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Szary, Janelle

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An Extended, Dynamic Account of Collaborative Remembering and Information Search

A dissertation submitted in partial satisfaction of the requirements
for the degree Doctor of Philosophy

in

Cognitive and Information Sciences

by

Janelle K. Szary

Committee in charge:

Professor Rick Dale, Co-Chair
Professor Christopher T. Kello, Co-Chair
Professor Jeffrey Yoshimi

2015

The dissertation of Janelle K. Szary is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

Professor Jeffrey Yoshimi

Professor Rick Dale, Co-Chair

Professor Christopher Kello, Co-Chair

University of California, Merced

2015

To the colleagues who became friends,
to the friends who became family.

And, most of all,
to my family,
who has always been everything.

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- - -

The text of Chapter 2 of this dissertation is a partial reprint of the material as it appears in "Memory Foraging in a Spatial Domain", co-authored by Christopher T. Kello and Rick Dale. The text of Chapter 3 is a partial reprint of the material as it appears in "Patterns of Interaction-Dominant Dynamics in Individual Versus Collaborative Memory Foraging", which was co-authored by Rick Dale, Christopher T. Kello, and Theo Rhodes. The text of Chapter 4 is a partial reprint of the material as it appears in "Dyadic Cooperation Enhances Retrieval and Recall of Crossword Solutions", which was co-authored by Rick Dale. The text of Chapter 5 is a partial reprint of the material as it appears in "Collaborative Memory Constraints: Familiarity, Cooperation, and Individual Skill", which was co-authored by Rick Dale.

Curriculum Vita

Janelle K. Szary

PhD Candidate, Cognitive and Information Sciences
University of California, Merced

email: jszary@ucmerced.edu
website: janelleszary.com

Education

Formal Training

2009–In Progress	PhD in Cognitive and Information Sciences, University of California, Merced
2006–2008	BA in Psychology, New York University
2004–2006	AA in General Studies, New York University

Additional Training

June 2013	Summer School. APA Advanced Training Institute: Nonlinear Methods in Psychological Research. *Cincinnati, Ohio.*
June–July 2011	Summer School. Neuromorphic Cognition Engineering. *Telluride, Colorado.*
August 2010	Tutorial. Cognitive Science Society: "Dynamic Field Theory: Conceptual Foundations and Applications in the Cognitive and Developmental Sciences". *Portland, Oregon.*
May 2010	Summer School. Cognitive Science and Machine Learning. *Pula, Sardinia, Italy.*
2008–2009	Partial coursework. Johnson County Community College: Computer Information and Technology Program. *Overland Park, Kansas.*

Publications

Refereed Articles

Szary, J., Dale, R., Kello, C. T., & Rhodes, T. (*In press*). Patterns of interaction-dominant dynamics in individual versus collaborative memory foraging. *Cognitive Processing, Special Issue: Complexity in Brain and Cognition.*

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Johnson, D., **Szary, J.**, Sharot, T., & Phelps, E. (2008). The mechanisms underlying the optimism bias. New York University's *Inquiry*, vol. XI.

Presentations

Oral Presentations

Szary, J., Kello, C., & Dale, R. (2015). Memory foraging in a spatial domain. *37th Annual Conference of the Cognitive Science Society.* Pasadena, California, United States.

Szary, J. (2015). Inter- and in-dependence in collaborative memory foraging: An empirical and computational investigation. *4th Meeting of the Society for Complex Systems in Cognitive Science.* Pasadena, California, United States.

Szary, J., & Dale, R. (2014). Modeling the effects of interaction and resource landscape on search. *44th Annual Meeting of the Society for Computers in Psychology.* Long Beach, California, United States.

Szary, J., & Dale, R. (2014). Familiarity modulates the dynamics of collaborative inhibition in a trivia game. *36th Annual Conference of the Cognitive Science Society.* Québec City, Canada.

Szary, J., & Dale, R. (2013). Dyadic cooperation enhances retrieval and recall of crossword solutions. *5th Joint Action Meeting.* Berlin, Germany.

Szary, J., Kello, C., Dale, R., & Rhodes, T. (2013). Collaborative recall: Interacting memory foraging. *3rd Meeting of the Society for Complex Systems in Cognitive Science.* Berlin, Germany.

Szary, J., Kerster, B., & Kello, C. (2011). What makes a brain smart? Reservoir computing as an approach for general intelligence. *4th Conference on Artificial General Intelligence.* Mountain View, California, United States. *Presented by C. Kello.

Szary, J. K., & Kello, C. T. (2011). Visual motion perception using critical branching neural computation. *33rd Annual Meeting of the Cognitive Science Society.* Boston, Massachusetts, United States.

Szary, J., & Kello, C. (2011). Motion perception using a critical branching neural network. *32nd Annual Central California Research Symposium.* Fresno, California, United States.

Szary, J. (2011). Cognitive and Information Science: Approaches to understanding the brain's intelligence. *Women in Science and Engineering Spring 2011 Graduate Student Speaker Series.* Merced, California, United States.

Poster Presentations

Szary, J., Chiu, E. M., & Balasubramaniam, R. (2014). Tap it out: Exploring the role of cross modal feedback on rhythmic sequence production. *36th Annual Conference of the Cognitive Science Society.* Québec City, Canada.

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Hartley, C. A., Meltzer, E. P., Salman, R., **Szary, J. K.**, & Phelps, E. A. (2008). The role of agency in modulating conditioned arousal. *2nd Annual Social and Affective Neuroscience Conference.* Boston, Massachusetts, United States. *Presented by C. Hartley

Hartley, C. A., **Szary, J. K.**, Fischl, B., & Phelps, E. A. (2008). Brain structure correlates of individual differences in the acquisition and regulation of conditioned fear. *Annual Meeting of the Cognitive Neuroscience Society.* San Francisco, California, United States. *Presented by C. Hartley

Hartley, C. A., **Szary, J. K.**, Fischl, B., & Phelps, E. A. (2007). Brain structure correlates of sensitivity to anticipated aversive outcomes. *Annual Meeting of the Society for Neuroeconomics.* Hull, Massachusetts, United States. *Presented by C. Hartley

Awards & Honors

2015	Student Travel Grant* (among top student papers), Cognitive Science Society
2015	Travel Fellowship*, CIS Graduate Group, UC Merced
2015	Summer Fellowship*, CIS Graduate Group, UC Merced
2015	Outstanding Woman Nominee, Office of Student Life Women's Programs, UC Merced
2015	Featured Researcher, Kolligian Library Graduate Student Research Showcase, UC Merced
2014	Birnbaum Award for Student Membership, Society for Computers in Psychology
2014	Summer Fellowship*, CIS Graduate Group, UC Merced
2014	Travel Fellowship*, CIS Graduate Group, UC Merced
2013	Summer School Fellowship*, CIS Graduate Group, UC Merced
2013	Summer Fellowship*, CIS Graduate Group, UC Merced
2013	Travel Fellowship*, CIS Graduate Group
March 2013	First Place*, Research Week Graduate Student Poster Competition, UC Merced
2010–2011	Faculty Mentor Program Fellowship*, Graduate Division, UC Merced
2008	University Honors Scholar, NYU
2008	Dean's Honor Roll, NYU
2008	Certificate of Achievement in Psychology Dean's Award, NYU
2008	Student-Athlete Academic Achievement Award, NYU
2005, 2007, 2008	President's Honor Roll, NYU
2006, 2007, 2008	All-Academic Recognition, University Athletic Association
2005, 2006, 2008	Intercollegiate Athletics Advisory Committee's Honor Roll, NYU

**Funding awards*

Teaching

Instructor of Record

Summer 2014	Cognitive Neuroscience, UC Merced

Teaching Fellow

Spring 2015	Research Methods in Cognitive Science (Prof. Rick Dale), UC Merced
Fall 2014	Service Science (Prof. Paul Maglio), UC Merced
Spring 2014	Logic and Critical Reasoning (Prof. Rolf Johansson), UC Merced
Fall 2013	Introduction to Cognitive Science (Prof. Michael Spivey), UC Merced
Spring 2013	Cognitive Neuroscience (Prof. Anne Warlaumont), UC Merced

Teaching Assistant

Fall 2012	Decision Making (Prof. Evan Heit), UC Merced
Spring 2012	Research Methods in Cognitive Science (Prof. Ben Pageler), UC Merced
Fall 2011	Service Science (Prof. Paul Maglio), UC Merced
Spring 2010	Research Methods in Cognitive Science (Prof. Chris Kello), UC Merced
Fall 2009	Introduction to Psychology (Prof. Diane Odom-Gunn), UC Merced

Teaching Mentor

Spring 2008	Introduction to Psychology (Prof. Elizabeth Phelps), NYU
Fall 2007	Introduction to Psychology (Prof. David Amodio), NYU

Service & University Involvement

May 2015	Ad Hoc Reviewer, Behavioral Research Methods
April 2015	Panelist, Peer Mentor Program: “How to Find and Prepare for a Committee”
March 2015	Ad Hoc Reviewer, PLoS ONE
March 2014	Ad Hoc Reviewer, Psychonomic Bulletin & Review
2014	Member, Graduate Professional Advancement Initiative Teaching and Mentoring Sub-Committee
2013–2014	Graduate Student Representative, Graduate Professional Advancement Initiative
2012–2014	Graduate Student Representative, Student Fee Advisory Committee
2012–2014	Internal Vice President, Graduate Student Association
2012–2014	Chair, Graduate Student Association Delegate Assembly
2013	Co-Organizer, Cognitive and Information Science Group Weekly Seminar
March 2013	Presenter, UC Merced Creative Research Week Exhibition
2012	Graduate Student Representative, Vice Chancellor’s Student Advisory Board
August 2012	Panelist, Graduate Student Orientation Week
2010–2012	Vice President, Women in Science and Engineering
2011–2012	Board Member, University of California, Student Association
2011–2012	External Vice President, Graduate Student Association
June 2011	Graduate Program Advocate, University of California Advocacy Day (Washington, D. C.)
May 2011	UC Merced Advocate, Graduate Research Day at the State Capitol (Sacramento, California)
2010–2011	Graduate Student Representative, Chancellor’s Sustainability Committee
2010–2011	Graduate Student Representative, Commission on Women Committee
2009–2010	Participant, Graduate Student Peer Mentor Program

Professional Memberships

Society for Computers in Psychology
Cognitive Science Society
Women in Cognitive Science
American Psychological Association
Psi Chi National Honor Society

Abstract

Our memories are collections of the information we have experienced and learned over the course of our lives. While the nature of memory has been studied extensively in the history of the cognitive and psychological sciences, relatively little is known about how we sift through that information space to bring up any given thought at a given moment. According to the extended, dynamical systems framework, the mind is interwoven inextricably into its environment, and so the process of memory retrieval must be considered from a contextually-situated perspective. The goal of the current project is to highlight the importance of a key component of any memory system's context: the social interactive context. Using both empirical and computational methodologies, the interdisciplinary studies described herein compare the processes employed by individuals and collaborating dyads while searching through information space. Inspiration is drawn from the domains of ecological foraging and particle diffusion in statistical physics to explain foraging dynamics, and from complex systems science to explore collaboration dynamics.

Ultimately, the project argues that not only is the social collaborative context an important modulator of memory processes at an individual level, but that in some cases people might be able to coordinate their memory processes, coming together to act as one. Through technological advancements, we are increasingly able to communicate and work collaboratively on all sorts of projects. Thus, a call is made for ongoing research to consider the conditions in which we can optimize information retrieval in these collaborative scenarios.

This dissertation, *An Extended, Dynamic Account of Collaborative Remembering and Information Search*, is submitted by Janelle Szary in 2015 in partial fulfillment of the degree Doctor of Philosophy in Cognitive and Information Sciences at the University of California, Merced, under the guidance of dissertation committee co-chairs Rick Dale and Christopher T. Kello.

Chapter 1

Introduction

The evidence from cognitive science and associated fields suggests that the common notion of the self as a distinct, autonomous and internal agent may be misguided: the self is more appropriately thought of as a delicate but powerfully interconnected balance between self, other, and environment. This dissertation focuses, more specifically, on the connection between self and other. It is readily understood that we are social creatures, and that social influence can have drastic effects on an individual's own perceptions and actions. We contagiously catch yawns, can be tickled by others but not by ourselves, fall victim to peer pressure, and put great amounts of effort into changing our appearances or behaviors to impress potential dates (to name a few common examples). But there are also widespread social influences that are not as easily detectable and that generally don't even enter into conscious awareness affecting the way we speak, the way we move and behave, and even the way we think about and remember the world around us. In illuminating these effects, and suggesting the possible mechanisms behind them, scientists have revealed an interesting twist to how fluid and dynamic is our sense of 'self'.

The study of how individuals fit within a larger social context is not new, or even modern. Aristotle wrote about *koinonía*, which can be translated to meaning community or joint participation, and with regards to the Aristotelian literature, is the communal striving for the "common good" that can be achieved through participation in community (and, specifically, through citizenship in a political state or *polis*; see Shields, 2015). Rousseau writes about the collective or general will (*volonté generale*) in the context of political statehood, as well:

> As long as several men in assembly regard themselves as a single body, they have only a single will which is concerned with their common preservation and general well-being. (Rousseau, 2009, p.48)

Modern literature has focused on describing the social group as a unit of analysis unto itself. Searle (1990) invites readers to consider individuals in a park who, once it starts raining, all run towards a shelter. In another scenario, a group of dancers in a park converge towards a common location as part of their dance routine. Both situations include groups of people who, on individual levels, are engaged in the same action of converging towards a central location. Only in the dance troop scenario, however, does it make sense to think of a group level action that is somehow collective and shared by its participants. Bratman (as cited in Roth, 2011) has suggested that shared agency on the group-level requires that each individual have the intention of doing some action together and, further, that there is consistency in their intentions. Gilbert (as cited in Roth, 2011) goes further in requiring an explicitly expressed commitment to this joint action, in order for it to be considered shared intention. While this theoretical foundation is helpful in describing collective behavior in some domains, it is unclear what it means for others. For example, explicit agreement about a shared goal, and the roles that must be played in order to achieve said goal, would be important in the context of group decision-making or teamwork. This might suggest, however, that in the absence of intention to behave collectively, we behave independently. From an empirical perspective, a hypothesis might be that individuals studied in isolation are similar to individuals in the context of other people, but without the intention of interacting with them.

However, in *Radical Embodied Cognitive Science*, Chemero describes the increasingly popular perspective that the individual should be treated as a system that is deeply embedded and distributed within its context (environmental or social). Consistent with Chemero's approach, this dissertation reviews and adds to the growing number of studies suggesting that others can influence our own cognitive behaviors in important ways. As a testbed, I consider the cognitive faculty of memory–how processes of remembering and thinking can behave as extended dynamic, self-organizing systems. The introduction will provide a substantial review of the literature which motivated the dissertation work. First, collective cognition is explored in three sections: linguistic alignment, motor coordination and synchronization, and finally collaborative remembering (Sections 1.1 and 1.2). Next, because collaborative remembering is the focus of the experimental work discussed in the remainder of the dissertation, I review the literature on memory as a cognitive process. Here, I also introduce the idea that remembering is a special case of a more general search process, which is a fundamental aspect of human cognition and can be likened to animal foraging. Here, I will spend some time exploring memory and information search as a dynamic process that unfolds over time, and is context dependent (for example, Kerster, Kello, Rhodes, & Bien-Aime, 2013).

Following this review of background literature, each chapter will describe a study investigating memory and information search in both individuals and collaborators using variations of two different tasks requiring participants to access and integrate their unique stores of existing knowledge. One task was the semantic fluency task (adapted from Rhodes & Turvey, 2007), in which participants were required to name as many items from a given category as possible. This was performed with different types of categories: animals or cities and towns in California. The cities study is allows us to integrate memory and information search with animal and spatial foraging, while the animals study allows us contextualize findings within the context of the existing literature on memory and recall. Another (slightly) more naturalistic task required individuals and dyads to come up with the correct answers to trivia questions, and to recall those answers later on. We performed this study using dyads composed of both strangers and friends, and explored how familiarity modulated collaborative memory processes. The results of these initial empirical investigations have been mixed. Sometimes a dyad works well (as compared to theoretical nominal combinations of the individuals composing the dyad), but sometimes a dyad performs worse than either of the individuals would have been expected to, if working alone. Analysis of the results suggests that quantity and/or quality of interaction may play a modulating role in whether the dyadic network succeeds or fails in optimal information sharing. Next, a computational model is built to simulate foraging on the individual and collaborative levels, and to explore some of the parameters that may modulate the role of interaction. Preliminary simulations and results of this model are provided in Chapter 6. Each of the empirical projects (described in Chapters 2 through 5) has been presented at a conference, and has been published as a stand-alone refereed article. Thus, the projects are reproduced here with only minor changes, and those required for formatting and consistency.

Finally, the discussion will suggest extensions of this work, as well as its theoretical implications.

1.1 Background: Collective Cognition

The first part of this section (1.1.1) uses work from linguistics and behavioral science to show how our speech is influenced by others. The speed of our talking, our accents, our choices of words and grammatical structures, and even our interpretations of word or semantic meanings can be influenced by conversational partners. Most research points out that as we speak to others, we become more and more “linguistically entrained” with our conversational partners–meaning that we begin to speak more and more like each other. However, it is easy to imagine the other end of the spectrum: if we begin to speak too much like each other, we will begin saying the same thing in the same way and no longer convey any interesting information. The concept of a dialogue has the built-in assumption that there are two different entities exchanging some type of information (however meaningful or informative that information may be). The conversational analysis literature demonstrates how linguistic features are continuously changing throughout a conversation, though, balancing entrainment and uniqueness.

Next, Section 1.1.2 considers the implications for linguistic entrainment on other behaviors. Specifically, the models accounting for this entrainment need not stop at the level of linguistics–why not apply them to the entire concept of cognition and, for example, our motor behaviors? Behavioral researchers have discovered a wide class of motor behaviors that become unconsciously synchronized between people as they interact. It is noted, however, that there is also a kind of synchronous de-synchronization where people adopt complementary, rather than identical, motions. Similar to findings from the linguistics domain, then, the deep influence of social context on our behaviors is shown to fall on a spectrum from convergent behaviors (imitating, or acting similarly) to divergent behaviors (acting differently but complementarily).

In the next Section (1.1.3) we come back to the notion of self-constructs by describing how something as personal as memory can be influenced by others. Who we are can be thought of as the bundle of memories and experiences that make up who we are and what we know, and it has been shown that our memories have a powerful effect on our physical perceptions of the present (Gregory, 1998) and our expectations for the future (Sharot, Riccardi, Raio, & Phelps, 2007). Remembering, unlike speaking or moving as described previously, has a very internal feeling to it. It feels very personal, as if what you are remembering in your mind is somehow *yours*, and makes up who you are. However, increasing evidence suggests that memories, like other behaviors, can be deeply influenced by others. The popular work of Elizabeth Loftus (1996), for example, shows that our memories can be very easily manipulated, a fact which requires us to think very critically about the role of eyewitness testimony in the criminal justice system. The idea of a “group mind” extends back to Rousseau and Hegel, and describes the phenomena in which people begin to think as one unit, losing track of their own individual ideas (Wegner, 1987). So, is there another end to this spectrum, where people begin to think in complementary rather than identical ways? Some research suggests that this is, in fact, the case. If we were to better understand the way our memories and thoughts can be influenced by others, and when this influence is helpful and when it is not, applications could be extended from the criminal justice system to benefit a range of problem-solving and more common tasks (applications are discussed in the discussion).

1.1.1 Talking Together

This section will present the background of lexical and linguistic entrainment research. It demonstrates that social context plays a role not only in the words we use in referring expressions, but also in grammatical choice and even situation models. Models are presented that account for the increasingly convergent linguistic behaviors between interlocutors, while ideas from conversational corpus analysis show that conversations are continuously changing over time, so we can't (and shouldn't) fully converge.

Lexical Entrainment

An intuitive understanding of conversation is that we use it to transmit some kind of information from one party to another. One party, whether an individual, a group, or otherwise, is the sender of information while another party is the receiver. It has been recognized for quite some time that these communicative episodes are interactive, in the sense that a sender's choice of words depends in some ways on the information receiver. For example, when trying to get a sender to correctly identify an object amongst distracters, a *referring expression* must be constructed that will allow the receiver to distinguish the target object from the others. Brennan and Clark (1996) discuss three factors that were originally considered to influence a speaker's choice of referring expression: *informativeness*, *lexical availability*, and *perceptual salience.* Informativeness is demonstrated by the influential philosopher of language H.P. Grice, in his Maxim of Quantity, which proposes that speakers will choose referring expressions that are informative enough to make the target object unique amongst alternatives, but no more so Grice (1975). For example, a brown loafer might be referred to as a "brown loafer" in a set of other loafers, a "loafer" in a set of other shoes, or just a "shoe" in a set of household objects (from Brennan & Clark, 1996). Lexical availability can sometimes override informativeness, though, such as when a more available basic-level noun such as "dog" is used to distinguish from alternatives including a bicycle and a hammer (Cruse, 1977). According to Grice's Maxim of Quantity, "animal" would have been the most minimally informative category. Still, perceptual salience can also override Grice's Maxim of Quantity, such as when highly salient features (even if not informationally useful) are used, such as "little black dog" in the example above (Brennan & Clark, 1996).

Brennan and Clark (1996) pointed out that these three factors do not account for observed strategic choices in referring expressions. They argue that a strategy also (and perhaps more importantly) involves consideration of previous and future communications with the particular partner in what they call a "historical model". That is, as a dyad talks about a novel object, the referential expressions they use will become increasingly similar as they agree upon how to describe the object (becoming "lexically entrained", as coined by Garrod & Anderson, 1987. Even if the agreed-upon expression isn't the most informative, accessible, or salient as predicted by the factors in ahistorical models, it increases simplicity and efficiency in dyadic communication over time. Brennan and Clark talk about four main factors that distinguish their historical account from ahistorical accounts: *recency*, *frequency of use*, *provisionality*, and *partner specificity.* People are more likely to use the same expressions they used most recently. The overall amount of times each expression has been used (even if not used most recently) will also play a role in determining which expression is chosen. Recency and frequency alone still don't explain the observed adaption of expression-choice over time, however. Provisionality refers to the fact that utterances are provisional suggestions for how to reference an object, and will be modified over time as the dyad comes to an agreement or as contexts change. Partner specificity suggests that referential utterances are established for particular dyads, and new partners will need to re-establish which utterances they will use together.

Brennan and Clark's historical model shows that conversational dyads engage in conceptual pacts, or temporary agreements about how they will conceptualize and refer to objects. This results in *lexical entrainment*, or the repeated use of a particular phrase by a particular dyad over time. Using the historical account, Brennan and Clark provided compelling evidence that speakers become lexically entrained and showed that the social interactivity of communication plays a strong role in determining the nature of that communication. While social influence had been noted previously, this demonstrated the inextricability of social context from lexical studies.

Linguistic Entrainment at Higher Levels

Pickering and Garrod (2004) build upon these ideas with their *interactive alignment model*, describing how interlocutor entrainment happens automatically at many levels–not just lexical choice. Even at lower levels, speakers become aligned at a phonological level. For example, as a speaker repeats a certain expression within a dyadic interaction, the articulation of the expression becomes shortened (Fowler & Housum, 1987). Bard et al. (2000) replicated this finding, and then switched the listener-speaker roles. The previous listeners, during their first time speaking, matched the shortened articulation they had just heard. Accent and speech rate have also been shown to become aligned in dyadic interlocutions (Giles & Powesland, 1975; Giles, Coupland, & Coupland, 1991). At higher levels, the syntactic structures used by speakers during an interaction can become aligned (Branigan, Pickering, & Cleland, 2000), as people are more likely to use a syntactic structure they recently heard. Reusing syntactic structures has been shown to facilitate the semantic understanding of sentences. Sheldon (1974) demonstrated that sentences are easier to understand if repeated noun clauses have the same function in their respective clauses, while Smyth (1994) showed that syntactic alignment facilitated the resolution of ambiguous pronouns. Thus, alignment at the syntactic level seems to enhance semantic alignment–or having the same understanding of features of the conversation which, perhaps, could enhance global understanding of the conversation.

Zwaan and Radvansky (1998) describe situation models as representing this overall conversational understanding. Situation models are commonly seen as the height of full understanding between interlocutors, and are described (by Zwaan & Radvansky, 1998) as multidimensional representations of the situation being discussed (containing the key dimensions of space, time, causality, intentionality, and references to subjects). Thus, Pickering and Garrod (2004) identify a key goal of successful communications to be rough alignment of situation models, which can be roughly equated to a deeper level of understanding. Importantly, they posit that there is strong interconnectivity between levels, so as lower-level joint priming between interlocutors causes alignment at lower levels, this alignment "percolates" up to higher levels:

> In this case, hearing an utterance that activates a particular aspect of a situation model will make it more likely that the person will use an utterance consistent with that aspect of the model. This process is essentially resource-free and automatic. (Pickering & Garrod, 2004, p.5)

This means that interlocutors do not need to constantly update models at multiple levels. Instead, in naturalistic conversation, speakers are constantly priming each other at multiple levels, leading effortlessly to the "global" alignment of their linguistic comprehension and production representations. Figure 4.1, from Pickering and Garrod (2004), shows a schematic representation of these levels and their proposed interactions during a dyadic conversation. Beginning with the long-accepted evidence that features

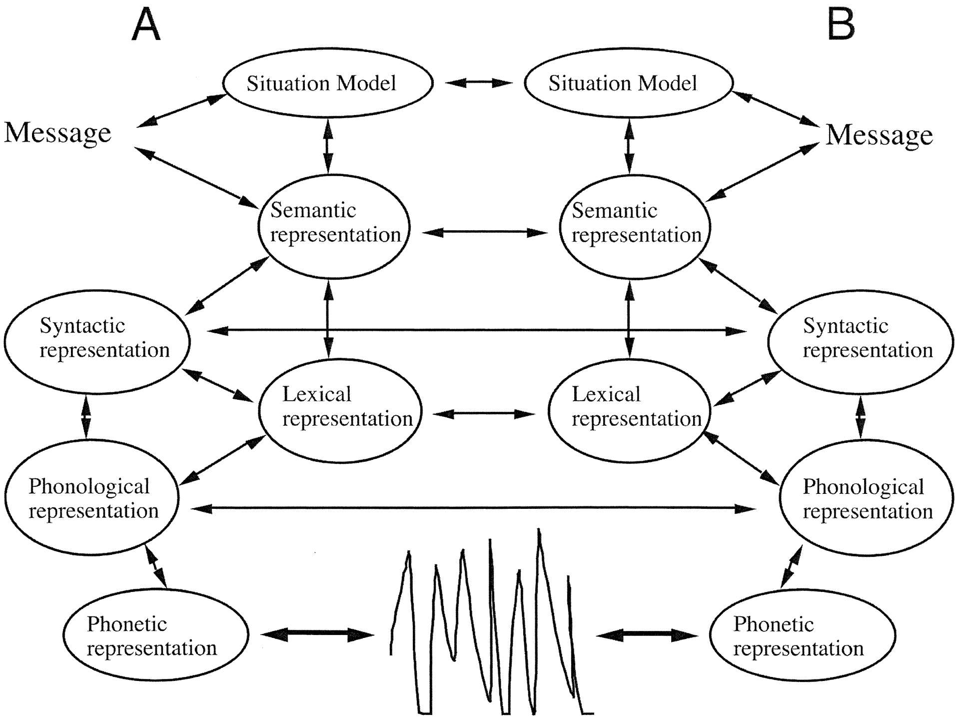

Figure 1.1: Pickering and Garrod's 2004 interactive alignment model of conversation. A and B represent two speakers engaged in dialogue, with schematic representations of their respective levels of language comprehension and production.

of verbal speech can be primed, the research described here shows that this priming is hardly an innocuous by-product, but rather a key mechanism of verbal communication whereby alignment can be achieved at a higher, "cognitive" level. Evidence from neural imaging studies supports the finding that speaker and listener become aligned at many levels. Stephens, Silbert, and Hasson (2010) used fMRI scanners to capture the brain activities of two people engaging in natural conversation. They found that the speaker's brain activity is spatially and temporally correlated with the listener's brain activity, and that the degree of these correlations reflects the amount of understanding. Thus, the alignment created in conversation is reflected by the alignment of brain activities.

Conversation Analysis

In the conversational and corpus analysis, the repetition of words, phrases, or structures is referred to as *persistence*. *Syntactic persistence* is defined in Jaeger and Snider (2007, p.27) as "the tendency for speakers to repeat a syntactic structure that they have processed previously". They contrast Pickering and Garrod's (2004) account with what they call an "implicit learning" account. While Pickering and Garrod's account assumes that persistence (or, entrainment) happens through a priming mechanism where the processing of a certain structure will cause transient activation facilitating the use of that structure in subsequent production, the implicit learning account (suggested by Bock & Griffin, 2000) relies on learning about the probabilistic distributions of different syntactic structures across conversations. The assumption here is that an implicit learning system allows listeners to have weighted access to several of the syntactic structures heard previously–so it is not always the most *recent* structure that is most likely to be used. Rather, speakers may be primed to use different structures in different contexts.

The idea of context-based priming is also shown by corpus-based investigations. While confirming findings from psycholinguistic experiments that speakers can become syntactically entrained, Gries (2005) used corpus analysis to measure the effect of primes in different sentences. He showed that primes can be verb-specific. That is, the syntactic structure of sentences using some verbs can be quite easily primed, while sentences with other verbs seem to be resilient to priming, having a “particular construction that overrides the prime structure,” (Gries, 2005, p.369). The idea of these “particular construction(s)” is compatible with the implicit learning account, as these priming-resilient verbs could have associated sentence-structure probability distributions from earlier in the conversation(s) that favor other structures.

While interlocutors’ speech may not always become increasingly similar, as would be predicted by a strict interpretation of the interactive alignment model, it is not wholly incompatible with the previously mentioned research. Brennan and Clark’s historic account (1996) for lexical entrainment identifies provisionality as a parameter: throughout a conversation, a referring expression can be modified as contexts change. Provisionality could, theoretically, be added as an additional parameter to the interactive alignment model, modulating the effects of certain words, structures, or syntaxes given different contexts.

