LarKC

The Large Knowledge Collider
a platform for large scale integrated reasoning and Web-search

FP7 – 215535

D4.2.1

Experimental Designs for Mapping Human Search Strategies

Hansjörg Neth, Lael J. Schooler,
Jörg Rieskamp, José Quesada (MPG)
&
Yulin Qin, Jie Xiang, Ning Zhong,
Haiyan Zhou, Shengfu Lu (WICI)

Document Identifier:	LarKC/2008/D4.2.1/Vx.x
Class Deliverable:	LarKC EU-IST-2008-215535
Version:	version 1.6
Date:	January 13, 2009
State:	final
Distribution:	public

Executive Summary

This document describes several experimental designs for mapping human search strategies and is structured into an Introduction, two separate lines of research (Chapters 2 and 3), and a Conclusion.

Chapter 2 (authored by Hansjörg Neth, Lael J. Schooler, Jörg Rieskamp, and José Quesada, at the Max-Planck Institute for Human Development in Berlin, Germany) is entitled "Stopping Rules for Information Search" and aims to uncover the factors that affect people's decisions to terminate memory search. By drawing an analogy between human search processes and animal foraging the proposed research will compare human performance to normative models of optimality and determine the factors that people take into account when deciding to continue or stop processes of information search. Building on prior research on memory search termination and task switching the chapter sketches a series of studies that are designed to illuminate the proximate rules, or heuristics, that people use, and machines could use, to decide when to stop searching.

Chapter 3 (authored by Yulin Qin, Jie Xiang, Ning Zhong, Haiyan Zhou, and Shengfu Lu, at the International WIC Institute, Beijing University of Technology, China) is entitled "Human Heuristic Search in Problem Solving" and aims to uncover the processes that people use heuristics in problem solving by fMRI (functional Magnetic Resonance Imaging) experiments. Heuristics may enhance the ability to solve a problem efficiently and effectively. Brain imaging will offer much more detailed information than traditional behavior experiments on heuristic search. With deeper understanding of heuristic search in problem solving, this study may offer cues to help us to improve the performance of searching and reasoning in LarKC. The tasks in an fMRI study, however, are usually finished within 10 or 20 seconds and the participants should be controlled to use the consistent strategy to the same task. These requirements make it difficult to directly use the traditional human problem solving tasks. In this chapter, a new human heuristic problem solving paradigm, simplified 4x4 Sudoku, is introduced, the design of an fMRI experiment with this paradigm is briefly described along with a short description of the future experiments.

Document Information

IST Project Number	FP7 – 215535	**Acronym**	LarKC
Full Title	Large Knowledge Collider		
Project URL	`http://www.larkc.eu/`		
Document URL			
EU Project Officer	Stefano Bertolo		

Deliverable	**Number**	4.2.1	**Title**	Experimental Designs for Mapping Human Search Strategies
Work Package	**Number**	4	**Title**	Reasoning and Deciding

Date of Delivery	**Contractual**	M7	**Actual**	31-Dec-08
Status	version 1.6		final ☐	
Nature	prototype ☒ report ☐ dissemination ☐			
Dissemination Level	public ☐ consortium ☒			

Authors (Partner)	Hansjörg Neth, Lael J. Schooler, Jörg Rieskamp, & José Quesada (MPG) Yulin Qin, Jie Xiang, Ning Zhong, Haiyan Zhou, & Shengfu Lu (WICI)			
Resp. Author	Hansjörg Neth (MPG)		**E-mail**	`neth@mpib-berlin.mpg.de`
	Partner	MPG	**Phone**	+49 30 82406-696

