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The microstructures of network recall: How social networks are encoded and represented in human memory☆

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ABSTRACT

A growing number of studies indicate that aspects of psychology and cognition influence network structure, but much remains to be learned about how network information is stored and retrieved from memory. Are networks recalled as dyads, as triads, or more generally as sub-groups? We employ an experimental design coupled with exponential random graph models to address this issue. We find that respondents flexibly encode social information as triads or groups, depending on the network, but not as dyads. This supports prior research showing that networks are stored using "compression heuristics", but also provides evidence of cognitive flexibility in the process of encoding relational information.

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1. Introduction

How are social networks encoded into human memory? Numerous studies using both human and animal models have demonstrated a connection between physical brain structure and social networks (Bickart et al., 2011; Dunbar, 1992, 1993, 1995; Goncalves et al., 2011; Meyer et al., 2012; Sallet et al., 2011; Stiller and Dunbar, 2007; Zahn et al., 2007). Other research has shown links between social network structure and personality traits (Burt et al., 1998; Casciaro, 1998; Clifton et al., 2009; Kalish and Robins, 2006; Klein et al., 2004; Mehra et al., 2001; Totterdell et al., 2008), cognitive development in childhood (Leinhardt, 1973; Schaefer et al., 2010), and strong predispositions towards specific network types (Daniel et al., 2013; Hallinan and Kubitschek, 1988). Moreover, research indicates that perceptions and mental representations of networks often vary with one's position in the graph or sense of power (Krackhardt, 1987, 1990; Kumbasar et al., 1994; Simpson and Borch, 2005; Simpson et al., 2011), and that humans use schemata to simplify the recall of networks (Brashears, 2013; Brewer and Garrett, 2001; Brewer and Yang, 1994; De Soto, 1960; Freeman, 1992; Freeman et al., 1987; Killworth and Bernard, 1982). In general, this body of research indicates that cognition is an essential, even primary, factor in explaining interpersonal networks (e.g., DiMaggio, 1997). Nevertheless, despite an earlier stream of research (e.g., Brewer, 1995, 2000; Brewer and Webster, 1999; Brewer and Yang, 1994; Hlebec and Ferligoj, 2001; Killworth and Bernard, 1982), we know relatively little about a critical aspect of network cognition: how are social networks encoded and represented in memory? Do humans remember the individual dyads that comprise a social network, small microstructures (e.g., triads), or do they somehow encode the entire structure as a simplified whole (e.g., clusters)?

This is a particularly troubling oversight because of its deep connections to the origins of social network structure. Much of the overall structure of social networks can be attributed to dyadic (e.g., Faust, 2007), availability (e.g., Blau, 1977; Mayhew and Levinger, 1976a), and foci (Feld, 1981) effects. Nevertheless, individual agency remains essential to many explanations of the origins of network structure and network dynamics (e.g., Granovetter, 1973; Burt, 1992; Heider, 1946). Individuals make choices about alters (e.g., to form a tie with a similar other) and network microstructures (e.g., to close a triad rather than leave it open) based on their preferences, and also use networks as exogenous opportunity structures (Burt, 1992), taking advantage of an opportunity or transferring information (e.g., Burt et al., 1998; Ibarra, 1992). Because individual, preference-driven decisions will be based not on the actual state of the network, but on the *perceived* state of the network (e.g., Kilduff and Krackhardt, 2008: Ch. 3), the manner in which social networks are encoded and represented in memory can have a profound impact on the ultimate structure of a network and the behavior of network members. However, while research has considered motivational predictors of network structure (e.g.,

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Mehra et al., 2001; Totterdell et al., 2008), correlates of recall for network members (e.g., Killworth et al., 2003; Marin, 2004) and circumstances that improve or degrade network perception (e.g., Krackhardt, 1987, 1990; Simpson and Borch, 2005; Simpson et al., 2011), we know considerably less about how social networks are cognitively stored and manipulated. Our understanding of the social environment fundamentally constrains the choices we make (e.g., form or eliminate a tie), and we cannot act to produce, or avoid, a social situation that we cannot perceive (e.g., developing a friendship with a person central in a conflict network, or asking for advice from a low status individual). Therefore, if we are to understand why individuals prefer certain configurations of ties, we must first understand how networks are made cognitively available for preferences to act upon.

We address this puzzle by using an innovative experiment employing human subjects in combination with sophisticated exponential random graph models to determine how individuals mentally store social network information. Our results, based on data collected from three hundred individuals, indicate that humans encode relationships primarily in terms of triads, but can also use group-based methods, depending on the information available in the network. In contrast, individuals do not appear to encode relationships as dyads. These results are important for two reasons. First, they reaffirm that humans have a preferred approach to encoding networks: as triads. We argue that the use of triads rather than dyads in memory encoding reflects a tradeoff between cognitive economy, reducing the demands on the organism by remembering clusters of ties, while still permitting an individual to encode cleavages within a group, which may have been essential to the evolution of human intelligence (Humphrey, 1976; Silk, 2007). Moreover, triads appear essential to social processes across a variety of non-human social species (Chase et al., 2002; Cheney and Seyfarth, 2008; Cheney et al., 1986; Paz-y-Miño-C et al., 2004), implying that they are a key aspect of sociality generally. Encoding relational information as triads may also partially explain the prevalence of triadic structures in empirical data collected using respondent recall. Second, our results also show that our respondents displayed cognitive flexibility, changing their encoding strategy based on the information available in the network. This is important because the type of bias expected when recalling network information, and therefore when taking action, depends on the information available to individuals about the structure of the network.

We begin by describing the research linking cognition and network structure and deriving our hypotheses. We then introduce our unique research design, which allows us to analyze an aggregate of three hundred experimentally derived social networks using exponential random graph models. We present our results, discuss their implications, and conclude by suggesting additional key directions for future research.

2. Background

2.1. Theories of network structure

Social networks are valuable for many tasks, including locating and obtaining jobs (e.g., Bewley, 1999; Granovetter, 1973, 1995; Marsden and Gorman, 2001; McDonald, 2011; McDonald et al., 2009), attaining status (e.g., Son and Lin, 2012), and acquiring needed household services (e.g., Wellman and Wortley, 1990). As a result, it is hardly surprising that considerable effort has been expended to understand the mechanisms that give rise to particular network structures. This effort has generally focused on two research streams: structural accounts and agency-based accounts. The first stream holds that network structure is largely shaped by the overall availability of others for association (e.g., Blau, 1977; Mayhew and Levinger, 1976a), their presence within voluntary associations (e.g., McPherson and Smith-Lovin, 1982, 1987) and the influence of foci (Feld, 1981). In combination, these processes help explain the prevalence of homophily (Lazarsfeld and Merton, 1954; McPherson et al., 2001), or a tendency to associate with those like oneself; because mainly persons with similar characteristics are available in the environment, networks tend to be dominated by connections between similar individuals. Network structures above the dyad, such as triads, have also been partially explained using the distribution of dyads (Faust, 2007), suggesting that structure in general is constrained by the distribution of dyads in the graph.

The second stream of research relies on the concept of agency: individuals come to occupy particular network structures because of their own (in)actions. These agentic accounts can be broadly categorized by their favored mode of action: differences in preferences or differences in perceptions. In the former, individuals occupy different network structures because they prefer those structures. Early research in this vein attempted to explain variation in male and female networks (e.g., Marsden, 1987) using alleged differences in disposition (Lincoln and Miller, 1979), although this account has not gone uncontested (e.g., Moore, 1990). Other research has found that individuals tend to direct ties to more powerful alters (e.g., Brashears, 2008; Ibarra, 1992), indicating that networks are influenced by the strategic preferences of their members. Research also suggests that personality traits influence the motivation of individuals to pursue specific network configurations (e.g., Burt et al., 1998; Kalish and Robins, 2006; Klein et al., 2004; Mehra et al., 2001; Totterdell et al., 2008) or their inclination to perform well in specific network roles (e.g., Emery, 2012).

Alternatively, network structure is sometimes attributed to differences in individual perception or understanding of networks. Classic research in this stream has found that more central persons in a network tend to have more accurate perceptions of its structure (Krackhardt, 1987, 1990; Kumbasar et al., 1994), while later research has concluded that low power actors have more accurate perceptions (e.g., Simpson and Borch, 2005; Simpson et al., 2011). Other researchers have presented evidence that a number of personality traits are related to accurate network perceptions, including extraversion and self-monitoring (Casciaro, 1998). In all of these cases, individuals are thought to make different choices because they have divergent understandings of the network itself.