Another implication of provisionality is that as a phrase is used over and over, it may become shorter. For example, my use of the referent “Powell’s famously enormous bookstore in Portland, Oregon” might become “Powell’s”, “the bookstore” or even “it”, had I continued to discuss... it. This is consistent with the given-new theory (see Prince, 1981) in linguistics which describes how a speaker constructs sentences by considering what a listener knows or could predict. Once something is known, either through common knowledge or because it has been discussed previously, it is classified as “given”. The given-new theory explains that sentences are constructed by building new information onto the given information. New sentences need to be detailed, but once we know about the subject (say, Powell’s bookstore) it is a given, so we can begin referring to it in less detailed ways or with pronouns (for example: “*it* is a large store”). Each new phrase should add something new to the given information. From this perspective, conversations are continually evolving as new information is continually added. If too much new information is added, without building upon given information, the listener is likely to become confused and the conversation wouldn’t go anywhere. On the other hand, if interlocutors were to become fully aligned, conversation would become pointlessly repetitive and unnecessary. A delicate balance, it seems, must be struck between the convergence and divergence of linguistic properties in order for a conversation to be successful.

In sociolinguistics, Howard Giles developed the *communication accommodation theory* (CAT) that describes a similar optimal balance between convergence and divergence in communicating dyads (see Giles & Olgay, 2006). CAT considers the majority of the linguistic accommodation literature, as described above, to be examples of convergence. In CAT, however, this is a goal-driven process whereby we accommodate with the intention of increasing social bonding or affiliation, whether consciously or not. CAT points out that sometimes we try to create social distance, however, by exaggerating or highlighting our linguistic uniquenesses (this would be an example of divergence). For example, Giles and Olgay (2006) describe a study which analyzed convergence and divergence between Larry King and the guests on his talk show. The researchers found that

King changed the pitch of his voice according to his guest's status. With a higher-status interviewee such as President Clinton, he accommodated his vocal pitch to Clinton's, but the lower-status interviewees (such as Vice-President Quayle) accommodated more to King than he did to them. In this way, Giles points out, we use convergence and divergence to signal social status, in-group/out-group identity, and feelings of closeness.

As a whole, research on the social influences of conversation shows that we generally adapt in a convergent manner to make ourselves speak more similarly to others. It is likely that this convergence functions to increase our understanding of each other and aide in success of the communication. However, complete convergence would cause our communication to lose its information-transmitting value, and would also cause us to lose our personal uniquenesses. Thus, the self seems to orient itself quite closely to the other, but maintains some sense of 'self- ness'.

1.1.2 Moving Together

A great deal of communication is non-verbal. Gestures, nods and glances can all have informative meanings. Many of our interactions with others, however, are not intended to convey information at all. In many cases, we interact with others as we go about our daily activities, working with or around each other. For example: when pedestrians weave between each other on crowded streets, when roommates carry a refrigerator up a staircase, or when dancers twirl across a dance floor. Words may be exchanged, but in large part these interactions utilize non-verbal cues. Sebanz, Bekkering, and Knoblich refer to this as *joint action*, which they define as "any form of social interaction whereby two or more individuals coordinate their actions in space and time to bring about a change in the environment" (Sebanz et al., 2006, p.70). Although simple joint actions seem to come so naturally, even the simplest of joint actions (carrying something together) still requires the non-trivial coordination of bodies and minds (Allport, 1924). This section presents basic work describing joint action, as well as models from philosophy that describe the integration of joint action with the previously described work on linguistic entrainment. These philosophical contributions also suggest that joint action could have a divergent component as well.

Joint Action

Sebanz et al. (2006) propose that coordinating for successful joint action depends on three abilities: (1) the sharing of representations, attention, or perceptions, (2) being able to understand and predict others' actions and action-goals, and (3) integrating the effects of self- and other-action. The target of attention can be indicated through cues such as gaze, pointing, or postures, and dyads can use this shared attention as the basis of shared object and event representations (D. Tollefsen, 2005), and as cues about action goals (Bayliss & Tipper, 2005). Similar to the priming effect seen in the linguistic domain, when we observe someone performing an action, our own motor system engages in some representation of the action (reviewed in Rizzolatti & Craighero, 2004), facilitating our understanding of the action and its goals (Kilner, Vergas, Duval, Blakemore, & Sirigu, 2004, for example). Evidence for the third ability, predicting the effects of integrated self- and other-action, is given by Richardson and colleagues' (see Marsh, Richardson, Baron, & Schmidt, 2006; Isenhower, Marsh, Carello, Baron, & Richardson, 2005) work showing that actors consider the affordances of other actors when planning their own actions in collaborative contexts. That is, when acting as a group, group members perceive the environment according to the resources and abilities of the group as a whole, rather than themselves individually. Taken as a whole, Sebanz and colleagues' theory is representative of a body of philosophical work amounting to the idea that the sharing of higher-level, motivational, and intentional states is necessary for successful joint action.

Recent empirical work in cognitive science, however, increasingly shows that lower- level motor constraints and higher-level cognitions and goals are deeply interconnected, and should not be considered in isolation. In *Continuity of Mind*, Spivey (2007) approaches cognition as a continuous process–continuous with respect to levels of cognition, but also continuous with respect to cognition and action. That is, cognition flows continuously into action, and action flows continuously back into cognition. In a series of influential experiments using computer mouse tracking, Spivey and colleagues have shown that the dynamic unfolding of cognition is represented in motor actions. When subjects evaluate fuzzy statements, their arm movement trajectories (which are used to report their decisions), reveal the uncertainty of the ongoing decision process (McKinstry, Dale, & Spivey, 2008; Dale, Kehoe, & Spivey, 2007; Spivey, Grosjean, & Knoblich, 2005). In addition to cognition effecting action, empirical work also demonstrates that the actions themselves can effect the underlying cognitions. In an oft-cited study by Strack, Martin, and Stepper (1988), it is shown that manipulation of the facial muscles to create a false smile (by asking participants to hold a pencil between their teeth) actually makes participants feel happier. Other work has shown that manipulating the way a person moves (causing them to move in more or less stereotyped fashions) effects the person's perception of others (perceiving more or less stereotyped features in the other; Mussweiler, 2006; see Rueschemeyer, Lindemann, Elk, & Bekkering, 2009 for review). Thus, cognition can be said to "smoothly flow" (D. P. Tollefsen & Dale, 2012, p.392) into action, while action continuously feeds back to influence cognition.

Integrating Top-Down and Bottom-Up Accounts: The Dynamic Account

This coupled cognition-action system is the basis of Tollefsen and Dale's (2012) *process-based model* of joint action. They present the verbal communication described by Pickering and Garrod's (2004) interactive alignment model as a special case of joint action. In fact, the effects of natural conversation can influence more than situation models, and can influence motor action as well. Shockley and colleagues showed that during natural conversation, interlocuters subtly align body postures (Shockley, Santana, & Fowler, 2003), and this might be caused by subtle matching of verbal cues during the conversation itself (Shockley, Baker, Richardson, & Fowler, 2007). In fact, individuals interacting through conversation, problem solving, or joint-action exhibit a range of coordinated, aligned behaviors including speech patterns and bodily movements (as described above) and even eye movements (D. C. Richardson & Dale, 2005). Tollefsen and Dale's (2012) process-based model extends the interactive alignment model of linguistics to account for philosophical ideas of intentionality, and empirical accounts of domain-general priming. They propose a framework in which *surface synchrony* (low-level effects such as priming) and *deep commitment* (high-level intentions) can differentially initiate or sustain the process of joint action in a general sense. Figure 5.1 illustrates the schematics of this process-based account.

By this account, the boundaries between levels of cognitive activity within an individual, which were originally treated as functionally independent modules, can be dissolved: high-level goals and opinions can be influenced by low-level actions, and vice versa. Further, our language, movement, and even our goals and opinions are actually deeply influenced by social context. Perhaps, then, the traditional boundaries between self and other can (to some extent) be dissolved as well.

Although much of the philosophical literature suggests that this coordination exists for the functional purpose of aligning cognitive representations, Shockley, Richardson, and Dale (2009) use the concept of *emergentism* to explore the idea that this co-

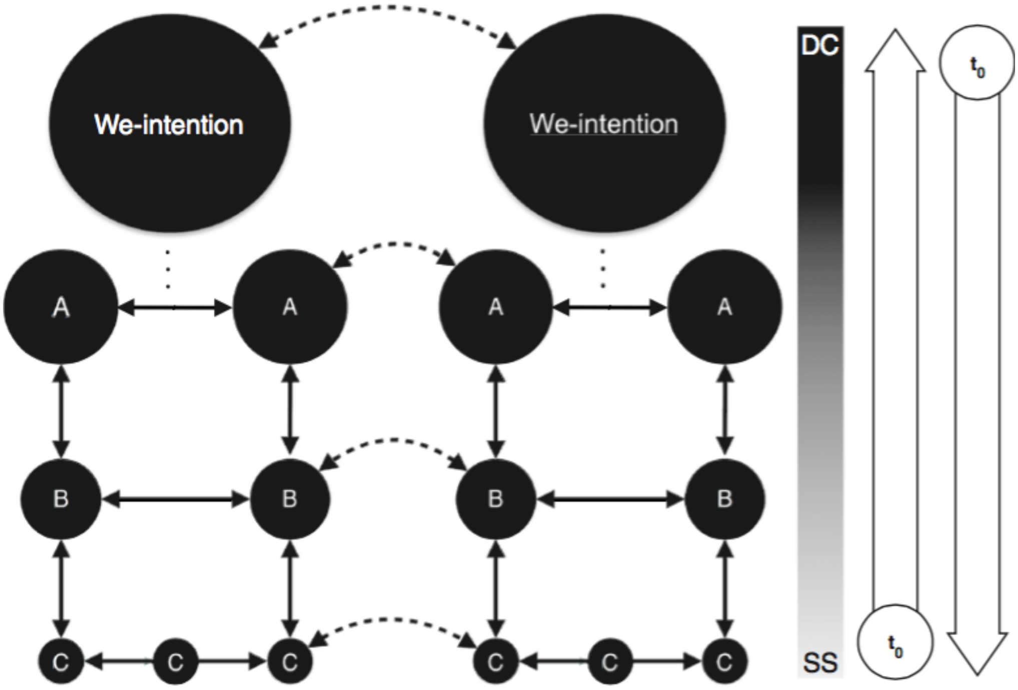

Figure 1.2: Tollefsen and Dale's 2012 process-based model of joint action. Here, the left and right sides represent two interacting individuals, while A, B, and C represent channels that can become aligned. For example, A might represent the linguistic level, B the attentional level, and C the perceptuo-motor level. Levels are arranged in descending order from deep commitment (DC) to surface synchrony (SS).

ordination is a naturally emerging property of the cognitive system. Emergentism is based on general principles observed in physics, and the quintessential example of this principle is in Kelso's (1995) book, in which he describes the movement of molecules in a fluid. Originally the molecules move randomly, but as heat is added to the system warmer molecules rise to the surface and cooler surface molecules sink, and soon characteristic "convection rolls" are exhibited, where the molecules swirl from top to bottom in a coordinated dance. Although the pattern becomes highly structured, there is no higher-level goal or intention of the system. Rather, the behavior emerges naturally from the local interactions and constraints of individual molecules in the dynamic system. Emergentism is a commonly used concept to describe the behavior of many dynamic systems in the fields of physics and biology. In philosophy, an emergent system is one in which high-level behavior and phenomena can't be completely understood from or explained by the system's lower-level behavior and phenomena. As such, it can be compared with reductionism–in which the high-level behavior of the system can be reduced into the behavior of its lower-level components. Standish (2001) notes that some tests of emergence ask if the macro-level behavior is surprising, given knowledge about the micro-level specifications.

Shockley and colleagues (2009) propose using the dynamic perspective to account for the emergence of coordination in human cognitions and behavios as well, rather than treating them as a unique case. By their account, the entrainment, alignment, synchrony, and coordination observed both within and between individuals are examples of a larger class of phenomena exhibiting *coordinative structure*, or a self-organized, softly assembled best of component parts that temporarily couple together and form a single functional unit (Bernstein, 1967). Such a system is highly versatile, as the component parts can fit together in a variety of different ways (and fulfill different functional roles), causing different behavior to be exhibited.

This dynamic account could explain why joint actions sometimes take a more divergent route. That is, sometimes people don't imitate each others' actions exactly, but instead figure out and execute a complementary action (Sebanz et al., 2006). For example, dance partners must often employ complementary but very similar moves, and when successful they appear to be a single functional unit. Sebanz and colleagues describe a scenario in which someone (actor A) observes a friend (actor B) dragging a large table with his hands behind his back. A purely bottom-up, priming-type model would hypothesize that B imitates A's motion exactly, but then the pair would be dragging the table in opposite directions. Instead, the appropriate way for B to help would be to recognize that A is only holding the table in such an awkward fashion so that he can avoid obstacles, but B himself can grasp it with hands in front. Figure 4.3 illustrates these alternatives. Sebanz and colleagues used this example to illustrate the importance of shared goals in joint action, but it is also consistent with the broader idea that individuals can become coupled components of a unified system. In this system, the components are versatile and able to move identically (convergence) or complementarily (divergence) depending on context.

1.1.3 Remembering Together

If, as we have shown in the previous two sections, multiple interacting individuals can jointly influence each other and create a unified linguistic or motor-action system, can the individuals become coupled to perform cognitive tasks such as remembering or problem-solving together? Tollefsen and Dale (2013) review relevant research and use the term *alignment system* to describe the self-organizing, soft-assembling components of cognitive systems that come toether to perform tasks such as those described above. They propose that this generic alignment system can also be extended to the domain

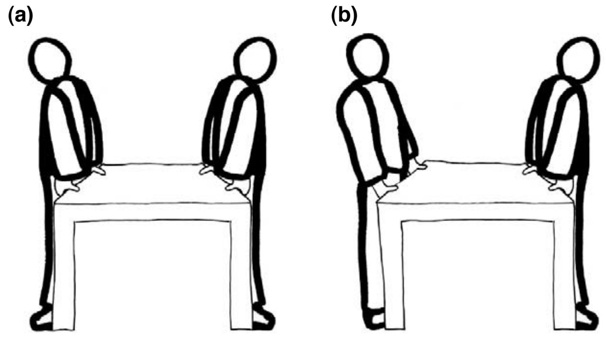

Figure 1.3: (a) Two people both grasping the table behind their backs; (b) complementary actions in which only one person grasps the table behind the back, the other grasps it in front (from Sebanz et al., 2006, illustration by Ellie Langenhuizen).

of memory research, and show how it can explain findings that social context effects memory. These findings fall into two major categories of effects: (1) *collaborative recall*, where others are treated as environmental context and can help prime or cue remembering, and (2) *transactive memory*, where individuals together form a single, coupled memory system.

Collaborative Recall

In collaborative recall studies, participants often study a set of stimuli (typically words) and are subsequently asked to recall the set either alone, or with a partner who studied the same things. Sometimes, participants are also given a second recall test, this time always alone, to look for effects of recalling together. Results suggest that collaborative groups recall more of the study than individuals (see Barnier, Sutton, Harris, & Wilson, 2008; D. Tollefsen et al., 2013), suggesting that working collaboratively enhances remembering. However, when results from a two-person group are compared with results from a nominal group, which is composed by adding the non-overlapping items recalled by two participants recalling individually, the collaborative-recall group actually does worse. This deficitt is known as *collaborative inhibition.* Collaborative recall is not all bad, though, and in subsequent really tests, individuals who previously recalled collaboratively remember more words than those who recalled individually (because they additionally remember the words introduced by their collaborators; Basden, Basden, & Henry, 2000).

To explain the collaborative inhibition effect, Basden and colleagues (1997) refer to the phenomena of part-list cuing inhibition, in which providing a partial-list of the stimuli to be remembered causes subjects to actually remember less than if they were to remember without the partial list. Although counter-intuitive, providing the partial list inhibits performance because it disrupts participants' natural recall strategies, distracting their focus and causing a restructuring of the strategies around the partial list. In collaborative recall contexts, then, each collaborator provides a partial-list that inhibits the recall of the other. However, there may be more going on in collaborative inhibition than accounted for in Basden and colleagues' explanation. D. Tollefsen et al. (2013) point out that collaborative recall, at least insomuch as it involves conversation, might be influenced by alignment at the linguistic level.

As discussed, social interaction facilitates alignment on multiple levels. Since memory requires the successful encoding, storage, and retrieval of information, a disruption in the retrieval strategy could prevent successful recall (such as in Basden and colleagues' partial-list cuing explanation). If surface-level synchrony gives rise to aligned, temporarily coupled systems acting as one, it would follow that as a dyad aligns their individual recall systems or strategies towards each other, they would not be able to access their individually-encoded memories as well. This theory, put forth in D. Tollefsen et al. (2013), integrates memory with the growing body of alignment literature and provides a more ecologically robust explanation than partial-list cuing alone. Collaborative recall effects are exhibited when multiple individuals become coupled during the retrieval phase of memory. Transactive memory, on the other hand, describes the coupling of entire memory systems, from encoding, to storage, to retrieval.

Transactive Memory

The concept of shared or collaborative memories is not a new one. As far back as the 19th century, philosophers and behavioral scientists considered groups as having "sentience" in the same way as individuals, but that view has since fallen out of favor (Wegner, 1987). The concept of transactive memory was first introduced by Wegner's 1987 writing, which also gives a historical account of research in memory and group mind. Memories, he notes, are connected concepts–such as the concept "tomato" with the concept "red". The connections are formed through encoding, and retrieval of a concept can be done by calling one or more of its connected concepts. Wegner points out, though, that although traditional memory research has focused on memories stored in an individual, a great deal of our memories are stored externally (books, to-do lists, smart phones). When information is outsourced in this way, we only need to remember the location of the item and what the item is, but not the entirety of the content (for example, remembering that a grocery list is posted on the fridge, or that my mom's phone number is accessed through speed-dial number one).

Further, other individuals could just as easily be our external memories: if my mother is a doctor I may consult her to ask about allergy treatments, but I would rely on my father (an auto-mechanic) to suggest the best kind of oil for my car. Both, however, would come to me for expert advice on how to use Facebook. In this way, a family can form a transactive memory system: a group of individuals whose memories are coupled such that each has access to all information simply by knowing what the others know. In these systems, information is generally "stored" by a person who is considered to be an expert in that domain, and it can be retrieved by asking that person.

Just as in individual memory systems, when multiple people form a transactive memory system there can be errors in encoding, storage, and recall. Wegner reviews literature on how and when transactive memory systems can be either advantageous or disadvantageous. When people are knowledgeable about who knows and is responsible for which information, such as in an intimate relationship, the system is generally quite successful–but it can go wrong when people don't know where the information is stored, or who should be responsible for storing what. Modern research confirms this idea, showing that collaborators with more familiarity are better at transactive memory tasks than non-familiar groups (Barnier et al., 2008).

Collective recall studies typically exemplify the ways in which our memories become more similar to the memories of others, demonstrating convergence. Transactive memory studies, on the other hand, show that social adaptation can take the form of complementary memory strategies, as the storage responsibilities are divvied up between people in the system (demonstrating divergence). Regardless of the convergent or divergent results, both approaches share the perspective that the individual should be studied as a component of a softly assembled system. This approach persists whether that system consists of an individual or a network of interacting individuals, since even the individuals are inextricably interconnected with the environment. Whether the environmental context is social at any given moment is only a parameter of the system. The nature of the system, though, is that we play deep and meaningful roles in the lives of the people around us–whether or not we realize or intend for it to be so.

1.2 Background: Search Processes

Although complex decision making is often thought of as a highly cognitive and special ability unique to intelligent beings, it might be related, on a more basic level, to search behavior strategies. In fact, an argument by Mobus (1999) proposes that advanced cognition might have evolved from mechanisms originally adapted by animals for searching for food. Mobus theorizes that in order for our early animal ancestors to survive, they needed to evolve strategies for finding physical resources even when those resources are sparsely distributed and dynamic in the environment. Over time, the mechanisms used for foraging in the physical world were generalized to foraging in a conceptual landscape.

Search strategies have been studied much more extensively in the domain of animal movement, and a picture has emerged suggesting that search behaviors are surprisingly ubiquitous across species, spatial and temporal scales, and even different types of search. This section begins with a review of key concepts for the statistical quantification of search processes (1.2.1), then discusses relevant findings from the ecological domain of animal foraging which have been applied to investigations of human behavior (1.2.2). Next, we discuss how these findings might relate to what we consider more advanced forms of cognition, such as human memory and cognitive search (1.2.3).

1.2.1 Studying Foraging

Moving is an important part of life for (most) living creatures. On basic levels, we move to gather resources and food, to find shelter, to find mates, and to avoid danger. We also move about when searching for car keys, a missing pet, or even missing children. If there are statistics and patterns that can describe these searches, they can be exploited to help understand movement trajectories. Researchers have determined that there are different types of search patterns, which can each be described statistically.

Descriptive Statistics of Movement

Physicists have long described the movement of energies through different mediums using the concept of diffusion. They have also used concepts of diffusion to describe the motion of particles. For example, consider dropping food coloring into a glass of water. At first the momentum of the food coloring droplet may cause a visible trajectory as it swirls through the water, but soon it starts to diffuse: particles of food coloring move from areas of high concentration to areas of low concentration. Soon, the food coloring particles have fully diffused themselves in the water, so they are equally distributed amongst water particles. In the early 1990s, when physicists began working with ecologists to describe the movement of animals, they wondered if this basic rule of diffusion applied to animals as well.

It turned out that simple diffusion *sometimes*, and in *some* conditions will describe animal movement, but more often than not the empirical data showed that animals do *not* behave according to principles of standard diffusion (Viswanathan, da Luz, Raposo, & Stanley, 2011). In 1999, physicists proposed a theory that accounted for the non-standard, non-diffusion phenomena using statistical formalisms (Viswanathan et al., 1999; the *Lévy flight foraging hypothesis*, discussed shortly).

In its most simple form, biological motion can still be thought of as a diffusion process, but more accurately it is treated as a *reaction-diffusion* process. The diffusive component would be transportation, which may or may not be simple diffusion across a gradient, as in the food coloring example; the reaction component would be a type of interaction such as mating or eating. The diffusive component is linear, and typically does not include interaction between agents (animals or particles, for example). The reaction process does include interactions, and because of this it can lead to nonlinear phenomena. Reaction-diffusion models for two interacting species, such as a predator and a prey species, accurately describe many ecological systems (Bartumeus, Catalan, Fulco, Lyra, & Viswanathan, 2002). But whether the predator is searching for prey or for a mate, or whether there is another kind of reaction component, reaction-diffusion models predict that the diffusive component remains the same. The study of *just* this diffusive component, this movement behavior, can thus be studied independently of the details of the reactive component.

In this body of research, the reactive component can be measured as encounter rates, or the number of times the reaction takes place–whether it be a mating, pollination, eating, or other interactive behavior. Because it is often important to encounter food and mates, or even to avoid predators, the encounter rate can be very important for different reaction-diffusion models of animal movement, and is used as a measure of the effectiveness of a diffusive pattern.

Normal Diffusion. Important to understanding the most basic kind of diffusion, such as the one described above in the food coloring example, is the *central limit theorem.* The central limit theorem states that a large number of independent and identically distributed random variables will have a mean that is normally distributed–producing the bell-shaped curve well-known and central to probability. This bell-shaped probability distribution function is so pervasive it is called the "normal distribution", but is also referred to as the "Gaussian distribution". When a particle in a fluid solution is acted upon by a number of random, independent impulses, its displacement will have a normal probability density distribution. When a diffusion process is characterized by displacement following the Gaussian distribution, it can be called "normal diffusion". Viswanathan et al. (2011) uses the Langevin Equation followed by the Fokker-Planck Equation (and, separately, the Master Equation) to show that the moments of a Gaussian distribution do not grow independently, and instead grow linearly with each other. Thus, the finite mean of a Gaussian distribution will always have a finite variance, as well.

The most typical case of normal diffusion is a *random walk.* In a random walk, an animal's movement can be described as a sequence of steps (or paths, or jumps) each in a random direction. The length of each step is chosen randomly from a Gaussian distribution of step lengths. Over time, a single random walker will appear to diffuse throughout the environment, and a large group of random walkers will diffuse similarly to the particles that diffused in fluid systems described by Einstein (Einstein, 1905). As described in his work, this type of movement is also known as *Brownian motion.*

When non-randomness is added to the direction of motion, a *correlated random walk* (C-random walk) is generated. In C-random walks, the selection of angular direction for each subsequent step is correlated to the most recent angular direction. This creates directional persistence related to the strength of the correlation. If the correlation is sufficiently low, there will be angular momentum on a small scale, but on a large scale the effects of the correlation will disappear (and an angle will be chosen independently of its distant predecessor). Eventually, that means, the behavior of a short-range C-random walk system will converge on a normal distribution. If the correlation is long-range, though, the behavior of the walking system may never converge, as each walker would continue more or less in a given direction, or repeat the same pattern infinitely (an example of a long-range correlated system that does not converge to normal, for those who are familiar with it, is fractional Brownian motion; Viswanathan et al., 2011).

Anomalous Diffusion. Einstein's description of particles moving via Brownian motion (Einstein, 1905) represented the dominant view of statistical descriptions of movement for a long time. These Brownian movers had finite variances and were subject to the central limit theorem. In a (1937) publication, Paul Lévy extended the central limit theorem to account for distributions with infinite variances, or diverging second moments. Diverging second moments would be created when, for example, step lengths do *not* follow the normal distribution. Instead, they may be characterized by a distribution where short path lengths are common and probable, and arbitrarily long path lengths are rare, but possible.

Lévy showed that the normal distribution was in fact a special case of the *Lévy stable distribution*, which is the more general class of distributions having the property that two instances of random variables with a certain distribution, when added together, will have the same distribution (Watkins, n.d.-b). These distributions are described by four parameters: (1) the stability parameter α, (2) the skewedness parameter β, (3) the scale parameter υ, and (3) the measure of centrality, or mean, δ (Watkins, n.d.-a). A normal distribution is a special case in which $\alpha = 2$ and υ is a finite number, equivalent to the standard deviation. Two other special cases of Lévy stable distributions are the Cauchy distribution (in which $\alpha = 1$, $\beta = 0$), and what is commonly referred to simply as the "Lévy distribution" (in which $\alpha = 1/2$, $\beta = 0$; "Stable Distribution", n.d.).

With Lévy's finding that there is a more general class of distribution, it follows that there are other classes of diffusion. Diffusion that doesn't converge to normal in the long time range is called *anomalous* (Havlin & Benavraham, 1987). Anomalous diffusion can be either superdiffusive or subdiffusive. In the normal diffusion paradigm, an agent's mean squared displacement grows linearly with time. The mean squared displacement (x^2) over time (t) is scaled by the Hurst exponent (H), where $x^2 \sim t^{2H}$ (Barabási & Stanley, 1995; Hurst, Black, & Simaika, 1965). A Hurst exponent of 1/2 is usually consistent with normal diffusion. When $H < 1/2$, mean squared displacement grows sublinearly in time, corresponding to subdiffusion; When $H > 1/2$, mean squared displacement grows superlinearlarly in time, corresponding to superdiffusion (Sokolov, 63). To reiterate, the two reasons a system may fail to converge to a normal distribution are (1) if there are long-range memory (correlation) effects, or (2) if step lengths do not follow a normal distribution, and are instead distributed such that arbitrarily long step lengths are possible, even if rare (Viswanathan et al., 2011). This second condition refers to the Lévy distribution (as described above, the stable distribution where $\alpha = 1/2$, $\beta = 0$), which is the best-known example of a superdiffusive- generating distribution.

Lévy Flights

For the standard Brownian random walker, it is assumed that the walker's steps are only to neighboring sites in a limited range. For walkers with Lévy distributed path lengths, steps can be arbitrarily far away. It is this property that makes Lévy flights diffuse superlinearly in time. That is, they tend to travel much greater distances much more quickly than Brownian walkers.

A Lévy flight is produced when a random walker's step lengths are Lévy distributed, so that a step of length L is chosen with probability $P(L) \sim L^{-\mu}$. This is a power law relation, because L is raised to $-\mu$. This generates a probability distribution with an asymptotic power law tail described by $\mu = \alpha + 1$ (Viswanathan et al., 2011).

The μ parameter is a key determinant of the type of diffusion. Solving for α shows that $\mu > 3$ would mean $\alpha > 2$, which corresponds to the Brownian regime described by normal diffusion. If $\mu \leq 1$, α would be negative or zero, which does not correspond to any distribution that can be normalized. For this reason, $\mu = 1$ is considered the ballistic limit. The interesting case, here, is when μ falls in the intermediary range of $1 < \mu < 3$. Here, we get diverging variance and superduffusive Lévy flights (Viswanathan et al., 2011). As suggested earlier, very frequent small-magnitude movements, and increasingly rare, very-large-magnitude movements characterize Lévy distributions.

Lévy flights have been used to describe a diverse array of systems and phenomena. A list provided in Viswanathan et al. (2011) includes: “bulk mediated excursions, finance and economics, protein folding dynamics, kinematics of ions in optical lattices, cavity quantum electrodynamics, climate and atmospheric physics, anomalous spin relaxation, soft-mode turbulence, dispersive sedimentation, optics (e.g., the Lorentz line shape), photonic superdiffusion, random lasers (and materials through which photons execute a Lévy walk), metastability, knots, bioturbation, and anomalous diffusion of surfactants”. This list is impressive, but does the relevance of Lévy processes extend to biological movement on the organism scale? The pioneering paper “Lévy flight search patterns of wandering albatrosses,” by Viswanathan et al. (1996) in *Nature* provided compelling evidence that yes, Lévy flights can describe movement patterns of animals during naturalistic foraging. Unfortunately, in a notorious scientific “oops” moment, the authors realized that the super-long flight times that qualified their flying albatrosses as “Lévy foragers” were, in large part, due to spurious data points[1,2].