Abstract (for dissemination)	This document describes several experimental designs for mapping human search strategies and is structured into an Introduction, two separate lines of research (Chapters 2 and 3), and a Conclusion. Chapter 2 (authored by Hansjörg Neth, Lael J. Schooler, Jörg Rieskamp, and José Quesada, at the Max-Planck Institute for Human Development in Berlin, Germany) is entitled "Stopping Rules for Information Search" and aims to uncover the factors that affect people's decisions to terminate memory search. By drawing an analogy between human search processes and animal foraging the proposed research will compare human performance to normative models of optimality and determine the factors that people take into account when deciding to continue or stop processes of information search. Building on prior research on memory search termination and task switching the chapter sketches a series of studies that are designed to illuminate the proximate rules, or heuristics, that people use, and machines could use, to decide when to stop searching. Chapter 3 (authored by Yulin Qin, Jie Xiang, Ning Zhong, Haiyan Zhou, and Shengfu Lu, at the International WIC Institute, Beijing University of Technology, China) is entitled "Human Heuristic Search in Problem Solving" and aims to uncover the processes that people use heuristics in problem solving by fMRI (functional Magnetic Resonance Imaging) experiments. Heuristics may enhance the ability to solve a problem efficiently and effectively. Brain imaging will offer much more detailed information than traditional behavior experiments on heuristic search. With deeper understanding of heuristic search in problem solving, this study may offer cues to help us to improve the performance of searching and reasoning in LarKC. The tasks in an fMRI study, however, are usually finished within 10 or 20 seconds and the participants should be controlled to use the consistent strategy to the same task. These requirements make it difficult to directly use the traditional human problem solving tasks. In this chapter, a new human heuristic problem solving paradigm, simplified 4x4 Sudoku, is introduced, the design of an fMRI experiment with this paradigm is briefly described along with a short description of the future experiments.
Keywords	information search, human experiments, stopping rules, foraging, heuristics, Sudoku, fMRI

Version Log			
Issue Date	**Rev No.**	**Author**	**Change**
October 21, 2008	1	Hansjörg Neth	MPG and WICI parts submitted to internal quality assessment.
October 22, 2008	2	WICI, Hansjörg Neth	First draft using LarKC template and combining MPG and WICI parts.
October 30, 2008	3	Hansjörg Neth	Second draft, incorporating feedback from external quality assessor (Dr. Michael Witbrock).
October 31, 2008	4	WICI, Hansjörg Neth	Version 1.0, incorporating changes from WICI.
November 06, 2008	5	WICI, Hansjörg Neth	Version 1.5, incorporating new parts from WICI.
November 07, 2008	6	WICI, Hansjörg Neth	Version 1.6, incorporating corrections from WICI.

Project Consortium Information

Acronym	Partner	Contact
Semantic Technology Institute Innsbruck `http://www.sti-innsbruck.at`	STI	Prof. Dr. Dieter Fensel Semantic Technology Institute (STI) Innsbruck, Austria E-mail: dieter.fensel@sti-innsbruck.at
AstraZeneca AB `http://www.astrazeneca.com/`	ASTRAZENECA	Bosse Andersson AstraZeneca Lund, Sweden E-mail: bo.h.andersson@astrazeneca.com
CEFRIEL SCRL. `http://www.cefriel.it/`	CEFRIEL	Emanuele Della Valle CEFRIEL SCRL. Milano, Italy E-mail: emanuele.dellavalle@cefriel.it
CYCORP, RAZISKOVANJE IN EKSPERIMENTALNI RAZVOJ D.O.O. `http://cyceurope.com/`	CYCORP	Michael Witbrock CYCORP, RAZISKOVANJE IN EKSPERIMENTALNI RAZVOJ D.O.O., Ljubljana, Slovenia E-mail: witbrock@cyc.com
Hchstleistungsrechenzentrum, Universitaet Stuttgart `http://www.hlrs.de/`	HLRS	Dr. Georgina Gallizo Hchstleistungsrechenzentrum, Universitaet Stuttgart Stuttgart, Germany E-mail : gallizo@hlrs.de
Max-Planck-Institut fr Bildungsforschung `http://www.mpib-berlin.mpg.de/index_js.en.htm`	MAXPLANCKGESELLSCH	Dr. Michael Schooler, Max-Planck-Institut fr Bildungsforschung Berlin, Germany E-mail: schooler@mpib-berlin.mpg.de
Ontotext Lab, Sirma Group Corp. `http://www.ontotext.com/`	ONTO	Atanas Kiryakov, Ontotext Lab, Sirma Group Corp. Sofia, Bulgaria E-mail: atanas.kiryakov@sirma.bg
SALTLUX INC. `http://www.saltlux.com/EN/main.asp`	Saltlux	Kono Kim SALTLUX INC Seoul, Korea E-mail: kono@saltlux.com
SIEMENS AKTIENGESELLSCHAFT `http://www.siemens.de/`	Siemens	Dr. Volker Tresp SIEMENS AKTIENGESELLSCHAFT Muenchen, Germany E-mail: volker.tresp@siemens.com
THE UNIVERSITY OF SHEFFIELD `http://www.shef.ac.uk/`	Sheffield	Prof. Dr. Hamish Cunningham THE UNIVERSITY OF SHEFFIELD Sheffield, UK E-mail: h.cunningham@dcs.shef.ac.uk
VRIJE UNIVERSITEIT AMSTERDAM `http://www.vu.nl/`	Amsterdam	Prof. Dr. Frank van Harmelen VRIJE UNIVERSITEIT AMSTERDAM Amsterdam, Netherlands E-mail: Frank.van.Harmelen@cs.vu.nl
THE INTERNATIONAL WIC INSTITUTE, BEIJING UNIVERSITY OF TECHNOLOGY `http://www.iwici.org/`	WICI	Prof. Dr. Ning Zhong THE INTERNATIONAL WIC INSTITUTE Mabeshi, Japan E-mail: zhong@maebashi-it.ac.jp

