracy—how accurate an individual is about the *specific* social connections in their social environment. However, no accuracy measure exists which accounts for individuals who may have a better intuition about the social network structure, or patterns of relationships, but are inaccurate about specific social connections. This research project seeks to address this gap.

1.2 Research Focus

When considering an individual's cognition of their personal social networks, it is not enough to simply argue for a single measure of accuracy. Current cognitive network accuracy measures focus on the correlations between specific ties in the social network, not explicitly measuring whether the individual is correct about the general network structure.

It is possible for an individual to know the general structure of their social network or components of the whole network (particularly the communities they reside in or where the communities are well known), without knowing the exact relationships which exist between members within the social network. In fact, it is possible that an individual may be mostly oblivious to the actual ties between specific actors and still be relatively accurate about the general structure of the network. For example, a manager in an organisation may know not be aware of which of his employees go to whom for advice but may accurately perceive that his employees tend to only go to higher ranked

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[1]The term 'actual' in this thesis refers to relationships which are derived from the perceptions of individuals rather than direct observation of the relationships (See Krackhardt, 1990:77). The definition of the 'actual' social network is addressed in Chapter 3.

individuals or that they tend to work in groups. The manager is therefore aware of the general structure of the interactions of his employees without necessarily knowing the specific interactions between his or her employees.

Some researchers have measured cognitive social network accuracy in other ways by restricting the standard interpersonal cognitive accuracy measure to a specific subset of actors. For example, Casciaro et al. (1999) makes a distinction between local and global accuracy. Specifically, Casciaro et al. defines local accuracy as a measure of the similarity between an actor's perception of their direct ties to others in social network and their actual direct ties in the social network, whereas global accuracy measures the similarity between the actor's perception of all the ties in their social network to the actual ties in the social network.[2] Casciaro et al. argues that "there are systematic cognitive differences between the perception of one's own social relationships and the perception of relationships between others in a group, and that these differences have distinct implications for individual outcomes in a social group" (1999:287). It is self-evident that people will have different degrees of accuracy in their perception of the relationships which are 'close' to them compared to the relationships between people which are 'further' away from them in the social network—however, in order analyse this phenomenon, Casciaro et al. proposed creating a new accuracy measure.

Although Casciaro et al. (1999) distinguishes between different measures of accuracy, they still rely on measuring judgements of relations at an interpersonal level. The alternative to measuring judgements is to measure judgements about the perceived structure or pattern of relations in the network. In fact, Ouellette (2008:2) points out that an individual's social network is not "merely the aggregation of dyads" and that other network structures, such as triads and cliques, may also affect the accuracy of an individual's perception of their social network.

To explore the perceptions of structural patterns in a network, it is important to understand the concept of heuristics. Heuristics are cognitive strategies used to reduce cognitive load in complex environments where optimal solutions may not be viable—where the cognitive load is too great, or knowledge of the

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[2]Global accuracy, as defined by Casciaro et al. (1999), is the same as the standard interpersonal accuracy measure.

social network is incomplete. Thus, we make use of cognitive strategies to make inferences or judgements about that which we do not know.

Since our social environments are typically dynamic and complex in nature, it is expected that people use some form of heuristic to understand their social environments. It is reasonable to expect that no individual would have perfect interpersonal judgement of relations about their entire social network. If we follow Dunbar (1992) the number of stable relations a person can comfortably maintain is 150. In terms of the number of possible relations in a social network, this translates into 11 175 possible relations.[3]

Thus, for all but the smallest social networks, it is inevitable that individuals will need to use some form of heuristic to make judgements of interpersonal relations. For example, individuals tend to judge that their friends are friends with each other to 'complete' perceived relations (Heider, 1958). Heuristics use a pattern or 'rule of thumb' to make judgements about the interpersonal relations within the network. Thus, it is possible for an individual to infer that a certain network is very collaborative (and thus will have high density) but tend to form very tight-knit groups (thus displaying clustering), without knowing much about the actual relationships between specific individuals.

It can be expected that some individuals will be more accurate in their employment of heuristics. This should translate into social network heuristics, leading to certain individuals having a more accurate perception of the network structure. Currently, no network measure exists which accounts for the use of heuristics when determining cognitive structural accuracy. This gap in cognitive social network research requires a new method to capture and compare an individual's perceptions of the social network against the actual social network. The focus of this study is therefore to explore a way to measure network structural accuracy.

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[3]The number of possible relations can be determined using the function $\binom{n}{k} = \dfrac{n!}{k!(n-k)!}$, where n is the total number of actors in the social network and k the number of actors selected at a time. In this case, two actors are selected at a time, but when investigating higher order structures, it may be useful to select multiple actors at a time.

1.3   Research Question

Social networks are complex due to multiple actors having multiple relationships with each other, contingent on their relationship with other actors. This means that even a small network requires individuals to keep track of hundreds of possible relationship pairs (Kilduff et al., 2008:15).

This complexity inevitability puts strain on the cognitive cognitive resources of the individuals who attempt to accurately perceive the relationships within their social networks (Krackhardt and Kilduff, 1999:772). Consequently, individuals resort to strategies to deal with the complexity encountered in their social networks. One common method of dealing with complexity is the use of heuristics.

An example of heuristics being used is in balance theory, where individuals adjust their perspective of their own or another's relationships based on their relationship with a mutual friend so that their relationships are cognitively consistent (Heider, 1958). This may result in individuals changing their own attitude towards the mutual friend so that it is consistent with their friend's or changing their perspective about their friend's relationship towards the mutual friend.

This approach is not only used in events where the relationships are known, but also where relationships are unknown. For example, Krackhardt and Kilduff (1999) found that individuals employ the balance schema not only for relationships close to themselves, but also when making judgements about more distant relationships between individuals.

However, heuristics may also lead to biases in judgements about relationships between actors. This is evident in the research done by numerous authors, particularly in a series of empirical studies by Bernard, Killworth and Sailer[4] (referred to as the BKS studies), who found that individuals could only accurately recall about half of their own interactions with others—indicating that most "people simply do not know, with degree of accuracy, with whom they communicate" (Killworth and Bernard, 1976).

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[4]Killworth and Bernard (1976, 1979), Bernard and Killworth (1977) and Bernard et al. (1979, 1982).

The aim is to measure how accurate individuals are about their social networks by introducing a structural approach for determining cognitive accuracy. There are two apparent methods to do this, but as will be shown, these methods are either too strict or too vague to reliably account for structural perception of social networks. A third method is therefore proposed as a more reliable method to represent structural perceptions of network structure. The two apparent methods will be outlined below, after which a third method is proposed.

Firstly, network structure can be compared directly. This approach involves comparing the individual's perceived interpersonal relations (cognitive slice) against the true ties within the social network. The most common method to calculate accuracy is to use the correlation score between the cognitive slice and actual network (e.g., Pearson correlation coefficient) or a distance measure between the cognitive slice and actual network (e.g., Euclidean distance).

For an individual to be accurate, according to this approach, they will need to have specific knowledge of each person's relationship with everyone else within the social network—a complex and difficult cognitive task. This is a strict approach to determining how accurate an individual is about the network structure.

Secondly, the network structure can be distilled into measurements of graph level indices (GLIs), which are network-level properties (e.g., density). This approach compares measures of the graph structure of the individual's perceived social network against measures of the graph structure of the actual social network. For an individual to be accurate, according to this approach, they need only be broadly aware of the network's properties in order to be considered accurate—thus it may be possible for individuals to be considered accurate about the network structure, but only on the broadest of terms, limiting the application of this approach.

It is proposed that instead of determining structural accuracy by directly comparing the structure of the networks or indirectly by comparing GLIs, a triad census be used to compare the networks. The notion behind the proposed use of triad census is, given that networks can be thought of as being built up by smaller local structures, that triad censuses can capture both the structural features of the social network as well as the network dynamics at a micro-level of analysis (Wasserman and Faust, 1994:557), and thus triad census can po-

tentially be used in some form as an intermediate approach for determining network structural accuracy.

The research question is therefore two-fold:

- How can triad census be used as part of an accuracy calculation procedure?

- How does it compare to the other two methods?

1.4 Objectives

The aim of this research project is to expand the current cognitive social network accuracy measures by introducing a triadic accuracy measurement. This measure will be applied to well-known and readily available cognitive social network datasets (e.g., Krackhardt and Kilduff, 2002) as a proof-of-concept.

This research project's research focus can be operationalised into the following objectives:

I. Identify existing social network accuracy measures

II. Analyse the relationship between existing accuracy measures to the proposed accuracy measures

III. Evaluate the proposed accuracy measures

IV. Formulate recommendations

1.5 Value of Research

This research contributes to current research in the social and behavioural sciences in a variety of ways.

Firstly, this research introduces the conceptual notion of measuring and comparing cognitive social networks on a triadic-level. This approach to determining structural accuracy provides a new way of addressing social and behavioural questions, especially in the area of social network research.

Secondly, this research proposes and defines three new triad-based cognitive social network accuracy measures. Specifically, this research addresses the lack of an intermediate approach for determining network structural accuracy in a concrete manner by defining cognitive accuracy measures which allow researchers to analyse cognitive social network data at a semi-granular level.

Furthermore, this research provides interprets and evaluates the results of the various cognitive structural accuracy measures using case studies. This demonstrates the notion of measuring cognitive structural accuracy at a semi-granular level.

This research links the use of heuristics and decision-making research to social network research. This link between the behavioural sciences and social networks is not the emphasis of this research, however, it may provide some impetus for further research in linking how people make judgements under conditions of uncertainty and how they perceive the social networks in which they are embedded. Thus, the research project serves to re-emphasise the need to understand and analyse cognitive social networks in terms of the cognitive heuristics which people employ.

Finally, this research also opens the door for future research, especially regarding the contexts in which specific measures should be used to determine accuracy. This approach may also provide impetus for further research in the role of heuristics in social network perception.

1.6   Thesis Overview

This chapter provided the broad context of the research project as well as the focus and objectives of this research, concluding with the value which this research contributes to social network analysis. The following chapter provides a review of the literature on social network analysis, focusing on how cognitive accuracy is determined and concluding with some of the emerging issues (Objective I).

Chapter 3 details how the research was conducted, specifically, the data and measurements used for determining cognitive social network accuracy at both interpersonal and structural levels (Objective II).

In Chapter 4, the findings of the research project are detailed and a discussion of the results of the research in provided in Chapter 5. This provides an interpretation of the results presented in Chapter 4 (Objective III) and addresses the limitations of the research as well as possible future directions for research in this field (Objective IV).

The last chapter provides a summary of the research project.

Chapter 2

Literature Review

2.1   Introduction

The shift towards understanding the impact of living in a more connected environment birthed a new, network-centric, perspective through which to interpret and understand the world around us. This network-centric approach is interdisciplinary, but is more than just a methodological extension, as this perspective entails explicit assumptions about the connectedness of entities (Robins, 2015:4).

Social networks—defined as the stable patterns of social interaction between actors in a group (Casciaro et al., 1999:285)—are not a modern phenomenon. However, it was only in the early 20th century when researchers in sociology started to move away from using metaphorical language to more formal conceptions of what constitutes a social network. The social network approach is a relatively new research perspective in the social and behavioural sciences, with the concepts, theories, methodologies, and empirical research starting in the early 1960s and gaining momentum with the advent of social networking services in recent years. This approach in social and behavioural sciences first emerged as a research perspective with George Simmel, who described social networks in terms of 'lines' and 'points.' This shifted the notion of social network thinking towards using more formalised terms rather than only metaphors to describe the interlinked nature of social networks. This shift in social network thinking provides a distinctive research perspective as it describes the interlinked nature of society in terms of nodes and relations (Marin

and Wellman, 2014:11).

SNA's focus on social networks provides new and potentially richer, answers to social and behavioural questions, but requires an equally unique set of methods and analytical concepts in order to address these questions (Wasserman and Faust, 1994:3). The primary objective of this chapter is to identify to key concepts in the field of SNA, expand what SNA entails, and evaluate the current trends and prominent issues in the field. This chapter identifies and addresses some the primary social network concepts, methods, and theories.

2.2   Social Network Analysis

SNA is a relatively new, distinctive perspective in the social and behavioural sciences and provides unique perspective for understanding and interpreting social networks, which places emphasis on the connections between individuals, rather than the individuals themselves (Wasserman and Faust, 1994:4–5). Many of the methods and concepts used in SNA have come from different fields of research—with key contributions and theories coming from sociology, psychology, social anthropology and mathematics.[1]

SNA focuses on the structural and relational aspects of the network, addressing social and behavioural questions in ways that most 'standard' social sciences typically ignore (Wasserman and Faust, 1994:6–7). Particularly, SNA uses graph theory to investigate and represent social structures, applying network[2] methods to social networks models. SNA is considered a distinct research perspective as the fundamental interest is the "*relationships* among social entities, and on the patterns and implications of these relationships" (Wasserman and Faust, 1994:3, emphasis in original). In other words, the primary concern in SNA is the social network—the collection of relationships (known as ties or edges) between social entities (known as actors or nodes). SNA is further distinguished as a research perspective by the following features (as listed by Wasserman and Faust 1994:4):

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[1]A more comprehensive overview of the development of SNA is provided by Freeman (2004, 2014) and Prell (2012), with the latter providing an overview of key contributions from sociology, social anthropology, and psychology.

[2]Brandes et al. (2013) provides an overview on SNA in the network science context.

- Actors and their actions are viewed as interdependent rather than independent, autonomous units

- Relational ties (linkages) between actors are channels for transfer or 'flow' of resources (either material or nonmaterial)

- Network models focusing on individuals view the network structural environment as providing opportunities for or constraints on individual action

- Network models conceptualise structure (social, economic, political, and so forth) as lasting patterns of relations among actors

The notion of social networks is not new. Generally spoken of in metaphorical terms, such as 'fabric' or 'web' of social life (Scott, 2013:1), it was not until the early 20$^{\text{th}}$ century that social network concepts became more formalised, with the key concepts such as 'points,' 'lines,' and 'connections' being used describe relations between social entities (Carrington and Scott, 2014:1).

Simmel (1964) emphasised the need to understand the patterns of connections between social entities. His work, as well as that of others, formalised the idea of the social network by providing the concepts and terminology needed to describe social networks and stimulated further research in social network thinking, especially in the fields of psychology and psychotherapy (Carrington and Scott, 2014:1). Consequently, social network thinking started to shift away from the metaphorical stage and began developing formalised concepts and theories to describe social networks.

SNA emerged from social network thinking and incorporated concepts and tools from other fields of study to examine social networks in a methodical fashion. Much of SNA has its theoretical roots in structural thinking, a long-held tradition in sociology. Among the earliest contributors to social network thinking is Simmel (1964), who emphasised the need to understand the patterns of connections between social entities. This created the impetus for other researchers, especially in the fields of psychology and psychotherapy, to formalise the key concepts such as 'points,' 'lines,' and 'connections' to describe relations between social entities (Carrington and Scott, 2014:1).

Among the most prominent early SNA research which emerged using social network concepts is Moreno's (1934) study on runaways from a girls' reformatory school. Moreno is widely credited as laying the foundations of SNA, developing the sociogram to visually represent the connections between the girls and their relationships with each other. He also is credited with development of sociometry to quantitatively measure social relationships (Carrington and Scott, 2014:1).

Graph theory forms the basis of SNA as it models the relations between nodes using links or edges (Scott, 2011:22). The relevance of graph theory to social networks can be easily seen in Euler's solution to the well-known Seven Bridges of Königsberg problem, where "Euler's great insight lay in viewing Königsberg's bridges as a graph, a collection of nodes connected by links" (Barabási, 2014). In Figure 2.1, the seven bridges problem is depicted as a sociogram, with the nodes in capital letters and the ties between them in small letters. From this depiction, Euler was able to prove mathematically that no path existed such that one could cross all the bridges exactly once.
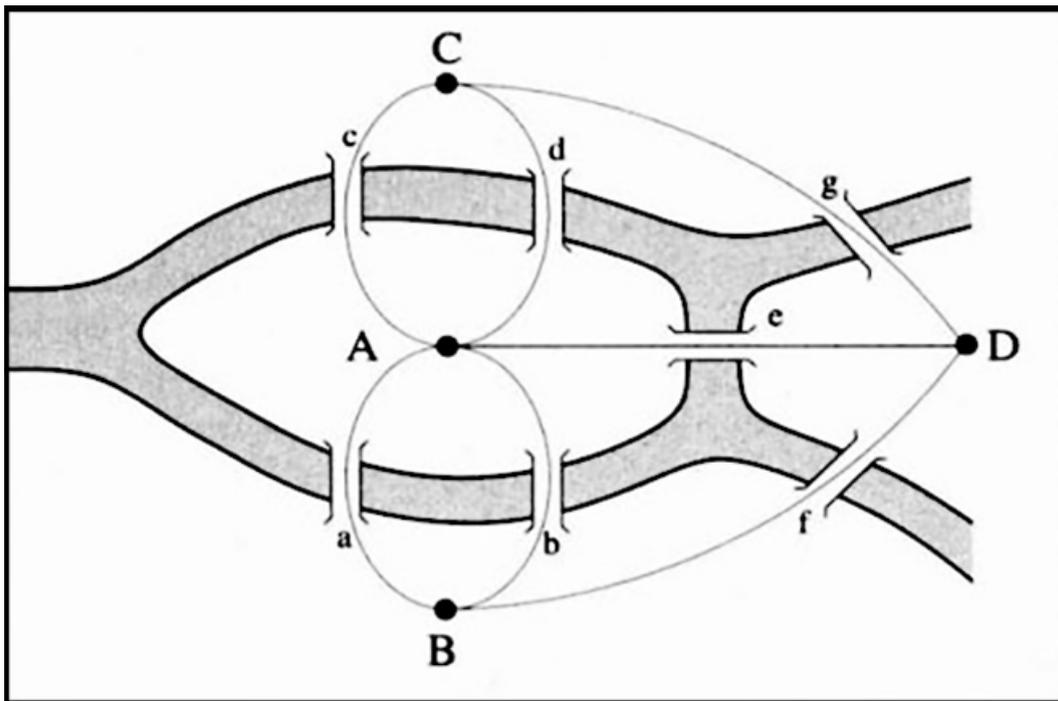
Figure 2.1: Königsberg's Seven bridges (Barabási, 2014).

This approach was later used by Moreno to map the social relations of run-

aways from a girl's reformatory school (though he made no reference to Euler's solution), where each of the runaway's relationship was depicted graphically using nodes to represent each of the runaways and edges to indicate the relationships between each of them (where relationships were perceived to exist). This graphical representation of an actor's social links to other social entities is known as a sociogram and is one of the first basic analytic methods used to depict and analyse a social network. This also had the implication that graph theory concepts and methods could be used to analyse social networks (Scott, 2011:22).