1.2.2 Empirical Evidence of Foraging

The first mention of Lévy flights being a theoretical possibility for describing animal movement was in a 1986 paper by Shlesinger and Klafter. In 1988, Levandowsky, Klafter, and White published the first empirical findings that supported superdiffusion in biological organisms, specifically zooplankton and protistan microzooplankton. As Viswanathan and colleagues were collecting data for their wandering albatross study, other researchers were also becoming interested in the possibility of anomalous diffusion in animal movement. In 1995, Cole showed that the activity and rest patterns of fruit flies have a fractal (scale-free) distribution, consistent with Lévy flights. In 1996, Schuster and Levandowsky found that even simple, single-celled amoebas exhibit superdiffusive movement (Levandowsky, White, & Schuster, 1997).

The wandering albatross study, however, was the first very large-scale study noting Lévy foraging behavior of an animal larger than a fruit fly. This finding represented a paradigm shift in the way researchers thought about animal movement: it required a more complex description than normal diffusion, or random walks, could provide. In a 1999 paper, Viswanathan et al. published what later became known as the *Lévy flight foraging hypothesis* to account for these findings, explaining how Lévy foraging might optimize encounter rates in certain conditions.

In the next decade, a number of studies provided empirical evidence for superdiffusion, suggesting that Lévy flights are ubiquitous in ecological foraging behavior.

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[1] Further analysis, however, did reveal that albatross flight patterns are consistent with *truncated* Lévy flights (Edwards et al., 2007).

[2] Over-reliance on Lévy as both a mechanistic and theoretical construct has been questioned as it gained in popularity over recent years. As two examples, the statistical identification of Lévy flights in empirical data using regression on log-log frequency plots, as it is often done, has come under scrutiny by Clauset, Shalizi, and Newman (2009). Next, it has been noted that other foraging processes might produce similar statistical distributions (see A. Reynolds, 2010). Still, I include this detailed description of Lévy distributions here as Lévy flights are a key inspiration in earlier projects, and mentioned several times in later projects.

To provide some examples, it was identified in microorganisms (Bartumeus, Peters, Pueyo, Marrase, & Catalan, 2003), butterflies (A. M. Reynolds, 2006), bumblebees (A. M. Reynolds et al., 2007), desert ants (A. M. Reynolds, 2008) and snails (Seuront, Duonchel, & Chapperon, 2007). Sims and colleagues (2008) identified Lévy flights in several marine mammals, and it was also identified in the behavior of jackals (Atkinson, Rhodes, Macdonald, & Anderson, 2002), spider monkeys (Boyer, Miramontes, Ramos-Fernández, Mateos, & Cocho, 2004), reindeer (Mårell, Ball, & Hofgaard, 2002), fallow deer (Focardi, Montanaro, & Pecchioli, 2009), and goats (Knegt, Hengeveld, Langevelde, Boer, & Kirkman, 2007).

Although modern human movement doesn't typically involve foraging, per se, superdiffusion has been identified in a number of human activities (but see González, Hidalgo, & Barabási, 2008). One interesting study tracked the movements of modern-day (but non-modernized) Dobe Ju/'hoansi hunter-gatherer tribesmen as they moved between temporary residence camps during the rainy season (Brown, Liebovitch, & Glendon, 2007). Dobe Ju/'hoansi live in the Kalahari Desert, in present-day Botswana (or at least they did, until they were recently relocated), and during the dry season they live near the permanent water source provided by the Dobe waterhole. During the rainy seasons, though, the tribe breaks into smaller groups that each go their own way, setting up temporary camps until local resources are depleted (which can take a few days or even a few weeks). Brown and colleagues showed that the distances between temporary camps are power law distributed with $\mu = 1.97$, and the amount of time spent at each camp is also power law distributed, with $\mu = 1.45$, providing evidence of Lévy distributions in the behavior of these non-modernized humans. Studies of modern fisherman have also found evidence of Lévy processes in human behavior. When foraging for their fish, Peruvian purse seiners, and North Sea Dutch and French fishing vessels have been found to follow Lévy flights (Bertrand, Burgos, Gerlotto, & Atiquipa, 2005; Bertrand, Bertrand, Vuevara-Carrasco, & Gerlotto, 2007; and Marchal, Poos, & Quirijns, 2007, respectively). Brockmann (2008) used dollar bills as a proxy for studying human movement, finding that the bank notes travel with power law distributed path distances ($\mu = 1.59$).

1.2.3 Memory: Cognitive Foraging

In a domain that is more easily thought of as cognitive, Rhodes and Turvey (2007) showed that foraging can be done in the context of memory. They studied how participants recalled words from a categorical set (for example, the set of animal names). To quote from their paper, "at an abstract dynamical level, foraging for particular foods in one's niche and searching for particular words in one's memory must be similar processes if particular foods and particular words are randomly and sparsely located in their respective spaces at sites that are not known a priori," (Rhodes & Turvey, 2007, p.255). In measuring the walk through semantic memory space, Rhodes and Turvey could not measure physical space, instead measuring the amount of time between recalled words. In their study, words tended to be recalled in bursts, where many words were remembered in groups together, followed by pauses where no words were recalled. Thus, the distributions of durations were consistent with Lévy processes. In fact, the closer the μ exponent was to 2, for each participant's individual distribution, the more successful that participant was at the recall task.

Rhodes and Turvey's results demonstrated that Lévy flights prevail even in a very cognitive domain. Other evidence is given by Cabrera, Bormann, Eurich, Ohira, and Milton (2004); Cabrera and Milton (2004) and colleagues in a study where participants tried to balance a stick on their fingertips. High-speed motion analyses of the movements in 3D revealed a truncated distribution of fingertip movements, but below the truncation a Lévy flight with $\mu \approx 2$ were evident. Interestingly, the truncated distributions for more skilled balancers had a higher cutoff point.

There is also evidence that Lévy patterns are produced in the movements of our eyes when searching visual scenes. On a broad, course level, eye behavior can be divided into two categories: fixating, and reorienting. Reorienting involves saccades, or movements of the eyes about a visual scene, looking from place to place. Brockmann and Geisel (2000) suggested that viewing a visual scene can be likened to a search process, as an observer is searching for information from the visual input. In fact, they found that the distribution of saccade amplitudes during free picture viewing exemplify a Lévy process. For a human observer, time and information are the analogs of energy (the resource that needs to be conserved) and food (the resource that is being foraged). During the fixation period, the eyes are not (as the name might suggest) actually fixed. Although this period is experienced as fixating on a given point without looking away, it is actually dominated by microsaccades. Microsaccades are involuntary, small-amplitude movements that occur an average of 1-2 times per second. Engbert (2006) investigated whether the same pattern of foraging would be found in these smaller-amplitude microsaccades. He found that the distribution of microsaccade amplitudes did fit a power law, but with $\mu = 4.41$, consistent with a normal distribution instead of Lévy. Thus, while the larger saccadic movements are Lévy distributed, the microsaccades do not appear so.

Hills (2006) offers a perspective from evolutionary neuroscience that may explain a link between animal foraging and modern human cognition. He argues that the "molecular machinery" that initially evolved for the control of goal-directed search behaviors (such as foraging for food, hunting for prey) was "co-opted over evolutionary time", through increased cortical connectivity, to control more advanced types of goal-directed behaviors. For example, Hills reviews a large number of studies demonstrating the importance of dopaminergic and glutaminergic signaling in the feeding behaviors of invertebrates, suggesting that related searches evolved as a primitive function for invertebrates, and possibly vertebrates, too. Overall, this work associates dopaminergic and glutaminergic mechanisms with perseverating, or focusing on goal-directed search behaviors such as foraging for food or hunting prey. With an over-abundance of dopaminergic activity, an animal will often persist stereotypically on one activity (or search continuously in one area). Conversely, a lack of dopaminergic activity is related to un-focused, non-persistent activity (obviously, a balance between these regimes is important for successful search). Interestingly, similar findings are observed in the behaviors of more advanced primates, but here the pattern of results applies to a wider range of goal-directed behaviors than foraging for food. Hills points out that the human basal ganglia, and specifically the striatum, also show similar modulation from dopamine. Dopamine is highly associated with rewards and goal-directed behavior, and with higher-level cortical systems such as the prefrontal cortex and nucleus acumens, humans are able to integrate reward information and predictions, goals, and working memory (for example).

> In the evolutionary history of vertebrates, it is therefore possible to witness a development from the dopaminergic striatal control of visuomotor focus in frogs and toads (Buxbaum-Conradi & Ewert, 1999; Patton & Grobstein, 1998) to the similarly controlled maintenance of ideas in working memory (Schultz et al., 1995)... In humans, general strategies also appear to be conserved across spatial foraging and more abstract or cognitive search. Normal individuals prone to perseverate in spatial foraging tasks also show tendencies to perseverate in cognitive problem-solving tasks, whereas those who explore globally in one task are likely to do so in another (Hills & Stroup, 2004). (Hills, 2006, p.18)

Chapter 2

Linking memory and information search to spatial search

Abstract

Search is a ubiquitous behavior for a variety of species. Converging evidence from several domains suggests that there may be common principles that apply to search processes regardless of the species, or contexts, in which they are observed. Theories of cognitive or memory search have been motivated by findings in the animal foraging literature, and have recently been the subject of increased attention (see Hills et al., 2015; Hills, Jones, & Todd, 2012, for example). This approach has been quite successful in terms of applying the principles of spatial search to cognitive search, but here we add additional justification by grounding cognitive search in spatial measures. We asked subjects to perform a semantic fluency task, recalling items from the category of cities in California, so we could use physical, geographic coordinates to characterize cognitive search. Our findings support the notion that cognitive search is similar to spatial search.

2.1 Introduction

A common metaphor for remembering is "a stroll down memory lane." This suggests that the cognitive act of remembering is like a traversal through some landscape, where the landscape is made of memories, knowledge, or information.

The nature of this landscape, of how information is organized and searched, is a fundamental question in the cognitive, psychological, and philosophical sciences. Implied by the "memory as landscape" metaphor is the idea that memory structure is semantic in nature, such that recalling the concept *birthday cake* may make you think of a semantically related concept such as *birthday candle*. Indeed, semantically related items have long been shown to prime one another (Meyer & Schvaneveldt, 1971). By this metaphor, then, as we stroll to the location in memory space that codes for birthday cakes, we are already close by, and might pop in on, the location for candles. There are, however, different accounts of what characterizes a "location" in memory space. Many of these accounts are from the domain of word learning (e.g. Osgood, 1952). These include representations of semantic meaning as networks of connected nodes (e.g. Collins & Loftus, 1975), as feature lists (e.g., Smith, Shoben, & Rips, 1974), and as high-dimensional spaces learned through, for example, statistical co-occurrences of words, such as in latent semantic analysis (LSA) and BEAGLE (see Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990; Jones & Mewhort, 2007).

While lexical accounts of semantics may be intuitively appealing with respect to concepts such as birthday cakes and candles, a relatively small amount of research has investigated the organization of geographic and spatial information in cognitive space (but see Montello & Freundschuh, 1995). That is, spatial knowledge is often acquired through means such as experience (navigation and locomotion) and visualizations (maps and other images), which are less easily fit into existing linguistic accounts of semantic memory. Still, Louwerse and Zwaan (2009) showed that language encodes quite a bit of geographic and spatial information, suggesting that spatial knowledge may not be qualitatively different from other semantic knowledge.

Spatial and semantic information is only useful for an agent, of course, when it can be retrieved and used. Spatial search has long been a topic of investigation in fields such as ecology, where animal foraging behaviors are examined (Pyke, 1984; Charnov, 1976), but more recently it has been noted that investigations of search problems in diverse domains are increasingly converging on similar solutions (e.g. Hills et al., 2012). Although a review of the posited search strategies is beyond the scope of this paper, we refer the reader Hills et al. (2015) for a review of search in a number of domains. The point we wish to make here is that research on cognitive search is increasingly being motivated by spatial search. The focus of the present paper, then, is to explore the "memory as landscape" metaphor as it relates to spatial search, and add to the conversation on whether the dynamics of cognitive information foraging are similar to the dynamics of spatial geographic foraging.

Other work relating physical space with cognitive processes has found that similarity and time are often understood in terms of space and spatial metaphors (Winter & Matlock, 2013; Boroditsky, 2000). In visual search, Kosslyn, Ball, and Reiser (1978) found that distances between sequentially foveated objects was related to scanning time, even when the material between the objects was manipulated. In another study, participants were asked to spatially organize a set of items which were produced previously, by other participants, in a categorical recall task. The spatial distances were found to correlate with the temporal distances observed in the preceding recall task (Montez, Thompson, & Kello, in press).

Similar to Montez and colleagues' study, here we seek to construct a spatial representation of recall behaviors. Using an extended version of the semantic fluency task (Bousfield & Sedgewick, 1944), subjects are asked to spend twenty minutes recalling locations in their home state of California. This task gives us coordinates for objectively calculating distance and associating spatial locations with cognitive processes. We also show that this task can be used to explore more complex cognitive search processes, such as interactive, collaborative search.

Specifically, we explore three main questions as they relate to the category of locations in California. The questions, and their associated hypotheses, are as follows:

Q_1 : Are items retrieved in an order consistent with their geographic coordinates? H_1 : Yes, and if so, randomizing the order of recall events in a dataset will cause the recall trajectory to span a significantly larger distance.

Q_2 : Do temporal dynamics reflect geographic distances? H_2 : Yes, and if so, there will be a correlation between the temporal and spatial distances for pairs of consecutive recall items.

Q_3 : Is the spatial coordination of a dyad related to that dyad's task success? H_3 : Yes, and if so, there will be a correlation between the quality of a dyad's interaction and the dyad's task performance. Since a precise quantification of coordination dynamics, both in search and in general, is beyond the scope of this paper, we adjust our hypothesis to touch on one small part of coordination that may reflect coordination dynamics: The distances, over time, between partners' recall items. Thus, our adjusted H_{3b} will be that distances between dyads' partners will be correlated with dyads' task successes.

Below we describe the experiment we used to address our research questions. Results significantly support H_1 and H_2, but are inconclusive (although show interesting patterns) with respect to H_{3b}. We conclude by discussing how these results contribute to the "memory as landscape" metaphor and the cognitive search literature.

2.2 Methods

Participants were recruited from a subject pool of University of California, Merced undergraduate students who participated for course credit (5 male, 26 female; mean age = 19.77 years, SD = 1.56 years). All participants reported having lived in California for the majority of their lives (mean time of residency in California = 19.16 years, SD = 2.41 years), and reported being native or proficient English speakers. Twenty subjects were randomly assigned to collaborating dyads, for a total of ten dyads, and eleven subjects worked individually. None of the dyads reported knowing each other before the experiment, so the dyads were given five minutes to introduce themselves to each other before the task began. The brief familiarization period was intended to enhance comfort and performance on the task [1]. Subjects were comfortably seated across the table from each other in a small experiment room, and wore Shure microphone headsets. Speech was collected using an M-Audio MobilePre recording interface and Audacity software.

2.2.1 Procedure

Dyads completed two sets of recall tasks, each of which lasted for twenty minutes (adapted from Rhodes & Turvey, 2007). The recall tasks included recalling from the category of animals, or the category of cities and towns in California. The order of the recall task categories was counterbalanced across dyads. Before receiving information about the category, subjects were given the following instructions: "In a moment, I'll give you the name of a category for the first session. Your goal will be to work together to think of as many items from that category as you can. When you think of an item, just say it out loud. You can be as specific or as general as you wish. For example, if the category were Food you could say 'Fruit', and you could also say 'Orange' or 'Mandarin Orange'. But keep in mind that your goal is to recall as many different items as possible. If you are unsure if an item does or does not belong to the category, just say it anyhow, don't spend time worrying about whether something counts or not," (adapted from Rhodes & Turvey, 2007). In order to minimize task constraints and make the task feel slightly more natural, we indicated to participants that extraneous conversation was allowed during the task, but that they should stay focused on the category, and keep attempting to recall additional items throughout the twenty minutes. After taking any questions, the category was assigned and the experimenter left the room for the duration of the task. Between recall rounds, subjects were given a 2-3 minute break. At the start of the second round, they were again reminded to keep trying to recall new items for the duration of the task.

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[1] Previous work, from ourselves and others, has shown that more familiar groups tend to perform better on memory tasks (Barnier et al., 2008; Szary & Dale, 2014).

Table 2.1: Datasets used in the analysis. Notations, given in parentheses, indicate condition with I (independent) or C (collaborative), with a subscript 1 or 2 to indicate the number of participants included in each level of analysis (individual or group, respectively). See text for details.

Condition:	*Levels of Analysis:*	
	Individual	Group
Independent	Solo (I_1)	Nominal (I_2)
Collaborative	Extraction (C_1)	Dyad (C_2)

2.2.2 Data Analysis

For the purposes of the present paper, we discuss only results from the category of cities and towns in California.

Audio Transcription

The speech recordings were loaded into Praat audio analysis software for annotation. Subjects were recorded onto unique channels, so their utterances could be considered individually. Onsets of recalled item utterances were marked, excluding any extraneous conversation. That is, “Oh, we can’t forget ‘Merced’,” would be marked at the onset of the recalled item ‘Merced’. All submitted items were transcribed, but consecutive repeats were removed. Incorrect items (“Reno”, which is in Nevada, not California), geographic landmarks (“Monterey Bay” bay, “Sierra Nevadas” mountains), and non-specific areas (”Bay Area”, which refers to several locations around the San Francisco Bay) were removed. Pronunciation errors (“Rancho Cucamongo” instead of the correct “Rancho Cucamonga”) and common abbreviations (“L.A.” instead of the official “Los Angeles”) were corrected. Districts, neighborhoods, planned communities and census-designated areas with names recognized by the U.S. Geological Survey (e.g. “Hollywood”, “Downieville”; *http://geonames.usgs.gov*, 2014) were retained.

After transcription, location names were matched with latitude and longitude coordinates in decimal degrees using databases retrieved from GeoNames and Wikimedia’s GeoHack tool (*http://www.geonames.org*, 2014; *https://wmflabs.org*, 2015).

Scoring

We use a two-by-two scheme where we consider two participation conditions (independent or collaborative) on two levels of analysis (individual or group). See Table 2.1 for a depiction of this scheme, and a description of the notations (I_1, I_2, C_1, and C_2) used herein. We refer to individuals participating alone as simply *solos*, or I_1. Datasets from multiple individuals who participated independently were later combined and analyzed at the group level, which is an approximation of a *nominal* comparison[2], noted as I_2. For participants in the collaborative condition, we can extract from the group level each individual’s datasets, which we refer to as *extractions*, or C_1. Finally, group level datasets from individuals who were performing the task collaboratively are *dyads*, noted as C_2.

For group level datasets (I_2 and C_2), the instantaneous onset times for each participant’s recalled items and their corresponding location coordinates are merged into one dataset. For each dataset, scores are computed as the unique number of locations

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[2] These nominal pairings, which included all possible (unique) combinations of individual participants, allow us to (roughly) address whether any observed group-level differences are truly related to the interaction between two participants, or simply because there are two participants instead of one.

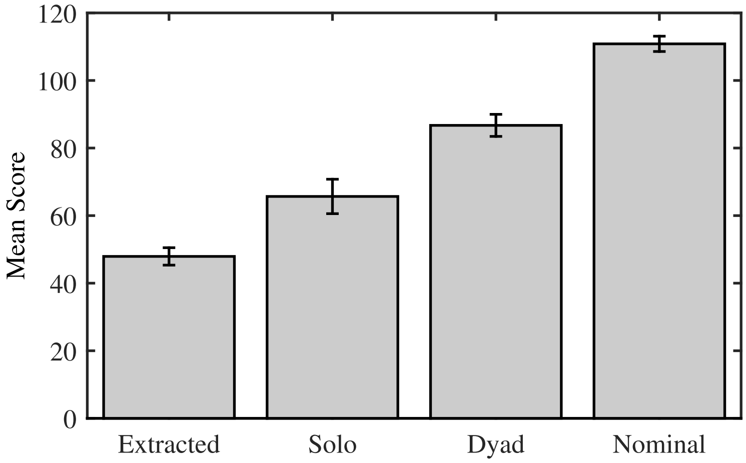

Figure 2.1: Mean number of locations recalled for each condition and level of analysis. Error bars show $+/-$ SE for the remaining data.

recalled (that is, repeats are excluded). Inter-retrieval intervals ($IRIs$) are measured as the amount of time (in milliseconds) between consecutive recall events. Geographic distances (GDs) are measured as the number of miles between consecutive recalled locations. GDs are calculated using the Haversine formula, which gives the great-circle distance between two points on an sphere (Sinnott, 1984). Finally, the distance between partners in the group-level datasets (inter-partner distance, IPD) is calculated using the Haversine formula, where points are each partner's most recently recalled locations over time.

2.3 Results

2.3.1 Scores

Outliers were defined as data points falling outside $+/-1$ standard deviation from the mean of each condition and removed. Mean remaining scores are shown in Figure 2.1. Dyads outperformed solos, recalling 86.7 ($N = 7,\ SE = 3.25$) and 65.7 ($N = 9,\ SE = 5.10$) locations, respectively, $t(14) = 3.25,\ p < 0.001$. Unsurprisingly, nominal pairs recalled 110.8 ($N = 38,\ SE = 2.27$), which is significantly more than dyads, $t(43) = 4.40,\ p < 0.0005$, and is consistent with the literature on collaborative inhibition (Basden et al., 1997). Extracted datasets were significantly worse than the next best (solo), recalling only 47.9 ($N = 13,\ SE = 2.58$), $t(20) = -3.39,\ p < 0.005$.

2.3.2 Recall Dynamics

Inter-Retrieval Intervals

The distribution of IRIs was fit to several different candidate models using the multi-model inference method and Akaike's Information Criterion, as described in Rhodes (2013). Candidate models included normal, exponential, lognormal, Pareto, and gamma distributions. The best fitting model for 1/11 solos was the lognormal distribution, and for 10/11 it was the Pareto distribution. For dyads, 6/10 were best fit

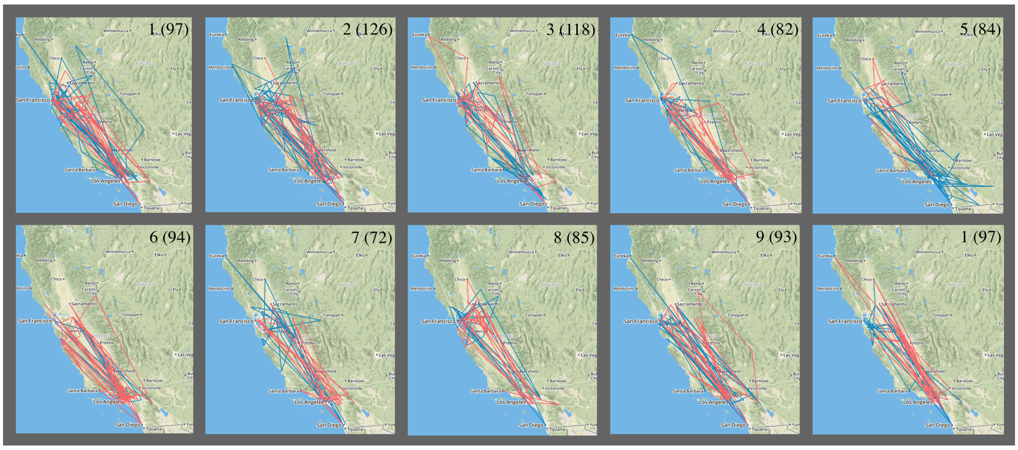

Figure 2.2: Each panel illustrates the recall trajectory of a collaborating dyad transposed on a map of California. For each dyad, one participant's recall events and paths are shown in blue, and the other in red. The overall score for each dyad is shown in the top right of each panel in parentheses. Maps were generated using *https://www.mapbox.com*, 2015.

by the lognormal distribution, and 4/10 were best fit by the Pareto distribution. For extracted datasets, 12/20 were best fit by the lognormal distribution, 1/20 was best fit by the exponential distribution, and 7/10 were best fit by the Pareto distribution. For nominal datasets, 49/55 were best fit by the lognormal distribution, 3/55 were best fit by the exponential distribution, and 3/55 were best fit by the gamma distribution. The finding that most IRIs (and, in fact *all* actual datasets, including I_1 and C_2) were fit by either Pareto or lognormal distributions is consistent with the IRI distributions exhibited in other categorical recall tasks (e.g., Rhodes, 2013; Szary, Dale, Kello, & Rhodes, in preparation)[3].

Geographic Distances

Figure 2.2 illustrates the series of recalled items as travel trajectories on a map of California for each of the ten collaborating dyads. Across consecutive recall events in each condition, we tested for correlations between GD and the log of IRIs[4]. The correlation was subtle but significantly positive for dyads, $r(1106) = .16$, solos, $r(955) = .26$, and extracted datasets, $r(1119) = .28$, (all with $p < 0.0001$). For nominal datasets there was no significant relationship between GD and IRI. Figure 2.3 plots GD against IRI for each condition and level of analysis.

The sequence of locations recalled by dyads and solos was shuffled (within each dataset), and new GDs were calculated. As illustrated in Figure 2.4, the mean of all GDs for each of the two conditions was significantly higher when sequences were in a random order compared to their original order. For dyads, mean GD in the original order was 135.12 ($SE = 4.03$), and in the shuffled order was 174.79 ($SE = 4.00$), $t(2214) = 6.99$, $p < 0.0001$. For solos, mean GD for the original order was 11.27 ($SE = 4.07$),

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[3] Best fitting distributions are noted here simply to relate our findings to those using the more familiar category of animals, but we will not go any further into the analysis or discussion of these distributions. For further information on these distributions and ideas about their relevance, see Rhodes, 2013; Szary et al., in preparation).

[4] To accommodate different scales of magnitude in the timeseries, IRIs were logged to show the effect, as in (Montez et al., in press).

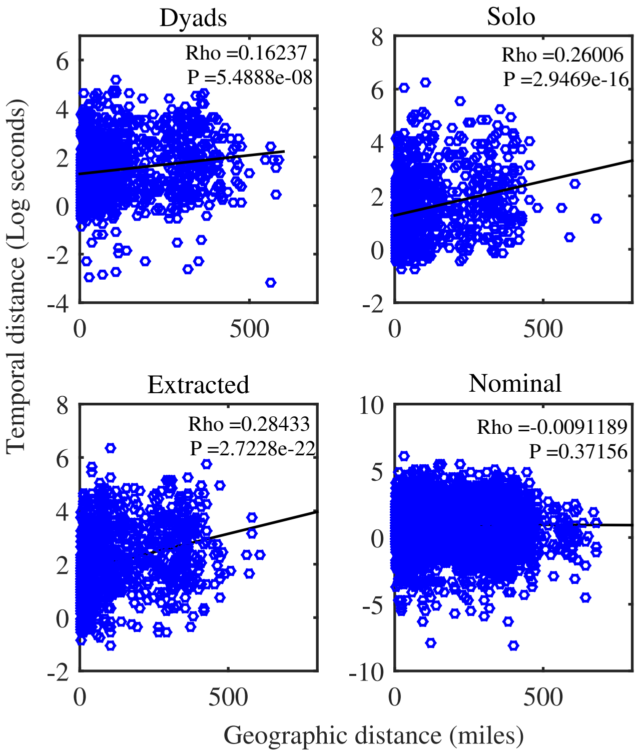

Figure 2.3: Each panel shows a scatter plot of geographic distance, in miles, plotted against the log of IRI times (in log seconds) for each pair of consecutive recall events in each of the four conditions. *Rho*, in the top left corner of each panel, shows Pearson's linear correlation coefficient and its significance, p.

while in the shuffled order it was 169.35 ($SE = 4.30$), $t(1912) = 9.82,\ p < 0.0001$.

Inter-Partner Distances

For group level datasets we computed IPD as described above. Although nominal pairs (I_2) did not actually work together, IPDs were computed using the simulated pairings of individuals' time series. Thus, I_2 IPDs do not actually measure any kind of interaction or collaboration dynamics. Instead, these IPDs might reflect differences in the composition of dyads with different hometowns and areas of expertise. For C_2, further research will need to tease apart whether different IPDs reflect this type of composition difference, or whether they capture collaboration dynamics.

Mean IPDs did not differ significantly by condition (for dyads, mean IPD $= 189.63$, $SE = 12.38$; for nominal pairs, mean IPD $= 204.25$, $SE = 5.45$). Figure 2.5 shows scores for each data set as a function of mean IPDs. Quadratic fits suggest a nonlinear relationship, where a certain IPD may be a somewhat "optimal" point for enhancing dyadic search. Interestingly, the optimal IPD may be smaller for collaborating dyads as compared to the simulated nominal groups. The effects are admittedly negligible, here, but we present them as a precursor to our computational modeling work on this same topic (in preparation).

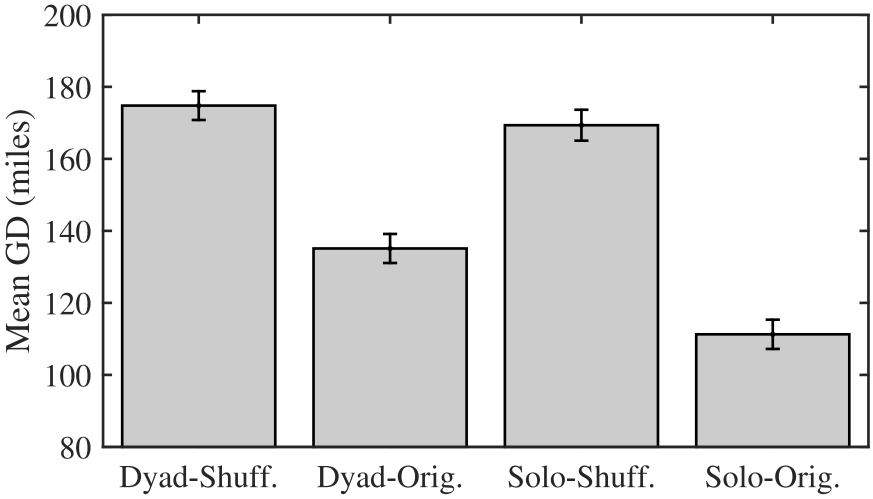

Figure 2.4: Mean geographic distance (GD) in miles for shuffled and original datasets in the dyad and solo conditions. Error bars show $+/-$ SE.