INTERNATIONAL AGENCY FOR RESEARCH ON CANCER http://www.iarc.fr/	IARC2	Dr. Paul Brennan INTERNATIONAL AGENCY FOR RESEARCH ON CANCER Lyon, France E-mail: brennan@iarc.fr

Table of Contents

1 Introduction

This document describes several experimental designs for mapping human search strategies and is structured into an Introduction, two separate lines of research (Chapters 2 and 3), and a Conclusion.

Chapter 2 (authored by Hansjörg Neth, Lael J. Schooler, Jörg Rieskamp, and José Quesada, at the Max-Planck Institute for Human Development in Berlin, Germany) is entitled "Stopping Rules for Information Search" and aims to uncover the factors that affect people's decisions to terminate memory search. By drawing an analogy between human search processes and animal foraging the proposed research will compare human performance to normative models of optimality and determine the factors that people take into account when deciding to continue or stop processes of information search. Building on prior research on memory search termination and task switching the chapter sketches a series of studies that are designed to illuminate the proximate rules, or heuristics, that people use, and machines could use, to decide when to stop searching.

Chapter 3 (authored by Yulin Qin, Jie Xiang, Ning Zhong, Haiyan Zhou, and Shengfu Lu, at the International WIC Institute, Beijing University of Technology, China) is entitled "Human Heuristic Search in Problem Solving" and aims to uncover the processes that people use heuristics in problem solving by fMRI (functional Magnetic Resonance Imaging) experiments. Heuristics may enhance the ability to solve a problem efficiently and effectively. Brain imaging will offer much more detailed information than traditional behavior experiments on heuristic search. With deeper understanding of heuristic search in problem solving, this study may offer cues to help us to improve the performance of searching and reasoning in LarKC. The tasks in an fMRI study, however, are usually finished within 10 or 20 seconds and the participants should be controlled to use the consistent strategy to the same task. These requirements make it difficult to directly use the traditional human problem solving tasks. In this chapter, a new human heuristic problem solving paradigm, simplified 4x4 Sudoku, is introduced, the design of an fMRI experiment with this paradigm is briefly described along with a short description of the future experiments.

Although the two research programs outlined in this report independently address important issues of interest to the scientific community they are united in their relevance to the LarKC project. While each of the research chapters will make its own case of contributing to the overarching LarKC endeavors the concluding Chapter 4 will argue that the basic issues faced by both humans and machines in the context of information search are sufficiently similar to mutually inform each other.

2 Stopping Rules for Information Search

2.1 Motivation

One of the most fundamental problems for any type of activity is knowing when to stop. The Large Knowledge Collider (LarKC) envisages a configurable platform for massive distributed reasoning that aims to transform the web by making large amounts of semantic information accessible to machines and useful to human users (Fensel et al., 2008). Abandoning the traditional panaceas of consistency and completeness the LarKC vision explicitly anticipates and embraces inconsistency and incompleteness. But incomplete processes (e.g., of data identification and transformation) need to be terminated at some point — and the quality of both the process and the end result can depend crucially on the precise stopping rules used.

In the context of information search and decision making the issue of stopping rules has both theoretical and practical implications. Theoretically, the termination of search directly affects possible outcomes by determining which facts or choice alternatives are considered. Practically, a principled understanding of stopping rules can be used to design more effective and efficient systems. As the amount of readily-accessible information increases knowing when to stop processing becomes a key skill of humans and a crucial component of technology. Without functional stopping rules both humans and machines could easily drown in data.

Stopping rules are important in many different tasks and domains. Most real-world problems do not have a pre-defined completion criterion. For instance, when trying to identify the leading experts on melanoma treatments, searching for genetic codes contributing to lung cancer, or simply attempting to remember what we did last summer the task itself is potentially infinite and does not provide clear guidance as to when search ought to be terminated. Importantly, both premature abandonment of a problem and excessive perseverance in its pursuit can have costly consequences. Failing to recall some symptoms when diagnosing a disease can be as dangerous as continuing to retrieve long lists of increasingly irrelevant symptoms before beginning treatment. The problem of search termination resurfaces in an aggravated form when a system is facing more than a single problem at once. When time and effort need to be allocated to multiple tasks finding the right moments to switch between tasks constitutes a difficult optimization problem.