Overall, the social network perspective provides a unique approach to addressing social and behavioural questions—an approach that requires an equally unique set of methods and analytical concepts in order to address these questions (Wasserman and Faust, 1994:3). SNA provides an approach for understanding how the social environments can affect individual outcomes, whether social position affects individual outcomes, how individuals affect social structure, the social dynamics of the social network, and the overall outcomes of the social network (Robins, 2015:1).

Much of social network analysis involves understanding how actors perceive their social networks and the outcome that this has on the individual as well as the network which they are embedded in. Understanding how social networks are perceived by the actors in it requires capturing their cognitive perceptions of the ties to the other actors in the network.

2.2.1   Social Network Cognition

SNA traditionally relied on actors' recall of interactions to construct their social networks—however, a series of empirical studies conducted by Bernard, Killworth and Sailer[3] found that an individual's reported interactions with others in their social network often bore no resemblance to the independently observed interactions (Bernard et al., 1982:63). The BKS findings challenged the long-held assumption that data captured by asking actors to recall who they interacted with (cognitive network data) can be used as a suitable proxy measure for behavioural network data.

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[3]Specficically, Killworth and Bernard 1976, 1979, Bernard and Killworth 1977 and Bernard et al. 1979, 1982—commonly referred to as the BKS studies.

Naturally, these findings caused considerable controversy in the field as it not only challenged the validity of all existing theories and findings based on this assumption, but also carried the implication that future behavioural research could no longer rely on the more easily collected cognitive network data as a proxy if researchers wished to determine the behavioural network or behavioural network properties (Killworth and Bernard, 1979:20). The results of the BKS studies called for the re-examination of the assumption of what cognitive data represents (Killworth and Bernard, 1979:46).

In a preliminary study of a university colloquium series, Freeman and Romney (1987) found that—consistent with the BKS studies—informants were inaccurate short-term, but that "the errors of recall data are biased heavily in the direction of the social structure" (1987:333). Furthermore, Freeman and Romney point out that behavioural data is in fact distinct from cognitive data as "verbal recall data are by their very nature produced by perceptual and cognitive processes, and that, in principle, such data cannot be understood in any other terms" (1987:330). Thus, Freeman and Romney argue that the 'actual' network structure—and that which is of interest to researchers—is the relatively stable long-term patterns of interactions of interactions between individuals (Wasserman and Faust, 1994:57) and propose that this bias be used as a 'weighting' mechanism.

In a follow-up study of the university colloquium series, Freeman et al. 1987 found that individuals were unable to accurately recall the details of a particular event. Freeman et al. (1987:311) found similar errors in recall as the BKS studies and Freeman and Romney (1987), but concluded that these errors were not random, but systematically biased. Freeman et al. (1987:310) addressed recall inaccuracy by arguing that researchers generally are more interested in long-term patterns than in a singular event, thus the 'problem' which the BKS studies uncovered is not as far-reaching as it may seem. Thus Freeman et al. (1987) use the informants' reports as a proxy for observed behavioural data and argue that this data (informant's recall) should be understood in terms of cognitive processes and memory as informants' recall is heavily biased towards the long-term patterns of the social structure (Wasserman and Faust, 1994:57).

Krackhardt (1987:110) addressed the BKS discrepancy between informant re-

call and observations most prominently, arguing that cognitive networks are of interest in their own right and that "the BKS findings simply constitute evidence that one should not bother collecting behavioural data, since they do such a poor job of capturing the cognitions which live in peoples' heads." Moreover, Krackhardt (1987:111) claimed that "the preoccupation with the BKS accuracy problem is symptomatic of a bias towards behavioral patterns even though the theoretical base is frequently cognitive or psychological." Thus, Krackhardt (1987:110) points out that the term "accuracy" should not be considered as an objective measure, but rather descriptive of perceptions. The BKS studies thus examined the validity (Marsden, 2014:382) of using reported ties as a surrogate measure of behaviour for what is a cognitive or physiological event (Krackhardt, 1987:110).

Subsequently, Krackhardt (1987) proposed using cognitive social structures (CSS) to represent cognitive social networks—opposed to behavioural social networks, which are based on observation. This created a new stream of research within social network research, focusing on the perceptions of individuals as opposed to traditional SNA, which focuses on the observed network interactions (Brands, 2013:82). Specifically, CSS research focuses on two questions: "First, how do individuals perceive and cognitively represent the social networks that surround them? And second, how do individuals' perceptions of their social networks affect their behaviors and outcomes?" (Brands, 2013:82). The perceptions that individuals have of their networks are likely to become increasingly important as it is evident that social network services such as Facebook and Twitter can be and are used to influence individuals' opinions towards or against certain agendas.

2.2.2   Cognitive Accuracy in Social Networks

Social network cognition, or how actors perceive their social networks, is a widely researched field in social network analysis. Understanding how people perceive their networks has been linked to both individual and organisational level outcomes. Specifically, a significant research theme with the cognitive social network perspective is how accurately actors perceive their social networks (Casciaro et al., 1999:286).

The term 'accuracy' is generally used to describe the degree of similarity be-

tween an actor's perception of the social network ties compared to the 'actual' ties within the network (Krackhardt, 1990:344; Casciaro et al., 1999:286). Accuracy, in the SNA context, can refer to both an individual's recall of their interactions compared to observed interactions (often referred to as recall accuracy) or to the degree of similarity between the social network as perceived by the individual compared to the social network as perceived by others in the network (referred to as cognitive accuracy).

Cognitive accuracy is simply the degree of similarity between an actor's cognitive map and the actual informal relationships in the network (Casciaro et al., 1999:286; Krackhardt, 1990:334). Both the actual and individual cognitive networks can be derived by using cognitive social structures, a method which was developed by Krackhardt which captures individuals' perceptions of connections between actors in a network Krackhardt (1990). This research project will focus on cognitive accuracy. Cognitive accuracy is a relatively well-studied concept in social network research.[4]

Cognitive social structures provide both the individual's perspectives of the network as well as the means to construct a representation of the actual network, allowing one to determine how accurate an individual's perspective is of the actual network. "With the use of the CSS paradigm, where the focus is on perception itself as a fundamental phenomenon to be explored and explained, the crucial issue related to accuracy of informants' reports shifted from the question of what relation an actor's recollection of his actions has to his actual behavior, as directly observed by the researcher, to the question of how close an actor's perception is to the perception of some other actor's in the same social system investigated" (Bondonio, 1998:302).

As it was found that respondents have poor recall of their actual interactions (e.g., the BKS studies), but that they were good at recalling enduring patterns of relations (e.g., Freeman et al., 1987; Freeman and Romney, 1987), Krackhardt (1990) proposed using an aggregate of actors' CSS as a proxy for the actual social network[5].

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[4]Cognitive accuracy, it should be noted, differs from perceptual congruence in that the latter measures the similarity between perceptions of ties between individuals' networks, whereas the former measures the individuals' network similarity with the target or actual network (Ouellette, 2008:9).

[5]Chapter 3 elaborates on the details of how these aggregations can be constructed.

An individual's cognitive maps—or mental representations—of the relationships may often be more effective at explaining particular outcomes than their actual relationships which individuals have. For example, being perceived as having a prominent friend by others in an organisation is positively correlated with an individual's performance reputation,[6] but actually having such a friend (where the friendship is acknowledged by both actors) has no apparent bearing on the individual's job performance reputation (Kilduff and Krackhardt, 1994:103), which suggests that "structure, as it exists in the minds of individuals, may be more predictive of important outcomes than has been recognized" (Kilduff and Krackhardt, 1994:103).

Cognitive accuracy has been used to explain a variety of social phenomena; for example, at an individual level Krackhardt (1990) showed that individuals who have a more accurate perception of the advice ties within their network were also considered more powerful regardless of their formal position in the organisation. Similarly, in another study, Krackhardt (1992) showed that a unionisation attempt failed due to key actors not accurately perceiving the relations within the organisation.

2.2.2.1   Network Causes of Cognitive Accuracy

In order to understand cognitive accuracy, it is meaningful to consider the various factors which may affect an individual's accuracy. Ouellette (2008:15) assigns three general classes to the predictors of cognitive accuracy, namely, the individual differences, position of the actor in the network, and the network topology itself. This section will cover all three classes when considering factors that may influence the cognitive accuracy of an individual in order to provide context for cognitive accuracy in social networks but also to elucidate factors which may need to be controlled when measuring cognitive accuracy.

Bondonio (1998) tested the hypothesis that a perceiver will be more accurate about their co-workers' ties due to their closer proximity in the network relative to their colleagues. In order to test this hypothesis, Bondonio proposed a 'dyadic' accuracy measure, which compares an actor's perception of the social network ties to the actual social network for each other actor in the network. Unlike the 'individual' level measure which provides a single accuracy score

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[6]A phenomenon known as basking-in-reflected-glory.

for the perceiver, the dyadic measure assigns an accuracy score for each actor in the network which represents the degree of similarity between the perceiver k's perception of sender i's ties and the actual social network ties resulting in a total of $N-1$ scores for the perceiver (Bondonio, 1998:304). This measurement of perceptual accuracy may be considered measure of local activity as it ignores rest of network (Ouellette, 2008:28).

Bondonio (1998) found that actors who are more central were more accurate and, additionally, if the perceiver and the sender were both central, or if they had a shorter geodesic[7] distance between each other, the perceiver was more accurate in their perceptions of the sender's ties. Thus the 'dyadic' level of measurement proposed by Bondonio provided unique insights as to the predictors of cognitive accuracy. Bondonio suggests a 'triadic' level of analysis where a third actor's ties with the perceiver's perception of ties between sender i and receiver j is compared to the existence of the tie between i and j in the actual social network be explored in future research.

Marineau (2012) investigated the relationship between an individual's formal power and how accurately they perceived the friendship and task trust networks. Specifically, Marineau (2012:9,22) measured both networks in terms of positive and negative relationships (i.e., friendship and dislike were elicited for the friendship network, task trust and task distrust networks were elicited for the task trust network), rather than assume the absence of task trust or friendship means the individual distrusts or dislikes the target. Marineau (2012) found that "individuals with formal power are more likely to perceive ties with task related consequences, and this applies especially to negative ties such as task distrust and dislike" (Marineau, 2012:128). Additionally, there was also weak evidence suggesting that managers are more accurate about their subordinates' networks than that of others (Marineau, 2012:129). Moreover, in contrast to Krackhardt's (1990) findings, Marineau concludes that "*power is associated with increased accuracy about the social networks, not less*" (Marineau, 2012:131, emphasis in original).

Grippa and Gloor (2009) compared an individual's centrality (degree and betweenness) in their social network to their accuracy in recalling their interactions with others in that network. Based on the perspective that high power in-

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[7]The shortest path between any two actors.

dividuals are typically less accurate than low power individuals (the literature is inconclusive as to whether this is the case), Grippa and Gloor (2009:256) test the hypothesis; "The lower the ratio between self-perception and alter-perception, the higher the probability for an actor to have leadership roles." The hypothesis is tested by means of two metrics: an index of asymmetrical perception (the number of self-reported interactions divided by the number of interactions reported by the alter), and a leadership index (the average value of trust, prestige, and contribution multiplied by betweenness centrality) (Grippa and Gloor, 2009:256). Grippa and Gloor (2009:259) found that the more central an individual is, the higher their score for trust, prestige, and contribution, and that individuals with a lower ration of self-reported interactions compared to alter-reported interactions (accuracy) negatively correlated with their leadership index. Thus, Grippa and Gloor (2009:260) argue that "by monitoring the degree of inaccuracy through the self/alter index it might be possible to predict the individual centrality and the reputation level, as well as to identify informal leaders."

Casciaro (1998) also explores a similar theme to Grippa and Gloor (2009), investigating what makes some people more accurate in their perception of their social networks. Specifically, Casciaro (1998:333) focused on an individual's position in the network (formal hierarchical level, work status, and centrality) as well as their personality traits (need for achievement, need for affiliation, self-monitoring, and extraversion) as factors determining their accuracy about their social networks. In her investigation, Casciaro (1998:343) found that there is a strong negative relationship between hierarchical level and accuracy of the advice and friendship networks. Additionally, part-time status was also negatively correlated with accuracy of the advice network (but not the friendship network) while centrality had a moderate positive relationship with friendship and advice network accuracy (Casciaro, 1998:343).

These "structural variables explain about 40% of the variance in accuracy in both the advice network ($R^2 = 0.405$, $F_3, 20 = 6.22$) and friendship network ($R^2 = 0.405, F_4, 19 = 6.21$)" (Casciaro, 1998:343). Moreover, Casciaro (1998:343–344) found that need for achievement had a "moderate positive association with accuracy in the perception of the advice network ($b\hat{} = 0.285, p = 0.56$) and friendship network ($b\hat{} = 0.0.318, p = 0.056$)." In a similar fashion,

the need for affiliation has a moderate positive relationship with accuracy of the friendship network, however, it has a weak negative relationship with accuracy in the advice network (Casciaro, 1998:344–345). Extraversion has a weak positive relationship with accuracy in the advice network and no relationship with accuracy in the friendship network, while self-monitoring has no relationship with accuracy of perception in both networks (Casciaro, 1998:345). The personality variables account for approximately six-and-a-half percent of the accuracy of perception of the advice network accuracy and about 15% of the accuracy in the friendship network (Casciaro, 1998:345). Overall, the variables examined explain about 60% of variance in accuracy of perception, with structural variables accounting for most of the explained variance (Casciaro, 1998:345).

Neal et al. (2016) investigated predictors of observer accuracy (i.e., what attributes affect perceiver accuracy about the network) and target accuracy (i.e., what target attributes affect a perceivers' accuracy about targets) in a school setting. Regarding observer accuracy, Neal et al. (2016:5) found that children in higher grades and in smaller classrooms were more accurate about others' relationships, but children who were perceived as being more popular were not more accurate in those same perceptions, and that girls are significantly more accurate than boys about classmates' relationships. Regarding target accuracy, Neal et al. (2016:6) found that targets are perceived more accurately if they are considered more popular and, moreover, "were more accurately observed when they occurred in smaller classrooms of higher grades and involved same-sex, high-popularity, and similar-popularity children. Interestingly, not only were same-sex targets more accurately observed than mixed-sex targets, but among same-sex targets, girl-girl targets were more accurately observed than boy-boy targets" (Neal et al., 2016:6).

Ouellette (2008) examined the effect of position and personality traits on cognitive accuracy in social networks. Among the factors which may affect cognitive accuracy according to Ouellette (2008) is attachment anxiety, cognitive balance schema, and egocentric cognitive bias (personal differences), as well as centrality (network position), and geodesic, tie strength, information flow efficiency, and density (network topology).

2.2.2.2 Network Effects of Cognitive Accuracy

Krackhardt (1990) argued that cognitive social network accuracy can itself be a base of power as a more accurate perceiver of the social network will have an advantage as he or she knows who is more central and powerful in the network, where the coalitions are in an organization, as well as the weaknesses in or between coalitions. Krackhardt (1990) tested the hypothesis that individuals with more accurate perception of the network (using cognitive social networks) have a higher informal power within the organisation, when controlling for advice and friendship network centrality as well as formal position in the organisation. Krackhardt (1990:354) finds that "only centrality in the friendship network is significantly related to power when controlling for formal position" and that the advice network centrality has no significant relation with informal power, thus any advantage of being central in the advice network is likely derived from the individual's formal position. Krackhardt (1990:354–355), however, found that individuals who are more accurate on the advice network have higher reputational power[8], though this relationship is does not exist between accuracy of the friendship network and informal power. Thus Krackhardt (1990:357) confirms the hypothesis that cognitive accuracy can also be considered a form of power.

Casciaro et al. (1999:287) argued, based on Bondonio's (1998) finding that actors are more accurate about relationships closer to them than those further away, that the difference in an actor's perception of 'local' ties and indirect ties have "distinct implications for individual outcomes" and that, subsequently, accuracy in social networks may be better understood in terms of an actor's accuracy about subgraphs—parts of the social network—rather than an actor's accuracy about all the ties within the entire social network.

Casciaro et al. (1999) investigated the relationship of positive affectivity with 'local' accuracy (an individual's sensitivity to how they are seen by others) and 'global' accuracy. Casciaro et al. (1999:297) found that positive affect was moderately negatively related to local accuracy in the perception of the advice network but had no relationship in the perception of the friendship network (i.e.,positive people tend to be inaccurate about their advice networks, but this trait had no bearing on their friendship networks). Additionally, the positive

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[8]Power not derived from a formal position—also referred to as informal power.

affect was also moderately positively related to global accuracy in friendship networks but had no relationship with the advice network (Casciaro et al., 1999:300). Thus, Casciaro et al. (1999:299–300) concludes, "positive affectivity enhances people's perception of the broader patterns of social relationships in their environment, while it hampers the accuracy of judgments concerning their own direct social connections."

Casciaro et al. (1999:301) points out that "local accuracy and global accuracy have different implications for individual outcomes, depending on the task at hand. For instance, in work organizations, the effective performance of boundary-spanning roles may depend more heavily on having an accurate map of broad patterns of social connections in the organizational environment than on having a realistic representation of one's immediate social world. Similarly, an accurate representation of social interaction in the organization may be particularly crucial to the effective performance of managerial roles. In work teams, however, healthy team dynamics may be best achieved when group members perceive accurately their direct personal and professional connections to other group members. In sum, both local accuracy and global accuracy may contribute to individual effectiveness, with global accuracy playing an increasingly important role as the social domain of one's task broadens." Casciaro et al. (1999:287) differentiates between local accuracy and global accuracy, where local accuracy refers to the similarity between an actor's perception of their direct ties to others and their actual direct ties in the social network. Global accuracy then refers to the similarity between an actor's perception of the all the ties between all the members of the social network.

Understanding the broader patterns of one's social network is thus becoming increasingly important (i.e.,a department on the same floor with some weak ties)—it may not be economical or even possible to be accurate about specific relationships between others in networks which are broad or where you have limited or interaction with others in your network. For example, the well-known six degrees of separation experiment by Milgram (1967) required individuals to make judgements about the relationships of others, where the initial sender could not know all the relationships within the large social network. Rather, the individual's may have made guesses—likely using heuristics—as to which individuals will be more likely to have ties to someone at the package

destination.

This may have involved choosing to send the package to someone higher up the social network hierarchy (e.g., local politician or pastor) or to someone who may have more connections with others (e.g., businessman or postman), without knowing/being accurate about what relationships they have with others. Rather, it seems, the individuals may have judged them to have a superior network position or patterns of relationships which would enable the package to travel towards the intended destination.