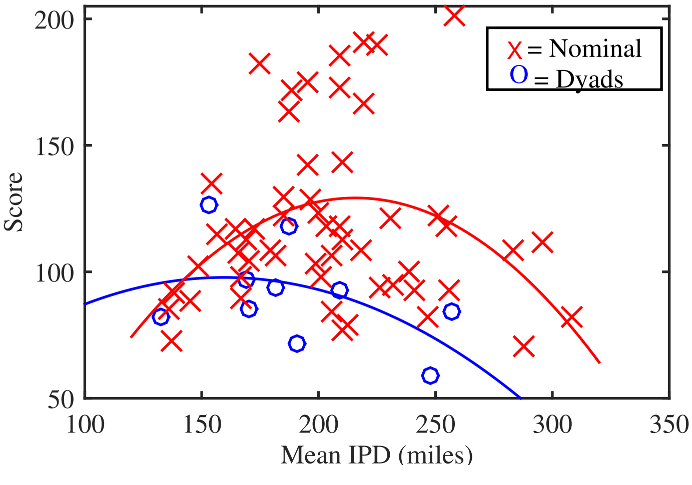

Figure 2.5: Data points represent average IPDs between partners for each dyad (blue) and nominal pair (red) across the entire task. Lines show quadratic fits to dyads (red; $y = -0.006x^2 + 2.6x - 150$) and nominal sets (blue; $y = -0.003x^2 + 0.95x + 22$).

2.4 General Discussion

Here, we discuss results only from the category of cities and towns in California. Future work will compare collaborative performance dynamics in the different (spatial versus semantic) task spaces, but here we simply note that the same general patterns are exhibited in the timeseries and score from the condition where participants recalled animals.

In the spatial domain, our results showed that simulated nominal pairs recalled significantly more items, on average, than interacting dyads, even though dyads recalled significantly more than individuals (or extracted dyad members; see Figure 2.1). This is unsurprising, as it is consistent with the existing literature on collaborative inhibition (Basden et al., 1997). However, we were more interested in investigating the dynamics of recall. Our next results showed that most inter-retrieval intervals were either power-law or lognormally distributed, which relates our categorical recall task using locations in California to the results of other recall tasks using animals (Rhodes, 2013; Szary et al., in preparation). Next, we correlated the sequence of inter-retrieval intervals to the sequence of inter-retrieval geographic distances and found subtle but reliably positive correlations. That is, cities that are closer together tended to be recalled closely in time, while cities farther from each other tended to be recalled with larger delays. This correlation held for all datasets *except* nominal pairs, in which two non-related datasets are merged into one (see Figure 2.3). It is interesting, although not altogether surprising, that the relationship between spatial and temporal dynamics is broken in this kind of artificial dyad. To further investigate the apparent spatial clustering in the sequence of recall events, we shuffled the order of recalled items within each dyad and nominal dataset. As further support of spatial clustering, shuffled datasets (in both conditions) had reliably larger average geographic distances (see Figure 2.4).

Finally, we used inter-partner distances (IPDs) as a coarse measure of collaboration. Overall, the mean distances were smaller for interacting dyads as compared to simulated nominal pairs, but this difference did not reach significance. This suggests that interacting dyads did not, on average, stay any closer to one another (in terms of their recall spaces) than would be predicted for noninteracting individuals foraging the same space, although we suspect that a more rigorous analysis with more data points might produce interesting results. As an example, quadratic fits suggest the possibility that a median IPD is related to better recall performance as compared to very small or very large IPDs. Median IPDs might reflect situations in which partners forage more-or-less in together (globally), but maintain a slight distance (locally) so as not to overlap with one another. This type of strategy has implications for research on coordination and alignment as well as optimal foraging theories, but further work is needed to explore it (and other) collaborative foraging strategies. As noted above, it is still unclear whether our IPD measure really taps into interaction dynamics, or whether it reflects something more basic, such as differences in group composition.

2.5 Conclusion

Overall, our results provide clear support for our H_1 and H_2: Items seem to be recorded in an order consistent with their geographic coordinates, and the temporal dynamics of their retrieval is reflected in geographic distances. Although H_3 could not be directly tested, H_{3b} was tested and gave mixed results: distances between partners during collaborative foraging are not linearly correlated with score, as hypothesized, but there may be an interesting nonlinear relationship for further research to explore.

These results add justification for the growing notion, popular in both intuitive and scientific accounts, that remembering can be likened to and investigated as a spatial search process. Rather than making any claims about the structure or nature of memory itself, we suggest that these results support the notion that search can be investigated as a general cognitive phenomenon, independent of the domain in which it is performed.

2.6 Acknowledgments

The authors would like to thank Jacqueline Pagobo and Maxine Varela for their assistance with data collection, and Riccardo Fusaroli and Theo Rhodes for helpful discussion.

Chapter 3

Characterizing the dynamics of collaborative memory search

Abstract

The extent to which a cognitive system's behavioral dynamics fit a power law distribution is considered indicative of the extent to which that system's behavior is driven by multiplicative, interdependent interactions among its components. Here, we investigate the dynamics of memory processes in individual and collaborating participants. Collaborative dyads showed the characteristic collaborative inhibition effect when compared to nominal groups in terms of the number of items retrieved in a categorical recall task, but they also generate qualitatively different patterns of search behavior. To categorize search behavior, we used multi-model inference to compare the degree to which five candidate models (normal, exponential, gamma, lognormal, and Pareto) described the temporal distribution of each individual and dyad's recall processes. All individual and dyad recall processes were best fit by interaction-dominant distributions (lognormal and Pareto), but a clear difference emerged in that individual behavior is more power law, and collaborative behavior was more lognormal. We discuss these results in terms of the cocktail model (Holden, Van Orden, & Turvey, 2009), which suggests that as a task becomes more constrained (such as through the necessity of collaborating) behavior can shift from power law to lognormal. This shift may reflect a decrease in the dyad's ability to flexibly shift between perseverative and explorative search patterns. Finally, our results suggest that a fruitful avenue for future research would be to investigate the constraints modulating the shift from power law to lognormal behavior in collaborative memory search.

3.1 Introduction

The category-based recall or semantic fluency task has a long tradition of use in empirical investigations of memory (Bousfield & Sedgewick, 1944). Typically, participants in these tasks are asked to recall as many items that belong to a given category as possible, within some time window. The pattern of responses is often clustered: short bursts of many items are remembered together, interspersed with longer intervals in which nothing can be recalled. Items that are recalled in temporal clusters also tend to be semantically similar (Bousfield & Sedgewick, 1944; Troyer, Moscovitch, & Winocur, 1997; Hills et al., 2012). This retrieval pattern, with frequent, clustered short intervals but occasional long intervals between clusters, is similar to the pattern of path lengths exhibited by animals foraging for food or other resources in physical environments (for example, see Sims et al., 2008; Viswanathan et al., 2011). This led Rhodes and Turvey (2007) to conceptualize memory retrieval as a foraging process across a cognitive or information landscape. They found that the intervals between consecutive recalls are consistent with Lévy flights–random walks in which path lengths (intervals) are power law distributed such that each length L is observed with probability $P(L) \sim L^{-\mu}$, and $0 < \mu \leq 3$. The Lévy flight has received a considerable amount of attention in the animal foraging literature, where it has been suggested that Lévy flights are an optimal search strategy (Viswanathan et al., 1999, 2011), but it has also been noted that other search processes (strategies) give rise to similar resulting search patterns, and in fact these patterns may not be optimal for all environments (Benhamou, 2007; Plank & James, 2008).

In the cognitive domain, Hills et al. (2012) have used the theoretically different but empirically related framework of area-restricted search modeled as a correlated random walk to describe the same free recall behavior. In the ecological domain, area-restricted search describes a strategy where a forager searches a restricted, or local, area with bountiful resources until the availability of those resources declines. At that point, the forager will move to a new area and begin the process again (Karieva & Odell, 1987). Notably, both strategies (Lévy flights and area-restricted search) produce approximately similar behavior: frequent short path lengths and occasional long path lengths (see A. Reynolds, 2010). Using a spatial search task with human participants, Hills, Kalff, and Wiener (2013) found evidence that both Lévy flights and area-restricted search might be used strategically by the same agent depending on the resource context. Since the cognitive and information landscape of memory is abstract, and presumably different across individuals, the actual foraging processes and the cognitive mechanisms which generate them can only be inferred from the resulting recall patterns. A common theme across these perspectives, though, is that retrieval patterns might be indicative of the underlying cognitive processes, whatever they may be.

In the exploratory project presented here, we consider whether retrieval patterns differ when remembering is performed collaboratively. Remembering is often performed in a collaborative context, but empirically this interactive context is almost always associated with negative performance outcomes (Rajaram & Pereira-Pasarin, 2010; but see Harris, Keil, Sutton, & Barnier, 2010). Increasingly, researchers are considering the processes by which the joint action of remembering occurs (D. P. Tollefsen & Dale, 2012) to help explain why collaborative memory performance is worse than (and conversely, why it can sometimes be *better than*) individual memory performance. Here, we consider both performance outcomes and retrieval patterns to investigate whether cognitive search processes change depending on social context. We predict that interactivity will alter the dynamics of individuals in a dyad compared to the dynamics of an individual performing the same task alone. Work by D. P. Tollefsen (2006), Schmidt and O'Brien (1998), Yoshimi (2012), and Dale, Fusaroli, Duran, and Richardson (2013), among others, suggests that the coupling between two agents will result in qualitative change in the distribution of their retrieval intervals.

In order to quantify timing distributions across conditions, we draw on tools from complexity science and statistical mechanics. In this domain, statistical distribution matching can be used to determine the nature of interaction amongst the component parts of a complex system. Cognitive scientists have begun using these techniques to determine whether cognitive processes are more component-dominant, in which case a system's subcomponents act and contribute independently to system-wide behavior, or interaction-dominant, in which case the effects of any one component depend on the behavior of another, so that its effects on system-wide behavior are nonlinear (Van Orden, Holden, & Turvey, 2003; Holden et al., 2009; Stephen & Mirman, 2010). To illustrate

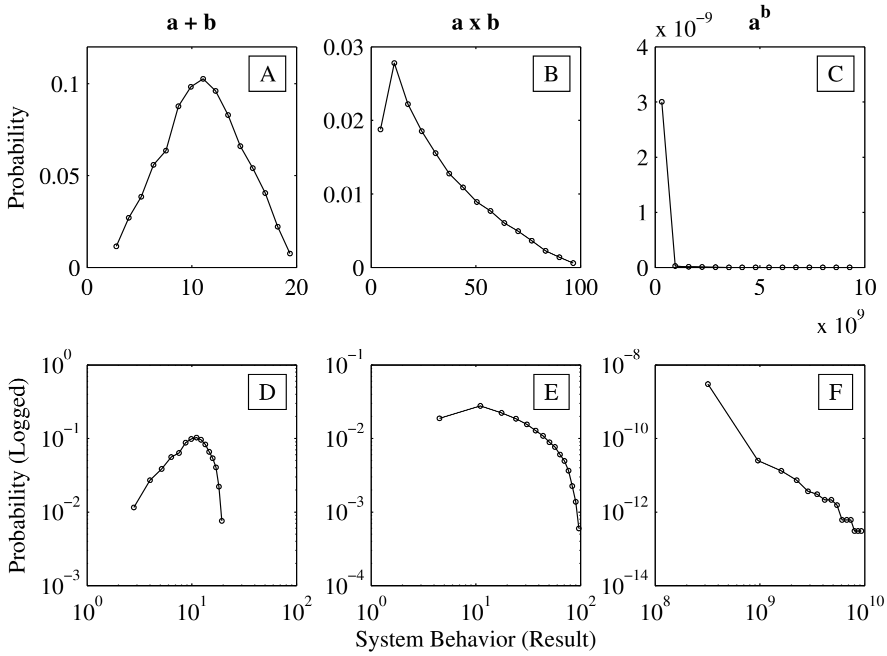

Figure 3.1: Example probability distributions for three types of systems, where system behavior $S = a + b$ (left column), $S = a * b$ (middle column), and $S = a^b$ (right column). The top row shows normalized histograms for 10,000 actual trials, where a and b are random numbers between 1 and 10. The bottom row shows the same data plotted on log-log coordinates.

the distinction between component- and interaction-dominance, consider a simple system S composed of two random variables a and b, which can each range from 1 to 10. System behavior depends not only on the values of a and b, but also on the relationship between them (see Stephen & Mirman, 2010). Mathematically, that relationship might be addition ($S = a + b$), multiplication ($S = a * b$), or even a power relationship ($S = a^b$). In the additive system, possible values of S range from 2 to 20, and a probability density function will be normally distributed (Figure 4.1A). This system is linearly decomposable in the sense that the effects of each component are independent: a will have the same effect on S regardless of the value of b. This is the strictest example of a component-dominant system. In the multiplicative system, $S = a * b$, resulting values of S range from 1 to 100, and the probability density function shows that the median and mode have shifted to lower values, with a longer tail extending to higher values (Figure 4.1B). This skewed distribution results from the multiplicative interaction between the variables. That is, the effect of variable a on S will be different depending on the value of b. The effects of each variable are no longer entirely independent, but instead depend on the context of each other's values. Compared to the additive system, this system is more interaction-dominant. In the system $S = a^b$, the effect of interaction is further amplified, resulting in the increased skew of the probability density function (Figure 4.1C).

These three examples do not exhaust the space of possible systems and interactions, but are meant only to illustrate the variation between component- and interaction-dominance in systems. Two other important concepts in this literature, which we will return to in the conclusion, are interdependence and feedback. In the examples above, the values of a and b are selected independently from one another. That is, a does not actually change the value of b, but may change the effects of b on system-wide behavior. However, a considerable amount of literature has noted the pervasiveness of scaling laws in cognitive systems, whereby a system exhibits self-similarity at different scales (Kello et al., 2010) and the relationship between component variables becomes more complex. Kello and colleagues have described, more specifically, the pervasiveness of $1/f$ scaling (Kello, Beltz, Holden, & Van Orden, 2007; Kello, Anderson, Holden, & Van Orden, 2008), which signifies long-range correlations in the temporal dynamics of a system, so that effects at any period of time have non-negligible effects into the future. One mechanism by which long-range correlations can be generated is through multiplicative feedback effects, where the perturbations to one component perturb other components, which in turn may come to perturb the initial component once again. That is, in these more complex systems (as compared to the simple, independent-component system described earlier), changes to a may cause changes to b, indicating *inter*dependence of the two variables, and these changes may reverberate back to a, illustrating an example of a feedback effect.

Stephen and Mirman (2010) have used the method of statistical distribution matching to fit distributions of eye movements to five candidate statistical distributions which vary from component dominant to interaction dominant. They found that their empirical data were best fit by and described as an interaction-dominant system. Rhodes (2013) used statistical distribution matching to identify patterns of interaction-dominance in individual memory retrieval during a category-based free recall task. Here, we expand upon Rhodes' study by using multi-model inference to investigate whether interaction-dominant patterns persist during collaborative recall. Because two interacting agents perform approximately as one coherent group, are individual-level dynamics constrained by higher-order constraints of the dyad, as a unit of analysis unto itself? Will the pattern of results from a cohesive dyad unit be comparable to that of an individual? We show that multi-model inference can tease apart changes in the dynamics of individual and collaborative recall behavior, and show how these patterns might relate to the success of group memory behavior, in terms of number of items retrieved. Finally, we use latent semantic analysis (LSA) to provide insights into the semantic similarity of items retrieved by the members in each group.

3.2 Materials and Methods

For the current study, either an individual or a dyad completed two twenty-minute semantic fluency tasks. One semantic category was the set of all animals, the other was cities and towns in California. The two categories were presented in counterbalanced order, with a break between sessions. Here, we discuss the results from only the animals category, so that our results can be considered in the context of other work (e.g. Bousfield & Sedgewick, 1944; Rhodes & Turvey, 2007; Rhodes, 2013; Thompson & Kello, 2013) on semantic fluency[1]. In addition to comparing the number of items recalled, we employ multi-model inference to characterize the distributional properties of the time series of recall events in order to investigate the search processes employed in the different conditions, and we use LSA to explore semantic differences between members of each group condition.

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[1] We refer the reader to Szary, Kello, and Dale (2015) for a description of and results from the California locations task.

3.2.1 Participants

Participants were recruited from a subject pool of University of California, Merced undergraduate students who participated for course credit. All participants reported fluency in English. The individual condition included 12 participants (4 males, 8 females), while the dyadic condition included 10 dyads composed of 20 participants (2 males, 18 females). None of the dyads included partners who knew one another prior to the experiment. Across conditions, the average age was 19.75 (SD = 1.55 years). Informed consent was obtained from all participants included in the study. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

3.2.2 Procedure

Before the study began, dyads were given five minutes to introduce themselves while the experimenter left the room. All participants were seated comfortably at a table in a small experiment room, with dyads facing each other across the table. Participants wore Shure microphone headsets, connected to a computer in another room via a USB preamp, to record verbal responses. Participants completed two twenty-minute recall tasks, with a short break of roughly three minutes in between. For each recall task, participants recalled as many items as possible from either the "animal" category or the "cities and towns in California" category, but as mentioned previously, only results from the animal category are presented here. Before receiving their category assignment, participants were given the following instructions: "In a moment, I'll give you the name of a category. Your goal is to (work together to) think of as many items from that category as you can. When you think of an item, just say it out loud. You can be as specific or as general as you wish. For example, if the category were 'food', you could say 'fruit', and you could also say 'orange' or 'mandarin orange'." In order to minimize awkwardness or discomfort, dyads were invited to converse freely with their partners during each session, but encouraged to stay focused on the task of coming up with as many items as possible.

3.2.3 Datasets

Participants' responses were transcribed using the Praat audio analysis software. The utterance for each retrieved item was isolated and its onset time determined, but extraneous conversation and non-category utterances were ignored [2]. Two variables of interest were collected for each dataset: (1) score (the number of unique items retrieved), and (2) the inter-retrieval intervals (IRIs; the milliseconds between the onsets of consecutive recalls).

In order to investigate the effects of collaboration on the recall task, we consider performance at both the individual level (one participant) and the group level (two participants). Group-level datasets are created by merging sequences of recalled items from individuals and treating them as one. The two original datasets we collected were single participants working alone (*independents*, $n = 12$) and pairs of two participants working collaboratively (*dyads*, $n = 10$). For the purposes of comparison, we also generated three artificial datasets: *single partners* ($n = 20$), *nominal pairs* ($n = 66$), and *mismatched pairs* ($n = 180$). The datasets, as illustrated in Table 4.1, vary on three dimensions: the number of participants included in the analysis (one or two), the

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[2] While obvious non-category utterances were removed, some items were retained such as imaginary, extinct, or incorrectly named animals. A second analysis was performed where these items were removed, but the relative between-condition scores were unaffected.

Table 3.1: Datasets. The composition of the five datasets used in analyses are illustrated. The two bolded datasets (independent, dyad) are those originally collected. The other three (partner, nominal, mismatch) are artificial datasets generated for comparison.

Level of Analysis:	*Interaction Condition* :	
	None (Independent)	Collaborative
One participant	**Independent** ($n = 12$)	Single Partner ($n = 20$)
Two participants	Nominal ($n = 66$)	**Dyad** ($n = 10$) Mismatch($n = 180$)

interaction condition (worked individually or worked collaboratively), as well as whether the datasets were real or artificially generated. The single partners dataset is created by isolating individual-level behavior from each participant who worked in a dyad, which allows us to see how individuals behave during collaboration. The mismatched dataset is all possible pairings of these collaborating individuals (all unique combinations of single partners), but matched with those with whom they had not actually participated. The nominal dataset is all possible pairings of individuals who worked alone (all unique combinations of independents). The mismatched and nominal groups allow us to tease apart whether any differences between individual and group performance are a product of having a different number of participants, or whether the collaboration itself is having an effect.

3.2.4 Data Analysis

As noted, we compare the recall performance of the different conditions by considering both the outcome (score) as well as the process of retrieving items from memory (IRIs). IRI distributions are characterized using multi-model inference, in which the relative fit of a set of candidate models is determined and a best-fitting model can be selected (see Rhodes, 2013). Here, we consider the normal, exponential, gamma, lognormal, and Pareto distributions. The normal distribution is indicative of a system with additive dynamics, while the exponential and gamma distributions are indicative of additive systems with slight multiplicative interactions. The two models that have received the most attention in the domain of search processes are the lognormal and Pareto distributions, both of which are indicative of systems with multiplicative, interaction-dominant dynamics. The lognormal distribution is considered a special case of multiplicative interaction in which feedback effects are sufficiently constrained (Farmer, 1990), while the Pareto (power-law) distribution is thought to be indicative of a multiplicative system with stronger feedback effects and interdependence. In multi-model inference, each candidate model is fit to each IRI distribution using maximum likelihood estimation (MLE). At each model's best-fitting parameters, negative log-likelihoods are used to determine Akaike's Information Criterion (AIC), which is used as a measure of the relative fit of the candidate models (see Burnham & Anderson, 2002). In addition to determining the best-fitting of the distributions using AIC, the log-likelihoods from MLE are used to compute log ratios for conditions in which two models appear to fit. The log ratio between two models is simply the difference in their log-likelihoods, and can be used to directly quantify the goodness-of-fit of one model over the other (Stephen & Mirman, 2010; Singer & Willett, 2003).

For those distributions that are best fit by the Pareto distribution, we consider the slope parameter $-\mu$, as generated by maximum likelihood estimation, in the context of the literature on Lévy foraging. As noted above, $1 < -\mu \leq 3$ is taken as indicative of Lévy foraging, and $\mu = 2$ is considered optimal (Viswanathan et al., 1999). For each

Table 3.2: Mean number of unique items retrieved and the number of items repeated (standard deviation of the means in parentheses).

	Retrieved	*(SD)*	Repeated	*(SD)*
Single Partner ($n = 20$)	84.85	(27.09)	7.15	(9.84)
Independent ($n = 12$)	116.58	(39.09)	27.67	(81.72)
Dyad ($n = 10$)	157.70	(18.32)	26.30	(20.30)
Nominal ($n = 66$)	186.38	(42.81)	102.12	(109.18)
Mismatch ($n = 180$)	144.59	(31.08)	39.41	(18.63)

dataset best fit by the Pareto, we calculated the magnitude of the deviation between the observed μ and the theoretically optimal $\mu = 2$. We then test whether these μ-deviation values are correlated with task performance, as in previous research (e.g. Rhodes & Turvey, 2007).

Finally, we look deeper into the effects of collaboration on group-performance using latent semantic analysis (LSA). LSA is a statistical tool that can quantify the similarity between two words or groups of words in some semantic space. Here, we use the online LSA tool (lsa.colorado.edu) described in Landauer, Foltz, and Laham (1998), specifying the semantic space as general reading (up to the first year of college). For the set of retrieved items from each participant, a term-document matrix is created which notes the occurrence of each word from the semantic space, without log entropy weighting. This matrix is then reduced using singular value decomposition. Finally, the cosine between the matrices for two datasets represents their similarity on a scale of -1 to 1, where 1 would reflect identical datasets.

3.3 Results

3.3.1 Number of Items Recalled

Mean retrieval scores for each condition and category are shown in Table 3.2. A one-way analysis of variance showed that the effect of condition was significant, $F(4, 283) = 41.56$, $p < 0.0001$. More items were retrieved by dyads ($M = 157.7$, $SD = 18.32$) than by independents ($M = 116.58$, $SD = 39.09$), a difference found to be statistically significant in a two-sample t-test, $t(20) = 3.04$, $p < 0.01$. Amongst both individual-level datasets, independent participants found significantly more items than single partners isolated from their collaborators ($M = 84.85$, $SD = 42.81$), $t(30) = 2.71$, $p < 0.05$. Amongst group-level datasets, actual dyads were outperformed by nominal groups ($M = 186.38$, $SD = 42.81$), with marginal significance $t(74) = 2.08$, $p < 0.05$, and did slightly better than mismatched groups ($M = 144.59$, $SD = 31.08$), although this difference did not reach significance. Table 3.2 summarizes the number of unique items retrieved in each condition, as well as the number of repeats that occurred. Figure 5.1 shows scores for all conditions.

3.3.2 Distribution of Recall Events

Table 3.3 shows the number of datasets from each condition that were best fit by each model, according to multi-model inference. None of the 288 datasets were best fit by the normal distribution. Sixty-seven were best fit by the exponential, 44 by the gamma, 156 by the lognormal, and 21 by the Pareto. Figure 4.3 plots the percentage of datasets from each condition that is best fit by each of these four models. Notably, the exponential and gamma distributions only appear as fits to the artificial datasets, but not to either of the two experimental conditions (independent and dyad). All datasets from

Table 3.3: Counts of the number of the best fitting distributions from each condition, from multi-model inference.

	Normal	Exponential	Gamma	Lognormal	Pareto
Single Partner ($n = 20$)	0	1	0	13	6
Independent ($n = 12$)	0	0	0	1	11
Dyad ($n = 10$)	0	0	0	9	1
Nominal ($n = 66$)	0	0	12	54	0
Mismatch ($n = 180$)	0	66	32	79	3

the experimental conditions are best fit by either the lognormal or Pareto distribution, which are the two models considered to be indicative of interaction dominance. However, the majority of dyad datasets (9/10) were best fit by the lognormal distribution, while the majority of independent datasets (10/11) were best fit by the Pareto distribution. Observed distributions for dyad and independent datasets, along with the best fitting distribution at their estimated parameter values, are shown in Figures 4.4 and 4.5. When considering the individual-level behavior of single partners extracted from the collaborating dyads, some single partners (6/20) maintained the Pareto distribution that characterizes individuals working independently, but the majority (13/20) switched to behavior fit by the lognormal distribution. A chi-square test of independence showed a significant relationship between condition and best model fit, χ^2 $(12, N = 288) = 209.07$, $p < 0.0001$.

3.3.3 Log Ratios

To quantify the relative degree to which the lognormal and Pareto distributions fit our data, we computed the log ratio, which is the difference in log likelihoods from MLE. The log ratios for independents favored the Pareto ($M = 36.13$, $SD = 41.47$), while the log ratios for dyads favored the lognormal ($M = -332.76$, $SD = 277.87$). Log ratios for the artificial single partner, nominal, and mismatched datasets also all favored the lognormal distribution ($M = -18.98, -522.55, -691.99$, $SD = 36.48, 327.23, 636.02$). The difference in mean log ratios was significantly different between independents and dyads, $t(20) = 4.56, p < 0.001$, and between independents and single partners, $t(30) = 3.93, p < 0.001$. Although single partners and dyads are both fit by the lognormal distribution most often, their log ratios are significantly different, $t(28) = 5.05, p < 0.001$. Dyads are not significantly different from nominal or mismatched groups, though. Log ratios are plotted in Figure 4.6.

3.3.4 Lévy Foraging

MLE was used to calculate the best fitting slope parameter $-\mu$ for each of the datasets best described by the Pareto distribution. All Pareto-distributed datasets had μ consistent with Lévy foraging, $1 < \mu \leq 3$ $(M = 1.49, SD = 0.10)$. Deviations between each estimated μ and the theoretically optimal $\mu = 2$ were calculated. Across all datasets, the μ-deviation was negatively correlated with score $r(19) = -0.64$, $p < 0.005$. That is, the closer the slope parameter of the search distribution is to 2, the higher the score. Correlations are shown in Figure 3.6. Amongst just the independent participants this correlation persists, $r(9) = -0.70$, $p < 0.05$, but it disappears for all other datasets.

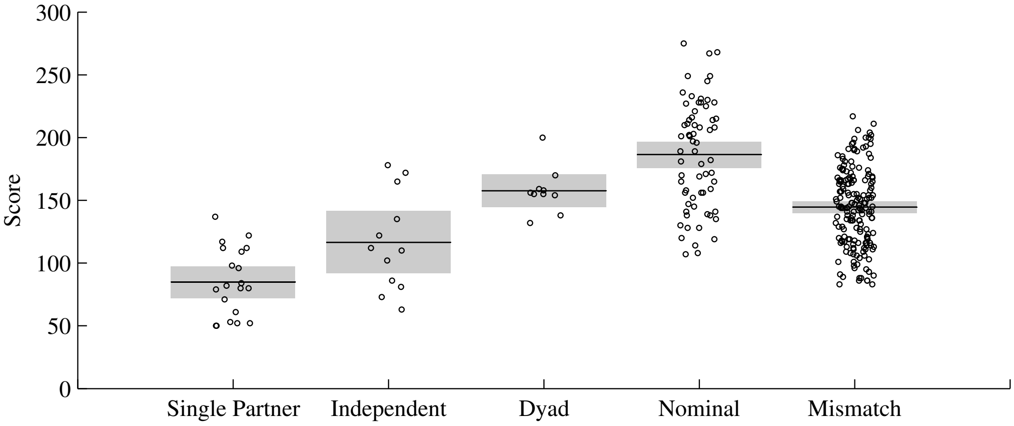

Figure 3.2: Data points show scores by condition (plus x-jitter). Lines show means, boxes show 95% confidence intervals for the means.

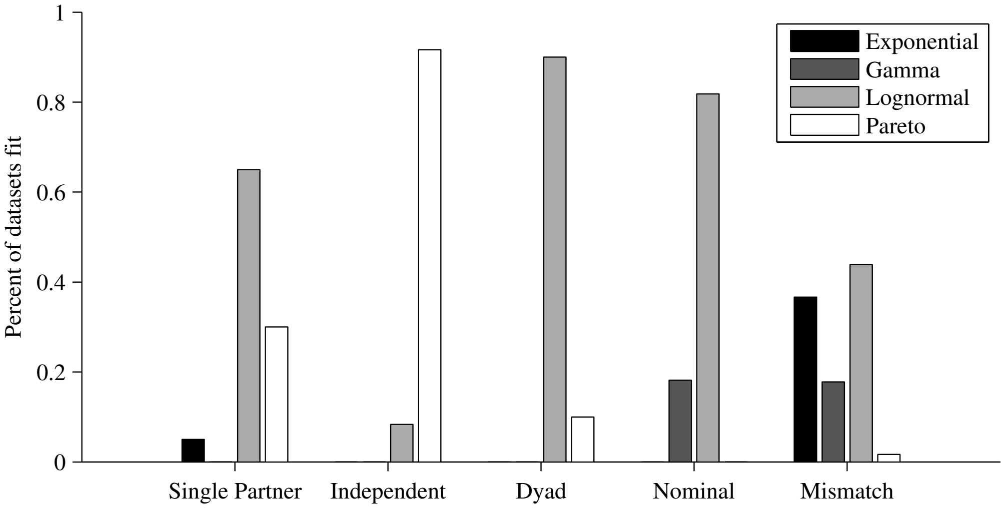

Figure 3.3: Normalized counts of the best fitting distributions for each condition.