Given the importance of stopping rules for all aspects of information search it is surprising how little psychological research has been conducted to specifically address this issue. We will attempt to remedy this situation by conducting a series of experiments designed to illuminate the stopping and switching rules that humans use when dealing with problems of information search. Although our research will initially focus on memory retrieval we assume that our findings will be applicable to other tasks like abstraction, decision making, reasoning, and problem solving.

The rest of this proposal is structured as follows: Section 2.2 reviews some previous research that is relevant to this project and motivates our initial use of foraging theory as a productive analogy to frame problems of human information search. Section 2.3 describes a series of empirical studies that we plan to conduct to better understand the factors and mechanisms that govern human decisions to terminate information search. The concluding Section 2.4 of this chapter elaborates some of our basic assumptions, discusses potential applications of our findings to related domains, and specifically addresses the relevance of our research to the LarKC community.

2.2 Background

Our proposed research aims to uncover the factors that determine decisions to terminate memory search, compare human performance to normative models of optimality and determine the proximate rules, or heuristics, that people use, and machines could use, to decide when to stop. This section will first outline several lines of research in psychology and cognitive science that are of particular importance to this endeavor. We then draw an analogy to a branch of biology that has addressed the issue of stopping rules in the context of animal foraging. As formal models on optimal foraging have successfully informed theories of human information search we will propose to carry this analogy even further by applying the foraging analogy to both unaided (internal) and extended (externally embedded) cognition.

2.2.1 Stopping Memory Search

Although memory is the most well-studied construct of cognitive psychology (see Tulving & Craik, 2000, for an overview) there is relatively little research on the rules that determine the decision to terminate memory search. The status quo of research on the stopping rules of memory retrieval is well-illustrated by the fact that Kahana and Miller (submitted)—in a recent re-analysis of 16 experimental conditions—had to operationalize memory termination as the occurrence of the last item recalled by a participant. When studying the probability of such termination as a function of number of items recalled or time they concluded that an item is more likely to be the last when more items have been recalled or it is later in a trial. Slightly more surprisingly, a last item is more likely preceded by a recall error than by a correct item. Among errors, repetitions were most likely to lead to termination, followed by prior-list intrusions, and then extra-list intrusions. The authors note that errors generally are bad retrieval

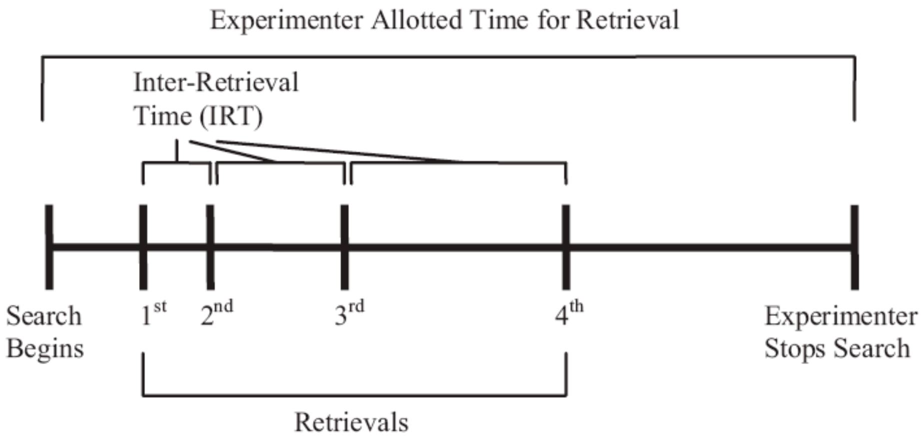


Figure 2.1: Schematic view of the traditional fixed-time retrieval paradigm (graphic from Dougherty & Harbison, 2007, p. 1109). The total retrieval time T is controlled by the experimenter. It remains unclear whether and when a participant terminated search.

cues for further items, thus emphasizing the consequences of errors, rather than their causes.[1]

Dougherty and Harbison (2007) attribute the lack of research on memory search termination to the almost ubiquitous use of fixed retrieval intervals in the study of free-recall tasks. When participants have only a limited amount of time to retrieve as many items as possible from memory and the duration of this interval is set by the experimenter the participant has no discretion about when to abandon memory search. Figure 2.1 illustrates that the traditional fixed time paradigm provides informative data on the order and temporal spacing of memory retrievals but does not address the issue of search termination. In fact, it remains unclear whether search was still continuing at the end of the interval (and if so, whether it could potentially yield additional items) or has been terminated at some point after retrieving the last item.