Both structural and agentic explanations of network structure fill vital roles, but both have limitations. Structural accounts show how our choice of associates is fundamentally limited by circumstance, but are generally less effective in predicting which choice is made. Put differently, if our pool of possible associates is likened to the menu in a restaurant, structural accounts are very good at predicting which menu is selected from, but are relatively poor at predicting which dish is ultimately chosen. Agentic explanations show how individuals choose from among their options, but are less effective in explaining which individuals become available for association in the first place.

Agentic explanations suffer from an additional significant, and understudied, drawback: a lack of understanding about how social information is cognitively processed and represented. Preference-based accounts essentially ignore this issue, assuming that individuals are equally, and perfectly, accurate in their understanding of a network. Perception-based accounts in contrast recognize that individuals may vary in their understandings, and have begun to show which factors increase or decrease accuracy, but remain agnostic about how such information is processed and represented in the first place. Much of the existing work on this issue has focused on the elicitation of names (e.g., Brewer and Garrett, 2001; Killworth and Bernard, 1982; Marin, 2004) or numbers of alters who meet certain criteria (e.g., Killworth et al., 2003), rather than the recall of structures, and thus provides only weak guidance. The manner in which networks are processed and stored will influence which structural features individuals become aware of, and thus will impact both what perceptions are possible as well as the raw material on which preferences can operate. In essence, the manner in which an individual cognitively stores networks is itself a type of structural constraint (e.g., Bernard and Killworth, 1973; Mayhew and Levinger, 1976b). By understanding these cognitive constraints, we can better understand the types of structures that humans can cognitively represent, thereby bridging the gap between structural and agentic accounts.

For example, research by Bearman et al. (2004) found that the adolescent sexual network in an American high school formed a "spanning tree" structure, or a network with a large connected component, low clustering and long average path lengths. Given the size of the network (800 nodes), it seems obvious that the students did not construct such a structure deliberately. Instead, Bearman et al. argued that the spanning tree emerged from individual adherence to a rule: do not have sex with the former sexual partner of your former sexual partner's current sexual partner. One obvious implication is that if the rule used by the adolescents had been different, then the overall network also would have been different. A less obvious implication is that because adherence to a rule requires the ability to recognize when the rule is violated, human networks will be structured by the cognitive abilities of their members. If individuals cannot recognize when a rule is and is not violated, then the rule cannot guide individual behavior. Hence, the specific manner in which each individual stores network information will directly influence what rules are available for use by constraining what network features are and are not recognized. Because, whole network structures (such as a spanning tree) are too complex to be cognitively represented in any detail, the choice of individuals was instead focused on smaller, cognitively accessible structures that aggregated into a spanning tree.

Human cognition likely detects and stores some features over others, and these features both influence individual perceptions, and form the basis for choices meant to achieve desired outcomes. Thus, in order to explain social network structure as an aggregation of actors' local network decisions, it is necessary to understand the cognitive processing of network information that guides and constrains these network decisions.

2.2. Cognition and social network structure

The importance of cognition for social networks has long been recognized, although the specifics of how social information is represented in the brain remain largely unknown. A substantial amount of this interest stems from the Machiavellian Intelligence or "social brain" hypothesis, proposed by Humphrey (1976), which argues that human intelligence evolved to cope with the social, rather than the physical, environment (for an excellent review see Cheney and Seyfarth, 2008: Ch. 7). Subsequent research has shown that brain structure in general, and the cross-primate ratio of neocortical volume to the remaining brain in particular, is associated with network size (Barton, 1996; Bickart et al., 2011; Dunbar, 1992, 1993, 1995; Goncalves et al., 2011; Kudo and Dunbar, 2001; Meyer et al., 2012; Sallet et al., 2011; Stiller and Dunbar, 2007; Zahn et al., 2007). Human social networks have been shown to be strikingly similar to non-human networks, at least for positive relations, suggesting that cognitive mechanisms supporting sociality are shared by many species (Faust and Skvoretz, 2002; Skvoretz and Faust, 2002). Other research indicates that social abilities increase during early childhood as individuals learn both to model the intentions of others (Karniol and Ross, 1979), and to manage triadic relations (Hallinan and Kubitschek, 1988; Leinhardt, 1973; Schaefer et al., 2010, but see also Daniel et al., 2013), thereby suggesting that social networks depend on the maturation of critical brain regions. However, while this research indicates that the brain is integral to social networks, it does not explain how it manages a complex and shifting mass of information about social networks. In other words, we know that the brain carries out operations that are necessary to social networks, but we do not know precisely what those operations are.

The basis for any investigation of the cognitive representation of social information is an understanding of how networks are stored in memory. Memory is generally defined as the ability to store and retrieve information unaided and processing can only occur on information that can be made available (i.e., held in the mind) in the first place. Obviously, one's ability to develop and maintain relationships with others depends at a basic level on the ability to remember those others and their past behavior, and memory has thus become a standard element in models of cooperation and defection (e.g., Macy, 1995; Welser et al., 2007). Research has additionally shown (Atkinson and Shiffrin, 1968; Baddeley, 1986) that memory can be sub-divided into several distinct types that are linked to specific regions in the brain. For example, episodic memory (i.e., memory for specific events) depends upon the medial temporal lobe while semantic memory (i.e., facts about the world or general knowledge) relies upon the lateral and inferior temporal cortex (Garrad and Hodges, 1999). The amygdala has been linked to the formation of conditioned fear associations (LeBar et al., 1995; LeDoux, 1996), while the basal ganglia appear to be involved in developing positive associations (Bartels and Zeki, 2000). An additional critical distinction can be made between long-term memory, or memory for events that happened more than a few moments ago, and working memory, or memory for items on which the mind is currently focusing. The diversity of memory systems, functions, and locations serves as a useful reminder that different tasks recruit different portions of the brain, and thus research on memory for facts or experiences may be of limited use to understanding the recall of social networks. Much of the existing research devoted to issues of network recall has been concerned with the accuracy of survey data rather than with mental representations of networks (e.g., Bell et al., 2007; Brewer, 2000; Brewer and Garrett, 2001; Brewer and Webster, 1999; Hlebec and Ferligoj, 2001; Killworth et al., 2003; Marin, 2004). Nevertheless, there does exist some research in this area.

One early stream of work challenged the notion that human network recall is reliable at all, finding that recollections of interaction failed to reproduce observed behavior at dyadic (Bernard and Killworth, 1977), triadic (Killworth and Bernard, 1979/1980), or clique (Bernard et al., 1979/1980) levels. This led to the disturbing conclusion that memory for interaction is so poor that self-report network data are entirely unreliable. However, later studies found that patterns of interaction could be inferred from perceptions (e.g., Romney and Faust, 1982), although there was not a simple correspondence between what was recalled and what occurred. Additional research (Freeman and Romney, 1987; Freeman et al., 1987) showed that individual recall tended to be an inaccurate indicator of any specific encounter (e.g., attendance at a colloquium talk), but a reliable measure of typical patterns of behavior (e.g., typical attendance at colloquia). Moreover, human recall for subgroups in a social community has been shown to match well with observed patterns of association (Freeman et al., 1988, 1989). As such, while errors in recall are certainly present, it appears that humans are strikingly accurate at recalling the regular patterns of interaction that form social structure.

De Soto (1960) performed some of the earliest work on network structures and cognition using a paired-associates learning experiment, finding that structural configurations are learned faster when they are built from the appropriate type of relation. For example, hierarchical structures are learned more quickly when composed of "influences" relations rather than "is friends with". De Soto interpreted this to mean that subjects possessed schemata (1960: 420), or pre-existing frameworks for understanding information, that allowed them to organize the learning experience and complete it more rapidly (Bartlett, 1932; Neisser, 1967). Schemata have been shown to be integral to memory for many types of information (e.g., Brewer and Treyens, 1981; Martin, 1993), and thus it is no surprise to find that they are important for social knowledge as well. Later researchers have confirmed the importance of schemata generally, and schemas pertaining to affective balance (Cartright and Harary, 1956) in particular (e.g., Picek et al., 1975; Fischer, 1968; Sentis and Burnstein, 1979; Walker, 1976; but see also Welch-Ross and Schmidt, 1996). Schemas derived from geographic location (Brewer and Garrett, 2001; Killworth and Bernard, 1982), context (e.g., Brewer and Garrett, 2001), kinship (e.g., Brewer and Yang, 1994) and typical behavior (e.g., Freeman et al., 1987) have also been found to influence the recall of social networks.