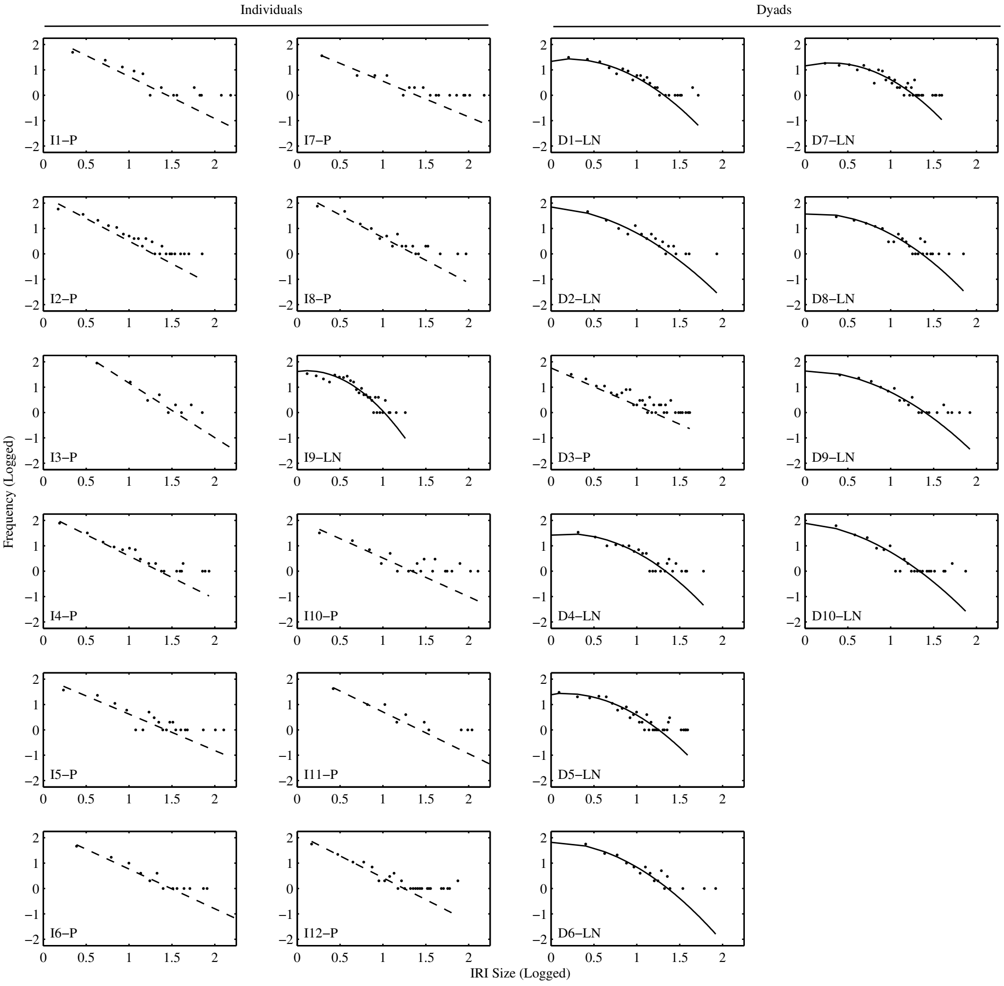

Figure 3.4: IRI distributions for each individual (two left columns, I1-12) and dyad (two right columns, D1-10), along with the best fitting distributions for each. Dotted lines (with '-P' suffix) are Pareto fits, solid lines (with '-LN' suffix) are lognormal fits.

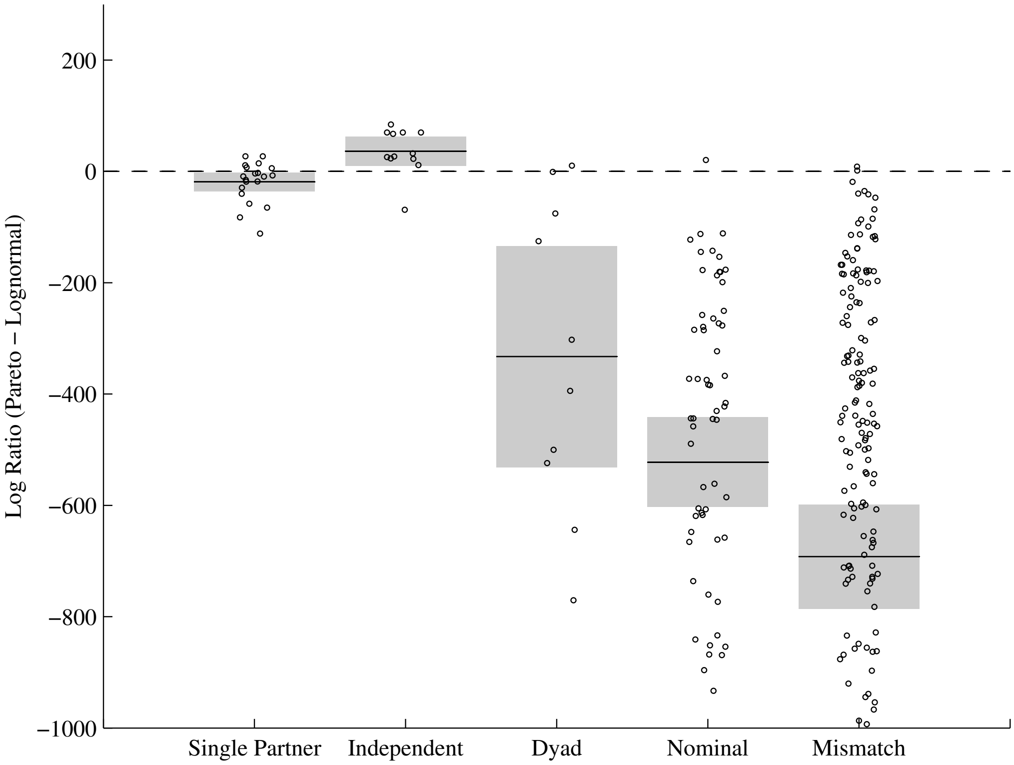

Figure 3.5: Log ratios for Pareto compared to lognormal for each condition (plus x-jitter). Positive log ratios (above the dotted line, $y = 0$) indicate better relative fit for the Pareto distribution, negative log ratios indicate a better relative fit for the lognormal. Datapoints below $y = -1000$ (appearing only in the mismatch condition) are not shown. Lines and boxes show means and the 95% confidence intervals for the means.

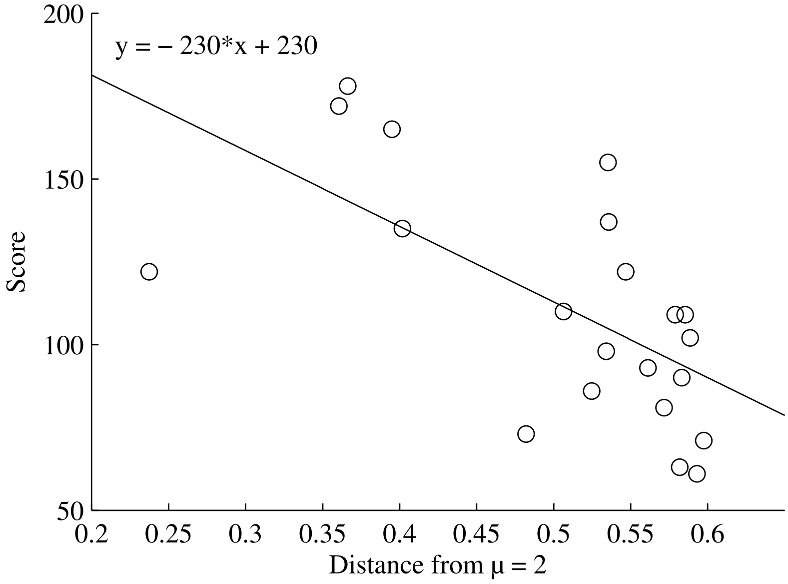

Figure 3.6: Correlation of score and deviation of μ-parameter estimate. Line shows least-squares fit.

3.3.5 LSA

Similarity ratings between the two participants from each group-level dataset did not differ between dyad groups ($M = 0.772$, $SD = 0.04$) and nominal groups ($M = 0.772$, $SD = 0.05$), but were slightly lower for mismatched groups ($M = 0.757$, $SD = 0.05$). Similarity measures are plotted in Figure 3.7. A one-way analysis of variance did not show a main effect of group condition. Across all groups, the LSA similarity measure was positively correlated with score $r(254) = 0.233$, $p < 0.001$, but the pattern changes within groups. That is, both mismatched and nominal groups showed positive correlations between LSA similarity and score, but this only achieved significance for the mismatched group, $r(178) = 0.248$, $p < 0.001$, which likely drove the significant effect across condition. Within just the dyads, however, there is no significant correlation between LSA similarity and score, but there is a slight trend in the reverse direction. That is, for collaborating dyads, there is a subtle (though non-significant) negative relationship: Increased LSA similarity may be related to decreased score. Figure 3.8 plots LSA similarity measures against score for all groups.

3.4 Discussion

Consistent with previous work (Barnier et al., 2008; Szary & Dale, 2013, 2014) we found that dyads retrieved significantly more unique items than individuals, but significantly less than a nominal grouping of those individuals, demonstrating the classic collaborative inhibition effect (Rajaram & Pereira-Pasarin, 2010). Our task differs from the larger body of collaborative inhibition tasks, though, in that it tests the retrieval of existing knowledge using a categorical free recall task, instead of requiring lists to be learned during the task. We also find that correctly-paired dyads retrieved more items than incorrectly-paired (mismatched) groups, but this trend did not achieve significance.

In terms of the distribution matching results, we find that only the artificially

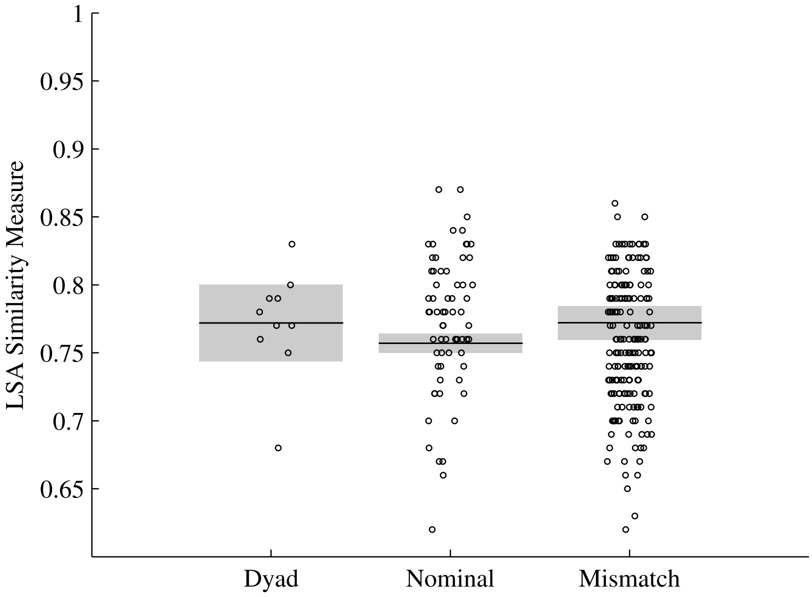

Figure 3.7: Data points show LSA similarity scores for group conditions (plus x-jitter). Lines show means, boxes show 95% confidence intervals for the means.

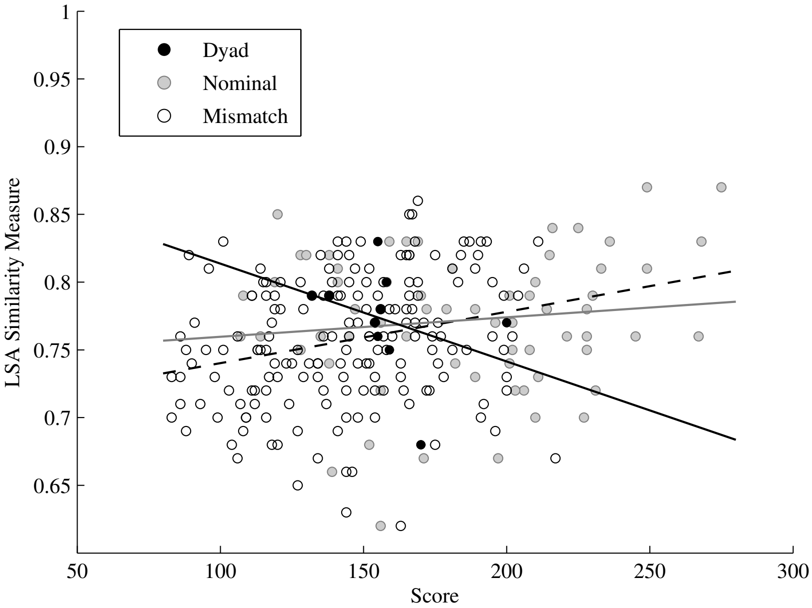

Figure 3.8: Correlation of LSA similarity rating and score, by group. Lines show least-squares fits for dyads (black, $y = -0.00072 * x + 0.89$), nominal groups (gray line, $y = 0.00014 * x + 0.75$), and mismatched groups (dotted line, $y = 0.00038 * x + 0.7$).

generated datasets are ever best-fit by component-dominant models (exponential and gamma). This is unsurprising, given that these datasets actually contain two independent components that are only combined afterwards. Of the two models indicative of interaction-dominance, we replicate Rhodes' (2013) finding that individuals' retrieval patterns are almost entirely best-fit by the Pareto distribution, which is considered to be the strongest indicator of an interaction-dominant system. When two people are working collaboratively in a dyad, the dyad as a unit unto itself generally produces retrieval patterns that are lognormally distributed, indicative of an interaction-dominant system with relatively stronger constraints (such as the need to work collaboratively with another person). Interestingly, although the Pareto distribution is prevalent in retrieval patterns of individuals working alone, it is comparatively rare in the retrieval patterns of individuals working as members of a collaborating dyad. The majority of these collaborating individuals produced lognormally distributed retrieval patterns.

We looked deeper into this result by computing the log ratio for Pareto over lognormal distribution fit. Given the counts of best fitting distributions for each condition, it is unsurprising that the independent condition is the only one where retrieval patterns are reliably best-defined by the Pareto distribution (indicated by the positive mean on Figure 4.6). By illustrating the relative fit of Pareto versus lognormal distributions, the log ratio shows that while individuals working collaboratively have retrieval patterns that are most often fit by the lognormal, they are still somewhat "Pareto-like", as indicated by the small negative value of their mean log ratio. Of the other lognormally-inclined retrieval distributions, those from dyads are the next most Pareto-like, followed by nominal groups. Mismatched group datasets show the strongest fit to lognormal as compared to Pareto, indicating that system behavior is increasingly constrained.

Of all datasets fit by the Pareto distribution, we computed the difference between the estimated slope parameter (from MLE) with the theoretically optimal value for Lévy flights. We found a significant correlation between this difference and performance–slope parameters closer to the theoretically optimal $\mu = 2$ were associated with higher retrieval scores. Within conditions, this correlation only remains significant for independent participants, but we note that the other conditions have significantly less power. Accurately determining whether the effect is driven by independents, or whether the correlation remains for all conditions, will require additional data.

Although more detailed and rigorous investigation of the content of retrieved items is necessary, LSA provides initial insights about the semantic similarity between the sets of items retrieved by the two members of each group. Although LSA similarity measures didn't differ drastically across the three group conditions, our results suggest that semantic similarity may play different roles for different group compositions. That is, we find an overall positive correlation between semantic similarity and score–but this effect is largely driven by the artificial (mismatched and nominal) groups. The fact that this correlation is only present for the artificial groups may reflect that individuals who remembered more items tended to remember items that were more or less generic than the less successful individuals, which would cause consistent but non-interesting (for the present purposes) patterns in similarity measures. What is more interesting, here, is that for actual collaborating dyads we see a trend towards the opposite relationship: semantic similarity may be associated with *decreased* performance (but more work is necessary to see if this trend is retained with increased data points). If this result does hold, one explanation worth investigating is that when collaborative dyads employ a "divide-and-conquer" strategy across information space, they are able to recall more items than when exploring the space together. In the collaborative memory literature, there is also precedent for this pattern (e.g., Hollingshead, 2001). This suggests that optimal collaboration may require semantic divergence at either a strategic level (choosing different areas of focus) or even a component level (where different participants have different areas of expertise). LSA is a relatively coarse measure of the semantic recall trajectories in our dataset, so further research is needed to build a fuller picture of how the content of retrieved items may change in itself, or may cause changes to the actual search processes in different collaborative conditions.

3.5 Conclusion

The temporal distributions of memory retrieval differ depending on social-interaction contexts. Specifically, when participants work collaboratively on a free recall task, their recall behavior becomes less Pareto and more lognormal, on both the individual and group level. This indicates that collaborative memory behavior should be regarded as an interaction-dominant process, but with feedback constraints. We note, however, that our results don't indicate a perfect fit to either lognormal or Pareto distributions for any dataset. The log ratio results, which show that interacting dyads have distributions that are closer to being fit by the Pareto as compared to distributions from the artificial, non-interacting groups, suggest that collaborating groups may still exhibit some interdependent feedback processes. In fact, Holden et al. (2009) propose a "cocktail model" in which a system's behavior is a mixture of lognormal and power law, the proportions of which are determined by the existing constraints on component interactions. Constraints, which are decreases in degrees of freedom for the behavior, could come from the nature of the task, the collaborative context, or simply the current state of the mind and body.

A cocktail model makes sense given the perspective of "active internalism" described by Yoshimi (2012), in which two relatively independent systems (two people) may have some intrinsic internal dynamics, but those dynamics can become coupled through interaction. The partial independence of their cognitive processes, along with the constraints introduced by their interaction, may bring about stable behavior that flows fluidly into a performance that "stands between the two extremes because it combines independent, random variables with multiplicative interactions" (Holden et al., 2009, p. 321). This is not to say that each separate system (each person), unto itself, would exhibit Gaussian behavior. Instead, it suggests that there are processes in each system that are *not* direct participants in the coupling. Aspects of each system that do not become coupled may act as sources of instability in the combined behavior that renders lognormal distributions.

Considering our findings from this perspective, we suggest that a common process may underlie both individual and collaborative memory search, but that the constraints imposed by collaboration transition behavior (on the individual level) from power law dominant to lognormal dominant. This transition reflects a decrease in the feedback effects which allow for small perturbations to be amplified over time and space (scaling laws). In the complex systems literature, this amplification property leads power law distributions to be considered symptomatic of (although not sufficiently indicative of) self-organizing systems operating near critical points or phase transitions (Bak, Tang, & Wiesenfeld, 1988; Bak, 1996, also see Kello et al., 2010; Van Rooij, Nash, Rajaraman, & Holden, 2013). In these systems, components flexibly and adaptively organize themselves to achieve a context-appropriate balance between independence and interdependence (Kelso, 1995; Van Orden et al., 2003), which is considered to be optimal for information transmission through networks (Kello, 2013). It is from this high-information, memory-laden metastability that emergent properties of cognition can be exhibited (Kello et al., 2007).

In our task, this means that constraints introduced by interaction are driving the composite memory systems further from their metastable critical points. From the Lévy foraging perspective, this might suggest that effective search behavior is lost as a system moves away from its critical point. The members of a composite search system are moving more independently than as a cohesive search system. From the area-restricted search perspective, the loss of power law behavior might reflect a loss of the ability to move flexibly and adaptively between perseverative search paradigms, indicated by short paths within a local area, and exploratory search paradigms, indicated by longer jumps to different areas. Regardless of one's theoretical inclinations, our results suggest that collaboration brings about important, qualitative changes to the dynamics of composite search systems.

Future work will need to develop these ideas further, but we conclude the present discussion by reiterating that our findings are consistent with the notion that memory is an interaction-dominant cognitive process, and remains so even in the case of collaborative memory. Still, there are measurable differences in the interaction-dominant dynamics of independent versus collaborative memory, reflected even at the individual level. Understanding the interaction processes in the collaborative memory system, and not just the isolable components (individuals) comprising them, will be important in understanding how people remember in social contexts. Understanding what it is about collaboration that causes the shift from power law to lognormal behavior, and especially the individual differences whereby this happens for some dyads more than others, may explain why some groups just "click" while others are "out of synch", and may help in the designing of more cohesive group units.

3.6 Acknowledgements

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The authors declare that they have no conflict of interest.

Chapter 4

Dyadic cooperation enhances retrieval and recall of crossword solutions

Abstract

The benefits of collaborative activities have been demonstrated in many domains, but there remain mixed results across several others as to whether collaborative groups can achieve greater performance than individuals, and can achieve greater performance than nominal group comparisons. Here we develop a task that is especially suited to testing collaborative gains. In a collaborative crossword game, two individuals solved puzzle questions either alone or collaboratively through discussion. When talking, participants solved more puzzle questions, solved them more quickly and accurately, and in general seemed to recall the words from collaborative contexts better than from matched independent contexts. By extracting the audio of their interaction, we also demonstrate interesting relationships between spoken interaction and performance on the collaborative tasks. This task environment further substantiates the notion that, in the context of knowledge retrieval, two heads are better than one.

4.1 Introduction

Knowledge can be thought of as a probabilistic distribution. As samples are repeatedly taken from this distribution, a more complete picture emerges of the underlying knowledge. Often, as is implied by the phrase "the wisdom of crowds", the probability distribution is quite accurate with respect to its information representation–so that as samples are collected, an increasingly accurate picture emerges. For example, when eight-hundred attendees of a stock and poultry exhibition were asked to estimate the weight of a large ox, the mean of their estimates was very accurate (Galton, 1907). The error of the mean estimate was in fact much lower than the mean error of each individual's estimate. This "wisdom of crowds" effect has continued to be demonstrated in a number of domains: aggregate financial forecasts tend to be better than individual forecasts (Clemen, 1989), polls of the audience in game shows tend to reveal correct answers (Surowiecki, 2004).

The probabilistic nature of knowledge is also apparent when an individual accesses his or her own knowledge over time. When individuals were asked to make quantitative estimates of worldly information on two separate instances, the average of their estimates tended to be more accurate than either individual estimate (Vul & Pashler, 2008). When multiple individuals work interactively on a joint decision, however, the "two heads are better than one" intuition does not always hold. In general, the literature on group performance shows that groups rarely outperform their best members–the whole is rarely greater than the sum of its parts (Bahrami et al., 2010; Hastie & Kameda, 2005; Kerr & Tindale, 2004). In fact, across a large number of contexts, individuals tend to remember *less* when they're working with others (Rajaram & Pereira-Pasarin, 2010).

In these studies, subjects are usually presented with a list of items and must study and reproduce the items either individually or as a group. On average, groups tend to recall more items than individuals, but recall fewer items than nominal groups (consisting of the pooled, non-overlapping items recalled by individuals working alone; Barnier et al., 2008). That is, individuals working in a group context don't perform at their full potential. The leading explanation for this observation is the *retrieval disruption hypothesis* (Basden et al., 1997). According to this hypothesis, individuals use their own, idiosyncratic, strategies to organize and encode information. When recall takes place in an interactive context, the output of one member disrupts the retrieval strategies of the other(s), inhibiting recall performance.

The large body of empirical work providing evidence for the detrimental effects of collaboration on memory is unified by the term *social contagion* research (Barnier et al., 2008; and see Rajaram & Pereira-Pasarin, 2010, for a review). In addition to disrupting the recall of correct items, collaborators can even introduce the recall of incorrect items. When a confederate collaborator misleadingly recalled an incorrect item, participants later recalled that item themselves, as if it had been in the original recall list (Roediger, Meade, & Bergman, 2001). This effect extends beyond laboratory recall studies, as individuals can often misremember important life events. Loftus (1996) has worked extensively on issues surrounding the fallibility of memory, especially as it applies to false memories and eyewitnesses, showing that social context can significantly impact the accuracy of memory.

A related example of the negative consequences of social context is groupthink–a phenomenon where groups of people may end up making poor decisions, generally because of a motivation to reduce conflict and reach consensus, therefore failing to continue the search for an optimal solution (see Esser, 1998). This collaborative inhibition may be related to both retrieval disruption or *social loafing* (reduced effort or motivation when in a group context; Weldon, Blair, & Huebsch, 2000).

Despite the abundance of theories and supporting evidence for social contagion, there exists an intuitive feeling that we should benefit from working with others. In addition to social contagion research, Barnier et al. (2008) define two other approaches to investigating the effects of social context on memory: collaborative recall, and transactive memory. These approaches tend to seek out the beneficial effects of social context. In *collaborative recall* research, the social context is conceptualized as part of a broader environmental and situational context which can facilitate an individual's recall through priming. This priming could be detrimental, such as in retrieval disruption, or could be beneficial through cueing or triggering of correct information.

Bahrami et al. (2010) found that group performance interacted dynamically with social context. They designed a low-level perceptual decision-making task where members of a dyad reported their own decisions then agreed on a joint decision to report. When members of a dyad had unequal performance levels, the dyad tended to do worse overall than the better-performing member. However, performance exceeded aggregate individual performance when members had equal visual sensitivities and could communicate openly to discuss their observations (Bahrami et al., 2010), and when they used similar task-relevant linguistic forms (Fusaroli et al., 2012). In order to come to an agreement regarding an ambiguous low-level stimulus, members of a dyad must attempt to communicate subjective and graded confidence levels. The combination of information for higher-level decision-making tasks, such as those involving knowledge and memory, may be very different. For example, if two friends are attempting to recall the Spanish word for "countryside" from a long-ago language course, one may offer: "I think it was something like *camping*", which may trigger the other to remember the correct "campo". In this sense, members of a dyad can prime each other and iteratively build greater information.

Finally, in *transactive memory* research, the group is conceptualized as the unit of analysis: individuals are components of a coupled, distributed memory system (Wegner, 1987). In these transactive memory systems, group members may share the tasks of encoding, storing, or retrieving information in any combination. Wegner (1987) notes that memories are connected concepts–such as the concept "tomato" with the concept "red"–and these connections are formed through encoding, which can be done at the group level. As an example, consider a couple discussing the odd behavior of a mutual friend. The male partner mentions that their mutual friend seemed quiet at a recent party, while the female partner instead thought he seemed overly friendly. This reminds the man that their mutual friend had been thinking about splitting from his wife, which leads the couple to conclude that their mutual friend had been flirting with the female partner, and subsequently acted awkwardly around the male partner (from Wegner, Giuliano, & Hertel, 1985). Through collaboration (discussion), the couple in this example was able to bind information and encode a quantitatively and qualitatively different memory than either would have achieved individually. Conceptualizing the distributed storage of memories is more intuitive: We already store much of our information externally (books, to-do lists, smart phones), and in much the same way we could rely on a partner to remember something for us (essentially "outsourcing" the storage of that information to another person).

From the perspectives of both the collaborative recall and the transactional memory traditions, the performance of a group can come to be greater than the performance of its members. In this paper, we work from these intersecting perspectives to investigate the potential benefit of working with two minds instead of one on a knowledge-based trivia task. Individuals are randomly assigned to dyads and given trivia questions, which they solve either independently or collaboratively. These general knowledge trivia questions provided a set of stimuli on which subjects' knowledge varied widely, and allowed for rich discussions during collaborative sessions. Following four rounds of ten trivia questions, subjects were given individual recall tests for the answers to the preceding trivia questions.

As described by Hare (1976), research on social influence can be characterized by two factors: the "social climate", which could be either individuals collaborating or individuals working independently; and the "task completion", which is a measure of either the group product or the individual product. Consistent with previous work on joint performance measures (i.e., Hill, 1982), the current study design allowed us to first compare [1] the group product of collaborating individuals (group performance on collaborative trivia rounds) to [2] the individual product of individuals working alone (individual performances on independent trivia rounds). The recall task allowed us to compare [1] the individual product of collaborating individuals (individual recall of trivia items from collaborative rounds) to [2] the individual product of individuals working alone (individual recall of items from independent rounds).

By analyzing task performance and efficiency at the group and individual levels, and resultant memory at the individual level, we substantiate the beneficial gain of collaborative cognitive performance. Our results suggest that in knowledge-based tasks,

Figure 4.1: Experimental setup.

two heads are indeed better than one.

4.2 Methods

Sixty two participants were recruited from a subject pool of University of California, Merced, undergraduate students who participated for course credit. The participants had an average age of 19.6 ($SD = 1.7$) and were mostly female (16 male; 46 female). The participants were grouped into thirty-one dyads. Each dyad participated in four rounds of a trivia game, where each round of ten questions was to be solved individually or collaboratively, followed by a surprise recall task after all four rounds.

Participants were seated directly across from each other at a small table with IBM ThinkPad laptop computers. This allowed each participant to have a private workspace during the independent tasks, but also enabled easy communication during the collaborative tasks. Participants wore Shure Beta 54 supercardiod microphone headsets, and their conversations were recorded using an M-Audio MobilePre recording interface and Audacity software.

4.2.1 Materials

Trivia questions were collected from a variety of crossword puzzles, retieved from www.bestcrosswords.com. Questions were all straight-forward (i.e., not “cryptic”) type clues. In total, 140 questions were collected with types that were categorized as culture ($n = 23$), general knowledge ($n = 21$), definitions ($n = 27$), logic ($n = 22$), fill-

Table 4.1: Example trivia types.