This makes a case for the need to measure structural cognitive accuracy— i.e., how well an individual's perception of the social network structure and patterns of the social network estimates the actual social network structure. Thus individuals who make more accurate judgements about their broader network, even if they may not be aware of the specific relationships, may still draw benefit from being accurate about the network structure—i.e., the senders likely did not send the package to a nearby friend with very few connections or friend with many connections, but who stays in distant country.[9]

This experiment relied on several of sequential judgements each by different individuals about their immediate relationships and *their* possible paths of social connections which were more distant—thus each participant needs to be accurate about their direct connections and the patterns or structure of their relations' social connections.

Consequently, it may be, given that the initial (or any subsequent) judgements about the actor's position does in fact make a shorter path to the end destination, the actor (who receives the package) may be in a better position to judge who to send the packet to next, assuming that judgements about the path to the final destination become more accurate the closer the sender of the package is to the final destination. This could also apply to other large social networks, such as those spanning multinational corporations, which are less random, presumably, than the social network which Milgram (1967) investigated, and thus may have significant implication for individuals who are

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[9]Barabási (2014) noted that individuals may not necessarily have chosen the shortest route as they did not know all the possible links, however it is plausible that the use of heuristics may have led to what may be the most economical route in terms of time and energy needed to make the decision, rather than to try map out entire network to n[th] degree.

more structurally accurate in their perceptions of the network.

2.2.3   Measuring Cognitive Social Network Structures

An individual's perception of their social relationships may begin with their direct ties to others, but higher-order structures, "such as triads and cliques, may also affect perceptual accuracy..."[10] (Ouellette, 2008:2). Ouellette (2008:2) points out that "A sufficiently inclusive analysis necessitates a methodological approach that can comfortably move across these level" and that SNA provides this methodological approach. Within SNA, however, no cognitive structural accuracy measures exist which take into consideration both the dyadic-level and higher-order structures which may be present in the social network. This research proposes that the triad be used a basis for an intermediate cognitive structural accuracy measure.

Among the smallest network structures from which it is possible to see some network characteristics is the triad. Wasserman and Faust (1994:557) state that "at the heart of triadic analysis is the *triad census*, a set of counts of the different kinds of triads that arise in an observed network," and that since it does not condense the original data as much as the dyad census, providing 16 data points opposed to three, "there is considerably more that we can learn from the triad census" (1994:557).

Each type of triad can be identified by means of a M-A-N label, where the first digit indicates the number of mutual (M) ties, the second digit the number of asymmetric (A) ties, and the last digit the number empty or null (N) ties (De Nooy et al., 2016:206). Additionally, the M-A-N label for a triad type may also include the letter after the last digit to indicate the direction of the asymmetric dyads within the triad, namely, 'D' indicates downward ties, 'U' indicates upward ties, 'C' indicates cyclic ties, and 'T' indicates transitive ties (De Nooy et al., 2016:207).[11] For example, the presence of a triad type 201 indicates that, between three actors, one actor has a mutual relationship with two of the other actors and the other two actors have no relationship with each other. Figure 2.2 shows the 16 different triad types.

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[10]An ellipsis is used to contextualise the quote.

[11]The terms 'upward' and 'downward' appear to be relative terms, but are defined in terms of the the sociogram, as shown in Figure 2.2.
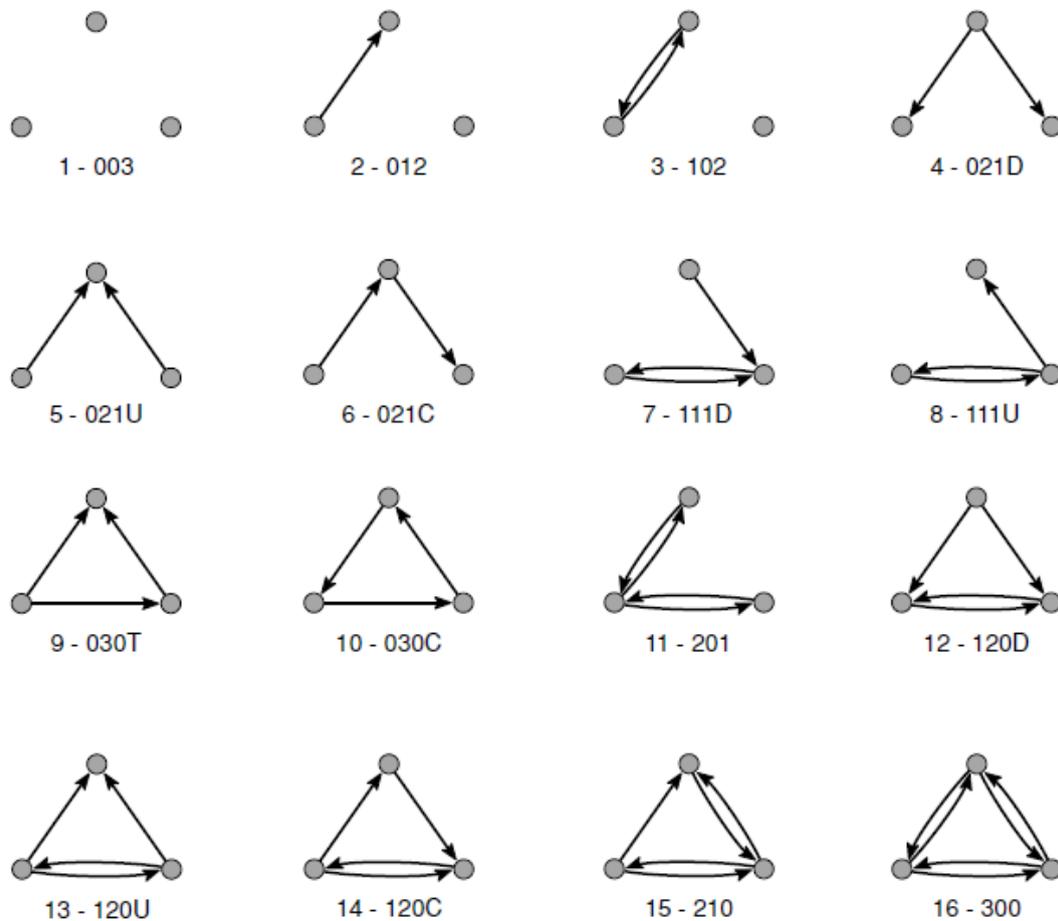
Figure 2.2: Sequentially numbered triad types with M-A-N labelling (De Nooy et al., 2016:207).

Wasserman and Faust (1994:557) points out that "Triads themselves can manifest many interesting structural properties, such as tendencies toward clustering, transitivity, and ranked clusterings." This provides the impetus to use triadic census to investigate social network structures. Features such as structural balance and transitivity are deterministic—mathematically calculable based on the number and types of triads in the social network. For example, Wasserman and Faust (1994:559) state that transitivity in a network means that intransitive triads, where the first actor chooses the second actor but not the third and the second actor chooses the third (i.e., triad type 021C in Figure 2.2), should not exist in the social network data. Nonetheless, Wasserman and Faust (1994:559) point out that it may be more useful to interpret empirical network data using a statistical framework to determine the degree to which

the network is transitive or displays certain graph theory properties rather than expecting absolute conformance to the mathematical interpretation.

Triadic analysis is particularly prevalent in research involving balance theory and structural balance (Wasserman and Faust, 1994:220). Heider (1958) is first to emphasise that actors who are friends can be expected to share similar sentiments or attitudes (Wasserman and Faust, 1994:220). This can be extended to a third party as well; two individuals who are friends with each other are expected to have the same signed relation (positive or negative) towards a third individual.

Similarly, triadic analysis also has application in structural balance. A group may be considered structurally balanced if all the actors in the group are balanced—that is, if actor 1 and actor 2 are friends with each other, then actor 1 and actor 2 will both be friends with (or not be friends with) the same people in the group (Wasserman and Faust, 1994:221) and likewise other actors will have consistent views of others compared to their friends (either both negative or both positive). Both balance theory and structural theory are cognitively-based social network research (Krackhardt, 1987:111), thus it rests on the actor's perception of the ties between themselves and between other actors in the network—regardless of whether the ties exist or not (Krackhardt, 1987:111).

Krackhardt and Kilduff (1999) found that individuals perceived close relationships and distant relationships as more balanced compared to intermediate relationships.

Much focus is given to an individual's accuracy about dyadic relations, neglecting the consideration that an individual's perceptions of the network's structure may also have an impact on their interactions and, ultimately, performance within the network. This research project proposes measuring the accuracy of an individual's perception of the general structure of the relations within a network, e.g., do people tend to collaborate ('network') with each other or operate in a more isolated fashion? An individual who is unfamiliar with the specific dyadic relations within their network may still have a sense—and formulate a perception—of how people tend to interact within the network.

Interpersonal accuracy is defined as the degree of similarity between an actor's perception of the specific relationships in their social network and the actual relationships of the individual their social network (Krackhardt, 1990:344). Each actor's cognitive slice therefore is simply their estimate of the relationships in the social network and their interpersonal accuracy is an indication of how closely their estimate matches the actual relationships in their social network (Ouellette, 2008:14).

An actor's interpersonal accuracy can be measured by comparing their perception for each possible relationship to the actual relationship in the social network. Both correlation measures and distance measures can be used to determine the similarity (or dissimilarity) between the perceived and actual networks. One of the more popular measures is to use the Pearson's correlation coefficient between each actor relationships according to the perceived network to the corresponding actor's relationships according the actual social network (Ouellette, 2008:14). This measure of accuracy is used to establish how accurate individuals are about the specific relationships in a social network or a subset of a social network (e.g., Bondonio, 1998; Neal et al., 2016).

Structural accuracy, however, refers to the degree of similarity between an actor's perception of a social network's structure and the actual social network's structure. Current structural accuracy measures, however, still compare the social networks on the similarity between the interpersonal structure of the cognitive slice and the actual social network.

This means that, for an actor to be considered structurally accurate, they effectively need to be accurate about the specific relations within the social network, rather than about general network properties. Effectively, measuring structural accuracy on the interpersonal level does not significantly differentiate it from interpersonal accuracy measures.

The perceiver does not have to know about each relation within the network in order to formulate a perception of the general network—such information is often communicated by members of the network themselves. This metric thus measures an individual's accuracy about the topography of the network in general.

Consequently, it is possible for an individual to be inaccurate about the specific

relations between members of the network, but to still be accurate about the general topography of the network, e.g., a new member of a department may be unfamiliar with the specific friendships within the network, yet have a perception that there are either few or many friendships within the department or that the friendships are clustered or that a hierarchy exists.

It is possible for individuals to be accurate about a network's structure, e.g., if it is hierarchical, clustered, or transitive, even if they do not know the specific relationships within the network. This is intuitively obvious; many organisations have a formal hierarchy which may be reflected in the social network's hierarchy, likewise different divisions or teams within the organisation can be expected to have more ties between themselves thus forming clusters within the network.

2.2.4   Illustration

In order to illustrate the difference between interpersonal accuracy and structural accuracy on an intuitive level, consider the following social network: Person 1 goes to Person 2 for advice, who, in turn, goes to Person 3 for advice. This social network, depicted in Figure 2.3, represents the actual social network of the three actors. It has six possible ties: each of the three actors can be connected to a maximum of two other actors.
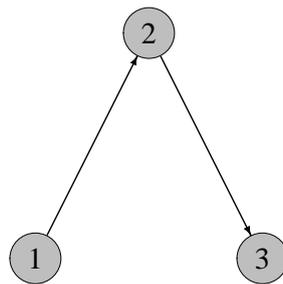
Figure 2.3: Example of an actual social network.

Similarly, each of the three actors' cognitive slices are depicted in Figures 2.4, 2.5, and 2.6. Person 1 perceives that Person 2 goes to Person 3 for advice and that Person 3 goes to Person 1 for advice, while Person 2 perceives only that

Person 3 goes to Person 1 for advice, and Person 3 perceives that no-one seeks advice from the other actors.
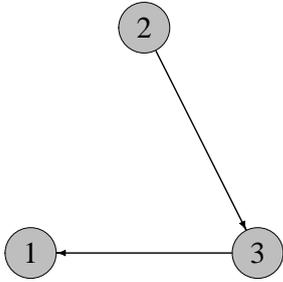
Figure 2.4: Person 1's cognitive slice.
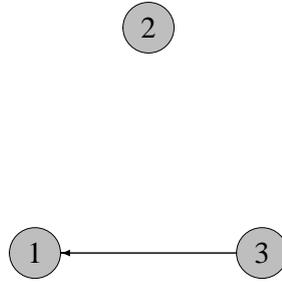
Figure 2.5: Person 2's cognitive slice.
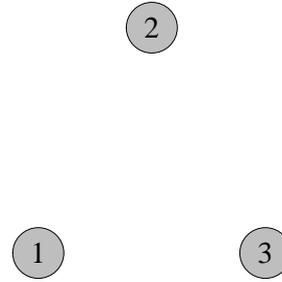
Figure 2.6: Person 3's cognitive slice.

When inspecting the sociograms of the cognitive slices and the actual social network visually, it is immediately apparent that none of the actors are completely accurate about the all the social ties in the actual social network.[12] However, it is also clear that Person 1's perceived network shares a similar pattern to the actual social network, whereas Person 2 and 3 do not share a similar pattern.

Specifically, the interpersonal and structural accuracy measurements of Person 1 illustrate the difference in measurement between structural accuracy and interpersonal accuracy. On an interpersonal level, Person 1 correctly judges that no tie exists from 2 to 1, 3 to 2, 1 to 3, as well as between 2 to 3. However, Person 1 also incorrectly perceives that a tie exists from 3 to 1 and that no tie exists from 1 to 2. Thus Person 1 is only moderately accurate in their perception of the social network when measuring accuracy[13] about *specific* ties.

However, when measuring the similarity between the *structure* of Person 1's cognitive slice and that of the actual social network, it is apparent social networks share the same general pattern—specifically, the triad 021C. Thus, de-

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[12]Note: for the purposes of this illustration, the cognitive slices were selected which emphasize interpersonal and structural accuracy, therefore the actual network will not match a CSS constructed using LAS or CS rules.

[13]Chapter 3 expands on how these accuracy measures are calculated.

spite being only moderately accurate about the *specific* ties in the social net-
work, Person 1 was accurate about the *structure* of the actual network.

2.3   Summary and Emerging Issues

The BKS findings resulted in a shift away from understanding self-reported
data as a proxy for behavioural data towards understanding this data as pri-
marily capturing the cognition of actors in the social network—i.e., captures
the actors' perceptions of the social networks in which they are embedded
(Killworth and Bernard, 1979:46). This shift required a new methodology to
interpret the data.

Krackhardt's cognitive social structures proved to be well-suited for represent-
ing cognitive data and has subsequently been widely adopted in social network
research as a method for representing actors' perceptions of the relationships
within their social networks. This shifted the focus towards understanding
and investigating social networks in terms of the actors' cognition of the social
networks which they are embedded in.

Much research in social network analysis has revolved around understanding
the relationship between an actor's perception of their network (i.e., their cog-
nition) and certain outcomes. Specifically, a significant theme in social network
analysis research calculating the cognitive accuracy. Most cognitive accuracy
research has looked at the predictors of cognitive accuracy (e.g., network po-
sition, personal attributes, cognition) or has investigated the consequences of
cognitive accuracy on both the individual level or the organisation level. Both
the predictors and consequences of being accurate is linked to the degree of
similarity between an actor's cognitive slice and the actual social network.

Generally, cognitive accuracy is determined by comparing the cognitive slice
of an actor for a given pair actors in a network against the same pair of ac-
tors in the actual network—confining accuracy measures to the dyadic—or
pairwise—level. This is a limitation when it comes to determining accuracy; it
is possible—at least theoretically—for individuals to be accurate about their
social network's general structure or patterns of relations even if they are not
very accurate about the specific relations within the network, however, current
methods of determining cognitive accuracy measure cognitive accuracy on a

dyadic/pairwise level. The current methods do not provide an accuracy measure based on the network structures which considers the pattern-recognition or heuristic-based decision-making nature of human judgements.

This research project proposes and demonstrates a method of calculating how accurate an individual is about their social network's patterns of relationships opposed to how accurate they are about specific relations within their social network.

Chapter 3

Research Methodology

3.1   Introduction

The purpose of this research project is to explore a way of measuring cognitive structural accuracy (as described in Objective II) based on the notion that individuals conceptualise their social networks not only in terms of the specific relations which they are aware of but also by making use of heuristics to inform their perception of the wider social networks.

Current accuracy measurements are limited to defining structural accuracy as either very narrowly defined (exact same structure) or very broadly defined (only accounting for specific network properties). Consequently, a new measurement level is proposed which measures the similarity between the actor's perception of the social network structure and the actual social network structure and which accounts for both the broader structural properties while also considering the granular patterns of relations among the actors in the social network.

Specifically, this research project proposes measuring accuracy on the triadic level, as this captures the microstructural patterns and links it to the macrostructural patterns (Wasserman and Faust, 1994:557). This makes triadic level accuracy measurements a versatile means to measure how similar an actor's perception of the social network is compared to the actual network.

To illustrate the cognitive structural accuracy as a semi-granular measure of accuracy—between the precise dyadic-level accuracy measures and the gen-

eralised structural accuracy measure (GSCOR)—two datasets collected by Krackhardt in 1987 and 1990 at two small entrepreneurial firms are used.

3.2   Research Strategy

The aim of this research project is to propose and evaluate a cognitive structural accuracy measure (Objectives II and III). In order to accomplish this task, several tasks must be undertaken:

1. Source cognitive social network data

2. Define structural accuracy measures

3. Analyse cognitive social network data

   3.1 Calculate interpersonal accuracy of each respondent

   3.2 Calculate the triad census of respondent's social network

   3.3 Calculate structural accuracy of each respondent

4. Compare structural accuracy measures

The first task, collecting cognitive social network data, involves asking respondents to complete a survey about their perceptions of the social connections in their social environment. This task can be tedious and complicated, and researchers need to consider various factors other than those associated with conducting surveys in general (see Scott, 2013:42-43). For example, when collecting cognitive social network data, defining the network boundaries (i.e., which actors to include as part of the social network sample) may be problematic if groups are not formally defined (Marsden, 2014:371).

Moreover, cognitive social network data can be particularly tedious to collect from even a relatively small social network (Krackhardt, 1987:113). For example, collecting the cognitive social network data from a relatively small social network consisting of 20 actors would yield a CSS of order $20 \times 19 \times 20, (i \neq j)$, meaning that each respondent in the network is required to evaluate 7600 possible social connections. This may result in fewer or no respondents completing the survey.

Alternatively, existing cognitive social network data can also be used for conducting analysis. This approach is only suitable when new cognitive social network data is not needed. Using existing data is significantly more efficient in terms of time and resources required. Additionally, numerous cognitive social network datasets have been made publicly available and are included as standard cognitive social network datasets in some SNA software. This provides researchers with access to multiple datasets on which to conduct analysis.