More recent research (Freeman, 1992) shows that individuals tend to misremember small networks in ways that are consistent with a schema and that respondents mentally divide alters into mutually exclusive, rather than overlapping, groups. Similarly, Janicik and Larrick (2005) found that those with more missing relations in their personal social networks learned incomplete networks more rapidly, that the skill is specifically social and not a consequence of general pattern recognition ability, that prior practice with incomplete triads enhances learning speed, and that individuals who learn incomplete networks faster also appear to make better strategic coalition choices. The uniqueness of social network recall as a cognitive function has also been confirmed by later research (Simpson et al., 2011). Finally, research by Stiller and Dunbar (2007) indicates that network size and structure are positively related to individual memory capacity and intentionality (i.e., theory of mind).

The above research is important, but suffers from a number of limitations. Much of the existing research (e.g., Bernard and Killworth, 1977; Bernard et al., 1979/1980; Brewer and Yang, 1994; Killworth and Bernard, 1979/1980; Freeman et al., 1988, 1989; Freeman and Romney, 1987; Freeman et al., 1987) has measured existing, natural networks. This has obvious advantages for external validity, but raises serious difficulties since any particular series of observed interactions or set of recollections reflects a sample drawn from the underlying social structure (e.g., Freeman and Romney, 1987). Unless memory is perfect, those ties that are recalled are a subset of all ties that an individual participates in. Similarly, any particular set of interactions observed in a specific series of encounters (e.g., parties, colloquia, etc.) represent the activation of only a subset of the ties connecting individuals together. Thus, both recall of naturally occurring networks and observation of interaction in specific settings provide estimates of the true social structure, rather than a complete elucidation of that structure. Comparisons are further complicated by the presence of outliers, as well as differences in the distributions between recalled and observed networks (e.g., Romney and Faust, 1982). Respondents also differ in their thresholds for including ties in data collection (e.g., Feld and Carter, 2002), and vary in the quality of their recall based on their structural location (Krackhardt, 1987, 1990; Kumbasar et al., 1994), level of power (Simpson and Borch, 2005; Simpson et al., 2011) and degree of involvement in the community (Freeman et al., 1987). As a result, it is exceedingly difficult, though not impossible, to obtain reliable measures of recall accuracy using naturally occurring networks.

The remaining research has generally adopted an experimental design (e.g., De Soto, 1960; Fischer, 1968; Janicik and Larrick, 2005; Picek et al., 1975; Sentis and Burnstein, 1979; Simpson et al., 2011), which allows the researcher to know the "true" structure of the network perfectly. Unfortunately, and with few exceptions (e.g., Simpson et al., 2011), these experiments have examined learning speed, rather than overall capacity, and have relied on small four-person networks. The former issue makes it difficult to link this experimental work to natural studies of network recall, while the latter represents a network of such trivial size that it is unlikely to challenge a respondent, and therefore will not reveal the limits of recall.

Recent research by Brashears (2013) avoids these issues by using 15-person target networks to show that schemata also function as "compression heuristics," allowing social information to be stored in a reduced form. As a result, larger numbers of relations can be recalled more accurately when the networks adhere to certain patterns than when they do not. He also found, consistent with earlier research (e.g., Freeman, 1992), that respondents exhibited an increased tendency to incorrectly close triads when primed with a schema suggesting triadic closure, and were less prone to this error otherwise. These results indicate that perception of social networks is not a relatively passive process of observation, but instead requires the active use of compression heuristics to organize and encode information into memory. Moreover, the heuristics that are used will systematically bias respondents in favor of certain types of mistakes, and thus induce consistent changes in their perceptions of social networks.

The overall conclusion that must be drawn from the preceding research is that memory serves as the foundation for the mechanisms that permit human sociability. However, while the existing research demonstrates that memory is important, that schemata and compression heuristics are critical, and that recall is an active process, it does not show the form in which networks are stored in memory. It is to this issue that we now turn.

3. Theory and hypotheses

Based on prior research it is clear that humans use schemata to simplify and compress the information contained in a network for easier, more efficient storage. But what features of a social network are actually encoded in memory? The selection of features for recall is likely shaped by two forces: the need for accuracy and the need for economy.

Memory for social relationships must be accurate if it is to be useful. Numerous prior studies suggest that events occurring in one relationship are often constrained by the presence of other relationships; an individual is often more reluctant to cheat or harm an alter if they have associates in common who can apply sanctions (e.g., Granovetter, 1985; Uzzi, 1997). High quality memory for relationships is thus essential both to detecting others who can be taken advantage of, and to ascertaining whether one is relatively safe from being victimized in turn. Moreover, even small numbers of ties can have a substantial impact on the overall connectivity and performance of a network (Watts and Strogatz, 1998; Watts, 1999), suggesting that failure to recall even one tie out of many could radically change individual perception of the network, leading to sub-optimal decisions. If the social brain hypothesis (e.g., Humphrey, 1976) is correct, individuals who out-perform their associates on social tasks should generally obtain more rewards and reproduce more successfully, suggesting that human memory for social networks should be structured to ensure high accuracy. Existing research shows that complex network structures are often constrained by their dyad distributions (Faust, 2007), suggesting that recall of dyads provides a relatively large amount of information on overall network structure. Additionally, ties are known to vary in strength (Granovetter, 1973) based on the unique investment of time, mutual confiding, affect, and reciprocal services that characterize the tie. Different types of ties are used for different kinds of functions (e.g., Wellman and Wortley, 1990) and one of the strongest types of relationships, a committed romantic relationship, is also one of the richest sources of support (Wellman and Wellman, 1992). Similar kinds of pair-bonded relationships are also of critical importance to non-human primates (e.g., Cheney and Seyfarth, 2008; Cheney et al., 1986), particularly in avoiding infanticide. Taken together, this suggests that dyads possess unique features that grant them different capabilities to perform useful work, and that these differences have likely been present to some extent for a considerable period of evolutionary time. This suggests that human memory should be geared to remembering dyads as individual units so as to afford maximum detail, constituting a bottom-up representation of social structure, and leading to the following hypothesis:

- **Dyadic Recall Hypothesis:** Networks are preferentially recalled in human memory in terms of individual dyads.

While accuracy of recall is indisputably important, it is nevertheless the case that cognition imposes costs on an organism. First, while the brain accounts for only two percent of adult body mass it consumes roughly 20 percent of the body's metabolic energy (Dunbar, 1992); thus increasing brain activity or mass in order to accommodate greater social capability will rapidly lead to diminishing returns. Second, human memory systems have finite capacity. While an unknown and apparently very large amount of data can be maintained in long-term memory, working memory, when measured using digit span (e.g., Halford et al., 1994) or word span (e.g., Radvansky and Copeland, 2004) exercises, has been estimated as having the capacity for four to seven discrete pieces of information (Reisberg, 1997). Because working memory contains the information used to inform decisions, individuals will have difficulty recognizing or manipulating structures that are too large to fit in working memory, even if they can store all of the information to build such structures in long-term memory. If networks are encoded as individual dyads, this implies that humans cannot hold in memory, and therefore reason about, networks composed of more than four to seven dyads. While the accuracy of dyadic-encoding is desirable, it may also be too expensive to be practical. As an alternative, humans may tend to encode social information primarily in terms of in-groups and out-groups, greatly simplifying problems of recall. Balance theory (Cartright and Harary, 1956), with its prediction that social systems will develop into pairs of mutually exclusive groups, is consistent with this notion. Indeed, when balance is perfect one's own feelings towards third parties are the same as the feelings of one's associates (e.g., I like all of the same people that my friends like). Thus, instead of keeping track of their sentiments individually (i.e., $n(n-1)-(n-1)$ distinct relations) it is only necessary to keep track of one's own views (i.e., $n-1$ distinct relations), as these contain the same information. The pleasing nature of balanced relations may thus stem from the comparative ease with which they can be recalled and cognitively represented (see also Kilduff and Krackhardt, 2008: Ch. 4). Likewise, Freeman's (1992) finding that subjects tend to divide alters into non-overlapping groups suggests that the root structure of cognitive recall is the group, with elaborations added to account for exceptions or particularly important relations. Additional studies (e.g., Freeman et al., 1987, 1988, 1989) find that humans are quite good at remembering individual membership in subgroups, and that recall of group members often follows chains of social proximity, and thus tends to elicit group members as part of their local sub-structure (Brewer, 1995; Brewer et al., 2005; Brewer and Yang, 1994). This is consistent with the encoding of networks in terms of group membership, and constitutes a top-down representation of social structure, leading to the following hypothesis:

- **Group Recall Hypothesis:** Networks are preferentially recalled in human memory in terms of group membership.