Type	Question	Answer
Culture	"Kill Bill" star Thurman	Uma
Knowledge	U.S. spy organization	CIA
Definition	Gift to charity	Donation
Logic	Hour subunits	Minutes
FITB	"If all _____ fails"	Else
Categories	Tulips and irises, for example	Flowers
Sayings	"Rolling in dough" meaning	Rich

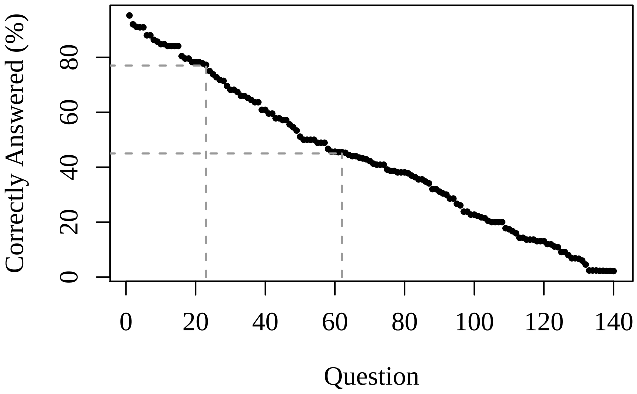

Figure 4.2: Question norming. Potential questions are ranked by the percentage of participants who answered correctly. Dotted lines show the question rankings we used.

in-the-blank (FITB, $n = 20$), categories ($n = 16$), and sayings ($n = 11$). Table reftable1 gives examples of each type.

The trivia questions were normalized for difficulty. 449 University of California, Merced undergraduate students with an average age of 18.4 ($SD = 1.4$; 200 male, 249 female) were given surveys containing trivia questions. There were 10 versions of the survey, each of which contained 14 trivia questions with lines indicating the number of letters the answers. Participants were allowed to leave answers blank, but were instructed to do the best they could to answer to each question, guessing when possible. Results showed that questions varied widely in difficulty (see Figure 5.1). For the present study, 40 questions were chosen that were answered correctly about half of the time. As shown in Figure 5.1, these trivia questions were solved by 45-77% of participants, and they contained all types: culture ($n = 6$), general knowledge ($n = 8$), definitions ($n = 4$), logic ($n = 8$), fill-in-the-blank (FITB, $n = 8$), categories ($n = 2$), and sayings ($n = 4$). The examples in Table 4.1 were each used.

Trivia Program

The experimental interface was programmed by the authors using Adobe Flash CS5. The program led participants through four experimental blocks (rounds) containing ten questions each. For each round, the program instructed participants to work either individually (I) or collaboratively (C). During collaborative sessions, participants were asked to work together and discuss each answer as a team. Across all subjects, the order of questions and condition (I-C-I-C or C-I-C-I) was randomized and counterbalanced between dyads, but was kept the same within each dyad.

Each question was provided alone on the screen with a sequence of blank squares indicating the number of letters in the answer. The space-bar was used to submit answers, and subjects were given feedback about their submission. If correct, a green checkmark appeared briefly before moving on to the next question. If incorrect or missing, a red "X" marked the incorrect or blank boxes. Subjects were given 20 seconds to correctly answer each question (with as many tries as necessary) before being automatically moved on to the next question. Between blocks, subjects were given the new condition and asked to wait for their partners before moving on. Progress was indicated using flip cards with "Working" on one side, and "Ready when you are!" on the other (see Figure 4.1).

4.2.2 Procedure

Participants were given five minutes to introduce themselves at the beginning of the study, in order to facilitate comfort and camaraderie (consistent with previous findings that more familiar groups tend to perform better on collaborative tasks; Barnier et al., 2008). After this brief familiarization period, headsets were fitted and the Flash program was started. The program began with instructions, which the researcher read aloud and subjects read on their respective screens, then the researcher left the room. After completion of the four trivia rounds, subjects removed their headsets and summoned the researcher. The trivia program was closed and each subject was given a blank text editor. Subjects were instructed to recall and type as many of the answers to the previous trivia questions as possible. They were given five minutes and asked to work individually.

4.3 Results

Thirty-one dyads participated in the experiment, but one dyad's audio was not recorded due to equipment error. Thus, task performance results are given for thirty-one dyads, while the audio results reflect thirty dyads.

For each question, the Flash program recorded (1) whether a correct answer was submitted before time ran out. If a correct answer was achieved, it also recorded (2) how much time elapsed from the beginning of the trial to the submission of the correct answer, in milliseconds, and (3) the number of incorrect attempts before the final, correct submission. Because each participant worked on his own computer, two independent data sets were collected for each dyad. For purposes of data analysis, results for each trial were averaged over the members of the dyad. These aggregated results were used to compare each dyad's performance on individual versus collaborative rounds. Dyads are independently sampled (though, individual performance is not, as one is not independent of one's partner), and hence at the dyad level, conditions (I vs. C) can be compared using paired-samples t-tests (unless otherwise noted below).[1]

4.3.1 Trivia Performance

On all three aggregate measures, collaborative dyads outperformed their non-collaborative counterparts. Out of the twenty questions presented in each condition, the average correctly answered by collaborative dyads was 14.94 (SD = 3.77), while the average correctly answered by non-collaborative dyads was 12.35 (SD = 3.11).

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[1] We also examined individual-level performance across most measures, and results are consistent with the dyad-level analyses.

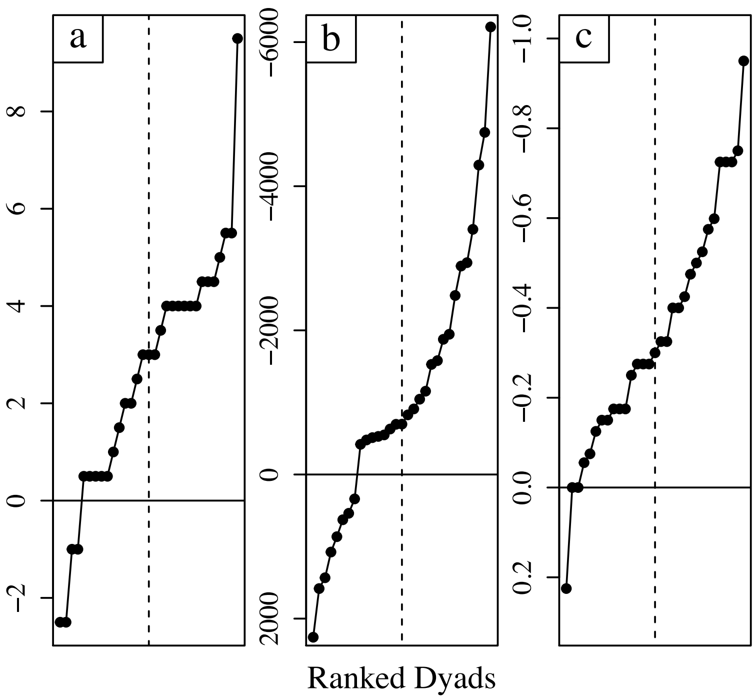

Figure 4.3: Collaboration gains for the following measures: (a) average number of correct answers, (b) average time taken to achieve a correct answer (ms), (c) average number of incorrect attempts, per question. Gain for each dyad is calculated as the difference between aggregate performance on collaborative versus non-collaborative rounds. All points above $x = 0$ show dyads benefitting from collaboration. For illustration, dotted lines show median ranked dyads.

This difference was significant, $t(30) = 5.58$, $p < .0001$. Dyads were also faster to submit correct answers while they were collaborating ($M = 5527$ms, $SD = 1212$ms) as compared to when they were not collaborating ($M = 6611$ms, $SD = 1181$ms), and this difference was also significant, $t(30) = 3.17$, $p < .005$. Finally, the number of incorrect attempts made before achieving a correct answer was smaller for collaborative dyads ($M = .26$, $SD = .16$) than for non-collaborative dyads ($M = .61$, $SD = .27$), which is also significant, $t(30) = 7.19$, $p < .0001$.

Thus, working collaboratively conferred benefits on all three measures of task performance: it increased the number, speed, and accuracy of successful submissions. Figure 4.3 shows the performance gain results, where gain for each dyad is calculated as average performance on collaborative rounds, minus average performance on non-collaborative rounds.

4.3.2 Recall

The list of recalled items for each participant was first checked for accuracy and incorrect recalls were removed. This was relatively rare, however, as incorrect recalls represented only 5.7% of the total recalled items across participants (36 out of 629). Each recalled item was matched to the round and condition in which it was encountered. At the group level (i.e., averaged within dyads), the average number of items recalled from

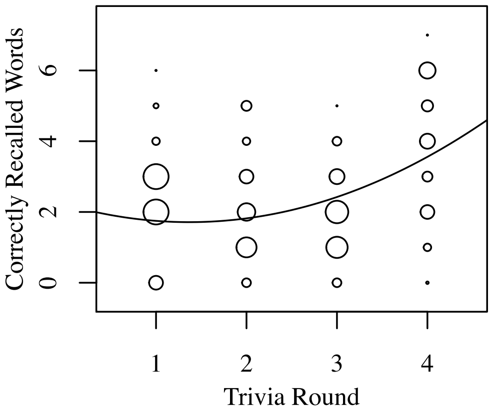

Figure 4.4: Binned individual-level recall per round. Circle sizes illustrate the number of individuals that recalled the corresponding number of items from each round. The line shows the fit of a generalized linear model with quadratic term.

each round was, respectively, 1.60 (SD = .74), 2.27 (SD = 1.35), 1.97 (SD = .91), 3.71 (SD = 1.57). Items from the last round were recalled significantly more often than any other round, $t(30) = 4.25$, $p < .001$, indicating a serial position effect of recency. Although the mean recall from the first round was the lowest, there was also evidence of a serial position effect from primacy. This pattern is shown in Figure 4.4, which plots the number of recalled words from each round, binned by the number of individuals recalling each number of items. A generalized linear model, fit to the data, shows both the recency and the (more subtle) primacy effects.

In general, subjects tended to remember more items from the rounds in which they participated collaboratively. Figure 4.5 shows ranked, aggregated dyads' recall from each round, separated by condition. For each round there was a tendency towards enhanced recall from collaboration, but this difference was only significant in the fourth round, $t(28.88)$, $p < .05$ (Welch's two-sample t-test). Overall, group level recall was not significantly better for items from collaborative rounds (M = 5.24, SD = 2.35) compared to non-collaborative rounds (M = 4.31, SD = 2.00). At the individual level, however, where dyad members are not aggregated and are instead treated as independent, there was a significant effect of condition. That is, individuals recalled more items they had encountered during collaborative rounds (M = 5.24, SD = 2.63) than during independent rounds (M = 4.31, SD = 2.47), $t(61) = 2.03$, $p < .05$. Thus, there appears to be a tendency for enhanced recall from collaboration. Admittedly, these effects are smaller than the performance measures, though more power may bear this out.

4.3.3 Conversation Analysis

In order to further quantify the effects of collaboration on performance, conversations during the collaborative sessions were recorded. A coarse analysis of these recordings allowed us to collect information on the total amount of time each dyad spent in the collaborative sessions, as well as the amount of this time that was spent talking. On average, dyads spent 241.13 seconds (SD = 71.37) in the (summed) collaborative rounds, and used, on average, 109.29 of these seconds (SD = 34.72) conversing. Because the amount of time spent in the collaborative part of the task varied between dyads,

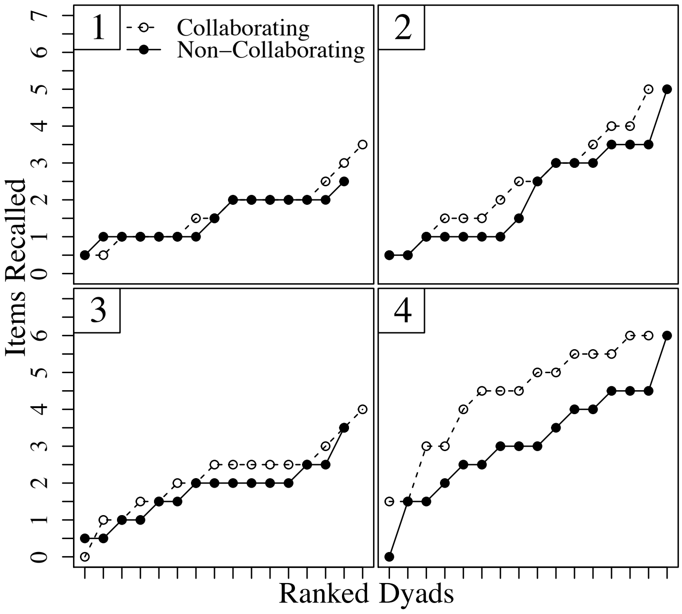

Figure 4.5: Recall for items from Rounds 1-4 for each dyad, ranked in order of performance. Dotted lines with empty circles show the aggregated number of items recalled by dyads working collaboratively; Solid lines with filled circles show recall by dyads working non-collaboratively.

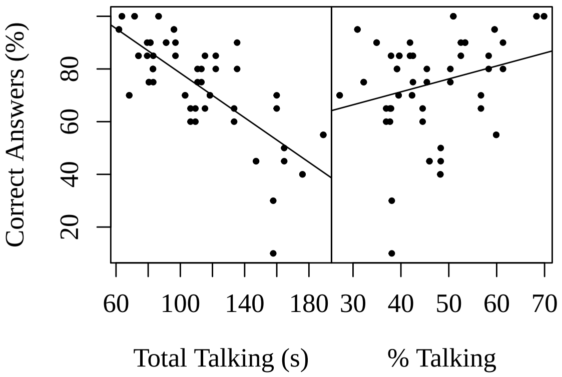

Figure 4.6: Relationship between talking and performance. The scatterplot on the left shows each dyad's performance (percentage of questions answered correctly) as a function of the total number of seconds spent talking (regression line $m = -0.4229$). On the right, performance is shown as a function of the percentage of time spent talking (regression line $m = 0.4724$).

a measure of percent talking was also calculated for each dyad. This percent talking measure varied from about 27% to 70% ($M = 46.54$, $SD = 10.76$).

As in the previous analyses, results were aggregated over dyads and each data point represents the group-level mean, across a dyad's participants. The total amount of time each dyad spent talking was negatively correlated with their performance, as measured by the number of correct answers they submitted during the collaborative rounds, $r(28) = -.77$, $p < .0001$. That is, the more talking they did, the worse they performed. This negative correlation may reflect the fact that when uncertain of an answer, dyads spend more time in discussion in order to figure it out. Indeed, when considering the *percentage* of time spent talking, there was a positive correlation with performance, $r(28) = .27$, although this trend did not achieve significance. Figure reffig6 shows the relationship between talking and performance, as measured by both absolute and percentage metrics of talking.

4.4 General Discussion

On all measures of performance for the trivia task, there appeared to be a collaborative benefit. Aggregate dyads achieved more correct answers in the collaborative rounds than in the independent rounds, and they did so with greater accuracy. Interestingly, aggregate dyads were actually faster in the collaborative rounds than in the independent rounds, despite the fact that they had the added task of communicating with their partner for each question. With respect to the terminology described earlier (Hare, 1976), we observed that the group product, produced by collaborating individuals, was better than the individual product, produced by individuals working alone. The recall task also suggested a benefit from collaboration. Previous work has shown that participating collaboratively in recall enhances future independent recall (Basden et al., 2000), but our results also suggest that collaborative encoding could enhance independent recall: the individual recall product of collaborating individuals was (slightly) greater than the individual recall products of individuals acting alone.

It must be noted, however, that the present study was specifically designed to enable us to look for evidence of a collaborative gain. The collaborative benefit apparent in this situation may not apply to other situations, as previous work described earlier has found that the degree of collaborative gain is highly influenced by social context. Future work is needed to elaborate on the specifics of the social, environmental and task contexts which allow for these collaborative gains. We would also like to address the current findings in the context of interpersonal alignment, in future work. It was noted earlier that the use of similar task-relevant linguistic forms benefits dyadic cooperation (Fusaroli et al., 2012), and a growing body of research addresses how interpersonal interactions can cause automatic alignment to spread between physical, linguistic, and other cognitive states (D. P. Tollefsen & Dale, 2012). This raises the question of whether collaborative performance on knowledge-based and memory tasks can be influenced or indicated by various levels of behavioral, linguistic, and cognitive alignment.

4.5 Acknowledgments

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Chapter 5

Familiarity modulates the dynamics of collaborative inhibition in a trivia game

Abstract

A number of questions are still unanswered about whether and how dyads perform better compared to individuals on memory tasks. The literature on collaborative recall demonstrates a robust collaborative inhibition effect, where participants do worse when remembering in collaborative contexts. However, a growing body of research suggests that this inhibition can be ameliorated, or even reversed, under certain task and social conditions. Here we construct nominal groups (hypothetically optimal aggregates of individual performers) to compare to collaborative groups. We observe collaborative inhibition on two performance metrics (number of trivia clues answered, speed of answering), but we find a *facilitatory* effect of collaboration on two other performance metrics (accuracy, number of clues subsequently recalled). We also show that familiarity can reduce this collaborative inhibition in many ways.

5.1 Introduction

In knowledge-based, joint-action tasks such as working on crossword puzzles or playing team trivia games, success depends not only on the knowledge of each individual, but the way that this knowledge is transferred, synthesized, and generated at the interactive, group level. The current paper uses a trivia task to allow us to connect the well-established work on collaborative memory (and specifically, the collaborative recall paradigm) with the emerging joint-action literature. The collaborative recall paradigm is one of the most frequently used methods of studying collaborative memory. In this paradigm, participants are asked to reproduce a known or learned list of items, either individually or in collaborative groups. Although the overall group product is often higher than the product of controlled individual participants, it almost always fails to outperform the nominal group product, consisting of the pooled, non-overlapping (i.e., a hypothetic, optimal combination of) items recalled by individuals (Barnier et al., 2008). That is, at the individual level, people remember better when working alone, and don't perform at their full potential during collaboration. This robust finding is known as *collaborative inhibition*, and is thought to result from participants' disruption of each others' unique retrieval strategies during recall (Basden et al., 1997). Collaborative inhibition has been observed in a number of studies, many of which give specific support to the retrieval disruption hypothesis (for a review, see Rajaram & Pereira-Pasarin, 2010).

An innovative study by Meade, Nokes, and Morrow (2009) challenged the ubiquity of collaborative inhibition. Memory for previously studied flight scenarios was tested for groups composed of expert pilots, novice pilots, or non-pilots. While novices and non-pilots exhibited the standard collaborative inhibition effect, expert pilots did not. In fact, the experts exhibited *collaborative facilitation*–they were better at remembering together than remembering alone. Meade and colleagues (2009) note that these results are consistent with the retrieval disruption hypothesis, in that experts have similar training and knowledge that allows them, presumably, to encode and retrieve information similarly (or, at least, *non-disruptively*). Harris and colleagues (2010), however, note that these results provide empirical justification for the *transactive memory* (TM) *systems* approach (cf. Wegner, 1987).

In TM systems, groups of individuals share the burden of remembering. Although some information is stored only within the individuals, through communication a successful group can share and combine information, resulting in group-level knowledge that exceeds that of any of its individual members. In some cases, the pieces of information held by individual group members can be combined into knowledge that none of the members individually possessed, and in this sense, the whole can truly come to be more than the sum of its parts. According to Wegner, Erber, and Raymond (1991), these emergent memory systems are more likely to succeed when group members are familiar with each other (as expertise and role within the group are already known and can be exploited). Harris et al. (2010; and see Harris, Keil, Sutton, Barnier, & McIlwain, 2011) found evidence for this kind of TM system in their study of couples who had been married for over 20 years. Many of these couples were able to demonstrate collaborative facilitation, but the pattern of results was complex: facilitation was not stable across couples, tasks, nor across within-task topics. Similarly, Hollingshead (1998) found that couples were more likely to form TM systems, but only under certain communication and task conditions.

A successful TM system can be conceptualized as a special case of the more general *coordinative structure* framework described by Shockley et al. (2009). A coordinative structure is a self-organized, softly assembled (i.e. temporary), set of components that emerges naturally, under certain conditions, and behaves as a single unit (see also Bernstein, 1967). The domain of joint-action is ripe with examples of how people coordinate to move together, either in service of a shared goal (M. J. Richardson, Marsh, & Baron, 2007), or even unintentionally (M. J. Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007; and see Marsh, Richardson, & Schmidt, 2009). D. P. Tollefsen and Dale (2012) point out that when individuals are engaged in a joint task or joint action, they become aligned at multiple levels, including body posture (Shockley et al., 2003), linguistic form choice (Pickering & Garrod, 2004), and higher-level cognitive states (D. P. Tollefsen & Dale, 2012; Sebanz et al., 2006) and alignment at any of these levels can "percolate" up to others. Ultimately, we seek to integrate this dynamic account of interpersonal coordination and collaboration with the substantial body of literature on the social consequences of memory and collaborative recall.

Here, we take preliminary steps in this direction by examining collaboration on a relatively unconstrained memory task utilizing trivia-type clues. The trivia clues allow us to conceptualize the dynamics of remembering as a search process across pre-existing memory space, as participants consider many possible solutions before narrowing down on an objectively correct answer. Extending the work of Szary and Dale (2013), the current study presents four rounds of trivia clues to dyads who work either independently or collaboratively on each round to find solutions. After the game, a more traditional recall test measures recall for the solutions achieved during the trivia game.

Results from Szary and Dale (2013) showed that, on average, dyads performed better (answered more clues correctly, answered them faster, answered them more accurately, and were more likely to remember them later in a surprise recall task) during collaborative rounds as compared to individual rounds. However, these results did not address the performance of nominal groups, nor the effects of familiarity on group performance. The current study uses the trivia paradigm with the primary modification that familiar and non-familiar dyads were recruited, and results are presented in terms of the more stringent nominal comparisons. In order to increase the quantity and quality of interactions, the trivia game was extended to include more clues and provide more time for each clue. Although our familiarity measure was extremely limited, we present our encouraging findings that (1) collaborative inhibition can be eliminated by even a short period of familiarity; and (2) collaborative facilitation is stronger for dyads with more familiarity.

5.2 Methods

5.2.1 Participants

Participants were recruited from a subject pool of University of California, Merced undergraduate students who participated for course credit. For the non-familiar condition, two independent timeslots were posted on the SONA research participation system. For the familiar condition, one timeslot was posted and each participant was asked to bring a friend. After the task, participants were surveyed to determine the extent and nature of their relationship, if any, in order to categorize them into the appropriate conditions. In total, we collected data from 68 participants (46 female; 22 male), with a mean age of 19.9 *(SD = 2.8)*. Both the familiar and non-familiar conditions included 17 dyads (34 participants; 20 females, 14 males in non-familiar; 26 females, 8 males in familiar). Given our lenient recruitment procedure, the length of relationships in our familiar condition ranged from 2 months to 3 years ($M = 15.59$ months, $SD = 10.52$).

5.2.2 Procedure

Upon arrival, all dyads were given 5 minutes for introducing and familiarizing themselves with one another[1]. Partners were seated across from each other at a table with two HP Chromebook laptops between them, on which the stimuli were presented. The partners could see only their own workspaces, but were able to observe one another over the tops of their screens. Each dyad participated in multiple rounds of a trivia game, working either individually or collaboratively on each round. After all rounds of the trivia task were finished, the experimenter instructed each participant to open a blank text file and, working independently, spend 5 minutes recalling and listing as many of the trivia game answers as possible. Finally, a brief post-experimental survey was performed and participants were dismissed.

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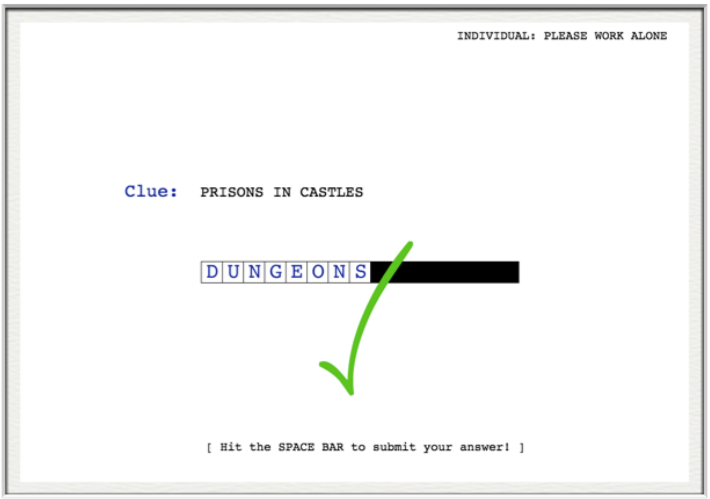
[1] In our (unpublished) experience, this familiarization period was crucial for non-familiar dyads to become comfortable interacting with one another during the task. This procedure was replicated for familiar dyads for the purpose of consistency.



INDIVIDUAL: PLEASE WORK ALONE

Clue: PRISONS IN CASTLES

DUNGEONS

[Hit the SPACE BAR to submit your answer!]

Figure 5.1: Screenshot from the trivia game, showing a successfully answered clue.

5.2.3 Materials

Trivia Game

The stimuli consisted of 60 trivia clues of medium-level difficulty (answered correctly about half of the time) as described in Szary and Dale (2013). The clues represent a variety of types of question: cultural knowledge (“Kill Bill” star Thurman: *UMA*); general knowledge (U.S. spy organization: *CIA*); word definitions (Gift to charity: *DONATION*); logic (Hour subunits: *MINUTES*); fill-in-the blank (“If all ____ fails”: *ELSE*); categories (Tulips and irises, for example: *FLOWERS*); and sayings (“Rolling in dough” meaning: *RICH*). Examples show the answers in italics.

Clues were presented using a trivia computer game developed by the authors using Adobe Flash CS5. Clues are sorted into 4 rounds of 15 clues each, and participants are instructed to complete each round either collaboratively (C), or independently (I). During the collaborative rounds, partners are encouraged to discuss clues and work together to solve them as a team. Across dyads, the order of the clues and condition (which could be either I-C-I-C or C-I-C-I) was randomized and counterbalanced. Clues were presented one-at-a-time, along with blank squares corresponding to each letter of the correct answer. After an answer is typed in, the space-bar is used to submit the answer. If correct, a checkmark icon appears briefly and the program moves on to the next clue, as shown in Figure 5.1. If incorrect, a red “X” marks each incorrect letter, which can then be corrected. Participants may try as many times as necessary to submit a correct answer, but if they don’t succeed within 30 seconds, the program displays a “Time’s Up!” icon and moves on to the next clue.

Between each round, participants are given their new conditions and asked to wait for their partners (if necessary) so they can move on together. Partners indicated their progress to each other (“Working”, or “’Ready when you are!”) using flip cards placed on the table beside their computers. For each clue the program recorded whether a correct answer was submitted before time ran out and, if so, the elapsed time before the answer was submitted, as well as the number of incorrect attempts preceeding each correct answer.

(Case 1): If both P^1_{ij} and P^2_{ij} are correct, D_{ij} is also correct. Time is computed as the smaller (faster) of P^1_{ij} and P^2_{ij}, and errors are computed as the smaller (most accurate) of P^1_{ij} and P^2_{ij}. If either P^1_{ij} or P^2_{ij} is correctly recalled, so is D_{ij}.

(Case 2): If only one of P^1_{ij} and P^2_{ij} is correct, D_{ij} is correct and time, errors, and recall are set equal to those of whichever P_{ij} was correct.

(Case 3): If neither P^1_{ij} nor P^2_{ij} is correct, D_{ij} performance is {no; null; null; no}.

Post-experimental Survey

After the trivia game and recall task, participants were asked to privately rate their team's effectiveness when working together. Ratings were performed on a 1-7 scale where 1 represented "not at all effective" and 7 represented "perfectly effective". Participants were also surveyed to determine whether they knew each other before the experiment or not and, if so, the length of their relationship.

5.2.4 Data Analysis

The current study used a 2 (familiar or non-familiar; a between-dyad manipulation) x 2 (collaborative or individual solving; a within-dyad manipulation) mixed design. Our dependent variables included (1) the number of correct answers achieved; (2) speed, measured as the amount of time in milliseconds that elapsed before each correct answer was submitted; (3) the number of errors (incorrect submission attempts) that preceded each correctly submitted answer; and (4) the number of correct answers recalled (that is, during the subsequent recall task).

Nominal Aggregation

Because both participants used their own computer workstations to submit answers, we have two unique datasets for each dyad. Here, we combine individual members' performances into one group-level dataset (per dyad). That is, for each dyad $\mathrm{D}_{i=[1,...,n]}$ (where n is the number of dyads) we compute the dataset D_i as the combination of both its participants' datasets (P^1_i and P^2_i). Consistent with the literature on collaborative recall, we combine unique datasets into one using an extension of nominal aggregation to compute nominal performance (which is the hypothetical, optimal combination of P^1_i and P^2_i). To illustrate how we calculated nominal aggregate performance in our task, consider stepping through each clue $j = [1, ..., 60]$ for each D_i. The performance measures {correct (yes/no); time (ms); errors (#); recall (yes/no)} for our nominal D_{ij} are calculated as follows:

For internal consistency, the same nominal aggregation procedure was used for both collaborative and independent rounds (because even during collaboration participants had their own computers, resulting in two datasets for *all* rounds). However, aggregation is expected to play a negligible roll for the collaborative datasets, as dyads talked and submitted answers together resulting in largely similar datasets. For the sake of consistency with the literature, we refer to aggregated collaborating groups as simply "collaborative groups", while we refer to the aggregated (hypothetical) groups computed from independent rounds as "nominal groups". We then compute a difference measure as collaborative minus nominal group performance (or the reverse, for our reverse measures of speed and accuracy). Thus, performance difference > 0 always indicates collaborative facilitation, while performance difference < 0 indicates collaborative inhibition.

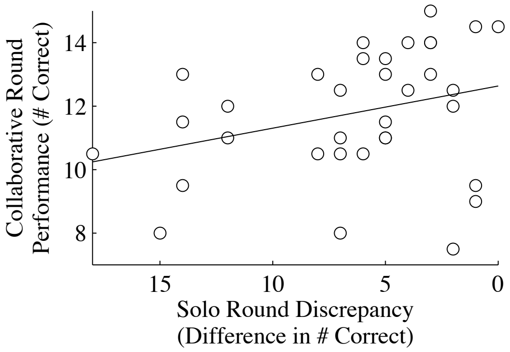


Figure 5.2: Collaborative performance plotted against discrepancy during the individual rounds, for each dyad. Regression line ($m = -0.13$).