Given that for this research project the data itself need not be novel and that existing cognitive social network data is suitable and readily available, this research project will make use of existing cognitive social network data. This data is accessible and available in the public domain and thus is not directly collected from respondents for this research project.

The second task is defining structural accuracy measures. This includes defining existing structural accuracy measures—such as GSCOR—as well as defining new network structural accuracy measures. Specifically, the proposed structural accuracy measures will be triad-based as to measure structural accuracy at an intermediate level of analysis. The definitions of intermediate measures of structural accuracy provides the cornerstone of this research project.

The third task, analysing the cognitive social network data, involves processing the data and interpreting the results. For the purposes of this research, R (R Core Team, 2018), a statistical programming language and environment, is considered to be suitable for conducting the various graph-based analysis (e.g., Hoff et al., 2002). Specifically, this program allows the installation of packages, such as 'sna' (Butts, 2016) and 'philentropy' (Drost, 2018), which provide various functions which can be used to conduct the triad census on social networks, correlations between directed graphs, plot sociograms, and calculate network properties, which is crucial to determining both interpersonal- and structural accuracy.

Lastly, the structural accuracy measures—existing and new—will be evaluated. This requires interpretation of the results. Specifically, the outcome of the research project is described—whether cognitive structural accuracy can effectively be measured at an intermediate-level. This task requires answering the research questions proposed in Chapter 1: How can triad census be used

as part of an accuracy calculation procedure? And how do the proposed structural accuracy measures compare to the other methods of measuring cognitive structural accuracy?

3.3   Data

To demonstrate the structural accuracy measure and illustrate the difference between structural accuracy measures and interpersonal accuracy measures, four sets of empirical cognitive data were used. The cognitive social network data was collected from two different social environments: a high-tech manufacturing firm (referred to as High-Tech) and a small entrepreneurial firm (referred to as Silicon Systems).[1]

3.3.1   High-Tech Data

The High-Tech data was collected by Krackhardt (1987) from a small, high-tech, manufacturing firm. The data was captured by means of questionnaire from 21 people, who make up the management team of the firm. Each respondent was asked to whom they would go to for advice and to whom they think other managers would go to for advice.

Specifically, respondents were asked questions such as "Who would Steve Boise go to for help or advice at work?" followed by a list with 20 other managers where they could place a check mark next to the names of those they considered the manager in question was likely to go to for advice (Krackhardt, 1987:118). This was process was repeated for all the managers.

Similarly, the cognitive slice for each manager was also captured regarding whom they consider to be friends in the management team. All respondents completed the questionnaire. The High-Tech data consists of 21 cognitive slices for both the advice and friendship networks.

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[1]The High-Tech and Silicon Systems are publicly available and are included as standard datasets in several SNA software.

3.3.2   Silicon Systems Data

The Silicon Systems data was collected by Krackhardt (1990) from a small, entrepreneurial firm. Silicon Systems has three levels of distinct formal authority, with three owner-managers at the top of the hierarchy, with five managers below them, and the other 28 employees having no formal position (Krackhardt, 1990:348). All the employees worked on the same floor and saw each other regularly.

The data was captured from 36 employees by means of questionnaires, where each respondent was asked about the advice network and friendship network in the firm. In a similar fashion to the data collected from High-Tech, respondents were asked: "Who would this person go to for help or advice at work?" and given a list of 35 names next to which they could indicate from which employees the person in question was likely to seek advice (Krackhardt, 1990:348-349). Each respondent was also asked who they considered to be their friend. Three respondents failed to complete the questionnaire, thus there are only 33 cognitive slices for both the advice and friendship networks.

3.3.3   Network Bounds and Missing Data

The boundaries for High-Tech and Silicon Systems are well-defined. In the case of High-Tech, the network bounds were defined by the employees' formal position in the firm (all members of the management team). Silicon System's network bounds constituted the entire firm. This allowed the researchers to determine with relative ease which actors to include in their sample of the social network.

However, not all respondents answered the network survey. This could be addressed in three ways:

  I. Use blank slices for missing respondent data (zeroes)

 II. Replace missing cognitive slice data with approximate values

III. Omit or remove missing respondents from all calculations

The first option listed, using blank slices for the missing respondent data will not be an effective solution to address missing respondent data. Specifically, as

the friendship network makes use of LAS using the intersection rule, replacing the missing values with zeroes would skew all the cognitive social accuracy measures. Similarly, using blank slices for missing respondent data skews the the triad census to indicate more null triads than there actually are, thereby also distorting any structural accuracy measures based on triad census.

Alternatively, substituting the missing respondents' data with approximate values[2] for the relations has some precedent—even when used in accuracy calculations (e.g., Krackhardt, 1990). In this case, however, as the research project focuses on comparing interpersonal and structural accuracy measures, substituting values may undermine the reliability of the findings, as it will affect not only the actual network to which the cognitive slices are compared as well as the generate accuracy scores for individuals who did not partake in the survey.

Lastly, one could also omit the respondents who failed to complete the survey. This has the drawback that it decreases the total number of members in the social network. However, removing respondents who failed to respond from the survey should not bias the accuracy measurements significantly. In fact, this approach can effectively be considered a form of sampling (Borgatti et al., 2006:126). Thus, for this research project, missing respondents are omitted from the cognitive social network data.

All the social networks were captured using a census of the social network. That is, all members of the social network of advice and friendship in the given social environment are included. This prevents sampling error or bias.

3.4   Definitions and Measurements

In order to demonstrate structural accuracy measures and illustrate the difference between structural accuracy measures and interpersonal accuracy measures, the SNA concepts used in determining interpersonal and structural accuracy are defined here. Specifically, the respondent's perception of the social network and the actual social network are defined, as this is required to determine interpersonal accuracy and structural accuracy. Similarly, the equations

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[2]Typically, the approximate values are derived from the actual social network values for the relationship(s).

that are used to determine interpersonal- and structural accuracy are also detailed in this section.

3.4.1   Cognitive Social Structures

When describing social networks, the structure of the social network can be defined as "a set of relational statements between all pairs of actors in the system" (Krackhardt, 1987:113).

Specifically, each actor's perception of a relation in their social network can be expressed as follows: $R_{i,j}$, where R is the relationship being considered, i is the 'sender' of the relation, and j is the 'receiver' of the relation (Krackhardt, 1987:113). If a relation exists from i to j, then $R_{i,j} = 1$, else $R_{i,j} = 0$. Thus, if R is defined as "is friends with," then $R_{1,2} = 1$ means that Person 1 is perceived to be friends with Person 2. A respondent's perception of all the relational pairs in the network is referred to as their cognitive slice.

Subsequently, the cognitive social structure of a social network, is expressed as $R_{i,j,k}$, where i is the 'sender' of the relation, j is the 'receiver' of the relation, and k is the 'perceiver.' Thus, the expression $R_{3,1,2} = 1$ states that Person 2 thinks that Person 3 perceives Person 1 to be their friend (e.g., Figure 2.5). A cognitive slice, therefore, can also be thought of as a reduction of the cognitive social structure, where k is kept constant. The cognitive slice of a respondent is also referred to as the perceived social network for convenience.

Cognitive social network data for all respondents' perceptions of all the relationships can be stored in R N x N matrices for cognitive slices and R N x N x N for the cognitive social structure of the network, where N is the number of actors in the network and R is relations being described. Thus, the cognitive social structure contains all the perceptions of all the respondents for all the possible relations.

In order to effectively analyse cognitive social structures they are often reduced to a two-dimensional matrix by means of aggregation. Specifically, Krackhardt (1987:115) suggests three types of aggregations, namely, Cognitive Slices, Locally Aggregated Structures (LAS), and Consensus Structures. Notably, the latter two structures are widely used as a proxy for the actual social network

structure as it allows cognitive slices to be readily compared to the 'true' or 'actual' social network.[3]

3.4.2   Actual Social Network

In the context of cognitive accuracy, the actual social network refers to the cognitive social structure which contains the values of each possible relation against which the respondent's cognitive slice for the same relationship is compared. There are several ways to determine what constitutes the actual cognitive social network, with aggregating methods being better suited based on the type of interaction being captured.

3.4.2.1   Locally Aggregated Structures

The Locally Aggregated Structure (LAS) is an aggregation which reduces the three-dimensional cognitive social structure to a two-dimensional matrix. Specifically, the LAS considers only the inputs of the two actors involved in their relation when determining the aggregation. Krackhardt (1987) describes the four primary ways by which the LAS can be derived:

1. Row-dominated LAS

2. Column-dominated LAS

3. LAS from Intersection Rule

4. LAS from Union Rule

The row-dominated LAS (RLAS) is derived from the cognitive social structure using the following rule: $R'_{i,j} = R_{i,j,i}$, where R is the relationship being considered, i is the 'sender' of the relation, and j is the 'receiver' of the relation. Thus, the RLAS assumes that senders of relations correctly judge their own outgoing relations to other actors. In the case of the social network data for the advice networks of High-Tech and Silicon Systems, the assumption is made that individuals know to whom they go to for advice, even if these ties are not

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[3]The word "actual" indicates its familiar meaning; thus when referring to the actual social network, it does not refer to the observed ties between actors, but rather to an aggregate structure defined by the perceptions of multiple network actors (see Krackhardt, 1990:344).

perceived or evident to the individuals whose advice is sought. Consequently, the RLAS is the best proxy for the actual advice network.

The second aggregation, the column-dominated LAS (CLAS), is derived from the cognitive social structure using the following rule: $R'_{i,j} = R_{i,j,j}$. The CLAS thus assumes that the receivers correctly judge their own incoming relations from other actors. This aggregation is rarely used but is a more suitable proxy for the actual social network in the cases where the 'receiver' of the relation is has a more reliable perception compared to other members of the social network.

The LAS derived using the intersection rule (ILAS) considers a relation to exist only if both the sender and receiver of the relation consider it to exist. Thus, the ILAS can be derived using the following rule: $R'_{i,j} = \{R_{i,j,i} \cap R_{i,j,j}\}$. The ILAS is often used as a proxy for the actual social network when relations which require both actors to confirm its existence is being measured. For the friendship networks of the cognitive social network data, the assumption is made that both actors of the relation need to perceive the relation (though it need not be reciprocated) for it to be considered true (Krackhardt, 1987:117). Consequently, the ILAS is likely to be best suited when determining the actual friendship network (Krackhardt, 1987:117).

Lastly, the LAS derived using the union rule (ULAS) considers a relation to exist if either the sender or receiver considers it to exist. The ULAS can be derived using the following rule: $R'_{i,j} = \{R_{i,j,i} \cup R_{i,j,j}\}$. This is the least stringent LAS as it considers both the 'sender' and 'receiver' of a relation to be reliable when perceiving a relation to exist. The ULAS therefore tends to be a suitable proxy of the actual social network in the case where either actor of the relation can confirm its existence, but both need not agree about whether the relation exists.

3.4.2.2   Consensus Structures

The third method of reduction is Consensus Structures. Krackhardt (1987) describes this as a distinct method of determining the actual social network as the aggregate is derived from the broader social network, rather than only the local perceivers of the relations.

The Consensus Structure considers the all the actors' perceptions of i to j using a function. A commonly used function is setting a threshold, where a relation is considered to exist only if a proportion of the network considers it to exist:

$$R'_{i,j} = \{1 \quad if \frac{1}{N} \sum_k R_{i,j,k} >= Threshold, 0 \; otherwise.\} \qquad (3.1)$$

Therefore, should the threshold be set at 0.5 (a common threshold), a relation will only be considered to exist in the actual social network if 50% or more of the actors perceive that particular relation to exist as well (Krackhardt, 1987:117–118). Consensus Structures are used where the actors involved in the relation may not necessarily reliably perceive the existence of the relation.

Given that the High-Tech and Silicon Systems data is restricted to the advice and friendship networks, only the RLAS and ILAS are used as proxies for the respective actual social networks.

3.4.3   Measuring Social Network Cognitive Accuracy

As discussed in Chapter 2, this research project distinguishes cognitive accuracy measures into two broad categories: interpersonal accuracy and structural accuracy. The correlation and distance measures between the graphs serve as a proxy of accuracy.

3.4.3.1   Interpersonal Accuracy

One of the simplest and most widely used interpersonal accuracy measures is the correlation between the respondent's cognitive slice and the actual social network (Ouellette, 2008:14). The Pearson correlation coefficient is the most widely used as a proxy for interpersonal accuracy as it is well-suited to detecting general patterns between the ties of the perceived social network and the actual social network (Scott, 2014:182).[4]

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[4]Notably, there are various measures of interpersonal accuracy (e.g. Krackhardt, 1988, Krackhardt, 1990, Bondonio, 1998), however, given that this research project focuses on structural accuracy measures, these are not included in the analysis of the data.

3.4.3.2   Structural Accuracy

Currently, the primary measure which can readily be used as a proxy for structural accuracy is the structural correlation between two graphs. This is a generalised measure of the correlation between two graphs, where the both the graphs' nodes are relabelled (permutated) and then correlated to determine the structural correlation between two graphs (Butts and Carley, 2001:31). The structural correlation between the perceived and actual social networks can be calculated using the *gscor* function in R (Butts, 2016).[5]

As a measure of structural accuracy, GSCOR is agnostic to which specific actors share a relation, yet retains the relational data of all actors in the social network.[6] This is advantageous for measuring precise structural accuracy of an individual, as it retains the relational data on the dyadic level. However, this may not be desirable when measuring structural accuracy as it does not give an indication of the broader patterns which occur in the social network (perceived or actual). Additionally, it measures structurally accuracy on a very granular level, thus individuals generally need to be accurate about the specific relations among actors in the social network in order to be structurally accurate.

Using the triad census as the basis for determining structural accuracy allows for the inspection of the social networks on 16 data points, which may even be clustered into different relationship patterns. For example, if the triad census of an actor's perceived network yields a high proportion of type 300 triads, it immediately makes certain structural features apparent: the perceived network has high density, high reciprocity, and high transitivity.

Moreover, it may also suggest that the actor perceiving the social network relied on heuristics when making judgements about the relations in the social network. Thus, structural accuracy measures based on the triadic composition of the social network provides an intermediate measure of granularity when measuring the similarity between two social networks.

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[5]Consequently, this dyadic-level measure of structural correlation is also referred to as GSCOR for brevity.

[6]A useful analogy is that of a flock of geese in flight: while the geese may periodically switch positions among the other geese in the flock, their formation remains the same (Butts and Carley, 2001:23).

This research project proposes two approaches to determining structural accuracy, both based on the triad census:

1. Correlation between triad census of the cognitive slice and the triad census of the actual network.

2. Distance between the triad census of the cognitive slice and the triad census of the actual network.

The first approach proposed to determine an individual's structural accuracy is to calculate the correlation coefficient of the triad census of the cognitive slice and the triad census of the actual network. This is determined in a similar manner as interpersonal accuracy—with the distinction that the data is valued and condensed into a single vector containing 16 triad counts (one for each triad type). Specifically, two correlation methods can be used:

1. Pearson correlation coefficient

2. Spearman's rank correlation coefficient

The first correlation measure which is proposed as the proxy for structural accuracy is the Pearson correlation coefficient[7]. This correlation measure is widely used and is calculated in the same manner as with interpersonal accuracy. Thus, the 'closer' an actor's perception about the triad census in their social network is to the actual triad census in the social network, their structural accuracy will converge to a value of 1. Importantly, a structural accuracy score of 1 indicates the actor perceives an equal number of each triad type as exists in the actual network, but this does not indicate that the actor is accurate on the dyadic level. If the perceiver is highly inaccurate about the composition of the triad types in the social network, their structural accuracy score tends to -1, where 0 indicates no relationships between their perception and -1 indicates that they perceived the inverse number of triads to the actual number of triads per triad type. The Pearson-based structural accuracy measure can be determined as follows:

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[7]Referred to as the Pearson-based structural accuracy measure.

$$d_{cor}(G, H) = \frac{\sum_{i=1}^{16}(G_i - \bar{G})(H_i - \bar{H})}{\sqrt{\sum_{i=1}^{16}(G_i - \bar{G})^2 \sum_{i=1}^{16}(H_i - \bar{H})^2}}, \tag{3.2}$$

where G and H are graphs containing the triad count of the perceived social network and the actual social network, respectively (16 for each vector). $\bar{G}$ and $\bar{H}$ are the means of the respective graphs.

Alternatively, the Spearman's rank correlation coefficient can also be used[8]. Spearman's rank correlation coefficient can be interpreted in a similar fashion as the Pearson correlation coefficient, but should be understood as a broader measure of accuracy as it measures the correlation between the rank of the triads, not accounting for the specific values of the triad counts[9]. For example, in the case where an individual perceives the same proportion between all triad types except the 300 triad type, which they overestimate significantly, they will still score high in terms of structural accuracy as the *rank* of the other triad types correlate to the ranks of the actual social network, despite the fact that they are relatively inaccurate about the the actual composition of the social network.

Unlike the Pearson's correlation coefficient, Spearman's rank correlation coefficient does not assume a linear correlation between the variables and presents a more robust measure of correlation (De Nooy et al., 2016:192). However, the Spearman's rank correlation coefficient is also less sensitive as a measure of correlation. Effectively, by assigning each data point a rank value rather than using the triad count value, Spearman's rank correlation condenses the relational data further. The Spearman's rank correlation coefficient is determined as follows:

$$d_{spear}(G, H) = \frac{\sum_{i=1}^{16}(G_i' - \bar{G}')(H_i' - \bar{H}')}{\sqrt{\sum_{i=1}^{16}(G_i' - \bar{G}')^2 \sum_{i=1}^{16}(H_i' - \bar{H}')^2}}, \tag{3.3}$$

where $G_i' = rank(G_i)$ and $H_i' = rank(H_i)$ and $\bar{G}$ and $\bar{H}$ are the means of the triad counts of the perceived social network and the actual social network, respectively.

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[8]Referred to as the Spearman-based structural accuracy measure.

[9]Spearman's rank correlation is effectively a Pearson correlation on ranked data.

Correlation between network properties is a useful proxy for structural accuracy,[10] however, this research project also proposes a second means of determining structural accuracy, which may be more sensitive to valued data, such as generated by a triad census. Specifically, this research project proposes measuring structural accuracy by using the Euclidean distance to determine the distance between the triad censuses of respondent's cognitive slice and the actual social network. Specifically, the Euclidean distance can be calculated as follows:

$$d_{G,H} = \sqrt{\sum_{i=1}^{16}(G_i - H_i)^2}, \tag{3.4}$$

where G_i and H_i are the triad counts of per triad type of the perceived social network and actual social network, respectively. The Euclidean distance is calculated by finding the square root of the absolute value of the square of the difference between the triadic count of each triad type of the perceived social network and the triadic count of each triad type of actual network (a total of 16 triad types).