Finally, while the limits of working memory are a serious concern, strategies for circumventing these limits, such as "chunking" (Miller, 1956; Postman, 1975), have already been identified. For example, phone numbers are often remembered as two sets of three numbers and one set of four numbers, rather than as a string of ten individual digits. The amount of information is the same (i.e., 10 digits), but it is repackaged into a familiar form (i.e., a familiar schema) that is easier to retain in memory. Similarly, if an organizing principle (i.e., schema) can be identified in material to be recalled the raw information can be discarded in favor of the rule. For example a number sequence that increases by two each time (e.g., 2, 4, 6, 8, etc.) is much easier to remember than an equivalent sequence with no apparent organizing principle (e.g., 2, 9, 4, 7, etc.).[1]

In social terms, relations might be recalled not as individual dyads, but as larger "chunked" sub-structures. While these sub-structures abstract from the individual relations, and therefore provide less detail (and likely less accuracy) than dyad-based recall, they also provide more room for the recollection of within-group differences and disagreements than does group-based recall. While a graph can be broken down into its individual edges, in social networks the presence or absence of one edge depends intimately on the presence or absence of others. The interdependence of dyads is the foundation for Granovetter's "forbidden triad" (Granovetter, 1973) and the motivation for specialized network methods, such as MR/QAP (e.g., Hubert, 1985; Krackhardt, 1988) and Exponential Random Graph Models (e.g., Lusher et al., 2013). These dependencies can reflect key alliances or bitter rivalries between group members that can dramatically alter the social landscape for the individual and must not be ignored. Cognitively, encoding networks as dyads might tend to obscure these dependencies by forcing the individual to, in a sense, manually add other relevant dyads into memory.[2] In contrast, encoding networks as sub-structures allows these dependencies to be included automatically when the relevant dyads are brought into memory, and thus should confer an advantage. The social brain hypothesis (Byrne and Whiten, 2002; Humphrey, 1976) suggests that this improved detail should provide an advantage over group-based recall by permitting individuals to recognize and exploit within-group cleavages.

An obvious candidate for such a "chunked" structure is the triad. While there are 64 possible triadic configurations containing asymmetric ties, they reduce to a mere 16 isomorphism classes (Davis and Leinhardt, 1972; Holland and Leinhardt, 1970), representing a manageable schema for recall. Moreover, the triad has emerged repeatedly in research on human social networks (e.g., Burt, 1992; Granovetter, 1973; Skvoretz et al., 1996), pointing to its substantive utility. Among non-humans, primates have been shown to use knowledge of the relationships between others to shape their responses to social situations (Cheney and Seyfarth, 2008; Cheney et al., 1986), indicating that social behavior is conditioned on triadic sub-structures. This is particularly striking because primates exhibit considerably greater skill at making triadic inferences in social domains than in non-social domains (ibid). Likewise, Chase et al. (2002) have shown that linear dominance hierarchies among cichlid fish tend not to emerge without third-party observation (i.e., triads), and the dominance hierarchies of Pinyon jays rely on similar triadic processes (Paz-y-Miño-C et al., 2004). It thus appears that triad-based recall would both provide greater efficiency than

[1] See Cheney and Seyfarth (2008)Cheney and Seyfarth (2008: 117) for additional discussion of this issue and a strikingly similar example.

[2] We do not mean to suggest that the individual would be aware of this process.

dyad-based recall and is a better format for capturing critical social processes that unfold in many species, including humans. This constitutes a middle-out representation of social structure, and leads to the following hypothesis:

- **Triad Recall Hypothesis:** Networks are preferentially recalled in human memory in terms of triads.

In summary, human network recall is likely shaped by the benefits of accuracy and the necessity of economy. If accuracy is most favored, recall should be based on dyads. If economy is favored, recall should be based on groups. If these forces are in balance, recall should be based on efficient triads. And existing research provides reason to think that networks might be encoded at the dyadic, group, or triadic levels. Below we describe our data and the analytic method we employ to distinguish between these bottom-up, top-down, and middle-out models of human network memory.

4. Methods

4.1. Data

We reanalyze the data described in Brashears' (2013) study of schemata as compression heuristics. These data were gathered in controlled, experimental conditions and asked respondents to memorize and recall a novel network of 15 people, with the target networks varying either in their structure or in the type of labels used to describe the relationships. These data have several advantages. First, respondents are asked to recall a novel social network rather than a network in which they are actually embedded. Since memory is substantially aided by opportunities for rehearsal, variation in frequency of contact with alters in naturally occurring networks could produce inaccurate estimates of recall accuracy (e.g., Freeman et al., 1987). Second, because the target networks are provided by the experimenter, recall accuracy can be determined perfectly rather than inferred from either aggregated individual responses (e.g., Krackhardt, 1987, 1990) or observed behavior (e.g., Bernard and Killworth, 1977; Bernard et al., 1979/1980; Killworth and Bernard, 1979/1980), both of which provide imperfect measures of the underlying social structure (Freeman and Romney, 1987). Third, the target network of 15 individuals provides a larger and more challenging recall task than most other research in this area (e.g., De Soto, 1960; Freeman, 1992; Janicik and Larrick, 2005), which has relied on four-alter target networks. It is therefore more likely that any compression heuristics employed in managing real social networks will come into play. Fourth, the target networks always contain two components, and contrast a condition where the target network has closed triads with a condition where the target networks lack closed triads. This both makes group-based recall a feasible option, and allows us to discriminate between a general tendency to encode networks in triads and a tendency that is situational based on the target. Fifth, these data contrast a condition where all relations are described using kin terms and a condition where all relations are described using non-kin terms. Kin relations function as a schema for network recall (e.g., Brashears, 2013; Brewer and Yang, 1994) and are highly salient even among non-human primates (e.g., Cheney and Seyfarth, 2008; Cheney et al., 1986). Therefore, the contrasting conditions allow us to determine if, as we might expect, the preferred encoding strategy is partially conditioned on the activation of a kin schema. Finally, because data were collected from approximately 300 respondents, there is an unusually large amount of information on which to base conclusions.

Participants (197 female, 104 male) were recruited from among the undergraduate population of a mid-sized northeastern university in the United States using flyers and other direct solicitations. These participants were randomized into one of four experimental conditions with a minimum of 72 and a maximum of 78 participants per condition. All four conditions presented a vignette (i.e., paragraph of text) describing a network of relationships between 15 individuals (e.g., "Henry is Alyssa's brother. Henry is also Elizabeth's son . . ."). Vignettes were used because (1) they permit absolute control of the depicted network, (2) they allow the dyads to be presented in context, and (3) humans routinely exchange social information linguistically (e.g., gossip; see Dunbar, 2004). The vignettes lacked any plot or story and both characters and dyads were presented in the same order in all conditions. Each vignette included a structural reducibility manipulation and a cultural schema strength manipulation. A network was reducible if it contained triadic closure (Fig. 1a), while it was irreducible if it contained no closed triads (Fig. 1b). A network had a strong cultural schema if relations were described using kin labels (e.g., "Catherine is Thomas' mother", "Catherine and Alyssa are sisters"), and it had a weak cultural schema if the relations were described using non-kin recreational labels (e.g., "Catherine is Thomas' friend", "Catherine