Discrepancy

Lastly, we compute a discrepancy measure for each dyad that indicates how similar or dissimilar its members are to each other. This measure is computed as the magnitude of the difference between each dyad member's average performance during the (two) individual rounds.

5.3 Results

5.3.1 Performance

Across conditions, nominal groups performed significantly better than collaborative groups on two performance measures (number correct and speed), indicative of collaborative inhibition (details for all performance measures are given in Table 5.1). However, nominal groups performed significantly worse on the other two measures (minimization of errors and number recalled), indicative of collaborative facilitation. Non-familiar dyads displayed a similar pattern of results, showing significant indications of collaborative inhibition in terms of number correct and speed, but only showed collaborative facilitation in terms of minimization of errors (and not number recalled). Conversely, familiarity was found to ameliorate the negative consequences of collaboration. Within familiar dyads, nominal and collaborative groups were not significantly different from one another in terms of number correct or speed, but collaborative groups were (still) significantly better at minimizing errors and at subsequent recall, indicating collaborative facilitation. Unpaired t-tests between performance metrics for familiar and non-familiar dyads did not reach significance. The discrepancy measure for each dyad was weakly, negatively correlated with the dyad's collaborative performance, but this also failed to reach significance. Still, when the individuals composing a dyad performed more similarly during individual rounds, their collaboration tended to be more successful (Figure 5.2).

Recall By Round

We replicated previous findings (Szary & Dale, 2013) that dyads remember more from rounds on which they collaborated, and in general recall more from the later (more recent) rounds. This first result is presented in Table 5.1, which shows that the number of items recalled was higher during collaborative rounds across all dyads, as well

Table 5.1: Means and standard deviations (in parentheses) for each performance measure. Columns show nominal and collaborative conditions, as well as performance difference (where instances of collaborative facilitation are bold). Rows show overall ($n = 34$), familiar ($n = 17$), and non-famliar ($n = 17$) results, respectively, for each measure.

	Nominal	Collaborative	Diff.
# Correct	12.53 (1.77)	11.79 (2.00)	−0.74**
Fam.	12.38 (1.68)	12.09 (2.03)	−0.29
Non-fam.	12.68 (1.90)	11.50 (2.00)	−1.18**
Speed (ms)	6861 (1997)	7895 (1745)	−1034**
Fam.	6740 (2099)	7648 (2064)	−908
Non-fam.	6983 (1946)	8141 (1428)	−1158*
# Errors	0.25 (0.20)	0.11 (0.09)	**0.14****
Fam.	0.21 (0.19)	0.10 (0.08)	**0.11***
Non-fam.	0.28 (0.20)	0.12 (0.11)	**0.16*****
# Recalled	4.26 (1.28)	5.12 (1.74)	**0.86***
Fam.	4.29 (1.16)	5.38 (1.92)	**1.09***
Non-fam.	4.24 (1.43)	4.85 (1.54)	**0.61**

Note. Asterisks indicate a significant difference between a given row's nominal and collaborative means, using paired t-tests, where $^*p < 0.05$, $^{**}p < 0.005$, $^{***}p < 0.0005$.

as for familiar dyads, but not for non-familiar dyads. When comparing items recalled from each of the four rounds separately, it is apparent that this difference manifests largely in the superior fourth round performance of familiar collaborator groups. Table 5.2 shows the average number of items recalled from each round. There are no significant differences between any of the comparisons (familiar–non-familiar; nominal–collaborative; or any of the other 2x2 comparisons) in any round except round 4, where familiar collaborator groups recall significantly more than familiar nominal groups (unpaired $t(15) = 2.26, p < 0.05$). Figure 5.3 plots the data from Table 5.2 to further illustrate this effect.

5.3.2 Qualitative Measures of Familiarity

Length of Relationship

A preliminary analysis of the effect of relationship lengths on performance was computed for the number of correct answers achieved. Figure 5.4 shows the performance difference for number of answers achieved (from Table 5.1) as a function of each dyad's relationship length. Across all dyads, the difference measure is positively correlated with length of relationship, $r(32) = 0.42, p < 0.05$. That is, collaborative facilitation is greater for dyads who knew each other longer. This trend remains but is no longer significant when considering only familiar dyads. The existence of a subtle but noteworthy length-of-relationship effect can be further demonstrated by grouping dyads by the length of their relationships.

As shown in Table 5.1, dyads with no relationship ($rel_{length} = 0$) exhibited a performance difference of -1.18 ($SD = 1.24$), indicative of significant collaborative inhibition. Familiar dyads exhibited a performance difference of -0.29 ($SD = 1.29$), indicative of weaker collaborative inhibition. Among the 9 familiar dyads with self-reported relationship lengths of 12 months or less ($rel_{length} \leq 12$; $M = 7.67$ months, $SD = 4.30$),

Table 5.2: Mean recall and standard deviations (in parentheses).

	Nominal	Collaborative	Overall
Round 1	3.56 (1.36)	4.22 (2.07)	3.91 (1.78)
Fam.	4 (1.51)	4 (2.06)	4 (1.77)
Non-fam.	3.13 (1.13)	4.44 (2.19)	3.82 (1.85)
Round 2	3.56 (1.36)	4.375 (2.06)	3.94 (2.42)
Fam.	4 (1.73)	4.75 (1.73)	4.35 (2.26)
Non-fam.	3.11 (2.37)	4 (2.07)	3.53 (2.21)
Round 3	4.81 (2.14)	5.11 (2.37)	4.97 (2.24)
Fam.	4.5 (2.20)	5.89 (2.42)	5.24 (2.36)
Non-fam.	5.13 (2.17)	4.33 (2.18)	4.71 (2.14)
Round 4	5.11 (2.49)	6.88 (1.86)	5.94 (2..36)
Fam.	4.67 (2.12)	7 (2.12)	5.76 (2.39)
Non-fam.	5.56 (2.88)	6.75 (1.67)	6.11 (2.39)

a performance difference of -0.89 ($SD = 1.47$), indicating even weaker collaborative inhibition, was observed. For the 8 dyads with longer relationships ($rel_{length} > 12$), $M = 24.5$ months, $SD = 7.76$), there was a performance difference of 0.34 ($SD = 0.57$), indicating collaborative facilitation. Overall, more familiar dyads were more likely to experience facilitatory effects of collaboration. This distinction was reliable for $rel_{length} > 12$ as compared to: (1) $rel_{length} \leq 12$ (unpaired $t(15) = 2.27,\ p < 0.05$); (2) $rel_{length} = 0$ (unpaired $t(23) = 3.35,\ p < 0.005$); and (3) both $rel_{length} \leq 12$ and $rel_{length} = 0$ together (unpaired $t(32) = 3.04,\ p < 0.005$).

Subjective Ratings of Collaborative Effectiveness

Subjective reports of effectiveness during collaboration were collected individually for each participant. The mean of collaborative effectiveness ratings was 5.91 ($SD = 0.84$). Dyad level aggregates were computed as the sums of their component members' ratings, in order to look for a relationship between reported effectiveness and actual task performance. None was found: self-reports of effectiveness did not differ as a function of actual effectiveness (as measured by performance metrics), nor as a function of task condition.

5.4 General Discussion

The current paper builds upon the methods and results of Szary and Dale (2013) by considering the role of familiarity and reporting nominal group performance. While collaborative inhibition is observed, which is consistent with much of the collaborative recall literature, it is observed only for certain performance measures and for certain dyads. That is, across all dyads a significant collaborative inhibition is observed in terms of the number of trivia clues correctly answered, and the speed of achieving those answers. This significant inhibition remains for non-familiar dyads, but no difference is observed between collaborative and nominal groups who are familiar to one another. Familiarity, in this case, has protected against the negative consequences so often observed in the social remembering literature. In fact, we demonstrate here a

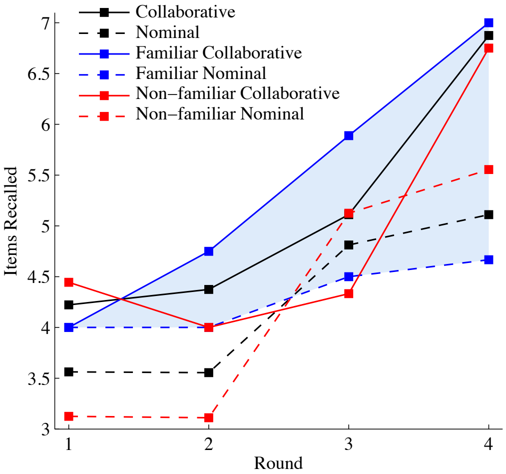


Figure 5.3: Recall by round for each group. Solid lines represent collaborative groups, dotted lines denote nominal groups. Black lines are means across all dyads, while blue and red lines are means for familiar and non-familiar dyads, respectively. The shaded area highlights the difference between familiar collaborative and familiar individual groups for illustrative purposes.

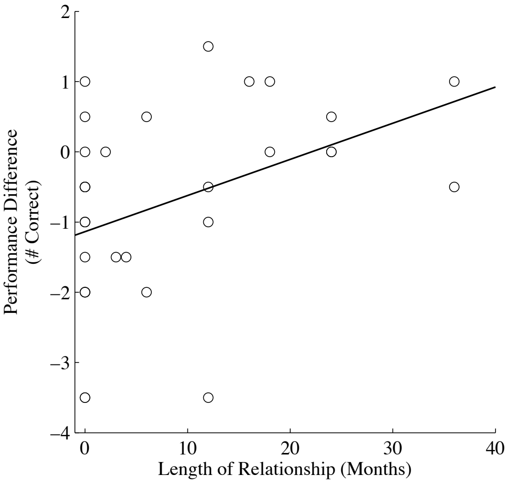


Figure 5.4: Performance difference as a function of relationship, in months. Regression line $m = 0.051$.

number of instances in which collaborative *facilitation* can actually be observed for a memory task. For example, dyads made less errors during collaborative rounds, and recalled more from the rounds on which they collaborated. This effect is even stronger for the subgroup of familiar dyads.

Despite the poverty of our familiarity measure, we uncovered a correlation between relationship length and collaborative facilitation. On most measures we were able to confirm that familiar dyads worked better together (consistent with Wegner et al., 1991; Harris et al., 2010, as discussed earlier). Additionally, we found that similarity between two participants was associated with their success as a dyad. This is consistent with existing work on joint decision-making, which shows that collaboration on low-level perception tasks is more successful when dyads are composed of members with similar perceptual abilities, and when those members use similar task-relevant linguistic forms (Fusaroli et al., 2012).

More than any single conclusion, this collection of results suggests that collaborative remembering is a complex task, the success of which is modulated by many interacting factors (familiarity, similarity) and changing components (different knowledge landscapes for each clue, different external contexts across rounds). It is perhaps most appropriately approached from the dynamic, joint-action perspective of a coordinative structure, as described earlier. Ongoing work seeks to investigate these data from this perspective, which will involve utilizing complex dynamics methods to uncover the mechanisms involved with what often feels, informally, like a qualitative shift from the paradigm of successful collaboration (which captures, for example, the concepts of TM and instances of collaborative facilitation) to the paradigm of unsuccessful collaboration (captured by collaborative inhibition and retrieval disruption, for example). See M. J. Richardson, Dale, and Marsh (2014) for a treatment of these methodologies and their theoretical implications.

5.5 Acknowledgments

The authors would like to thank Jacqueline Pagobo and Maxine Varela for their assistance with data collection, and the anonymous reviewers for their insightful suggestions.

Chapter 6

Simulating Collaborative Foraging

6.1 Introduction

As discussed in the Introduction to this dissertation (i.e. Section 1.2.2), human memory research has been inspired in many ways by animal foraging research. The ecological domain gives insight into the ways in which different situations might result in different search dynamics, strategies, and outcomes. In this chapter, I begin by reviewing some of the computational work on foraging processes, and then describe a preliminary project of my own which builds upon these models by adding multi-agent interaction.

Section 1.2.2 reviews several empirical examples of animals engaged in Lévy flights. Despite the seeming ubiquity of Lévy flights across species, a more detailed investigation of most of these studies reveals that these dynamics are dependent upon certain conditions. For example, Reynolds observed that when male butterflies search for female butterflies (for mating purposes) their search strategies depend on the female butterflies' movement patterns. If the female's motion is Lévy distributed, the male's will be Gaussian, and if the female's motion is Gaussian, the male's will be Lévy (A. M. Reynolds, 2006). Reynolds modeled the scenario computationally, and showed that this strategy would optimize the encounter rate between males and females. Fallow deer also change their behavior depending on encounters with other members of their own species. When foraging alone, the deer perform Lévy walks, but when foraging as a group, the Lévy patterns disappear (Focardi et al., 2009). Bartumeus et al.'s (2003) dinoflagellate study, and De Knegt et al.'s (2007) goat study both showed effects of environmental conditions on foraging behavior. In fact, both found evidence of Lévy walks only when resources were sparsely distributed, but not when resources were bountiful.

Recall from Section 1.2.1 that reaction-diffusion models can be compared using measurements of encounter rates. The findings of Bartumeus et al. (2003); Knegt et al. (2007) can be explained by modeling encounter rates as a function of target availability, or sparsity. Using computational models, it has been demonstrated that Lévy flights are effective in optimizing encounter rates when the target availability is low (Bartumeus et al., 2002; Viswanathan et al., 1999). Other than the overall availability, Viswanathan et al. (2011) did not find evidence that characteristics of target distribution effected encounter rates during stochastic searches. However, the distribution of resources in the natural environment is often *not* normally distributed, but is more patchy, or clustered, and often exhibits fractal properties (Ritchie, 1998). It is unclear whether the fractal distribution of environmental resources is causally related to the adaptation (or emergence) of Lévy foraging patterns, but the overall target density (availability) certainly seems to play a role in modulating search behaviors (Viswanathan et al., 2011).

If the overall target density is low, Lévy processes confer an advantage because they allow a forager to travel to a higher number of new potential target locations. Consistent with the idea of superdiffusion, Lévy foragers tend to move further away from their starting points, and are less likely to revisit a site they've already foraged. Computationally, Lévy flights in low density contexts optimize encounter rates (Bartumeus et al., 2002; Viswanathan et al., 1999). If the overall target density is high, however, then Lévy flights lose any advantage. In these scenarios, the forager has no reason to take superlong steps to move to entirely new areas, and small movements in a given area are sufficient to encounter targets. Even if a forager attempts to draw path lengths from a Lévy distribution, any superlong path length will be truncated as soon as the forager encounters a target. Thus, the superlong flights will disappear, and attempted Lévy walks will be indistinguishable from random walks. Indeed, Lévy walks and random walks are computationally shown to be equally effective in high density environments (Viswanathan et al., 2011).

The above models are built on the theoretical foundations of diffusion borrowed from statistical physics. Diffusion may feel explanatorily sufficient for the behavior of simple organisms such as Bartumeus et al.'s (2003) dinoflagellates, which are mostly single-celled, but one might expect that the foraging behavior of larger mammals with complex neural machinery, such as humans, do more than diffuse aimlessly through their environments. Although Lévy flights as a descriptive concept are not *inconsistent* with "intelligent" or goal-directed foraging behavior, as a strategy they have some limitations. For example, a random walker with Lévy distributed path lengths is agnostic to its performance. It is just as likely to jump miles away after a successful search in a given location as it is to stay in that location. In a uniformly-distributed environment this may be fine, but if the environment is patchy, it could mean the forager is leaving a dense cluster of resources before collecting them. In animal behavior, this sub-optimal behavior would mean a deer foraging for berries would leave a berry-dense bush after sampling just one or two of its berries, which would be evolutionarily disadvantageous.

A second flavor of computational foraging work is called **area-restricted search (ARS)** and explicitly models ongoing performance monitoring. In area-restricted search models, an agent will stay in a target-dense patch while it is successful there, and only once its resources are depleted will the agent move on to find a new patch. The decision of when to leave a patch is based on Charnov's (1976) marginal value theorem (MVT). In MVT, an agent compares the expected encounter rate within a patch to the expected encounter rate elsewhere. Once a given patch has been depleted so that the encounter rate has fallen below the encounter rate expected elsewhere, the agent will leave the patch. Hills and colleagues have found evidence for this behavior in human subjects searching through physical space (Hills et al., 2013) as well as semantic space (Hills et al., 2012). They also used computational models to show that ARS optimized search across these semantic networks.

The simulation described in this chapter takes some inspiration from both stochastic (Lévy flights and random walks) and memory-driven (ARS) search literatures. In the model, two agents move across a space searching for resources. Their basic movement patterns are random walks, but with longer path lengths becoming more likely as the time between target encounters grows. Essentially, agents are more likely to move further away as they become less successful. This algorithm is similar to MVT in that it results in smaller movements while an agent is being successful in a local cluster, and larger movements to other areas when the cluster is small, or otherwise depleted. In contrast to ARS, the agents don't need to make predictions about or retain specific memories for the environment, but are still more likely to stay in an areas in which they are succeeding. This simple, modified random walk algorithm allows us to examine the effects of interaction between two (or more) agents on search processes, as well as how this multi-agent interaction may be modulated by environmental parameters (such as sparsity and patchiness). The current simulation tests the effects of these three parameters on multi-agent search processes. First, an interaction parameter allows us to investigate whether forced interaction between agents helps or hurts the search process. Next, we manipulate the patterns of resource distribution in the environment by parameterizing resource availability, and uniformity, which is a measure of clustering or patchiness.

In contrast to each of the previous chapters, this chapter has not been peer-reviewed or published elsewhere, although the model and results have been presented orally at conferences. The simulation was designed in collaboration with Professor Rick Dale, and the design of the environment was informed by Bryan Kerster's work (Kerster et al., 2013).

6.2 Foraging Simulation

We tested the effects of interaction on two foraging agents across different resource distribution environments. We developed a simple, abstract simulation in which two virtual agents move across a virtual landscape searching for resources. The following sections describe the details of the simulation.

6.2.1 Model Details

The two virtual agents are randomly placed in the simulated foraging environment. At each of 5,000 time steps, a new movement vector is determined for each agent. An **interaction** parameter, I, is implemented as a perturbation of the movement vector of the least successful agent towards the location of the more successful agent.

The resource distribution (environmental context) is manipulated using two other parameters: **resource availability**, A, and **uniformity**, U. A is the percentage of spaces in the environment which contain resources. Thus, a low A would be a very sparse environment, while a high A would be a very bountiful environment. U is the degree to which those resources are spread uniformly throughout the environment, as compared to in clusters. In our environment generation algorithm (discussed below), U reflects the likelihood of a resource to appear in certain areas over others, and at $U \neq .5$ (50%) this spatial bias results in clustering. Thus, a low U would be a very clustered environment, while the maximum U (0.50) would be a perfectly uniform environment.

Here, we consider 8 levels of interaction, $I = \{0, 0.01, 0.05, 0.10, 0.25, 0.50, 0.75, 0.90\}$, 4 levels of availability, $A = \{0.01, 0.05, 0.25, 0.50\}$, and 4 levels of uniformity, $U = \{0.01, 0.10, 0.25, 0.50\}$. Thus, our design was 8 by 4 by 4, resulting in 128 unique conditions. Each condition was simulated 10 times. Each simulation consisted of 5,000 time steps, during which two agents moved across the virtual resource environment collecting resources.

Environment

The environment is a two dimensional square grid with side lengths (s) of 128, where some number of locations are designated as targets containing a resource. Resources are nonrenewable, such that once a resource is collected it disappears. The total number of resources (r_{total}) is determined by parameter A:

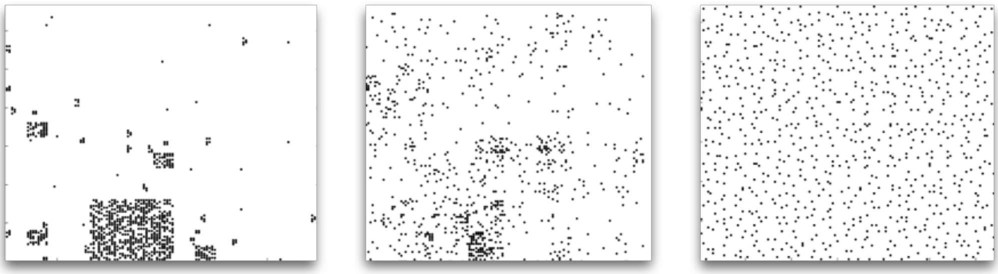


Figure 6.1: Three environments with $A = 0.05$ illustrating (from left to right) low ($U = 0.10$), medium ($U = 0.30$), and high ($U = 0.50$) uniformity.

$$r_{total} = A \times s^2. \tag{6.1}$$

The distribution of resources is determined by parameter U, and uses an algorithm presented in Kerster et al. (2013), in which the square environment is recursively split into two rectangles (vertically or horizontally, at random), which are each split into two squares. At the first iteration, where the square consists of the entire environment, $r_{square} = r_{total}$. After a square is split into rectangles, one rectangle (a, chosen at random) receives

$$r_a = U \times r_{square} \tag{6.2}$$

resources, and the other rectange (b) receives the remainder

$$r_b = r_{square} - r_a. \tag{6.3}$$

Next, each rectangle is split into two squares, where one square (i, chosen at random) receives

$$r_i = U \times r_{\{a,b\}} \tag{6.4}$$

resources, while the other square (ii) receives the remainder

$$r_{ii} = r_{\{a,b\}} - r_i. \tag{6.5}$$

The process then repeats, setting $r_{square} = r_{\{i,\ ii\}}$ for each square. When the number of available spaces in a given rectangle (or square) is such that the next split would result in more resources than spaces on one of the sides, the recursion stops and resources are placed randomly within that rectangle. If only one resource remains in a given rectangle, it is randomly placed within that rectangle. Each space may only contain one resource. Figure 6.1 shows three example environments with the same number of resources, but different levels of uniformity. A unique environment was generated for each of the 10 simulations for each condition.

Individual Movement

An agent's location at a given time step t is indicated by coordinates $\{x_t,\ y_t\}$. The agent's location at the next time step, $\{x_{t+1},\ y_{t+1}\}$, is determined by movement vector $\vec{M}$. $\vec{M}$ is defined by random angle θ, where $0 \leq \theta < 2\pi$, and random distance D, where $1 \leq D \leq H$. H is history, which is a simple count of the number of time steps since the agent last collected a resource, where $1 \leq H \leq s$. Thus, each agent's movement vector $\vec{M}$ is calculated as

$$\begin{aligned}\Delta x &= D \times \cos(\theta);\\ \Delta y &= D \times \sin(\theta)\end{aligned} \tag{6.6}$$

and

$$\begin{aligned}x_{t+1} &= x_t + \Delta x;\\ y_{t+1} &= y_t + \Delta y.\end{aligned} \tag{6.7}$$

Agents must move at least one space during each time step, and are stopped in their tracks by the boundaries of the environment.

Interaction

To simulate the effects of interaction on the search process, parameter I has the effect of pulling one agent towards the other. For simplicity, here we implement this interaction as a perturbation of the movement vector of only one agent at a time. Specifically, only the agent who has been *least* successful over the last 5 time steps is subject to the effects of interaction, and is essentially drawn towards the location of the more successful agent. Thus, we can refer to the least successful agent as the "follower", and the more successful agent as the "leader". The interaction vector $\vec{I}$ is defined as the distance between agents:

$$\begin{aligned}\Delta x_I &= x_{Leader} - x_{Follower};\\ \Delta y_I &= y_{Leader} - y_{Follower}.\end{aligned} \tag{6.8}$$

The leader's movement is entirely determined by $\vec{M}$, but the follower's movement is determined by a combination of $\vec{M}$ and $\vec{I}$ which depends on the interaction parameter I. That is, for the leader, the total movement vector at the next time step is simply

$$\vec{V}_{Leader} = \vec{M}_{Leader}, \tag{6.9}$$

while the total movement vector for the follower is

$$\vec{V}_{Follower} = (\vec{M}_{Follower} \times (1 - I)) + (\vec{I} \times I). \tag{6.10}$$

Parameter I functions by weighting the percentage of movement determined by the interaction perturbation. A low I (of 0.01, for example) would mean that only a small percentage of each movement can be modified by interaction, so interaction does not play a large role in search behavior. Conversely, a high I (of 0.90, for example) would mean that interaction explains 90% of those movements subject to the interaction force. Essentially, parameter I weights the degree to which the follower's movement is determined by the location of the leader. This is not unlike what may happen even in a cognitive task. For example, joint remembering may involve one person 'pulling' another towards some set of concepts or ideas while they try to recall together. In addition, the very concept of 'group think' means that people draw each other towards a similar set of ideas or procedures. The question we pursue here is how this interactivity, or this tendency to pull, relates to performance when the agents are navigating worlds of various resource structures.

Table 6.1: Collaborative benefit. For illustrative purposes, green cells show positive collaborative benefits, red cells show negative benefit (i. e. collaborative inhibition). Dark cells show significant t-test comparisons between best scoring interactive conditions and non-interactive conditions. See text for details.

		Very clustered ⟵			⟶ *Uniform*
	A	$U = 0.01$	$U = 0.10$	$U = 0.25$	$U = 0.50$
Sparse	0.01	8.96∗	5.30	3.23	2.99
↑	0.05	5.87∗	3.79	0.53	4.25∗
↓	0.25	1.87	−1.38	2.02∗	0.24
Bountiful	0.50	−1.81∗	−0.61	−0.29	−0.38

$*p < 0.05$

6.3 Results

We discuss the model's performance in terms of both product (search success, or score) and process (search dynamics).[1] Because one of the environmental parameters was the number of resources available, the dependent variable score is a normalized measure of the proportion of available resources that were collected across the two agents in each trial.

6.3.1 Search Success

Linear models predicting score (across all 1280 trials) were constructed. The model

$$Score \sim U + A + \varepsilon \tag{6.11}$$

was found to be significant, $F(2,\ 1277) = 6246$, $p < 0.0001$, with adjusted $R^2 = 0.9071$. Adding the interaction parameter to the model,

$$Score \sim U + A + I + \varepsilon \tag{6.12}$$

was also significant $F(3,\ 1276) = 4702$, $p < 0.0001$, and increased the adjusted R^2 to 0.9168. A comparison of these models indicated that the interaction parameter provided a significant increase in fit, $F(1, 1277) = 150.57$, $p < 0.0001$.

Figure 6.2 shows mean score (across the 10 trials) for each condition. A collaborative benefit measure was calculated for each condition by comparing the best mean score of the collaborative conditions ($I \neq 0$) to the mean score of the individual condition ($I = 0$). Results are shown in Table 6.3.1. Colors help visualize the direction (facilitatory or inhibitory) and strength (significant or not) of the collaborative benefits. Green cells illustrate positive collaborative benefits, which can be interpreted as the percentage of resources collected by collaborating agents above and beyond those collected by independent agents, for the given environmental condition. Red cells indicate collaborative *inhibition*, and indicate that independent agents performed best. The dark green and red cells indicate significant t-test comparisons between the ten trials of each (collaborating versus non-collaborating) condition.

In Figure 6.3, all scores are shown as a function of I, divided into subplots for each environmental condition. For each subplot, polynomials of degrees 1-4 were fit to the data, and adjusted R^2 values were calculated. The polynomial with highest adjusted

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[1] N.B.: Because the project is still in an exploratory phase, statistical analyses are quite preliminary, as well.

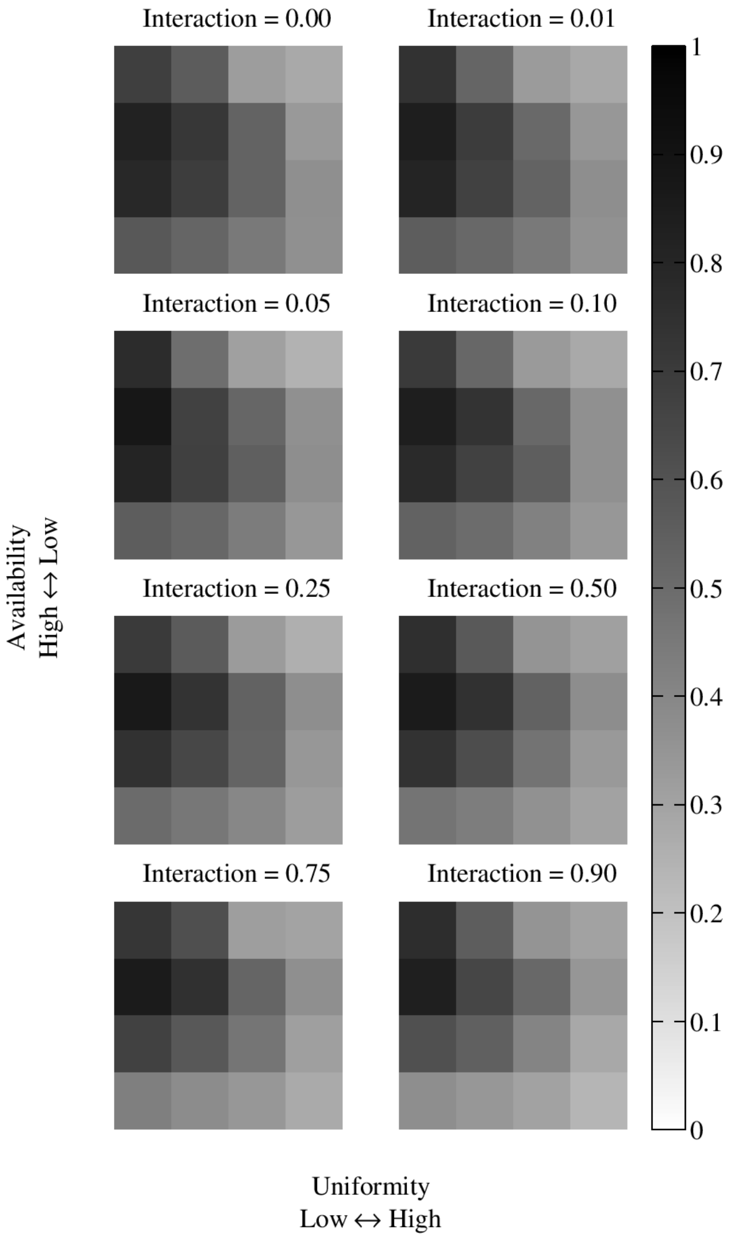

Figure 6.2: Mean score shown as a grayscale heatmap for each condition. Each subplot shows one of the 8 interaction conditions. Within each subplot, the x-axis shows the 4 uniformity conditions ($U = \{0.01, 0.10, 0.25, 0.50\}$, with uniformity increasing from left to right), while the y-axis shows the 4 resource availability conditions ($A = \{0.01, 0.05, 0.25, 0.50\}$, with number of resources increasing from top to bottom).