Euclidean distance measures the dissimilarity between the perceived social network and the actual social network, where a large distance indicates an inaccurate perception of the social network and a score of 0 indicates perfect accuracy. The maximum Euclidean distance for a triad count of a given social network is $\binom{n}{3}$, where n is the number of actors in the social network. This measure is useful as it retains the value of the difference between the two social networks, however, it also means that comparing the distance measures across different social networks is somewhat complicated when the social networks are not the same size. Consequently, this research project recommends incorporating the Euclidean distance measure in an equation for determining structural accuracy as follows:

$$d_{G,H} = 1 - \frac{\sqrt{\sum_{i=1}^{16}(G_i - H_i)^2}}{t}, \tag{3.5}$$

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[10]Krackhardt (1987), for example, correlated the indegree, outdegree, and betweenness centrality between different aggregations to measure the similarity between the different 'actual' social networks.

where G_i and H_i are the triad counts of per triad type, and t is the total number of possible triads. The total number of triads is equal to $\binom{n}{3}$, where n is the number of actors in the social network. The Euclidean distance is normalised by dividing by the total number of possible triads. To compare the results of the normalised Euclidean distance it is transformed to a measure of similarity by subtracting the normalised Euclidean distance[11] from 1. This generates an accuracy score where 1 indicates the triad counts are identical and 0 indicates that the triad counts are completely dissimilar.[12]

Both the correlation and distance structural accuracy measures are potentially useful measures of similarity between a respondent's perception of the social network structure and the actual social network structures. For the purposes of this research, the three triadic-level proposed structural measures will be compared to existing accuracy measures (Objective II).

3.5   Comparing Accuracy Measures

This research project evaluates the interpersonal accuracy measure and four structural accuracy measures, all of which produce a single score for the respondent whose accuracy is being determined. The evaluation of structural accuracy measures requires an examination of how effectively they capture the similarities between the perceived social network and actual social network's structural properties. Subsequently, this research project also considers cognitive social network properties, such as density, transitivity, and reciprocity.

In order to determine the various accuracy scores, the interpersonal accuracy scores of the respondents must be compared to the structural accuracy scores of the same respondents in the same social network. Correlation between the interpersonal accuracy measures of respondents and their structural accuracy measures is an effective measure to determining if a relationship exists between interpersonal and structural accuracy measures. Specifically, calculating the Pearson's Correlation Coefficients between the interpersonal accuracy measure and each of the structural accuracy measures will provide an indication of the

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[11]Referred to as the Euclidean-based structural accuracy measure.

[12]It worthwhile noting that structural equivalence—i.e., how similar two actors' positions are in the same social network—is also calculated using the Euclidean distance between the two actors (Wasserman and Faust, 1994:367).

how closely the two variables move together as well as the direction of the movement.

Chapter 4

Findings

4.1   Introduction

This chapter presents the key findings of the analysis conducted on the High-Tech and Silicon Systems friendship and advice networks regarding the proposed structural accuracy measures (see Objective II).

Firstly, the results of the triad census of both the perceived and actual networks of the all the social networks are examined. These findings determine the case for using the triad census of social networks as the basis for structural accuracy measures. Specifically, the relationship between different triad types and structural properties of the perceived and actual networks are examined.

Secondly, the respondent's interpersonal accuracy as well their structural accuracy measures are evaluated for the advice and friendship networks of both datasets. This presents the comparison across the different networks for robustness and internal consistency amongst the three proposed structural accuracy measures.

Lastly, the relationship between the proposed structural accuracy measures and key network properties is presented. This forms the key component of the research project, as the notion that triads serve as an intermediate level of analysis by retaining some of the dyadic-level information while also allowing analysis of some of the structural features of the network is central to the use of triad censuses as the basis for structural accuracy measures.

4.2   Triad Census

The first measure required to determine a respondent's structural accuracy is a triad census of the respondent's cognitive slice and the actual social network.

A triad census was conducted on the cognitive slices of all respondents for the friendship and advice networks of the High-Tech and Silicon Systems datasets. The type 003 triad is dominant in the all the datasets for both friendship and advice, except for the High-Tech advice network, where the type 012 triad is slightly more dominant than the type 003 triad (See Appendix A). This is not particularly interesting other than indicating that most respondents do not consider their networks to be particularly dense. This is evident from the fact that, as a proportion of the total number of triads, triad types with isolated nodes (i.e., 003, 012, and 102) are dominant.

Similarly, a triad census was also conducted on the actual friendship and advice networks for both datasets. The type 003 triad is dominant compared to the other triad types in the friendship networks, but not in the advice networks. In the High-Tech advice network (Figure 4.1), the type 012, 021D, and 030T triads were more prominent and in the other two datasets the type 003 triad and type 012 triad occurred nearly an equal number of times. Consequently, it is apparent that the actual advice networks of both the High-Tech and Silicon Systems are generally denser relative to the actual friendship networks.

The triad census of respondents allows researchers to readily summarise the structural properties of a respondent's social network. For example, from the triad count of Respondent 1 of Silicon Systems (shown in Figure 4.2)[1], it is easy to perceive the general triadic pattern. Respondent 1 generally perceives the friendship network to be more dense in terms of social connections compared to advice network, as their perceived friendship network contains a larger proportion of the type 300, 210, and 201 triads compared to the advice network.

Additionally, it is also evident Respondent 1's perception that the advice network contains fewer reciprocated relations as the triad census of their advice network did not yield any of the type 300, 210, and 201 triads. However, the friendship network does contain significantly more reciprocated ties, as

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[1]Note that Figures 4.1, 4.2 and 4.3 are shown on a logarithmic scale.
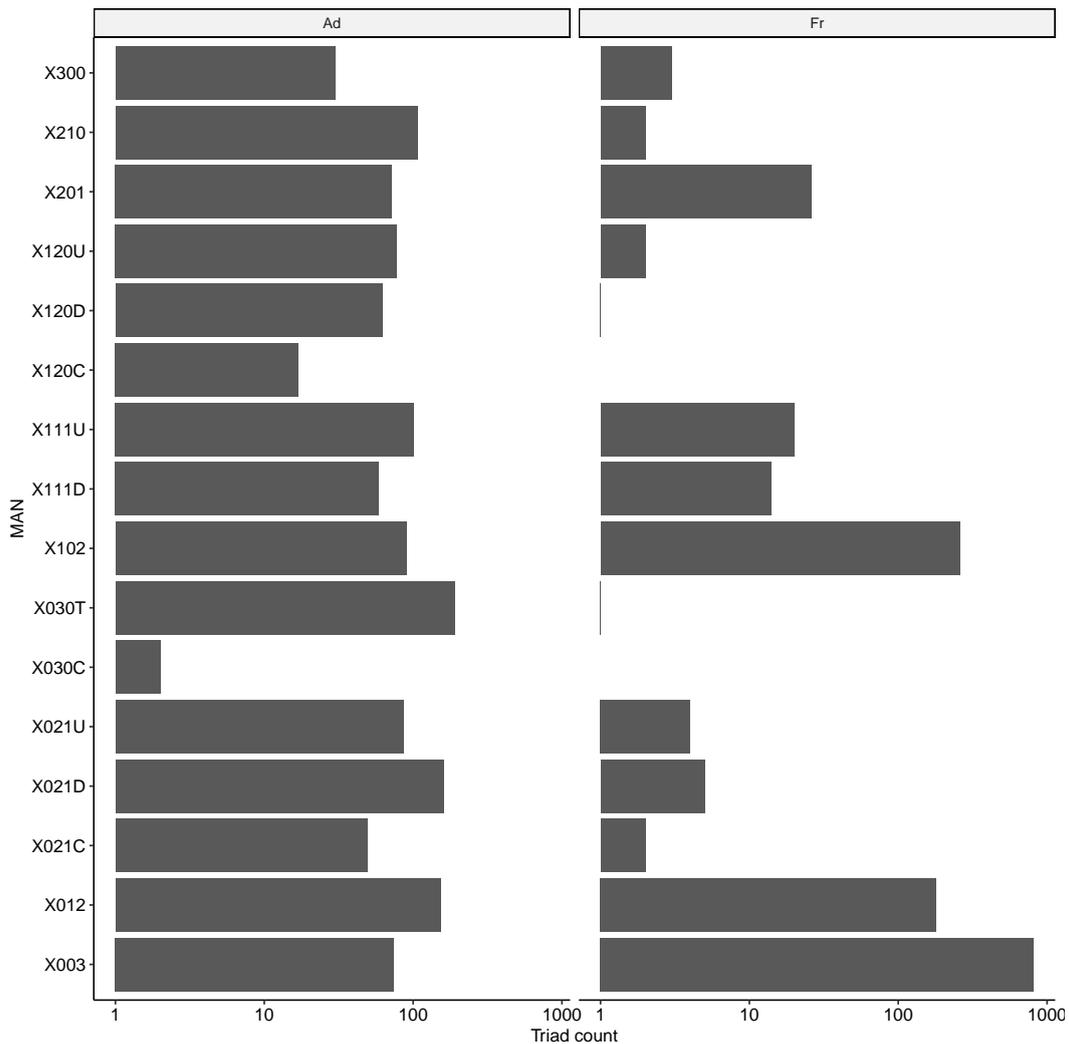
Figure 4.1: Triad census of High-Tech actual advice (Ad) and friendship (Fr) networks.

indicated by the presence of the type 300, 210, 201 and 111U, 111D and 102 triads.

Having summarised the cognitive slice of a respondent, comparing the triad census of perceived social network to the triad census of the actual social network allows for a preliminary examination of the structural accuracy of the respondent. For example, Figure 4.3 shows the triad census of the actual advice and friendship networks of Silicon Systems. Comparing the triad census of Respondent 1 of Silicon Systems (Figure 4.2), it is apparent that the actual advice network has significantly fewer empty ties compared to that which was
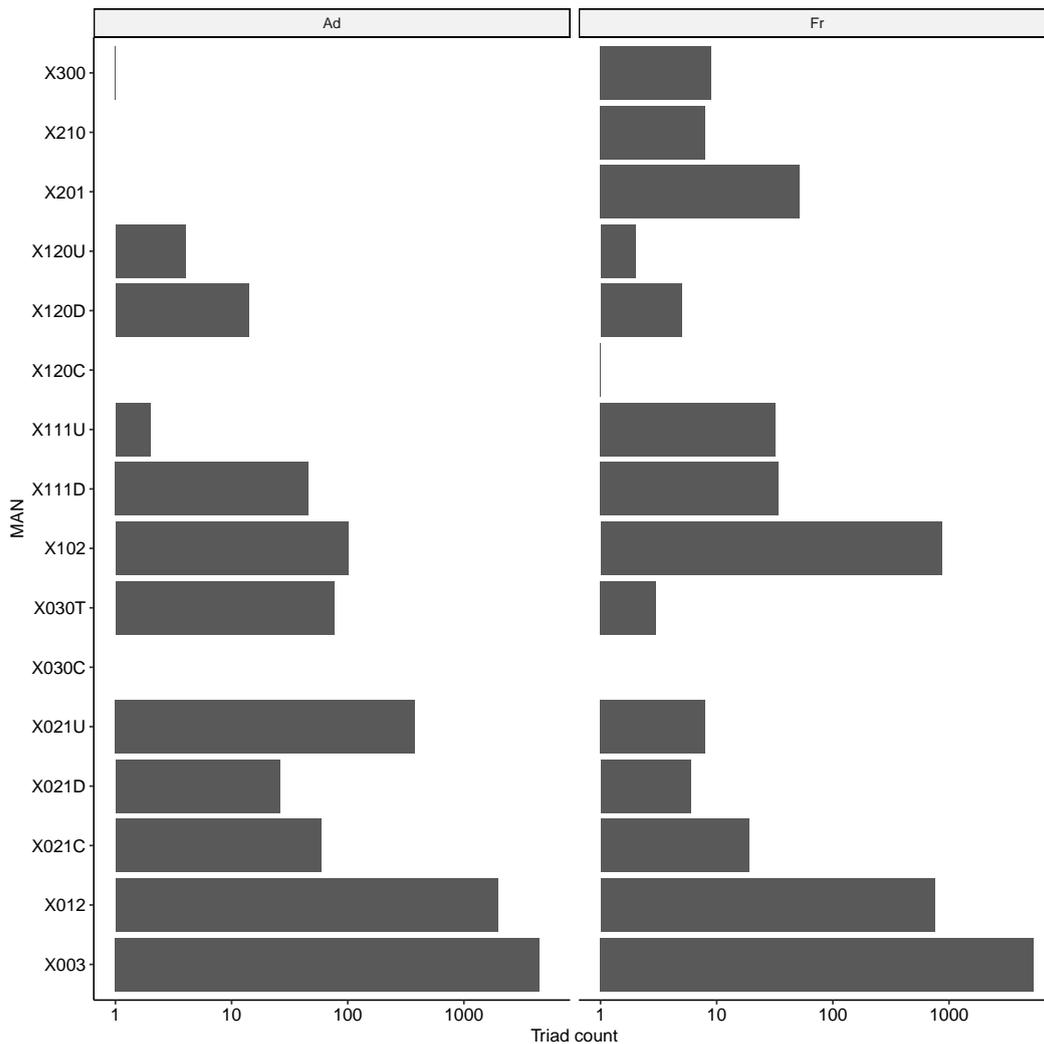
Figure 4.2: Respondent 1's triad census of Silicon Systems' advice (Ad) and friendship (Fr) networks.

perceived by Respondent 1. Specifically, Respondent 1 perceived 2 357 more empty triads (out of a total of 7 140 possible triads) compared to the actual network.

Furthermore, Respondent 1 also perceived fewer triads with mutually reciprocated ties compared to the actual social network, with the perceived number of triads containing reciprocated ties differing by 342 triads compared to the actual advice network. Given this comparison of the triad censuses of the perceived and actual advice networks for Respondent 1 it is possible to deduce that the actual advice network is denser compared to that perceived by Re-
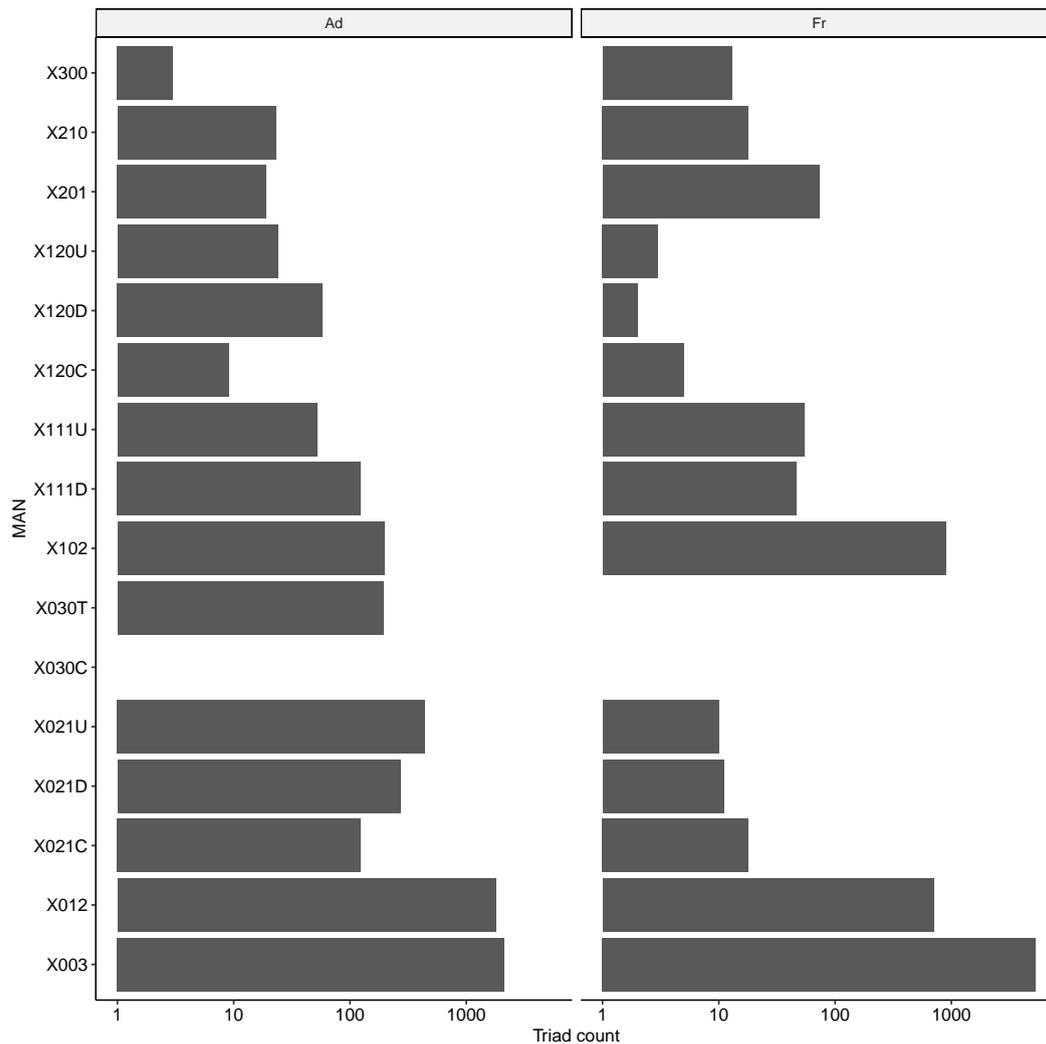
Figure 4.3: Triad census of Silicon Systems actual advice and friendship networks.

spondent 1, and actors in the social network have a relatively high reciprocity compared to that perceived by Respondent 1. This suggests that Respondent 1 is relatively inaccurate on a structural level, as the respondent incorrectly perceives that the advice network has relatively low reciprocity and that it has relatively fewer relations compared to the actual social network.

However, the triad census of the friendship network of Respondent 1 is similar in proportion to the triad census of actual friendship network. Specifically, it can be noted that none of the triad counts for the perceived social network differ by more than 51 triads from the actual friendship network. Thus, Respondent 1 can be considered structurally accurate regarding the friendship

network, as the respondent's perception of the structural patterns of relations corresponds to that of the actual friendship network.

This illustrates the purpose of selecting triad census to calculate structural accuracy: a triad census is an informative way to summarise cognitive social network data, including the characteristics of the microstructural tendencies, yet allows researchers to make deductions about some of the macrostructural properties.

4.3   Cognitive Structural Accuracy

The proposed cognitive structural accuracy measures are calculated using two broad approaches, namely correlating the triad census of the respondent's cognitive slice with the triad census of the actual network and calculating the normalised Euclidean distance between the triad census of the respondent's cognitive slice and the triad census of the actual social network (Equation 3.5). Thus, each respondent in the social network has four structural accuracy scores (the three proposed structural accuracy measures and GSCOR) and one interpersonal accuracy score (See Appendix B).