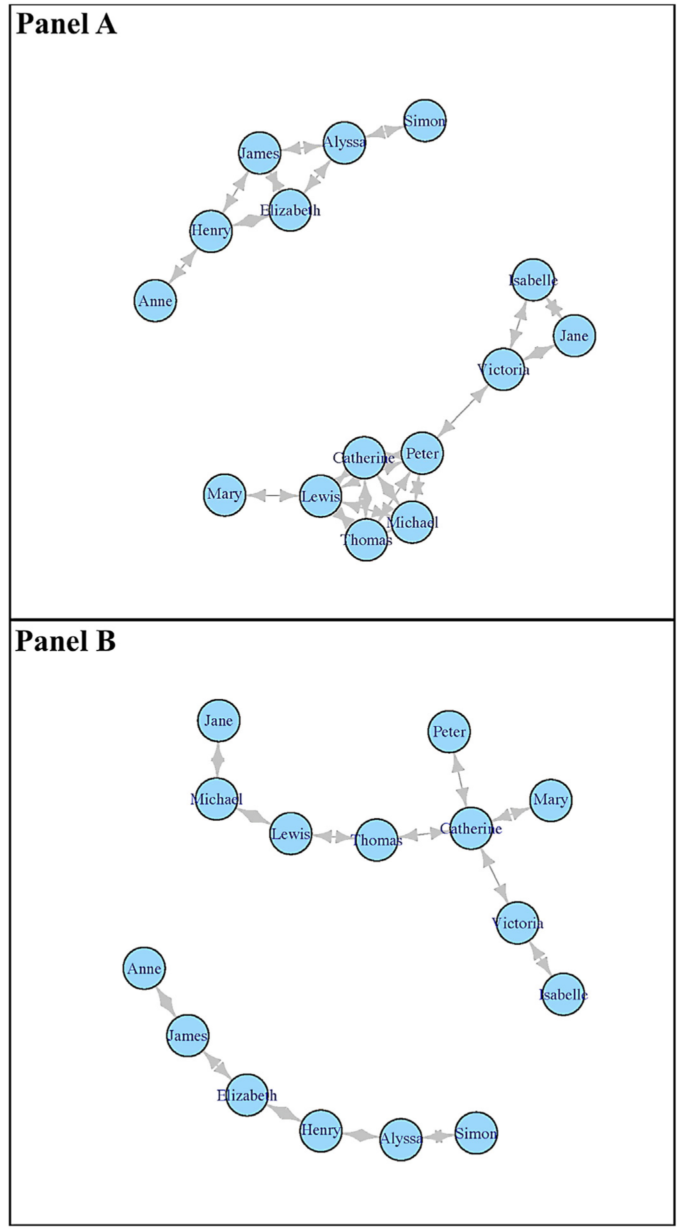


Fig. 1. Reducible (Panel A) and irreducible (Panel B) network structures.

and Alyssa are members of a chorus"). Spouses were considered to be kin because they are fictive kin, because they often share genetic relationships to shared children, and because they represent a durable kin-like alliance. The structural reducibility manipulation allows us to distinguish between an overall tendency to rely on triadic encoding and a situational tendency. If triads are always preferred, for example, we should observe tendencies to recall ties in triangles in both conditions. However, if encoding schemes are selected based on the properties of the network that is to be recalled, then different methods should be used for the reducible (triadic) and irreducible (non-triadic) conditions. Thus, this manipulation allows us to explore whether encoding is fixed, or flexible. The schema strength manipulation allows us to determine whether the presence or absence of a kin schema, a highly salient method of organizing relationships across species, influences which substructures are used for encoding networks. The two manipulations, reducible versus irreducible and strong versus weak schema, were crossed to produce four conditions (i.e., Reducible/Strong, Reducible/Weak, Irreducible/Strong, Irreducible/Weak). The network depicted in the vignette for a respondent's condition is the "true" network for purposes of our analysis.

All conditions contained 15 nodes, but all reducible conditions contained 46 reciprocated directed ties while all irreducible conditions contained 26 reciprocated directed ties and no condition contained unreciprocated ties. These constraints yielded network densities (Wasserman and Faust, 1999) of 0.219 and 0.124, respectively. Because the number of nodes was constant in all conditions and the specified constraints were imposed (e.g., triadic closure), the reducible and irreducible conditions were forced to have unequal numbers of ties. The network size of 15 was chosen with the intention of stressing the participants; the number of individuals depicted exceeds the estimated maximum capacity of working memory by roughly a factor of two, and the potential number of relations (i.e., 210) is more than an order of magnitude greater (Reisberg, 1997). All vignettes contained two disconnected components (i.e., sub-groups with no connections between them), and the components did not vary in size by condition. The schema strength manipulation only impacted the terms used to describe the network and did not impact its structure. Thus, all conditions with the reducible (i.e., closed triad) manipulation depicted the target network presented in Fig. 1, Panel A, while all conditions with the irreducible (i.e., open triad) manipulation depicted the target network presented in Fig. 1, Panel B.

Participants began the experiment by sitting at a prepared computer terminal and answering a series of simple demographic questions. The computer then chose a vignette at random and presented it as a paragraph of text on the screen. The participants were instructed to commit the information contained in the vignette to memory. One vignette was presented to each participant and all participants who were in the same condition saw the same vignette. Participants had unlimited time to study the vignette and were allowed to take notes on provided sheets of paper, but knew that the notes would be confiscated before the recall phase. The amount of time spent studying the vignette was measured without the participants' knowledge.

Once the participant finished studying the vignette, they completed a word span exercise (Daneman and Carpenter, 1980) with the experimenter. The participant read a series of sentence sets out loud and, at pre-determined times, recalled the last word in each preceding sentence in the current set. The number of sentences in each set gradually increased from a low of two to a high of seven, and three sets of a given number of sentences (e.g., three sets of three sentences, three sets of four sentences, etc.) were presented in sequence before the next larger sets were encountered. The exercise continued until the participant was unable to recall the final words correctly for two out of three sets of a given size (e.g., two sets of six sentences out of three sets presented) or obtained the maximum score (i.e., 7+). A participant's score was equal to the largest set where they were successful at remembering two out of three sets at that length. In other words, if a subject remembered the final words for two out of three sets of five sentences, but only remembered the final words for one out of three sets of six sentences, their word span score would be five. The sentences were drawn from popular press books, ensuring a high degree of readability, and all contained between 13 and 16 words, keeping the memory demands of each sentence constant. This provides a conventional measure of working memory capacity, and clears the participants' working and sensory (i.e., auditory and visual) memory stores. Because the word span task required the subjects to speak the sentences out loud no more than one participant was permitted in the lab at a time, so as to prevent contamination of their scores. At the end of the word span task the experimenter entered the participant's score into the computer terminal, and the participant used the terminal to complete the remainder of the study.

In the recall phase participants checked a series of boxes to indicate which characters had relationships with each other. On a second screen the participants then indicated the type of relationship (e.g., spouse, friend) they believed characterized each tie they identified in the preceding set of questions. Participants could return to the first part of the recall phase and change their selections as often as desired, but this cleared the relationship type choices, and participants received no feedback on their answers. Finally, participants were compensated and debriefed. All participants were told that the amount of compensation they would receive for completing the study was contingent on their success at recalling the vignette, but in fact all participants were compensated equally. The deception ensured that the participants were motivated to recall the information accurately. The experiment typically required forty minutes to complete, and all participants completed it. All procedures were approved by the IRB.

In contrast to Brashears (2013), who was only concerned with overall accuracy of recall, we analyze these data for consistent patterns of recall in order to discover how networks are cognitively represented. This means that we must search the recalled networks for particular sub-structures (i.e., dyads, triads, clusters) that are recalled more often than would be expected by chance, controlling for the target network structure. However, it is well understood that network sub-structures are not independent of one another, making standard statistical techniques inappropriate, and we adopt exponential random graph models (explained in greater detail in the next section) to compensate (see Lusher et al., 2013). Given that these data contain the recalled networks from roughly 300 participants, we can adopt one of two aggregation strategies: either we can estimate separate models for each participant and then combine them using a meta analysis (somewhat analogous to aggregating individual-level data in a regression), or we can analyze the consensus networks provided in Brashears' original paper (2013: 5), thereby fitting separate models to a smaller number of already aggregated networks. Below we explain the consensus networks in more detail, and then discuss why we prefer to present the results from this approach rather than the meta analysis of individual network models.

The consensus networks are produced by aggregating responses across participants and a tie is considered to exist between two nodes if a pre-specified proportion of the participants claimed that it exists. For example, a consensus network with a threshold of 0.80 would include a tie between two nodes if 80% or more of the respondents claimed it exists, and would exclude it otherwise. Similarly, a consensus network with a threshold of 0.10 would include a tie between two nodes if 10% or more of the respondents claimed it exists, and so on. This aggregation is equivalent to Krackhardt's (1987) "consensus structures," with the exception that we are aggregating participant recollections of a target network supplied by the researcher, rather than participant recollections of a natural network in which they participate. Eleven consensus networks were calculated for each condition at 100%, 90%, 80%, 70%, 60%, 50%, 40%, 30% 20%, 10% and 5% consensus, for a total of 44 networks. Because the structure of the target network is unaffected by the schema strength manipulation, and analyses indicate that the effects of this manipulation on our results are negligible, we collapse the strong and weak schema conditions together. In contrast, the reducible and irreducible conditions contain structurally different target networks (see Fig. 1), and should not be aggregated even in principle. Aggregating the strong and weak cultural schemas reduces the set of consensus networks to 22 rather than 44. Because the consensus networks are produced by aggregating across respondents from data collected in a randomized laboratory study they cannot be explained using participant characteristics (e.g., race, sex, etc.).