R^2 is plotted along with the data in Figure 6.3, with color corresponding to the degree of best fit. The majority of conditions were best fit by a 3rd degree polynomial, and those that were best fit by higher degrees showed (subjectively) small improvements in fit. So, for those conditions best fit by 4th degree polynomials, 3rd degree polynomials are also shown for comparison.

From Figure 6.3, we can see a general trend such that increases in uniformity (moving from the left to the right columns) are associated with decreases in score. No obviously linear trend is apparent when considering the effects of availability (moving from top to bottom rows) on mean score, but it does seem that variance in scores, across the 10 trials, is higher when availability in the low availability conditions. The pattern of scores as a function of interaction, as shown by the polynomial fits on each subplot, suggests that there may be a nonlinear relationship between our interaction parameter and one or both of our environmental parameters. That is, for some conditions, polynomial fits suggest a simple linear relationship such that increases in interaction are associated with higher scores (for the two conditions on the top row of Figure 6.3 with light blue lines). The other fits, including the three conditions with 2nd degree polynomial fits (magenta lines) all include ranges in which the regression line is concave downward, suggesting the possibility that, for a given environmental condition, there may be some “optimal” level of interaction at which the score can be maximized.

6.3.2 Search Dynamics

For each agent, the length of the movement at each time step (L) is recorded (note that this may differ from the D variable calculated earlier). We use the set of all L, across both agents, as an approximate (exploratory) measure of search dynamics.

Lévy Flights

We test for Lévy flights using the logarithmic binning with normalization (LBN) method as described in Rhodes and Turvey (2007)[2]. For each series of time steps, LBN gives an estimate of the μ exponent from a regression line fit to the probability density function $f(L) \sim L^{-\mu}$. A series of path lengths (L) is considered a Lévy flight when $1 < \mu \leq 3$. Figure 6.4 shows a histogram of μ estimates for all 2560 movement length distributions in our dataset (from both agents, in all 10 trials of all 128 conditions).

In general, the distribution of all foragers' μ estimates was centered on 2, indicating near-optimal foraging behavior (according to, for example, Viswanathan et al., 2011). Notably, the simple conditions of our setup were sufficient to produce exponents that lie within Lévy range for over 95% (2450) of our simulated foragers. Of the 2560 foragers, 3 had $\mu < 1$, in which the probability density functions of their path lengths had a very shallow slope. This shallow slope indicates frequent jumps equal to the total length of the environment. In our model, this is consistent with the scenario in which a forager can never find food, so $H = 128$, and movements of any length are equally likely. All 3 of these foragers were in the most sparse ($A = 0.01$) and clustered ($U = 0.01$) resource environment condition. Conversely, 107 of the 2560 foragers (less than 5%) had $\mu > 3$. This is more consistent with normal, Brownian diffusion than the superdiffusion associated with Lévy walks. In our model, this reflects a scenario in which foragers are so successful that their H stays low, and large path lengths are almost never observed. All 107 of these foragers were in the dense ($A = 0.50$) resource environment condition.

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[2] But, see the limitations to this method as described in Chapter 3

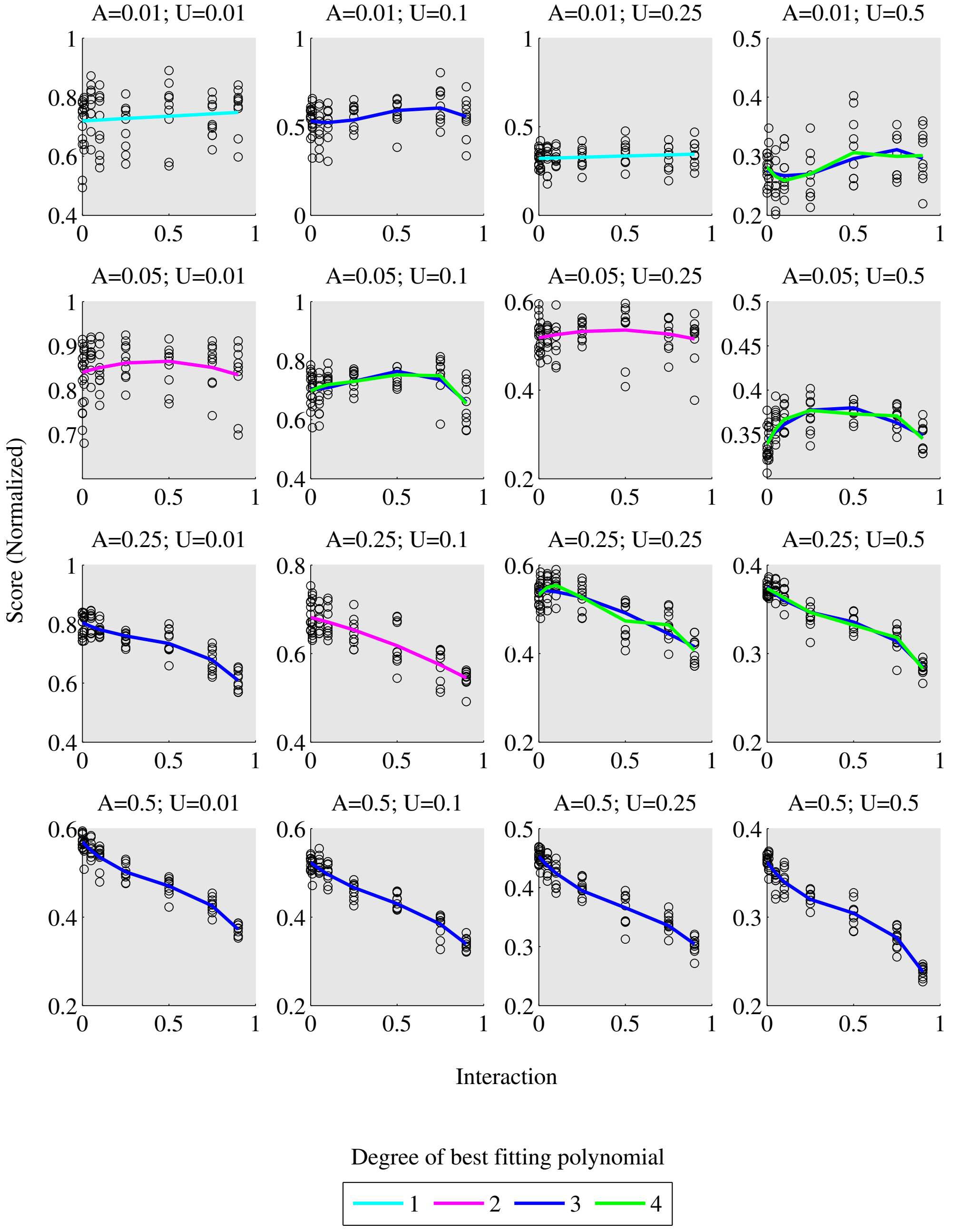

Figure 6.3: Scores for all trials. Each subplot shows one of the 4x4 environmental conditions. The rows are the 4 resource availability conditions ($A = \{0.01, 0.05, 0.25, 0.50\}$, with number of resources increasing from top to bottom), and the columns are the 4 uniformity conditions ($U = \{0.01, 0.10, 0.25, 0.50\}$, with uniformity increasing from left to right). Within each subplot, normalized scores (y-axis) are shown for each of the 10 trials of the 8 interaction conditions ($x - axis$). N-degree polynomial fits to each environmental condition are shown, where color of the polynomial corresponds to N (see text for details).

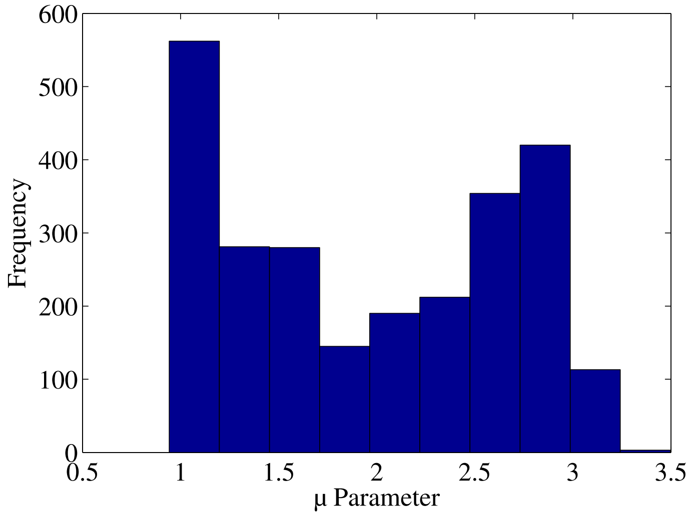

Figure 6.4: Histogram of LBN μ estimates for all trials.

Figure 6.5 shows slopes separates by environmental condition. Consistent with the observations above, foraging in more sparse environments results in a flattening out (lowering of μ) of movement length log histograms, while foraging in bountiful environments results in steeper (higher μ) movement length log histogram. Although the effect is less dramatic for different levels of U, more clustered environments generate flatter log histograms, while more uniform environments generate steeper log histograms.

Multi-Model Inference

Although Lévy flights have received considerable attention over the last few decades as a unique feature of natural search patterns, the theoretical implications and statistical methods (regression) used to estimate μ have still (and more recently) been subject to critique (for more information, see Chapter 3). Here we extend the analysis of our model dynamics by considering a multi-model inference approach, in which several candidate models are fit to each time series using maximum likelihood estimation and Akaike's information criteria (methods are identical to those described in Chapter 3). The best fitting model distribution is then identified as either normal, exponential, gamma, lognormal, or Pareto.

To motivate this analysis, we note the work of Holden et al. (2009) which argues that lognormal and Pareto distributions may be indicative of multiplicative interactions between components in a system. We have also previously noted a possible connection between these signatures and metastability in complex systems (Kello et al., 2010; Szary et al., 2015).

From the 2560 time series distributions, none were best fit by the normal or exponential distributions. 328 were best fit by lognormal, 665 by gamma, and 1,567 by Pareto distributions.

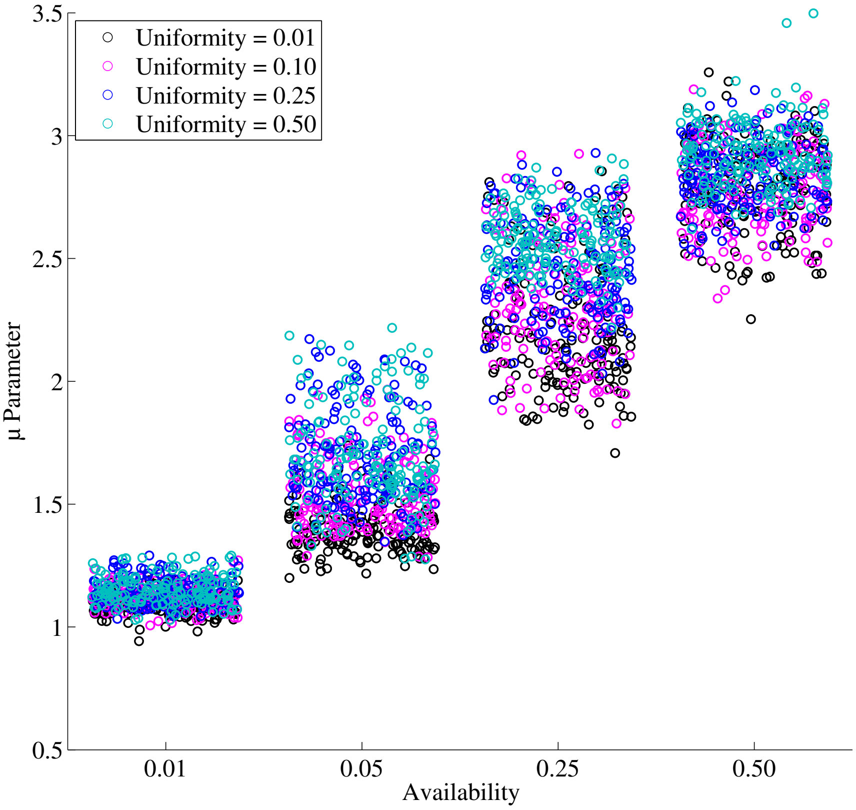

Figure 6.5: LBN μ estimates by environment condition. Data points are separated along the X-axis by resource availability, A, and include jitter. Colors indicate U.

6.4 General Discussion

In the introduction to this chapter, this model was framed as an exploration of whether interaction between agents can effect foraging, and whether interaction effects foraging differently in different environments. Our results suggest that interaction does, indeed, have an effect on the success of collaborative foragers. This effect interacts non-linearly with environmental conditions, however. In very sparse conditions, interaction may generally help, but as the environment becomes more bountiful, interaction is simply unnecessary. Consistent with other foraging models with memory (such as ARS), we find that our simulated agents are best suited for the more patchy environments (as indicated by the fact that the left-most columns indicate generally better performance than the right-most columns on Figure 6.3. While interaction does not seem to be beneficial for environments with bountiful resources in the most uniformly distributed environments (the bottom right plot in Figure 6.3), scanning to the left, as the number of resources remains the same but only the patchiness changes, suggests a shallowing of slope which indicates that the negative effects of interaction are disappearing in more patchy environments. This would make sense, because in a resource-rich environment it would be simply unnecessary for two agents to remain close to each other, and in fact it would be better for them to divide areas of responsibility and search their own resource-rich environments. Staying too close to one another would result only in "stepping on one another's toes", so to speak. But as the environment becomes increasingly clustered, it becomes increasingly beneficial for one agent to tip the other agent off to areas of high resource density.

This finding draws parallels to previous and ongoing work on collective behaviors and sensing. A classic finding in this domain is that the seemingly elaborate flocking or schooling movement patterns of animals (birds and fish, for example) can be simulated using relatively simple agent-based models with local interactions (C. W. Reynolds, 1987). That is, the large-scale schooling behavior emerges naturally as a consequence of smaller-scale behaviors at the level of each individual agent. Recent work stemming from this literature demonstrates that humans engage in similar "collective intelligence" schooling-type behaviors when moving across a landscape in search of hidden resources (instantiated as time-locked scores) in a computer game (Krafft, Hawkins, Pentland, Goodman, & Tenenbaum, 2015). While schools of fish typically require large groups of 50 or more in order to exhibit collaborative benefits (see Berdahl, Torney, Ioannou, Faria, & Couzin, 2013), the humans benefitted even from much smaller groups of only 3-5. In parallel to our work, Krafft et al. found that this collaborative benefit was environment-dependent. Further, the authors argue that the small-group collaborative benefit emerged from the fact that human players tended to follow their more successful conspecifics.

Because of the author's own background, this dissertation was framed in terms of search processes and, often, Lévy flights. However, as demonstrated by the converging evidence from other approaches (such as the ARS and schooling literature), the analyses presented here only scratch the surface of what can be done with this dataset. One obvious addition is to consider our results in terms of ARS. Although we didn't explicitly model any kind of "staying" versus "leaving", or any kind of expectations for encounter within or between patches, it would be interesting to consider whether any conditions resulted in ARS-like behavior. Additionally, our analyses have simply collapsed over the two agents, but of course more detailed analyses of individual agents, and characterizations of their interactions, is also possible. Further, the current simulation utilizes only one basic type of interaction, where the less successful agent is "pulled" towards the more successful agent. Interaction of different natures is of course possible, too. For example, agents might repel one another, or might even chase one another (in a predator-prey scenario). Considering these types of interaction, and scaling up to more than two agents, are some of the ideas for the continuation of this project.

At its current stage, though, our simulation proves successful in providing an arena to easily test these questions, and many more.

Chapter 7

Discussion

This chapter will review and summarize the projects presented in this dissertation and situate them within the larger literature. It will then close with some ideas about future research and theoretical implications.

The introduction (Chapter 1) begins by framing my research as an investigation into "self". From the perspective that the individual is deeply embedded and distributed within the larger social and environmental context (as argued in Chemero, 2009), how can we investigate the memory processes which result in the integral parts of what we call "self"? Although framed as such, the real focus of this research is on *memory*, and more generally on *information retrieval*, and how it can change depending on social context. The introduction reviews existing literature on how cognitive processes can be effected by collaboration, from movement dynamics, linguistic behavior, and finally memory processes. Although memory is (historically) one of the most extensively studied of the cognitive abilities, I focus here on reviewing the literature related to memory as a dynamic process which is a special kind of more general *search* process.

As discussed in the introduction, the literature has been quite successful in adapting concepts of physical, spatial search for the description of information search. Still, the larger body of research treated cognitive remembering and physical foraging as descriptively *analogous*, but not theoretically similar, processes. Chapter 2 provides evidence that remembering is a search process across cognitive space. We perform an empirical, behavioral study where subjects are asked to perform a memory task, but where the information which they recall is inherently spatial. That is, subjects are asked to recall locations in their home state of California. Our results are used to relate temporal, memory processes to physical, spatial processes. We see that the structure of memory processes during these events is tied to the structure of the physical environment. People remember California the way they would move around it. These results can be used to argue that remembering can really be thought of as more than just *analogous* to search. Rather, because remembering is search across an information landscape, it can be thought of as a specific example of more general search behaviors. Notably, this implies that the difference between remembering and foraging is not necessarily a matter of scale (whether it's performed at the neural-level or the organism-level), but instead a matter of landscape. The information landscape differs in important ways from the physical landscape, but where we can control that landscape we can see similarities between the two types of search process.

Although the main contribution of the project described in Chapter 2 was to situate remembering within the more general, inclusive framework of search processes, we also included results of a second condition in which the task was completed collaboratively. These results suggest that collaborating on memory tasks may change the way those tasks are completed, at both the individual and collaborative levels. While a number of researchers have begun looking at memory on the individual level as a search process, relatively few studies have investigated collaborative memory in the context of search processes. And while the collaborative nature of cognition has received increasing attention in some domains (see Section 1.1), collaborative memory processes have received relatively little. That is not to say that collaborative memory itself has been ignored. On the contrary, memory may have the longest history of being studied in the collaborative context (for examples, see Section 1.1.3). The difference is that the bulk of collaborative memory research has focused solely on the *outcomes* of collaborative remembering, and has only speculated on the processes which produce those outcomes (e.g. the perspectives espoused by the "collaborative contagion" and "retrieval disruption hypothesis", described in Section 4.1).

To fill this hole, Chapter 3 draws inspiration from the joint action literature which posits that interacting individuals can become coupled when engaging in a task together, and may even behave as one. Chapter 3 describes an empirical investigation that is identical to Chapter 2, except that it tests category recall from the semantic category *animals*, instead of locations in California. Statistical tools are borrowed from complex and dynamic systems sciences, and used to show that the search process itself may change during collaborative search. That is, behavioral differences may not arise solely because people disrupt each others' retrieval processes, but also because people may employ different search strategies when working together, perhaps out of the need to coordinate. Results suggest that some pairs behave as single search units, but others can't seem to achieve this. Another possibility for interpreting our data is that the need to collaborate introduces constraints that result in the loss of system flexibility. Here, that flexibility might mean flexibly switching between exploratory ("go") and exploitative ("stay") regimes, such as in the ARS model.

Despite the linkage between cognitive and spatial search, one main difference is that we often try to remember just one certain thing, so the success of a remembering task is measured in a more *qualitative* ("did I remember the right thing?") than *quantitative* fashion ("did I remember enough things?"). The literature on collaborative remembering, including the projects described in Chapters 2 and 3, has dealt almost exclusively with quantitative-type remembering tasks. But, as Chapters 2 and 3 add, remembering should be investigated as a dynamic search process, which differs only from other search processes insomuch as it has a different landscape. Chapters 4 and 5 consider the qualitative-style searches that happen more often through information landscapes, where there is one target amidst many distractors. These chapters use an experimental task in which participants played four rounds of a trivia game, alternating between individual and collaborative participation. In contrast to the large body of work demonstrating collaborative inhibition, our results (from Chapter 4) show collaborative facilitation on a number of performance measures (score, speed, and accuracy).

Chapter 5 extends this study in two key ways. First, we made the task more difficult by increasing time pressure and increasing the number of questions in each session. Second, we collected information on the relationship between participants using a simple survey measure of familiarity (the number of months the participants had known one another). On this more difficult task, we found evidence of collaborative inhibition on score and speed, but we found collaborative facilitation on accuracy and future recall. Further, the longer participants had known one another, the more likely we were to see a shift from inhibitory to facilitatory effects of collaboration. This finding is especially poignant considering that our dataset was relatively limited, in the sense that our participants had generally only known each other for 0.5-2 years. It is likely that the effect would be even stronger for dyads with greater familiarity (such as long-term friends, colleagues, and especially partners and families).

Finally, Chapter 6 added a simple simulation of foraging with which we could manipulate environmental parameters to test the effects of interaction. In our model, two agents move across a space searching for resources. The first parameter of interest is the strength and direction of interaction between the agents. The second set of parameters includes sparsity and clustering, which together change the patterns of resource distribution in the environment. With this model, we explored the effects of social and environmental context on both the processes (Lévy dynamics) and products (number of resources found). Higher levels of interaction may be more suitable for some subset of resource environments, while lower levels of interaction may be best for others. Though we simulate foraging in a two-dimensional landscape, it has an analogue to informational structure in cognitive domains: Category knowledge is clustered in semantic space (see Hills et al., 2013); Knowledge of some topics may be more sparse than information on others. Our early results suggest that these features of the environment (clustering versus uniformity, sparsity versus abundance) have a strong impact on foraging behaviors, and these different behaviors can determine whether collaboration has beneficial or destructive effects on foraging outcomes. Specifically, our results appear to be consistent with the large body of work suggesting that the appearance of Lévy flight behavior is landscape-dependent, as opposed to solely agent-dependent (Viswanathan et al., 2011). We conclude that the utility of interaction depends on the search environment. In general, interaction is more suitable for very sparse environments, but its relation to clustering is less straightforward: Different levels of clustering may be more suited to search with differing degrees of interaction.

These results suggest a number of possible extensions for the modeling project in future work, as described here.

The preliminary modeling results, along with the empirical results detailed above, suggest that the nature of a search task modulates the consequences of social collaboration. Chapters 2 and 3 describe an open-ended search problem in which a number of target items can be collected, so the nature of the search space (landscape) matters a great deal. Successful collaboration may be a matter of finding and co-cueing into patches of rich information. Interaction may facilitate single-answer search in a different way, though, and give way to subtly different patterns of facilitation and constraints (Chapters 4 and 5). This is something that I hope capture, to some extent, with the ongoing computational model. That is, our foragers are currently searching through a landscape of equally valuable targets, but changing the search landscape (while leaving the relatively simple movement simulation intact) might provide interesting results. For example, how might higher and lower value targets effect foraging behavior? What if there were negatively valued “distractor” targets? Could a gradient of increasingly valuable targets lead foragers to a single “goal” target most quickly?

Another modification of the search space might be to add dimensionality to the environment. Currently, the simulation is built to wander over a two dimensional, x, y coordinate landscape. Although it would require quite a bit of recoding to the current algorithm, there is no reason the landscape can’t be extended to an arbitrary number of dimensions. This might make it easier to consider that the search landscape could relate to a cognitive one, which in the dynamic systems approach to cognitive science is seen as a high-dimensional state space.

Further, that high-dimensional state space is unique to each individual. While there may be some “ground truth” to information in the real-world, the information inside each person’s memory is a function of his or her own past experiences and knowledge (which is to say nothing of current attention, mood, etc.). So, my more botanically inclined sister would certainly have a more detailed information landscape than I have for types of orchid. That, however, would be just a quantitative difference. One could also imagine that some information landscapes differ qualitatively between people–perhaps when people have differing opinions, such as republicans and democrats on hot-button political issues. One possible way to implement this in our simulation would be that we could generate different target distributions for each agent, but still have them interact on the same landscape. Or, our agents could move around entirely different landscapes but still perturb one another's movements in some way.

An idea related to the perspective that landscape can change foraging behaviors is demonstrated by the ARS approach to cognitive foraging. ARS has been very successful in characterizing search through space, and two-stage search models based on ARS have successfully characterized search through cognitive space (Hills et al., 2012). Inspired by this finding, a recent discussion has emerged about the important connection between process and landscape in models of cognitive foraging. These discussions have compared semantic spaces as generated by the BEAGLE model (Jones & Mewhort, 2007) and a network generated from free-association behavioral data (see Abbott, Austerweil, & Griffiths, 2015; Jones, Hills, & Todd, 2015). Whether a two-process ARS-type forager outperforms a simple random-walker is seen to depend on the representation of semantic space. An obvious extension of the simulation discussed in Chapter 6, then, is to compare my model performance to these two models, and to consider its performance on these other semantic spaces. Similarly, it is worth considering whether our model, which essentially involves random walks modified by hunger and social "push", might end up producing behavior consistent with a two-process ARS model (in which "staying" and "going" is explicitly built into the model).

As noted in Section 6.4, additional extensions for the modeling work are to manipulate the number of agents, and the type of interaction between the agents. Currently we use two agents, where one is always pulled towards the other, but other configurations are equally possible. The agents could repel one another, chase one another, or, perhaps most interestingly, could maintain a "goldilocks" balance between pushing and pulling. A cognitive interpretation of this type of scenario would be that when two people are talking, they are drawn towards similar topics (i.e., the topic of their conversation) but they don't say the exact same thing, in which case there would be no useful information transfer and the conversation would be quite boring. The goldilocks scenario, then, would describe a balance such that interlocutors are in a similar information space, but not directly on top of one another (not "stepping on each other's toes").

With regards to the empirical work, future directions have been suggested in the discussions of each chapter. One additional extension I wish to mention here is inspired by the recent work of Hills et al. (2015) on foraging through semantic space. While I am greatly interested in the concept of collaborative systems in itself, my empirical work on collaborative memory has offered a unique perspective of the ongoing strategies during semantic foraging. The ARS framework implies that semantic space is somehow clustered, and Hills et al. considers that the nature of these cluster boundaries may shift over the course of a task. That is, at a given time during the animal-category fluency task, are we "in" a patch defined as a pre-existing category (e.g. safari animals)? How do we define patch boundaries? Hills et al. found that pre-defined categories were not very well-matched to participants' behavioral patterns. In my empirical collaborative memory work, however, participants often explicitly define the categories in which they're working. Annotations of this dataset could provide rich information about strategy ("let's do animals from *The Lion King*") and process ("I was thinking about salmon and now I'm hungry. What other animals do we eat?"), useful for extending Hills' discussion about the nature of categorical boundaries.

Again, though, I note that collaborative memory should be considered both for its empirical merit in investigating individual memory processes, but also in its own right. In the collection of projects presented above I have explored how memory processes change in social, interactive contexts. From the most superficial level of minor behaviorisms to the deepest level of memories and knowledge, we unconsciously and unintentionally adapt to those around us. This social adaptation has been called priming, mirroring, entrainment, parallelism, alignment, synchrony, joint-X, group-X, and more. And while some of these domains have hypotheses about when this adaptation results in convergence or divergence, and some bridges have been forged, there is still no unifying theory to explain when and how these domains interact on a global level, and when and how the nature of the interaction becomes convergent or divergent. Throughout this dissertation, I have laid the preliminary groundwork for such a theory, at least in the domain of memory, based on the idea that environmental and contextual constraints may modulate the type of coordination that emerges.

A helpful concept to explore this idea is the *coordinative structure* framework proposed by Shockley et al. (2009). A coordinative structure is a set of components that is softly assembled (i.e. temporary) and self-organized, and which emerges naturally under certain conditions, behaving as a single unit. Inspired by this framework, I propose that individuals engaged in collaborative remembering might form a metastable collaborative structure, which seeks to strike a balance between exploratory and exploitive behavior, as well as between interdependence and independence (see Kello et al., 2010, 2007; and Chapter 2). The first distinction–exploration versus exploitation–is a balance that must be achieved for successful foraging in any domain (spatial or cognitive), and is best exemplified by the area-restricted search and marginal value theories (Hills et al., 2013; as mentioned in Chapter 2). The second distinction–interdependence versus independence–can be likened to the convergence and divergence ideas from the previous paragraph. In this case, it refers specifically to the conflicting needs of a collaborative rememberer to search his own memory, but in the context of collaborating interactively with another rememberer. If collaborative memory is this kind of coordinative, metastable structure, subtle changes in conditions could have significant effects on the large-scale behavior of the system as a whole, as well as the behavior of its composite individuals.

Overall, I advocate for a dynamic approach to the study of memory, which will necessarily include attention to how social and interactive contexts can change the way we remember. An extension of this dynamic approach to memory, I believe, is that “memory” as a cognitive process is not exactly unique. It can be investigated as a special case of the more general cognitive process of search, and perhaps that would be a more theoretically promising way to look at it. It is also a more promising direction for my own research program, as it allows me to extend my ideas about collaborative memory to collaborative search in general, whether the collaborators are searching their cognitive memory spaces, cognitive decision spaces, or some other information resource such as the internet. This is consistent with the perspective of Hills (2006) that selection pressures for foraging strategies in our early ancestors paved the way for sophisticated goal-directive strategies in other domains. It would make sense, then, that we should start to think about the implications of search processes on higher-level cognitions. A decision making task could involve deciding where to search for missing keys, or it could involve a search for a less-obvious target, such as finding the optimal solution to a problem (see Newell & Simon, 1972 for a discussion of problem solving as search), or even making decisions about one’s future. In the age of connectivity, where we are at almost all moments connected to our social networks, it is more important than ever to understand how to optimize such behaviors in a social-interactive context.

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