Table 4.1 shows the average of all the accuracy measures calculated for the two advice and friendship social networks. From the results, it is apparent that the interpersonal accuracy score is, on average, lower across both social networks than the structural accuracy measures. Specifically, the average interpersonal accuracy score is 0.349 across all the social networks, whereas the average GSCOR score is 0.463 and the proposed structural accuracy measures are all above 0.750.

Similarly, the average GSCOR is also consistently lower than the averages of the other measures of structural accuracy across the social networks, except for the High-Tech advice network, where the average Pearson-based structural accuracy measure (0.288) is significantly lower than the average GSCOR accuracy (0.428). The average GSCOR accuracy is about the same as the average Spearman-based accuracy measure (0.404) for the High-Tech advice network.

Among the proposed structural accuracy measures, the average structural accuracy score is relatively high, with the average Pearson-based structural ac-

Measure	Silicon Systems			High-Tech			Overall
	Friendship	Advice	Average	Friendship	Advice	Average	Average
Interpersonal	0.325	0.391	0.358	0.361	0.310	0.336	0.349
GSCOR	0.465	0.470	0.468	0.482	0.428	0.455	0.463
Pearson	0.984	0.908	0.946	0.971	0.288	0.629	0.823
Spearman	0.869	0.880	0.875	0.821	0.404	0.612	0.772
Euclidean	0.841	0.676	0.759	0.799	0.673	0.736	0.750
Average	0.697	0.665		0.687	0.420		

Table 4.1: The average interpersonal and structural accuracy measures for all social networks.

curacy score being the highest across all the social networks (except for the High-Tech advice network where the average score is 0.288). However, the High-Tech advice network's respondents have a relatively low average accuracy score (0.420) compared to the other three social networks examined, which all have relatively high average accuracy scores (all above 0.665).

4.4 Comparison of Interpersonal and Structural Accuracy Measures

In order to compare the interpersonal and structural accuracy measures, the interpersonal accuracy scores of all four social networks was correlated with the three proposed structural measures (Objective III). Specifically, a multivariate correlation is performed between the interpersonal accuracy scores and the structural scores, controlling for the density, reciprocity, transitivity, and hierarchy of the social networks.[2]

The results of the correlation between the interpersonal accuracy scores and the Pearson-based structural accuracy scores of the respondents of both advice and friendship networks for all datasets, when controlling for density, reciprocity, transitivity, and hierarchy, is shown in Table 4.2.[3]

Generally, correlation between the interpersonal and Pearson-based structural accuracy scores for the High-Tech friendship and advice networks is weak and not significant. Conversely, the interpersonal and Pearson-based structural

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[2]See Appendix C for network properties and cognitive accuracy scores of all respondents.

[3]The significance of the correlation is indicated in all the tables as follows: * that $p < 0.05$, ** that $p < 0.01$, and *** indicates $p < 0.001$.

Dataset	Relation	dens.est	trans.est	recip.est	hier.est
High-Tech	Ad	0.05	0.06	0.06	0.07
High-Tech	Fr	0.30	0.35	0.35	0.28
SilSys	Ad	0.58***	0.61***	0.61***	0.57***
SilSys	Fr	0.59***	0.25	0.25*	0.40*

Table 4.2: Interpersonal and Pearson-based structural accuracy measures controlling for density, transitivity, reciprocity, and hierarchy.

accuracy scores of Silicon Systems (SilSys) are almost all moderately correlated and significant. Specifically, about 60% of the variance of Silicon Systems structural accuracy scores for the advice network is explained by of the variance of the interpersonal accuracy scores.

Similarly, results of the correlation between the interpersonal accuracy score and the Spearman-based structural accuracy scores of the social networks, when controlling for density, reciprocity, transitivity, and hierarchy, is shown in Table 4.3.

Dataset	Relation	dens.est	trans.est	recip.est	hier.est
High-Tech	Ad	-0.09	-0.08	-0.08	-0.08
High-Tech	Fr	0.26	0.38	0.38	0.30
SilSys	Ad	0.36*	0.45**	0.45**	0.35*
SilSys	Fr	0.55***	0.62***	0.62***	0.58***

Table 4.3: Interpersonal and Spearman-based structural accuracy measures controlling for density, transitivity, reciprocity, and hierarchy.

The correlation between the interpersonal and Spearman-based structural accuracy scores is weak and not significant for the High-Tech social networks. However, for the Silicon Systems friendship and advice networks, the interpersonal accuracy scores are moderately and significantly correlated to the Spearman-based structural accuracy scores. Specifically, interpersonal accuracy scores of the friendship network is correlated relatively highly compared to the advice network: interpersonal accuracy explains about 60% of the variance of the Spearman-based structural accuracy scores for the friendship network, whereas it only explains about 40% of the variance of the variance of the Spearman-based structural accuracy scores of the advice network.

Lastly, results of the correlation between the interpersonal accuracy score and the Euclidean-based structural accuracy scores of the respondents of both advice and friendship networks for all datasets is shown in Table 4.4.

Dataset	Relation	dens.est	trans.est	recip.est	hier.est
High-Tech	Ad	0.16	0.11	0.11	0.23
High-Tech	Fr	0.26	0.42	0.42	0.36
SilSys	Ad	0.53***	0.28	0.28*	0.52***
SilSys	Fr	0.78***	0.68***	0.68***	0.77***

Table 4.4: Interpersonal and Euclidean-based structural accuracy measures controlling for density, transitivity, reciprocity, and hierarchy.

As with is the case with the Pearson-based and Spearman-based structural accuracy scores, the High-Tech social networks showed no significant correlation between the interpersonal accuracy scores and Euclidean-based structural accuracy scores. The interpersonal accuracy for the Silicon Systems friendship network, however, correlated relatively strongly with the Euclidean-based structural accuracy scores with high significance ($p < 0.001$). The Silicon Systems advice network showed only moderate correlation between the interpersonal accuracy scores and Euclidean-based structural accuracy scores, though the correlation was significant.

Chapter 5

Discussion

5.1   Introduction

This chapter makes recommendations as to the suitability of the proposed structural accuracy measures based on the examination of the findings in Chapter 4 (Objective IV).

In order to evaluate the case for using the proposed structural accuracy measures, it is necessary to consider if they provide a unique contribution to determining structural similarity between the perceived and actual social networks. Specifically, the use of the triad census as a basis for determining the similarity between social networks is discussed as a means to condense both macrostructural and microstructural features of the social networks being compared. The proposed cognitive structural accuracy measures were illustrated on four social networks and subsequently compared to the prevalent accuracy measure in SNA: interpersonal accuracy.

5.2   Triad Census

The triad census of both the perceived and actual social networks condenses the microstructural patterns, such as whether a set of actors share transitive ties, while retaining important macrostructural properties.

In the findings, this was demonstrated in the case of Respondent 1 of Silicon Systems friendship network. Respondent 1 generally perceived the same num-

ber of each triad type as that which occurred in the actual social network. Specifically, Respondent 1 perceived the friendship network to largely consist of triads containing isolates, namely the 003, 102, and 012 triads. This means that friendships—defined as existing when both local actors agree it exists—is relatively sparse. Additionally, Respondent 1 also perceived a relatively large number of triads containing at least one mutually reciprocated tie.

Subsequently, given these microstructural patterns, it is possible to infer certain structural properties of the perceived social network, such as the density of the network (based on the number of ties), the reciprocity (based on the number of triads containing mutually reciprocated ties).[1] This approach summarises redundant patterns of relationships which need not be detected in detail when determining structural accuracy.

5.3   Cognitive Structural Accuracy

Two of the three proposed structural accuracy measures involve correlating the triad census of the perceived social network to the triad census of the actual social network, while the third structural accuracy measure was determined using the normalised Euclidean distance between the triad censuses of the two social networks.

The first of the proposed structural accuracy measures, the Pearson-based structural accuracy, yielded the highest average structural accuracy scores for respondents across all the social networks, except for respondents of the High-Tech advice network, where the average Pearson-based structural accuracy score was the lowest (0.288). This is not unexpected, as the Pearson correlation coefficient is a relatively sensitive measure of how strongly a pair of variables are related.

However, the Pearson-based structural accuracy measure is relatively insensitive to *linear* transformations of the data. This has the implication that respondents with a low Pearson-based structural accuracy score are incorrect about the general relationship or trend between the different types of triads

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[1]Wasserman and Faust (1994) and De Nooy et al. (2016:205-212) provide a comprehensive overview of the various macrostructural properties which can be inferred from different triad types.

(e.g. perceiving mostly triads with isolates when the actual social network is composed of triads with mostly reciprocated ties), but that individuals who are correct about the general relationship between the triads should not necessarily be considered to be accurate about the structural composition of the social network.

The Spearman-based structural accuracy involves correlating the triad censuses of the perceived and actual social networks using Spearman's rank correlation. The advantage of using Spearman's rank correlation is that it is a more robust correlation measure as it does not assume a linear correlation between the variables (De Nooy et al., 2016:192). This characteristic is reflected in the average Spearman-based structural accuracy scores across the four social networks: despite yielding a lower average score for all the social networks compared to the Pearson-based structural accuracy measure, it yields a higher average score for the High-Tech advice network (0.404) compared to the average Pearson-based structural accuracy score of 0.288.

However, as the Spearman-based structural accuracy measure is effectively a Pearson correlation between the *ranked* triad censuses, it is also relatively insensitive to the magnitude of the differences between the triad censuses. This means that a respondent who is generally correct about proportions of the types of triads in the actual social network can still score relatively high in terms of structural accuracy, despite their triad counts differing significantly from that of the actual social network. Thus, the Spearman-based structural accuracy provides a broader measure of structural accuracy compared to than the Pearson-based structural accuracy measure but may provide a more robust accuracy score as it does not assume a linear relationship between the different triad types.

The third approach proposed for determining structural accuracy is the normalised Euclidean distance between the triad censuses of the perceived and actual social networks. The average Euclidean-based structural accuracy scores across the four social networks are lower than the average Pearson- and Spearman-based structural accuracy scores, except for the High-Tech advice network, where the average structural accuracy score was highest (0.673). Unlike the Pearson- and Spearman-based structural accuracy measures, the Euclidean-based structural accuracy measure does not assume a linear relationship be-

tween the triads or transform the data into ranked data. Thus, the Euclidean-based structural accuracy measure retains a relatively high degree of sensitivity to the differences between the triad censuses of the perceived and actual social networks.

This means that for a respondent to be considered structurally accurate, they need to perceive a social network with a similar number of triads as compared to the actual social network. Thus, the Euclidean-based structural accuracy measure provides a more granular measure of structural accuracy compared to the other proposed measures, as it requires a stricter agreement between the different triad types compared to the other proposed structural measures. Nonetheless, this measure still retains the benefits of having the triad census as the basis for determining an individual's structural accuracy despite having a stricter interpretation compared to the other proposed structural accuracy measures.

Notably, when considering the average GSCOR structural accuracy scores for all four social networks, the average Euclidean-based structural accuracy scores generally fell between the average GSCOR score and the average Pearson-based and average Spearman-based structural accuracy scores. As the GSCOR structural accuracy measure is determined on the dyadic-level, this suggests that the Euclidean-based structural accuracy measure is a semi-granular measure of cognitive accuracy, condensing both microstructural tendencies and macrostructural properties into a single cognitive structural accuracy measure.

5.4 Comparison of Interpersonal and Structural Accuracy Measures

The Pearson correlation between the interpersonal accuracy scores and the proposed structural measure scores for all four social networks yielded mixed results.

In the High-Tech advice and friendship networks, the interpersonal accuracy scores of the respondents are weakly correlated with all three proposed structural accuracy measures, with none of the correlations being significant. This, however, itself is potentially significant as it indicates that all three proposed

structural measures are not an 'echo' of interpersonal accuracy and do in fact measure the similarity between the perceived and actual social networks in a unique way.

Conversely, the interpersonal accuracy scores and all three proposed structural measure scores were moderately correlated in the Silicon Systems advice and friendship networks with all the correlations being significant ($p < 0.1$), except for the Euclidean-based structural accuracy scores when controlling for transitivity in the advice network and the Pearson-based structural accuracy scores in the friendship network. This suggests that the three proposed structural accuracy measures have significant overlap the with interpersonal accuracy measurement in capturing the similarities between the perceived and actual social networks.

However, it is also apparent that controlling for density reduces the correlation between the interpersonal accuracy scores and the Spearman-based structural accuracy scores relative to when controlling for transitivity, reciprocity, and hierarchy for the Silicon Systems friendship network, while resulting in a stronger correlation in the same network between the interpersonal accuracy and the Pearson- and Euclidean-based structural accuracy scores. A similar pattern also emerges when controlling for hierarchy. These discrepancies cannot be readily accounted for and could be a result of broader social environmental factors, such as the company culture, or the formal hierarchy of the company.

The three proposed accuracy measures, nonetheless, perform consistently within each organisation, which further suggests that the discrepancy between the organisations' social network may possibly be attributed to other contextual factors. This requires further investigation, possibly between more social networks in order to describe the relationship between interpersonal accuracy and the proposed structural accuracy measures.

5.5   Limitations and Potential Problems

This research project limits the scope of structural accuracy to the triadic level but acknowledges that determining the accuracy of an individual's perception of higher-order structures may also be a useful metric. For example, it

may be useful to consider structural equivalence among actors as a potential mechanism for determining the similarity between two social networks.

Additionally, this research project inherited some of the disadvantages of using the triad census as a basis for measuring structural accuracy, namely, that this method will likely not be useful on very small social networks or when the social networks contain numerous isolated actors (Wasserman and Faust, 1994:569).

Lastly, the network accuracy measures were tested on four social networks. This may have limited the theoretical contribution of the research as the research project may have been able to interrogate the discrepancies which were described in Section 5.4 across different contexts if more social networks were analysed.

These limitations, however, also present the opportunity for future research.

5.6   Future Directions

The proposed structural accuracy measures allow researchers to investigate social networks using an accuracy measure which is attuned to the notion that individuals rely on heuristics when forming their perceptions of relations in a social network.

Moreover, previous research on the antecedents and consequences of interpersonal accuracy can now be enriched using structural accuracy measures, as it allows for the reinterpretation of the findings considering the broader understanding of how individuals perceive their social networks.

The proposed structural accuracy measures can, of course, also be applied to the wider context of measuring similarity between two directed graphs, where there is a need to condense the information but preserve the microstructural tendencies and allow for the inference of key network properties.

Chapter 6

Conclusion

This research project sought to answer the question: How can one measure a person's perception of the *structure* of a social network and compare it to the actual social network? Given the notion that individuals use heuristics such as balance and network closure on a triadic level, the triad census was proposed to determine structural accuracy.

Three structural accuracy measures are defined and evaluated, with the Pearson-based structural accuracy measure best suited for measuring the general trend between the triad census of the perceived and actual social networks. The Spearman-based structural accuracy measure is a more robust measure of the similarity between the triad censuses of the perceived and actual social networks, but is less granular. Lastly, the Euclidean-based structural accuracy measure provides a more granular measure of the structural accuracy compared to the two correlation-based measures.

The structural accuracy scores were correlated with the interpersonal accuracy scores for four social networks, with only Silicon Systems friendship and advice networks showing moderate significant correlation between the measures. Conversely, both the High-Tech advice and friendship networks showed no significant correlation with the structural accuracy scores. Thus, the results were mixed and could not be generalised for all social networks.

Nonetheless this research project broadly achieved its aim of addressing the question: How can one measure a person's perception of the *structure* social network and compare it to the actual social network?

Appendix A

Triad Census of High-Tech and Silicon Systems Respondents

Description

The following four tables provide the data of the triad census conducted on each respondent's cognitive slice. Specifically, Table A.1 and Table A.2 show the triad count for each triad type (according to the M-A-N label) for the High-Tech advice- and friendship networks for each of the 21 respondents (Resp).

Similarly, Table A.3 shows the triad count for each triad type for the Silicon Systems advice network and Table A.4 shows the triad census of the Silicon Systems friendship network for each of the 33 respondents. Respondents 13, 24, and 35 are omitted for Silicon Systems as they did not complete the questionnaire.

A.1   High-Tech

Resp	003	012	021C	021D	021U	030C	030T	102	111D	111U	120C	120D	120U	201	210	300
1	1	56	33	20	13	1	72	83	92	92	53	80	137	115	294	188
2	287	387	59	45	195	1	97	71	81	16	9	47	14	12	4	5
3	179	177	9	10	27	1	11	238	141	71	9	20	7	199	114	117
4	75	193	50	35	35	0	39	234	133	95	17	45	27	131	127	94
5	65	186	53	58	129	1	138	128	123	76	25	66	88	49	108	37
6	680	404	22	6	129	0	17	17	38	0	1	11	1	1	3	0
7	251	217	34	18	177	1	45	78	122	77	28	57	14	72	101	38
8	184	364	19	37	181	0	74	157	122	24	5	63	31	18	40	11
9	175	317	46	31	25	4	21	247	115	57	25	26	12	106	94	29
10	220	286	34	12	23	0	15	272	115	81	16	16	17	106	73	44
11	488	434	44	20	113	0	35	72	56	22	10	19	5	5	6	1
12	219	398	44	74	105	3	88	79	54	73	21	34	31	53	47	7
13	667	450	24	21	97	0	15	24	23	1	2	5	0	1	0	0
14	230	251	14	176	110	0	115	109	68	70	4	75	58	14	26	10
15	481	317	31	33	37	0	13	119	51	94	8	17	12	61	40	16
16	650	481	41	8	91	0	21	16	12	1	0	8	1	0	0	0
17	780	352	32	9	59	0	10	48	27	0	0	6	0	1	6	0
18	272	304	30	41	41	2	25	191	69	50	11	23	14	129	88	40

Table A.1 continued from previous page

Resp	003	012	021C	021D	021U	030C	030T	102	111D	111U	120C	120D	120U	201	210	300
19	341	390	37	19	90	0	63	185	80	19	1	49	18	14	15	9
20	572	249	69	26	60	1	9	126	74	38	15	11	10	41	25	4
21	93	172	44	62	59	1	79	145	159	85	26	98	35	65	140	67

Table A.1: Triad census of the perceived advice networks in High-Tech.