Both a meta analysis of individual networks and an analysis of the consensus networks represent methods of data aggregation. In the former, the data are left fully disaggregated and we combine parameters to produce a single set of results for each condition. In the latter, the data are aggregated in a number of networks and we estimate a separate set of parameters for each set of networks in each condition. Both approaches produce consistent results (see the section on robustness checks), but we prefer to present the results based on the consensus networks. The main reason is that using a consensus approach enables us to vary the level of consensus for each condition, which we could not do if we were to analyze the networks at the individual level. Varying the level of consensus is important because it provides insights into respondents' systematic errors at different levels of certainty, as a group. For example, correct ties that appear at higher levels of consensus are those about which participants, as a group, are quite certain. By contrast, those that appear at lower levels of consensus are those about which participants are more uncertain. Similarly, errors that appear at low levels of consensus only are relatively uncommon, while those that appear at comparatively higher levels of consensus are the most appealing or cognitively accessible mistakes. The same is true of structural features; parameters that are significant at higher levels of consensus reflect stronger tendencies, than those appearing at lower levels of consensus. Furthermore, because respondent recall of the target networks is in general quite good (see Brashears, 2013), results deriving from the meta analysis approach would be dominated by accurate recall. Thus, while both methods produce similar results, we prefer the approach based on consensus networks for the additional detail it provides.

4.2. Analytic method

We use Exponential Random Graph Modeling (ERGM or p* modeling) to examine the structure of the consensus networks (see Lusher et al., 2013). ERGMs allow the examination of microstructural patterns that constitute a network structure and hence provide inferences about the processes that brought that specific structure to existence. ERGMs are tie-based models specifically designed to account for the dependencies between observations that characterize network data (Lusher et al., 2013). The dependent variable is the presence or absence of a tie between two actors as a function of the local structure of the network surrounding the two actors. ERGMs are based on the assumption that network structure is locally emergent, and hence that the repetition of local microstructures defines the general structural patterns observed in an empirical network. In our case, it means that the occurrence (or non-occurrence) of a specific microstructure in the consensus networks would be indicative of processes common to our respondents when recalling the target network. Because these local microstructures are not independent from each other (i.e., a dyad is embedded in a triad, which is itself embedded in a group structure), we need to be able to model the microstructures of interest together and assess the extent to which each of them participates in the processes that gave rise to the structure of the network.

The models are autologistic and commonly expressed under the form:

$$Pr(X = x)\frac{e[\,\Sigma\lambda_A Z_A(x)]}{K} \quad (1)$$

where x is the observed network; A is the parameter corresponding to a local network configuration; λ_A are the parameter estimates; $Z_A(x)$ is the network statistic counting the frequency of subgraph A in the graph x; K is a normalizing quantity to ensure that the probability is a proper probability distribution (see Robins et al., 2009).

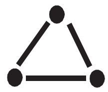
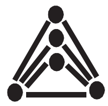
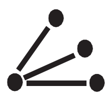
We use the PNet software package for undirected graphs (Wang et al., 2006) and include a set of predictors that enable us to distinguish the social processes prevalent in the consensus networks at the dyadic, triadic and cluster levels (see Table 1).

For our first hypothesis, at the dyadic level, we include an *Edge* term, which reflects the propensity for actors to recall the ties in the network as isolated dyads. A positive and significant parameter estimate would indicate that dyads tend to occur on their own, which would be consistent with a process of encoding focused on dyads and would confirm our first hypothesis. In order to address our group level hypotheses, we include higher order parameters for *Closure* and *Connectivity* (Robins et al., 2006; Snijders et al., 2006). Higher order parameters provide information about the extent to which a specific dyad is recalled within a configuration that includes multiple shared partners (i.e., clusters or groups). They are based on the assumption that a respondent's recall of a tie between actor A and actor B is dependent not only on the existence of one third party C who is tied to both A and B, but of k partners that are tied to both A and B. Higher order parameters reflect a process of structural embeddedness that is consistent with the broad group distinction that we present in our hypothesis. For our third hypothesis, at the triadic level, we include a Markov parameter (*Triangle*) that captures the extent to which ties are recalled within triadic configurations, but do not require the presence of multiple partners, hence distinguishing between the triad and a broader group.

Further, we control for the degree distribution in the consensus networks in order to assess the extent to which the observed structure is due to a degree-based mechanism (e.g., preferential attachment). Finally, we fix the ties that are present in the target network when modeling the consensus networks (using structural zeros[3]). Effectively, it means that we estimate the likelihood of a tie being recalled by the participants outside of the network that participants are asked to recall. We model the structure that remains in the consensus network once the target network is taken into account. The analysis therefore provides us with information as to whether the recall errors of the respondents follow specific patterns or not. This is essential because we should expect the recalled networks to approximate the target networks more or less closely. As a result, the organizing principles of network recall will be revealed in the types of mistakes made by our respondents. These mistakes can be dyadic, triadic, or group-based and therefore will signal how individuals are encoding social ties in memory. Put differently, recall of the ties depicted in the vignette

[3] Our results are robust to different specifications of the ERGM regarding the control for the target networks. We also estimated models using the target networks as dyadic covariates and obtained substantively similar results. We present the models using structural zeros because they represent a more conservative control for the structural features of the target network.

Table 1
Effects included in the exponential random graph models.

Name	Visual representation	Description
Edge		The propensity for a tie to be present (when no other effect is included)
Triangles		The propensity for ties to form as part of triangles
Closure		The propensity for ties to form as part of a multiple closure configurations
Multiple connectivity		The propensity for ties to form as part of formations involving multiple short paths between actors
Degree		The propensity for dispersion in the degree distribution

tells us little about how networks are stored in memory because the researcher determines the structure of the vignette network. In contrast, the extra ties recalled by respondents, but not presented in the vignette (i.e., false positives), provide information about how humans encode networks. If networks are encoded as dyads, then individual erroneous ties should appear independent of other structures. If networks are encoded as triads, then erroneous ties should tend to be recalled in triangles. And if networks are encoded as groups, then erroneous ties should tend to appear in the higher order structures we specified. Thus the patterning of recall net of the correct answers allows us to infer how networks are encoded into memory.

5. Results

Before entering into the ERGM analysis, we assess the extent of overlap between the consensus and the target networks and provide some basic descriptive statistics of the networks that we model. We find that at levels of consensus at or above 20% (i.e., 20% or more respondents agree that each tie exists), the overlap between the target and the consensus networks is greater than 90%, with typically only one tie deviating between the two networks. Substantively, this means that, as a group, respondents have a very accurate recall of the target network. Methodologically, this influences our use of the higher level consensus networks. Because we fix the ties of the target network in the consensus networks during the ERGM analysis, the results provide information about the structural patterns that deviate from accurate recall. Networks with a consensus at or above 20% are (almost) completely aligned with the target network and their analysis brings no information. We therefore discard them and focus the analysis on the networks with consensus 5% and 10% for the reducible and irreducible conditions.

Table 2 presents some basic network statistics regarding the consensus networks. The 5% consensus networks in the reducible and irreducible conditions are similarly dense, clustered and centralized. By contrast the 10% consensus networks in the reducible and irreducible conditions differ more substantially. The 10% consensus reducible network is denser, more clustered and less centralized than its irreducible counterpart. We were not expecting the two networks to be similar, because the target networks themselves have a different structure. However, we make note of these issues because of the potential for the density differential to affect our results (see below). Furthermore, respondents correctly recalled all ties from the target networks in the 5% and 10% consensus networks (0 false negative). The number of false positives differs between the two consensus levels, with a shaper reduction of the number of false positives at the 10% level relative to the 5% level in the irreducible condition (approximately divided by 2 in the reducible condition and by 4 in the irreducible condition).

Table 3 presents four models, two for each condition (reducible and irreducible). We will first describe each model separately and then identify common trends that can provide insights into respondents' patterns of recall. Model 1 corresponds to a 5% consensus for the reducible condition. The only significant effect is at the triadic level, with a positive and significant triangle effect. In this network, triangles are more likely to be recalled than what would be expected by chance alone, taking into account the target network. In Model 2, which corresponds to a 10% consensus network in the reducible condition, we still see a significant and positive triangle effect. There is also a negative and significant degree distribution parameter, indicating that the degree distribution in the consensus network is more homogenous than what would be expected by chance.

Models 3 and 4 represent the irreducible condition networks with a consensus level of 5% and 10%, respectively. In Model 3, the edge parameter is significant and negative. Because the edge parameter is included in a model with several other parameters, the interpretation of a negative and significant effect is that ties do not tend to be recalled on their own; rather they are part of the structures identified in the model (Lusher et al., 2013). The triangle effect is significant and positive. Triangles are recalled more than expected by chance and taking into account the target network. The multiple connectivity parameter is significant and positive. The recalled networks tend to be composed of actors that are linked to multiple shared partners, even though the actors are not necessarily linked themselves. This tendency is above what could be expected by chance, when taking the target network into consideration. The degree distribution parameter is significant and negative. In Model 4, the edge parameter is significant and negative. The triangle parameter is non-significant. The closure parameter is significant and positive, while the multiple connectivity parameter is non-significant and negative. Hence, the recalled networks exhibit more dyads that are connected to multiple shared partners than what would be expected by chance, when taking the target network into consideration.

In summary, the dyadic level parameter is either non-significant and negative for reducible networks or significant and negative for irreducible networks, which indicates that dyads tend not to be

Table 2
Descriptive statistics reducible and irreducible consensus networks.

	Reducible 5%	Reducible 10%	Irreducible 5%	Irreducible 10%
Number of nodes	15	15	15	15
Number of edges (density)	148 (0.70)	102 (0.48)	146 (0.69)	58 (0.28)
Number of triangles (clustering)	1062 (53%)	504 (58%)	1032 (51%)	114 (32%)
Centralization	34%	18%	35%	34%
Number of ties in the target network	44	44	26	26
Number of ties correctly recalled	44	44	26	26
Number of false positives	104	58	120	32
Number of false negatives	0	0	0	0

Table 3
ERG models for undirected consensus networks, reducible and irreducible conditions.

	Model 1 Reducible 5%	Model 2 Reducible 10%	Model 3 Irreducible 5%	Model 4 Irreducible 10%
Dyadic level				
Edge	−6.017	−6.241	−6.493*	−6.046*
	(5.979)	(3.247)	(2.218)	(2.356)
Triadic level				
Triangles	3.504*	1.189*	1.750*	−2.102
	(1.233)	(0.518)	(0.517)	(2.017)
Group level				
Closure	0.212	1.980	Not included	3.603*
	(3.325)	(1.149)		(1.549)
Multiple Connectivity	6.694*	0.331	4.063*	−0.108
	(3.326)	(0.288)	(1.724)	(0.453)
Controls				
Degree distribution	−0.245*	−.0109*	−0.079*	−0.006
	(0.114)	(0.036)	(0.034)	(0.116)

Notes: Standard Errors reported in parenthesis.
* Significant at $p < .05$.

recalled on their own. This result contradicts our Dyadic Recall hypothesis, which was that recall would tend to occur through direct encoding of dyads. The triadic level parameter is significant and positive for the reducible networks and for one of the two irreducible networks. Our Triadic Recall hypothesis is therefore mainly supported; respondents exhibit a tendency to use triads to encode network information. Finally, group level parameters are significant and positive for the irreducible networks and non-significant for the reducible networks. The Group Recall hypothesis is partially supported; respondents exhibit a tendency to use broader group structures to encode network information for one of the two conditions.[4]

6. Substantive interpretation

Our main result is that respondents use both triad level and group level mechanisms to encode the target networks, but not a dyad level mechanism. This result provides evidence that respondents encode compressed social information in order to make recall more cognitively tractable. Respondents do not remember a network tie by tie, but rather use more complex relational schema, such as triads or small group structures in order to remember social network information.

Yet, there is an interesting nuance in this finding, which is that the relational schema condition (reducible or irreducible) affected the encoding mechanism used by respondents. Encoding in the reducible condition is solely based on triad level mechanisms with no group level parameter being significant. By contrast, in the irreducible condition, both triad level and group level parameters are significant. Because we model the deviation of the consensus networks from the target networks, our results should be interpreted as the mechanisms that characterize regular patterns of mistakes that individuals make in remembering the target network. Hence, for reducible networks, respondents tend to consistently identify more triads than those that were present in the target network. Because this tendency is above and beyond what could be expected by chance, we can infer that the result indicates a systematic tendency of participants to erroneously recall triads (and hence to use triads as a mechanism to commit the network information to memory). By contrast, for irreducible networks, group level parameters are significant. This means that respondents tend to consistently recall more group-like structures than those that exist in the target irreducible network in addition to triads.

This result suggests that because different structural features (triadic and group) are predominant in reducible and irreducible conditions, individuals tend to adapt the encoding mechanisms that they use based on the most appropriate, recognizable relational schema. The only difference between reducible and irreducible conditions is the extent to which the target networks exhibit triadic closure. In the consensus networks for the reducible condition, respondents accurately identify the existence of triads and use triadic structures to encode the information of the whole networks. By contrast, for the irreducible condition, respondents sometimes, and somewhat uncertainly, focus on triads, but also revert to broader recall categories represented by the group level parameters. Here, respondents tend to identify that individuals are part of a more general connective structure (i.e., a group) that is not specifically recognized as a triad. This tendency for individuals to adapt the recall mechanisms that they use can in turn be conceived as a demonstration of cognitive flexibility in the way in which social information is encoded in the respondents' memory.

[4] Note that the density differential between the 10% consensus reducible and irreducible networks is unlikely to explain our results. Given that the 10% reducible network is denser (and more clustered) than the 10% irreducible consensus network we might have expected the group level parameters to be more salient in the 10% consensus reducible network, but this is not the case.

A further interesting nuance emerges when considering the level of consensus in the irreducible networks. Consensus represents the degree of agreement between respondents regarding whether a given tie exists in the target network or not. The lower level of consensus represents a lower threshold of agreement between the respondents for each tie to exist. At 5% consensus, at least 5% of respondents (approximately 7 participants out of 148 for the reducible condition and 8 out of 153 for the irreducible condition) needed to agree that a given tie existed for it to be present in the consensus network. At 10% of consensus, 10% of respondents (approximately 15 participants out of 148 for the reducible condition and 15 out of 153 for the irreducible condition) needed to agree that the tie existed. At the higher level of consensus more respondents agree that a given tie should exist and the structural features exhibited by the consensus network should therefore represent more defined relational schemas. Given this, it is interesting that for the lower consensus network in the irreducible condition, both the triad and group level parameters are significant, but for the higher level of consensus, only the group level parameter is significant. We interpret this result as an indication that the mechanism that is most consistent with an absence of information about triadic structures in a social network is a group level mechanism. When individuals have limited information about the existence of triads in a network, they will tend to encode the social information as broader groups. The existence of a triad parameter in the lower level of consensus for the irreducible condition may be interpreted as a weak tendency for respondents to attempt to use triads as a way to encode the social information even if it is not present in the network to be recalled. These interpretations could suggest that the triadic level is the default level of encoding of social information and that humans can flexibility select other encoding mechanisms based on the amount of information contained in the network.

7. Robustness checks

While not presented here in order to save space, we carried out three robustness checks. First, while the vignettes included in Brashears' (2013) experiment did not include sufficient detail about the characters to provide an alternative schema for encoding, there was one potential schema that could not be eliminated: sex. Since the sex of each character could be inferred from their name, it is possible that subjects would preferentially (mis)remember sex-homogeneous (or heterogeneous) dyads. This is a key issue as previous research among non-human primates has identified considerable differences in how the networks of males and females are structured (see Cheney and Seyfarth, 2008: Ch. 4 and 5). However, fitting ERGMs that include a sex homophily parameter indicates no particular tendency to remember these dyads more readily than others. Sex-based encoding is thus not an issue.

Second, it is possible that our results might depend idiosyncratically on the specific levels of consensus that we examined. We therefore estimated models at levels of consensus increasing by one percentage point from 5% to 15% (e.g., 6%, 7%, 8%, etc.). These models indicate that triads are consistently and robustly identified by respondents in the reducible condition across a wide range of consensus values. In contrast, in the irreducible conditions, triads are identified somewhat inconsistently at lower levels of consensus while the closure and multiple-connectively parameters (i.e., group-level parameters) emerge most consistently at higher levels of consensus. While one should be cautious in interpreting these models because differences in rounding may play an unreasonably large role in distinguishing consensus networks separated by one percentage point, these results are supportive of our findings. When the network contains triadic closure, respondents robustly take advantage of triadic-based encoding methods. However, when the network contains no triads, respondents exhibit a substantially weakened, though non-zero, tendency to adopt triadic encoding methods, and develop a new affinity for group-based recall.[5] It therefore does not appear that our findings are uniquely dependent on the specific levels of consensus we chose as our focus.