Resp	003	012	021C	021D	021U	030C	030T	102	111D	111U	120C	120D	120U	201	210	300
1	757	153	4	2	2	0	4	331	21	13	2	2	0	25	5	9
2	1087	114	2	1	1	0	0	107	10	0	0	0	0	7	1	0
3	1239	52	0	1	0	0	0	36	0	1	0	0	1	0	0	0
4	914	208	3	6	2	0	0	159	4	19	0	1	4	5	3	2
5	642	288	11	10	39	0	14	205	45	16	1	5	5	26	18	5
6	998	163	3	2	5	0	0	128	11	7	0	1	1	6	4	1
7	553	355	29	14	76	0	20	120	68	20	4	21	15	15	15	5
8	1256	55	0	0	0	0	0	17	2	0	0	0	0	0	0	0
9	1254	38	0	0	0	0	0	38	0	0	0	0	0	0	0	0
10	882	151	4	3	4	1	0	225	11	9	1	2	1	29	5	2
11	625	316	20	13	19	0	2	202	19	27	3	6	1	50	21	6
12	1019	145	2	2	3	0	0	139	2	7	0	0	1	7	1	2
13	908	261	6	2	9	0	0	110	23	2	0	1	0	7	1	0
14	769	306	7	40	14	1	14	121	24	16	1	4	2	6	5	0
15	1003	99	1	0	0	0	0	188	4	1	0	0	1	21	6	6
16	983	240	9	2	4	0	1	78	3	5	1	0	0	2	2	0
17	943	116	3	74	1	0	2	101	5	66	0	2	1	8	6	2
18	1077	121	1	1	0	0	0	120	7	1	0	0	0	1	0	1
19	602	308	17	8	21	0	8	224	41	31	2	9	2	33	10	14

Table A.2 continued from previous page

Resp	003	012	021C	021D	021U	030C	030T	102	111D	111U	120C	120D	120U	201	210	300
20	1188	100	2	0	3	0	0	32	2	2	0	0	0	1	0	0
21	838	160	7	3	1	0	1	256	12	12	4	2	1	20	5	8

Table A.2: Triad census of the perceived friendship networks in High-Tech.

A.2 Silicon Systems

Resp	003	012	021C	021D	021U	030C	030T	102	111D	111U	120C	120D	120U	201	210	300
1	4476	1956	59	26	379	0	76	101	46	2	0	14	4	0	0	1
2	3662	2019	127	103	516	3	119	423	82	25	5	17	24	5	4	6
3	3890	2408	124	69	286	0	93	196	39	12	0	7	14	0	2	0
4	6048	945	16	0	96	0	1	16	18	0	0	0	0	0	0	0
5	5245	1398	29	6	247	0	20	118	57	1	0	11	1	1	4	2
6	4949	1484	43	21	303	0	38	201	71	9	1	12	5	2	0	1
7	5171	1444	83	15	179	0	14	177	40	2	0	9	4	0	0	2
8	5695	1169	32	18	117	0	8	68	17	10	1	3	1	1	0	0
9	4676	1843	94	18	227	0	48	156	61	2	0	8	4	0	2	1
10	3193	2871	275	119	288	0	193	111	45	15	4	20	3	1	2	0
11	4429	2000	54	26	242	0	56	239	55	12	0	15	7	2	1	2
12	947	630	74	18	548	1	108	2258	598	259	53	141	349	256	342	558
14	6320	662	18	1	105	0	0	27	6	0	0	1	0	0	0	0
15	3346	2303	185	106	381	0	134	384	153	42	3	62	15	7	16	3
16	4430	1295	56	19	286	1	36	604	198	42	8	41	36	25	46	17
17	4611	1868	52	13	261	0	49	142	107	2	2	16	0	4	10	3
18	5035	1306	30	15	127	0	14	526	43	8	0	7	0	14	11	4
19	2887	1896	212	34	688	1	149	470	371	29	16	203	32	29	86	37

Table A.3 continued from previous page

Resp	003	012	021C	021D	021U	030C	030T	102	111D	111U	120C	120D	120U	201	210	300
20	4284	1823	70	27	399	1	45	310	85	14	2	62	4	1	8	5
21	4262	1836	57	39	572	0	77	154	70	4	0	61	1	2	3	2
22	2394	2650	161	200	668	0	248	333	217	38	8	132	35	18	29	9
23	3401	2155	121	121	384	0	141	413	198	30	7	100	12	25	22	10
25	1565	1296	157	87	817	0	224	857	736	183	68	259	137	205	353	196
26	4239	2096	119	35	453	0	98	47	36	0	0	16	0	0	0	1
27	5086	1483	34	17	176	0	24	192	65	1	0	49	0	3	3	7
28	4178	1782	56	64	377	0	70	412	91	21	0	48	14	13	8	6
29	3515	1620	165	69	762	6	151	365	236	37	10	83	36	26	44	15
30	3973	1992	99	37	269	0	55	413	173	12	7	55	2	21	18	14
31	5972	910	20	0	136	0	2	71	26	0	0	2	0	0	0	1
32	2551	2284	285	125	548	5	207	497	263	76	43	110	38	40	53	15
33	3743	2133	173	78	171	0	69	530	89	59	11	32	16	11	18	7
34	4786	1347	47	7	502	0	31	183	167	6	1	40	3	9	9	2
36	3764	2059	77	23	336	0	51	426	232	13	4	79	6	23	29	18

Table A.3: Triad census of the perceived advice networks in Silicon Systems.

Resp	003	012	021C	021D	021U	030C	030T	102	111D	111U	120C	120D	120U	201	210	300
1	5341	753	19	6	8	0	3	867	34	32	1	5	2	52	8	9
2	4636	1291	29	18	78	0	15	787	155	33	4	13	5	51	18	7
3	3673	1652	96	47	58	0	14	1040	191	144	16	20	18	95	45	31
4	4063	1388	53	55	40	1	14	1082	136	90	17	14	7	109	43	28
5	6772	98	0	0	0	0	0	265	4	0	0	0	0	0	0	1
6	6204	486	6	3	5	0	1	403	19	5	0	1	0	6	1	0
7	6062	675	17	3	11	0	1	329	26	10	2	0	1	3	0	0
8	6847	96	0	0	0	0	0	185	5	1	0	0	0	5	0	1
9	5373	932	14	19	21	0	2	624	51	35	0	4	2	43	12	8
10	6212	546	6	0	4	0	0	359	10	0	0	1	0	2	0	0
11	5005	837	33	17	20	1	4	923	73	31	9	3	2	127	32	23
12	4134	1116	41	43	34	0	6	1248	110	145	12	13	9	143	41	45
14	3819	1036	51	36	30	2	10	1475	74	171	17	35	24	57	133	170
15	6039	555	5	5	7	0	3	465	27	14	0	2	1	15	1	1
16	3654	1594	89	144	46	2	25	947	132	227	22	20	48	114	50	26
17	6221	379	4	0	7	0	0	484	18	7	2	2	2	9	4	1
18	6376	299	1	3	3	0	1	418	17	4	0	0	0	14	3	1
19	2993	1458	95	33	119	0	23	1399	284	135	33	58	32	247	136	95
20	5159	796	14	17	22	0	0	827	76	53	2	11	1	101	29	32

Table A.4 continued from previous page

Resp	003	012	021C	021D	021U	030C	030T	102	111D	111U	120C	120D	120U	201	210	300
21	5423	889	24	9	29	1	1	626	69	19	0	4	0	33	7	6
22	6579	221	2	0	1	0	0	323	7	4	0	0	0	3	0	0
23	5976	392	4	2	4	0	0	655	41	12	0	1	1	43	7	2
25	6908	95	1	0	0	0	0	132	3	0	0	0	1	0	0	0
26	4706	1030	33	22	28	0	7	1060	80	59	4	5	1	78	18	9
27	6336	239	1	1	0	1	0	533	10	4	2	1	1	2	4	5
28	5950	570	2	4	12	0	0	559	25	6	0	3	0	5	3	1
29	5098	944	19	48	14	0	5	745	33	93	1	5	3	93	27	12
30	4069	1194	24	65	39	0	10	1209	142	131	14	21	13	130	55	24
31	4840	1126	51	46	20	1	11	821	51	78	12	12	4	40	17	10
32	2765	1916	155	143	192	3	80	969	196	245	41	47	76	134	132	46
33	4526	909	28	21	23	0	2	1185	106	107	4	9	7	105	48	60
34	5314	720	15	7	7	1	1	878	46	45	2	5	2	54	25	18
36	6970	0	0	0	0	0	0	170	0	0	0	0	0	0	0	0

Table A.4: Triad census of the perceived friendship networks in Silicon Systems.

Appendix B

Interpersonal- and Structural Accuracy Scores

Description

The following four tables provide the interpersonal and structural accuracy scores of the friendship and advice networks for both High-Tech and Silicon Systems' respondents. Specifically, Table B.1 and Table B.2 show the respondents' (Resp) accuracy scores for the advice networks for High-Tech and Silicon Systems, respectively, and Table B.3 and Table B.4 show the respondents' accuracy scores for the friendship networks for High-Tech and Silicon Systems, respectively. Respondents 13, 24, and 35 are omitted for both the advice and friendship networks of Silicon Systems as they did not complete the questionnaire.

The structural accuracy measures are divided into the GSCOR structural accuracy measure and the three proposed measures of triadic correlation, namely the Pearson-based structural accuracy measure (Pearson), Spearman-based structural accuracy measure (Spearman), and the Euclidean-based structural accuracy measure (Euclidean).

B.1   Advice Network Accuracy

B.1.1   High-Tech

	Interpersonal	Structural			
Resp	Pearson	GSCOR	Pearson	Spearman	Euclidean
1	0.269	0.421	0.031	0.103	0.737
2	0.427	0.481	0.389	0.435	0.698
3	0.207	0.400	0.081	0.244	0.727
4	0.383	0.498	0.247	0.281	0.788
5	0.270	0.519	0.693	0.729	0.886
6	0.326	0.355	0.158	0.312	0.454
7	0.286	0.445	0.242	0.344	0.769
8	0.343	0.425	0.417	0.591	0.740
9	0.261	0.400	0.294	0.268	0.737
10	0.361	0.411	0.229	0.159	0.718
11	0.323	0.385	0.245	0.409	0.572
12	0.307	0.483	0.503	0.729	0.753
13	0.281	0.325	0.187	0.267	0.451
14	0.210	0.515	0.648	0.764	0.825
15	0.250	0.418	0.204	0.429	0.620
16	0.296	0.355	0.197	0.389	0.450
17	0.277	0.308	0.114	0.384	0.402
18	0.382	0.492	0.296	0.464	0.731
19	0.348	0.403	0.321	0.493	0.667
20	0.333	0.440	0.102	0.238	0.568
21	0.368	0.502	0.441	0.444	0.845
Average	0.310	0.428	0.288	0.404	0.673

Table B.1: Interpersonal and structural accuracy measures
for the High-Tech advice network.

B.1.2   Silicon Systems

	Interpersonal	Structural			
Resp	Pearson	GSCOR	Pearson	Spearman	Euclidean
1	0.437	0.514	0.946	0.937	0.666
2	0.357	0.476	0.972	0.940	0.777
3	0.325	0.428	0.980	0.956	0.734
4	0.358	0.358	0.829	0.801	0.432
5	0.445	0.485	0.884	0.894	0.555
6	0.415	0.481	0.899	0.937	0.598
7	0.388	0.441	0.889	0.927	0.566
8	0.344	0.426	0.854	0.939	0.487
9	0.387	0.483	0.931	0.941	0.638
10	0.339	0.453	0.992	0.950	0.783
11	0.372	0.443	0.947	0.951	0.671
12	0.214	0.351	0.289	0.452	0.606
14	0.281	0.355	0.801	0.851	0.386
15	0.459	0.511	0.989	0.951	0.810
16	0.405	0.484	0.889	0.784	0.660
17	0.462	0.527	0.935	0.873	0.647
18	0.424	0.464	0.876	0.874	0.578
19	0.463	0.548	0.979	0.831	0.868
20	0.314	0.458	0.942	0.907	0.693
21	0.398	0.524	0.946	0.923	0.697
22	0.416	0.521	0.987	0.974	0.867
23	0.499	0.545	0.983	0.951	0.809
25	0.416	0.487	0.873	0.673	0.812
26	0.430	0.492	0.961	0.875	0.697
27	0.422	0.480	0.893	0.846	0.578
28	0.457	0.535	0.942	0.962	0.708
29	0.388	0.527	0.951	0.935	0.794
30	0.435	0.506	0.958	0.872	0.733
31	0.362	0.394	0.828	0.763	0.442

Table B.2 continued from previous page

Resp	Interpersonal Pearson	GSCOR	Structural Pearson	Spearman	Euclidean
32	0.377	0.519	0.993	0.940	0.892
33	0.332	0.376	0.967	0.941	0.758
34	0.394	0.443	0.893	0.860	0.618
36	0.393	0.465	0.967	0.838	0.760
Average	0.391	0.470	0.908	0.880	0.676

Table B.2: Interpersonal and structural accuracy measures for the Silicon Systems advice network.

B.2   Friendship Network Accuracy

B.2.1   High-Tech

Resp	Interpersonal Pearson	Structural GSCOR	Pearson	Spearman	Euclidean
1	0.369	0.577	0.994	0.830	0.929
2	0.483	0.517	0.973	0.786	0.757
3	0.293	0.350	0.949	0.690	0.624
4	0.433	0.537	0.990	0.924	0.889
5	0.504	0.583	0.977	0.849	0.839
6	0.359	0.531	0.982	0.929	0.827
7	0.310	0.404	0.915	0.653	0.732
8	0.295	0.295	0.945	0.710	0.607
9	0.324	0.324	0.948	0.684	0.612
10	0.248	0.508	0.997	0.906	0.936
11	0.338	0.513	0.967	0.865	0.819
12	0.467	0.527	0.983	0.961	0.816
13	0.271	0.487	0.978	0.854	0.852
14	0.485	0.531	0.970	0.783	0.852
15	0.210	0.424	0.986	0.775	0.834
16	0.338	0.492	0.972	0.771	0.805
17	0.369	0.492	0.969	0.864	0.826
18	0.450	0.584	0.976	0.868	0.769
19	0.440	0.479	0.967	0.896	0.811
20	0.085	0.372	0.954	0.801	0.663
21	0.516	0.606	0.999	0.835	0.973
Average	0.361	0.482	0.971	0.821	0.799

Table B.3: Interpersonal and structural accuracy measures
for the High-Tech friendship network.

B.2.2   Silicon Systems

	Interpersonal	Structural			
Resp	Pearson	GSCOR	Pearson	Spearman	Euclidean
1	0.352	0.511	1.000	0.954	0.988
2	0.373	0.463	0.990	0.845	0.874
3	0.350	0.484	0.954	0.932	0.735
4	0.309	0.441	0.978	0.951	0.800
5	0.327	0.400	0.986	0.688	0.759
6	0.307	0.455	0.994	0.832	0.851
7	0.309	0.468	0.994	0.753	0.866
8	0.186	0.186	0.985	0.865	0.746
9	0.419	0.549	0.998	0.910	0.949
10	0.220	0.391	0.993	0.687	0.849
11	0.392	0.534	0.999	0.963	0.954
12	0.289	0.453	0.985	0.964	0.820
14	0.279	0.492	0.973	0.922	0.771
15	0.359	0.509	0.995	0.815	0.877
16	0.282	0.480	0.959	0.898	0.736
17	0.325	0.516	0.994	0.874	0.850
18	0.276	0.483	0.992	0.902	0.824
19	0.297	0.457	0.923	0.936	0.650
20	0.411	0.599	1.000	0.958	0.974
21	0.392	0.453	0.998	0.878	0.950
22	0.242	0.466	0.989	0.874	0.791
23	0.329	0.479	0.996	0.964	0.889
25	0.068	0.290	0.984	0.627	0.735
26	0.377	0.485	0.995	0.929	0.903
27	0.340	0.472	0.993	0.824	0.832
28	0.270	0.443	0.997	0.834	0.894
29	0.432	0.549	0.998	0.928	0.951
30	0.399	0.511	0.983	0.943	0.809
31	0.404	0.548	0.995	0.875	0.912

Table B.4 continued from previous page

Resp	Interpersonal Pearson	Structural GSCOR	Pearson	Spearman	Euclidean
32	0.297	0.408	0.879	0.822	0.603
33	0.399	0.499	0.994	0.966	0.881
34	0.480	0.580	1.000	0.982	0.994
36	0.240	0.306	0.983	0.576	0.725
Average	0.325	0.465	0.984	0.869	0.841

Table B.4: Interpersonal and structural accuracy measures
for the Silicon Systems friendship network.

Appendix C

Network Properties and Triad Types

Description

The following four tables provide the data of the triad census conducted on each respondent's cognitive slice and the density (Dens), hierarchy (Hier), reciprocity (Recip), and transitivity (Trans) and well as the interpersonal- and structural accuracy scores for each respondent (Resp). Specifically, Table C.1 shows the results of the analysis of the respondent's (Resp) perceived advice network for High-Tech and Table C.2 shows the results of the analysis of the respondent's friendship network of the High-Tech.

Similarly, Table C.3 shows the results of the analysis of the respondent's perceived advice network for Silicon Systems and Table C.4 shows the results of the analysis of the respondent's friendship network for Silicon Systems. Respondents 13, 24, and 35 are omitted from the Silicon Systems results as they did not complete the questionnaire.

C.1 High-Tech

C.1.1 Advice Network

Resp	Dens	Hier	Recip	Trans	Pearson	GSCOR	Pearson	Spearman	Euclidean	X003	X012	X021C	X021D	X021U	X030C	X030T	X102	X111D	X111U	X120C	X120D	X120U	X201	X210	X300
		Network Properties			Interpersonal		Structural									Euclidean Distance									
1	0.660	0.000	0.729	0.751	0.269	0.421	0.031	0.103	0.737	73	97	16	140	73	1	118	7	33	9	36	18	59	43	187	158
2	0.262	0.592	0.273	0.568	0.427	0.481	0.389	0.435	0.698	213	234	10	115	109	1	93	19	22	85	8	15	64	60	103	25
3	0.455	0.000	0.806	0.597	0.207	0.400	0.081	0.244	0.727	105	24	40	150	59	1	179	148	82	30	8	42	71	127	7	87
4	0.474	0.000	0.714	0.620	0.383	0.498	0.247	0.281	0.788	1	40	1	125	51	2	151	144	74	6	0	17	51	59	20	64
5	0.452	0.095	0.516	0.666	0.270	0.519	0.693	0.729	0.886	9	33	4	102	43	1	52	38	64	25	8	4	10	23	1	7
6	0.124	0.865	0.154	0.432	0.326	0.355	0.158	0.312	0.454	606	251	27	154	43	2	173	73	21	101	16	51	77	71	104	30
7	0.374	0.000	0.561	0.581	0.286	0.445	0.242	0.344	0.769	177	64	15	142	91	1	145	12	63	24	11	5	64	0	6	8
8	0.319	0.261	0.433	0.643	0.343	0.425	0.417	0.591	0.740	110	211	30	123	95	2	116	67	63	77	12	1	47	54	67	19
9	0.367	0.000	0.662	0.497	0.261	0.400	0.294	0.268	0.737	101	164	3	129	61	2	169	157	56	44	8	36	66	34	13	1
10	0.357	0.000	0.707	0.515	0.361	0.411	0.229	0.159	0.718	146	133	15	148	63	2	175	182	56	20	1	46	61	34	34	14
11	0.183	0.575	0.286	0.425	0.323	0.385	0.245	0.409	0.572	414	281	5	140	27	2	155	18	3	79	7	43	73	67	101	29
12	0.312	0.000	0.412	0.529	0.307	0.483	0.503	0.729	0.753	145	245	5	86	19	1	102	11	5	28	4	28	47	19	60	23
13	0.117	0.920	0.122	0.333	0.281	0.325	0.187	0.267	0.451	593	297	25	139	11	2	175	66	36	100	15	57	78	71	107	30
14	0.329	0.095	0.377	0.710	0.210	0.515	0.648	0.764	0.825	156	98	35	16	24	2	75	19	9	31	13	13	20	58	81	20
15	0.240	0.000	0.574	0.455	0.250	0.418	0.204	0.429	0.620	407	164	18	127	49	2	177	29	8	7	9	45	66	11	67	14
16	0.117	0.976	0.082	0.419	0.296	0.355	0.197	0.389	0.450	576	328	8	152	5	2	169	74	47	100	17	54	77	72	107	30
17	0.102	0.866	0.233	0.374	0.277	0.308	0.114	0.384	0.402	706	199	17	151	27	2	180	42	32	101	17	56	78	71	101	30
18	0.343	0.095	0.667	0.540	0.382	0.492	0.296	0.464	0.731	198	151	19	119	45	0	165	101	10	51	6	39	64	57	19	10
19	0.250	0.486	0.438	0.621	0.348	0.403	0.321	0.493	0.667	267	237	12	141	4	2	127	95	21	82	16	13	60	58	92	21
20	0.205	0.095	0.512	0.340	0.333	0.440	0.102	0.238	0.568	498	96	20	134	26	1	181	36	15	63	2	51	68	31	82	26
21	0.471	0.000	0.616	0.661	0.368	0.502	0.441	0.444	0.845	19	19	5	98	27	1	111	55	100	16	9	36	43	7	33	37

Table C.1: Network properties and triad types of High-Tech advice network.

C.1.2   Friendship

Resp	Network Properties				Interpersonal	Structural				Euclidean Distance															
	Dens	Hier	Recip	Trans	Pearson	GSCOR	Pearson	Spearman	Euclidean	X003	X012	X021C	X021D	X021U	X030C	X030T	X102	X111D	X111U	X120C	X120D	X120U	X201	X210	X300
1	0.143	0.000	0.800	0.449	0.369	0.577	0.994	0.830	0.929	54	27	2	3	2	0	3	72	7	7	2	1	2	1	3	6
2	0.050	0.500	0.667	0.100	0.483	0.517	0.973	0.786	0.757	276	66	0	4	3	0	1	152	4	20	0	1	2	19	1	3
3	0.017	0.667	0.571	0.667	0.293	0.350	0.949	0.690	0.624	428	128	2	4	4	0	1	223	14	19	0	1	1	26	2	3
4	0.086	0.526	0.611	0.443	0.433	0.537	0.990	0.924	0.889	103	28	1	1	2	0	1	100	10	1	0	0	2	21	1	1
5	0.164	0.367	0.580	0.452	0.504	0.583	0.977	0.849	0.839	169	108	9	5	35	0	13	54	31	4	1	4	3	0	16	2
6	0.069	0.600	0.621	0.373	0.359	0.531	0.982	0.929	0.827	187	17	1	3	1	0	1	131	3	13	0	0	1	20	2	2
7	0.186	0.448	0.436	0.501	0.310	0.404	0.915	0.653	0.732	258	175	27	9	72	0	19	139	54	0	4	20	13	11	13	2
8	0.012	0.833	0.400	0.000	0.295	0.295	0.945	0.710	0.607	445	125	2	5	4	0	1	242	12	20	0	1	2	26	2	3
9	0.014	0.500	0.667	1.000	0.324	0.324	0.948	0.684	0.612	443	142	2	5	4	0	1	221	14	20	0	1	2	26	2	3
10	0.107	0.000	0.756	0.270	0.248	0.508	0.997	0.906	0.936	71	29	2	2	0	1	1	34	3	11	1	1	1	3	3	1
11	0.169	0.190	0.620	0.379	0.338	0.513	0.967	0.865	0.819	186	136	18	8	15	0	1	57	5	7	3	5	1	24	19	3
12	0.064	0.560	0.667	0.395	0.467	0.527	0.983	0.961	0.816	208	35	0	3	1	0	1	120	12	13	0	1	1	19	1	1
13	0.079	0.790	0.485	0.098	0.271	0.487	0.978	0.854	0.852	97	81	4	3	5	0	1	149	9	18	0	0	2	19	1	3
14	0.114	0.300	0.417	0.378	0.485	0.531	0.970	0.783	0.852	42	126	5	35	10	1	13	138	10	4	1	3	0	20	3	3
15	0.081	0.328	0.824	0.509	0.210	0.424	0.986	0.775	0.834	192	81	1	5	4	0	1	71	10	19	0	1	1	5	4	3
16	0.060	0.541	0.400	0.242	0.338	0.492	0.972	0.771	0.805	172	60	7	3	0	0	0	181	11	15	1	1	2	24	0	3
17	0.098	0.750	0.537	0.284	0.369	0.492	0.969	0.864	0.826	132	64	1	69	3	0	1	158	9	46	0	1	1	18	4	1
18	0.050	0.750	0.667	0.353	0.450	0.584	0.976	0.868	0.769	266	59	1	4	4	0	1	139	7	19	0	1	2	25	2	2
19	0.176	0.362	0.622	0.463	0.440	0.479	0.967	0.896	0.811	209	128	15	3	17	0	7	35	27	11	2	8	0	7	8	11
20	0.024	0.857	0.400	0.000	0.085	0.372	0.954	0.801	0.663	377	80	0	5	1	0	1	227	12	18	0	1	2	25	2	3
21	0.119	0.514	0.760	0.468	0.516	0.606	0.999	0.835	0.973	27	20	5	2	3	0	0	3	2	8	4	1	1	6	3	5

Table C.2: Network properties and triad types of High-Tech friendship network.

C.2   Silicon Systems

C.2.1   Advice Network

Resp	Network Properties				Interpersonal	Structural				Euclidean Distance															
	Dens	Hier	Recip	Trans	Pearson	GSCOR	Pearson	Spearman	Euclidean	X003	X012	X021C	X021D	X021U	X030C	X030T	X102	X111D	X111U	X120C	X120D	X120U	X201	X210	X300
1	0.083	0.976	0.096	0.524	0.437	0.514	0.946	0.937	0.666	2357	161	65	246	64	0	117	97	78	50	9	44	20	19	23	2
2	0.124	0.469	0.231	0.488	0.357	0.476	0.972	0.940	0.777	1543	224	3	169	73	3	74	225	42	27	4	41	0	14	19	3
3	0.100	0.954	0.127	0.443	0.325	0.428	0.980	0.956	0.734	1771	613	0	203	157	0	100	2	85	40	9	51	10	19	21	3
4	0.029	0.989	0.054	0.029	0.358	0.358	0.829	0.801	0.432	3929	850	108	272	347	0	192	182	106	52	9	58	24	19	23	3
5	0.059	0.947	0.162	0.422	0.445	0.485	0.884	0.894	0.555	3126	397	95	266	196	0	173	80	67	51	9	47	23	18	19	1
6	0.071	0.924	0.200	0.380	0.415	0.481	0.899	0.937	0.598	2830	311	81	251	140	0	155	3	53	43	8	46	19	17	23	2
7	0.060	0.967	0.184	0.294	0.388	0.441	0.889	0.927	0.566	3052	351	41	257	264	0	179	21	84	50	9	49	20	19	23	1
8	0.041	0.965	0.115	0.212	0.344	0.426	0.854	0.939	0.487	3576	626	92	254	326	0	185	130	107	42	8	55	23	18	23	3
9	0.075	0.966	0.147	0.346	0.387	0.483	0.931	0.941	0.638	2557	48	30	254	216	0	145	42	63	50	9	50	20	19	21	2
10	0.125	0.677	0.076	0.418	0.339	0.453	0.992	0.950	0.783	1074	1076	151	153	155	0	0	87	79	37	5	38	21	18	21	3
11	0.084	0.954	0.189	0.477	0.372	0.443	0.947	0.951	0.671	2310	205	70	246	201	0	137	41	69	40	9	43	17	17	22	1
12	0.410	0.000	0.743	0.744	0.214	0.351	0.289	0.452	0.606	1172	1165	50	254	105	1	85	2060	474	207	44	83	325	237	319	555
14	0.023	0.986	0.069	0.077	0.281	0.355	0.801	0.851	0.386	4201	1133	106	271	338	0	193	171	118	52	9	57	24	19	23	3
15	0.137	0.526	0.244	0.462	0.459	0.511	0.989	0.951	0.810	1227	508	61	166	62	0	59	186	29	10	6	4	9	12	7	0
16	0.113	0.654	0.465	0.516	0.405	0.484	0.889	0.784	0.660	2311	500	68	253	157	1	157	406	74	10	1	17	12	6	23	14
17	0.080	0.902	0.178	0.417	0.462	0.527	0.935	0.873	0.647	2492	73	72	259	182	0	144	56	17	50	7	42	24	15	13	0
18	0.071	0.773	0.422	0.415	0.424	0.464	0.876	0.874	0.578	2916	489	94	257	316	0	179	328	81	44	9	51	24	5	12	1
19	0.190	0.658	0.360	0.585	0.463	0.548	0.979	0.831	0.868	768	101	88	238	245	1	44	272	247	23	7	145	8	10	63	34
20	0.098	0.897	0.242	0.556	0.314	0.458	0.942	0.907	0.693	2165	28	54	245	44	1	148	112	39	38	7	4	20	18	15	2
21	0.098	0.942	0.145	0.617	0.398	0.524	0.946	0.923	0.697	2143	41	67	233	129	0	116	44	54	48	9	3	23	17	20	1
22	0.183	0.698	0.225	0.595	0.416	0.521	0.987	0.974	0.867	275	855	37	72	225	0	55	135	93	14	1	74	11	1	6	6
23	0.142	0.647	0.291	0.534	0.499	0.545	0.983	0.951	0.809	1282	360	3	151	59	0	52	215	74	22	2	42	12	6	1	7
25	0.331	0.333	0.556	0.627	0.416	0.487	0.873	0.673	0.812	554	499	33	185	374	0	31	659	612	131	59	201	113	186	330	193
26	0.090	0.986	0.053	0.467	0.430	0.492	0.961	0.875	0.697	2120	301	5	237	10	0	95	151	88	52	9	42	24	19	23	2
27	0.067	0.907	0.238	0.613	0.422	0.480	0.893	0.846	0.578	2967	312	90	255	267	0	169	6	59	51	9	9	24	16	20	4
28	0.106	0.801	0.286	0.557	0.457	0.535	0.942	0.962	0.708	2059	13	68	208	66	0	123	214	33	31	9	10	10	6	15	3
29	0.153	0.614	0.290	0.521	0.388	0.527	0.951	0.935	0.794	1396	175	41	203	319	6	42	167	112	15	1	25	12	7	21	12
30	0.113	0.761	0.322	0.467	0.435	0.506	0.958	0.872	0.733	1854	197	25	235	174	0	138	215	49	40	2	3	22	2	5	11
31	0.034	0.976	0.140	0.207	0.362	0.394	0.828	0.763	0.442	3853	885	104	272	307	0	191	127	98	52	9	56	24	19	23	2
32	0.190	0.506	0.310	0.481	0.377	0.519	0.993	0.940	0.892	432	489	161	147	105	5	14	299	139	24	34	52	14	21	30	12
33	0.119	0.655	0.320	0.415	0.332	0.376	0.967	0.941	0.758	1624	338	49	194	272	0	124	332	35	7	2	26	8	8	5	4
34	0.087	0.857	0.239	0.387	0.394	0.443	0.893	0.860	0.618	2667	448	77	265	59	0	162	15	43	46	8	18	21	10	14	1
36	0.125	0.683	0.342	0.509	0.393	0.465	0.967	0.838	0.760	1645	264	47	249	107	0	142	228	108	39	5	21	18	4	6	15

Table C.3: Network properties and triad types of Silicon Systems advice network.

C.2.2   Friendship Network

	Network Properties				Interpersonal	Structural				Euclidean Distance														
Resp	Dens	Hier	Recip	Trans	Pearson	GSCOR	Pearson	Spearman	Euclidean	X003	X012	X021C	X021D	X021U	X030C	X030T	X102	X111D	X111U	X120C	X120D	X120U	X201	X210	X300
1	0.072	0.249	0.703	0.325	0.352	0.511	1.000	0.954	0.988	49	51	1	5	2	0	3	26	12	22	4	3	1	21	10	4
2	0.097	0.410	0.557	0.304	0.373	0.463	0.990	0.845	0.874	656	589	11	7	68	0	15	106	109	21	1	11	2	22	0	6
3	0.144	0.056	0.582	0.380	0.350	0.484	0.954	0.932	0.735	1619	950	78	36	48	0	14	147	145	90	11	18	15	22	27	18
4	0.129	0.341	0.626	0.391	0.309	0.441	0.978	0.951	0.800	1229	686	35	44	30	1	14	189	90	36	12	12	4	36	25	15
5	0.015	0.467	0.842	0.600	0.327	0.400	0.986	0.688	0.759	1480	604	18	11	10	0	0	628	42	54	5	2	3	73	18	12
6	0.033	0.741	0.619	0.122	0.307	0.455	0.994	0.832	0.851	912	216	12	8	5	0	1	490	27	49	5	1	3	67	17	13
7	0.036	0.798	0.489	0.074	0.309	0.468	0.994	0.753	0.866	770	27	1	8	1	0	1	564	20	44	3	2	2	70	18	13
8	0.012	0.607	0.800	0.273	0.186	0.186	0.985	0.865	0.746	1555	606	18	11	10	0	0	708	41	53	5	2	3	68	18	12
9	0.067	0.633	0.595	0.331	0.419	0.549	0.998	0.910	0.949	81	230	4	8	11	0	2	269	5	19	5	2	1	30	6	5
10	0.031	0.780	0.564	0.091	0.220	0.391	0.993	0.687	0.849	920	156	12	11	6	0	0	534	36	54	5	1	3	71	18	13
11	0.094	0.287	0.712	0.367	0.392	0.534	0.999	0.963	0.954	287	135	15	6	10	1	4	30	27	23	4	1	1	54	14	10
12	0.136	0.293	0.702	0.413	0.289	0.453	0.985	0.964	0.820	1158	414	23	32	24	0	6	355	64	91	7	11	6	70	23	32
14	0.168	0.432	0.745	0.728	0.279	0.492	0.973	0.922	0.771	1473	334	33	25	20	2	10	582	28	117	12	33	21	16	115	157
15	0.040	0.315	0.627	0.189	0.359	0.509	0.995	0.815	0.877	747	147	13	6	3	0	3	428	19	40	5	0	2	58	17	12
16	0.150	0.217	0.561	0.387	0.282	0.480	0.959	0.898	0.736	1638	892	71	133	36	2	25	54	86	173	17	18	45	41	32	13
17	0.036	0.526	0.711	0.337	0.325	0.516	0.994	0.874	0.850	929	323	14	11	3	0	0	409	28	47	3	0	1	64	14	12
18	0.030	0.468	0.737	0.232	0.276	0.483	0.992	0.902	0.824	1084	403	17	8	7	0	1	475	29	50	5	2	3	59	15	12
19	0.206	0.205	0.680	0.501	0.297	0.457	0.923	0.936	0.650	2299	756	77	22	109	0	23	506	238	81	28	56	29	174	118	82
20	0.087	0.444	0.709	0.447	0.411	0.599	1.000	0.958	0.974	133	94	4	6	12	0	0	66	30	1	3	9	2	28	11	19
21	0.064	0.621	0.593	0.260	0.392	0.453	0.998	0.878	0.950	131	187	6	2	19	1	1	267	23	35	5	2	3	40	11	7
22	0.021	0.364	0.741	0.000	0.242	0.466	0.989	0.874	0.791	1287	481	16	11	9	0	0	570	39	50	5	2	3	70	18	13
23	0.049	0.394	0.774	0.198	0.329	0.479	0.996	0.964	0.889	684	310	14	9	6	0	0	238	5	42	5	1	2	30	11	11
25	0.009	0.667	0.727	0.333	0.068	0.290	0.984	0.627	0.735	1616	607	17	11	10	0	0	761	43	54	5	2	2	73	18	13
26	0.099	0.401	0.672	0.270	0.377	0.485	0.995	0.929	0.903	586	328	15	11	18	0	7	167	34	5	1	3	2	5	0	4
27	0.033	0.179	0.810	0.615	0.340	0.472	0.993	0.824	0.832	1044	463	17	10	10	1	0	360	36	50	3	1	2	71	14	8
28	0.044	0.640	0.655	0.313	0.270	0.443	0.997	0.834	0.894	658	132	16	7	2	0	0	334	21	48	5	1	3	68	15	12
29	0.084	0.276	0.642	0.327	0.432	0.549	0.998	0.928	0.951	194	242	1	37	4	0	5	148	13	39	4	3	0	20	9	1
30	0.137	0.117	0.674	0.385	0.399	0.511	0.983	0.943	0.809	1223	492	6	54	29	0	10	316	96	77	9	19	10	57	37	11
31	0.090	0.361	0.584	0.353	0.404	0.548	0.995	0.875	0.912	452	424	33	35	10	1	11	72	5	24	7	10	1	33	1	3
32	0.199	0.061	0.526	0.489	0.297	0.408	0.879	0.822	0.603	2527	1214	137	132	182	3	80	76	150	191	36	45	73	61	114	33
33	0.121	0.408	0.737	0.517	0.399	0.499	0.994	0.966	0.881	766	207	10	10	13	0	2	292	60	53	1	7	4	32	30	47
34	0.077	0.384	0.722	0.448	0.480	0.580	1.000	0.982	0.994	22	18	3	4	3	1	1	15	0	9	3	3	1	19	7	5
36	0.008	0.000	1.000	1.000	0.240	0.306	0.983	0.576	0.725	1678	702	18	11	10	0	0	723	46	54	5	2	3	73	18	13

Table C.4: Network properties and triad types of Silicon Systems friendship network.

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