Third, we conducted a meta analysis of results from ERGMs fit to the individual networks (see our earlier discussion at the end of the Data section). We fitted four different ERGMs to each individual network, all of which included a control for degree distribution (3 star) as well as a control for the target network. The first model included only an edge term, the second model an edge term and a triangle term, the third model an edge term and a multiple closure term and the fourth model an edge term, a triangle term and a multiple closure term. If the full model converged, we saved the sign and significance of the edge, triangle and closure parameters. If the full model did not converge, then we saved the sign and significance of the parameters of the model with the best goodness of fit. Because of a generally high level of respondent accuracy, many models did not converge (out of 301 models, 111 converged for the reducible condition and 109 for the irreducible condition). We then counted the number of times that edges, triangle and multiple closure parameters were positive or negative and significant for each condition. There results are striking in their agreement with our analysis of the consensus networks. The edge term is always negative and significant. There are 32 models with a positive and significant triangle term in the reducible condition versus 4 in the irreducible network condition. There are 15 positive and 9 negative multiple closure terms in the irreducible condition versus 6 positive and 24 negative in the reducible condition. Consistent with our main results, the analysis of individual networks also emphasizes the importance of triangles for the reducible condition and the importance of group like structures for the irreducible condition. Therefore, while we prefer to present the consensus results in detail, both approaches yield the same conclusions.

8. Discussion and conclusions

Our results indicate that humans exhibit a tendency to recall social networks in terms of triads, possibly even when the network they are attempting to recall is non-triadic (i.e., the irreducible network). In contrast, we never observed a tendency for respondents to encode relations as individual dyads, and only sometimes observed tendencies towards group-based recall. This suggests that when people attempt to recall networks they attend primarily to triads and we take this as evidence that the triad is the basic unit of network recall. This finding supports our Triad Recall Hypothesis, and is consistent with previous scholarly interest in triads (e.g., Burt, 1992; Chase et al., 2002; Granovetter, 1973; Paz-y-Miño-C et al., 2004; Skvoretz et al., 1996), suggesting that these features are not just convenient for theoretical or modeling purposes, but really are a fundamental unit of social networks generally, and of human social networks in particular.

Triads appear to be the default structure of human network recall, but they are not the only structure for recall. When the network to be recalled contained no triads our subjects seemed to

[5] It is additionally interesting that in the irreducible consensus networks, where both triadic compression and group-based encoding are attempted by our respondents, the group-based encoding mechanism, which is the most correct of the two, appears only at higher levels of consensus. While not direct proof, this is consistent with our argument that encoding is done using pre-set mechanisms such as triads or groups and that humans "choose" which mechanism best fits the structure that they are attempting to memorize and recall.

recognize this fact and activated an alternative group-based encoding scheme in response. This indicates that even if the triad is the default unit of network recall, individuals are nevertheless able to override this default when alternatives are more appropriate. This finding is consistent with prior research, largely on the elicitation of names, which shows that humans can encode and recall alters flexibly using a number of schemata (e.g., Brewer and Garrett, 2001; Brewer and Yang, 1994; Killworth and Bernard, 1982), though of course the recall of names is quite different from the recall of substructures. It is clear that humans exhibit considerable cognitive flexibility where networks are concerned, but it is less clear why this flexibility exists. A definitive explanation is beyond the scope of our research, but we suspect that three phenomena are to blame: idiosyncratic deviations, variations in tie strength, and information deficits.

Beginning with idiosyncratic deviations, it is clear that compression heuristics are valuable for reducing the cognitive burden of recalling large networks, but they are only useful if they match the network to be recalled. When a network does not exhibit triadic closure, adopting the triad as the basic unit of recall is unlikely to be beneficial (e.g., Brashears, 2013). But even if a network has many triangles, it is unlikely to be perfectly triadic. Applying a triadic schema by rote, with no ability to adjust for deviations, would impair network recall. And because unclosed triads may represent bridging opportunities to be exploited (e.g., Burt, 1992), or dangerous conflicts to be avoided, failure to recognize them might exert a disproportionate effect on the individual.

Second, it is well understood that some ties are stronger than others. A number of features define the strength of a tie (Granovetter, 1973) and the importance of these features varies depending on the outcome of interest (e.g., Aral and Van Alstyne, 2011), but stronger ties are generally thought to involve greater amounts of interpersonal knowledge and may require more maintenance than weaker ties. This implies that recalling these relationships purely through the use of compression heuristics is unwise, both because of the richer history imbuing the tie, and because of the greater penalties for recall errors. We might therefore expect triads to be the basis of recall for weaker ties, while dyadic recall dominates for strong ties.

Third, individual humans rarely possess perfect knowledge of all networks that they interact with. When only a handful of the ties in a given network are known the individual may adopt a group-based encoding scheme because it fits with their perceptions. Thus, we might expect humans to use non-triadic encoding for networks about which they have little information and to use triadic encoding for networks that they know in detail. Obviously this implies that humans should shift from group-level to triadic encoding as they become socialized into a new group and learn its structure. But less obviously, it suggests that humans may be prone to use triadic encoding for in-groups, about which they know a great deal, and to use group-level encoding for out-groups, about which they know considerably less (see also Kumbasar et al., 1994). As a result out-groups may often be perceived as monolithic, composed of unified "others" who have homogeneous opinions and relations, while one's own group will be perceived as containing diversity, nuance and disagreement. As such, the flexible application of compression heuristics to social networks may encourage the perception of out-groups as fundamentally different, and possibly more threatening, than in-groups.

Our apparent cognitive flexibility is advantageous, but also represents unique challenges for network analysis. We began this investigation by observing that the types of macro-scale networks that humans create will be shaped by the micro-structures that they use for network recall. This perspective is consistent with our findings, but is complicated by the fact that humans select their encoding method based on the characteristics of the target network. This suggests that there may be a network structural "Matthew Effect," such that the initial configuration of a network shapes how individuals encode it, which guides their behavior and thereby guides the ultimate configuration of the network. This implies that it may be possible to shape the evolution of networks by strategically priming particular schemas. Thus, it might be possible to use an individual-level intervention to improve the cohesion or social capital of a network. Finally, many highly influential network studies are based on respondent recall of their networks, and our results indicate that the nature of the encoding bias changes depending on the characteristics of the true network. Determining the properties of a true network from respondent recall will therefore require cautious exploration of the biases that are present (e.g., Feld and Carter, 2002), and use of this information to estimate the nature of the underlying network.

Future studies would benefit from using EEG or fMRI methods to chart the activity in the brain during various stages of the learning, encoding, and recall processes. However, it should be kept in mind that an fMRI may be able to tell the researcher that network encoding takes place in a particular part of the brain (e.g., the ventral medial prefrontal cortex) but cannot reveal what the brain is doing. Knowing that a program is executed by the CPU in a computer is different from knowing what the program is doing and, likewise, knowing that encoding occurs in a specific part of the human brain is different from knowing what the encoding is and how it works.

Future research should attempt to measure recall for artificially generated networks in which the respondent participates as this may increase the motivation to accurately track network information (although our deception should have compensated to some degree). However, this will require constructing a number of networks from scratch using confederates and thus will require considerable planning to execute without an unreasonable number of potential confounds.

Finally, a larger number of target network structures should be evaluated so as to uncover any additional encoding schemas that may exist. We found evidence that triads are frequently used, and that individuals can invoke a group-based encoding scheme, but there may be other encoding schemas in routine use. Uncovering these additional schemas, if they exist, cannot help but add to our understanding of how, and why, networks take on particular structures.

Ultimately work in this vein will hopefully improve the causal justifications for many network theories. It is tempting to explain the regularities of human social life by making reference to what individuals "prefer" or "like" (e.g., humans find affectively balanced relations to be "pleasant"). Yet, as pointed out by Mayhew (1980, 1981), such justifications boil down to a claim that people do certain things because they want to. This is a personally satisfying idea, but it is fundamentally at odds with the goal of predictive social science. The current line of work argues that some network structures are "liked" or "preferred" because they lower the information processing requirements on the organism. As such, it helps to root our network theory not in the ephemera of taste, but in the solid bedrock of capacity and cost.

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