To remedy this lack of information with respect to search termination the authors introduce an *open-ended* retrieval paradigm in which participants control when to terminate their retrieval attempts. Figure 2.2 illustrates that this change has two important consequences: First, when a participant B is willing to search his or her memory for a longer period of time, it is likely that he or she will retrieve more items. This implies that the number of items retrieved on any given task is not only dependent on the properties of memory encoding but also the participant's motivation or willingness to continue search. Secondly, in addition to the *inter-retrieval times* (IRTs) the *total time* T devoted to the task by the participant and the *exit latency* t_X,

[1] An error could have various roles in the retrieval process. While it clearly is a consequence of recall failure, it can also be seen as a meta-cognitive signal that retrieval is exhausted, or (by virtue of being a bad cue) a cause for subsequent recall failure. In addition to not providing data on true termination decisions the authors do also not report whether the last retrieved item is more likely to be an error.

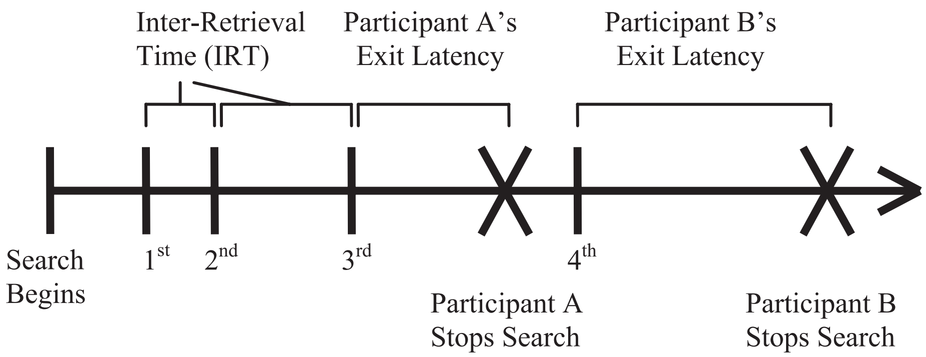


Figure 2.2: Schematic view of the open-ended retrieval paradigm (from Dougherty & Harbison, 2007, p. 1109). Different participants can have different retrieval intervals, affecting the total number of items retrieved and introducing two new dependent variables: The total retrieval time T lasts from the beginning to the stopping of the search process; the exit latency t_X from the last retrieval to search termination.

defined as the duration of time elapsed from retrieving the last item to abandoning the task, become meaningful dependent variables that are informative about the dynamics of memory recall.

Apart from this important methodological contribution, Dougherty and Harbison (2007) examine the effects of inter-individual differences in motivation[2] and working memory capacity[3] on memory search termination decisions. Participants memorized several lists of 10 items (low vs. high-frequency words to manipulate task difficulty) and had to retrieve as many items as possible from the appropriate list upon being presented with a cue. Exit latencies were correlated negatively with the number of items being retrieved: The more items were retrieved the more quickly the search was terminated after retrieving the last item.[4] Higher motivation coincided with lower willingness to continue memory search (or faster termination of memory search). However, this relationship was moderated by an order effect: Only when participants initially received difficult tasks did higher decisiveness scores reliably reduce exit latencies. Curiously, this relationship carried over to easier tasks as long as more challenging tasks were presented first.

Although introducing the open-ended retrieval interval provides new opportunities to research stopping rules, it also introduces new issues. For instance, the fact that search duration and the total number of items retrieved now is partially determined by the willingness of the participant necessitates a global view of the entire session (extending over multiple tasks). More specifically, what criterion is a participant really trying to maximize? If it really was the number of items on every experimental trial

[2]Motivation was operationalized as decisiveness on a Need for Closure scale.
[3]WM capacity yields a measure of how much information an individual can mentally store and manipulate, e.g., a digit span.
[4]Whereas WM span was not related systematically to exit latencies or decisiveness, there was a positive correlation between individual motivation (decisiveness) and exit rate.

(as per instruction) he or she would have to spend a lot of time on every task to ensure that memory has definitely been exhausted. However, it is not the primary function of memory to perform in laboratory tasks—and human participants typically are interested in leaving the experimental laboratory to resume their normal life. Thus, they are effectively negotiating a trade-off between satisfying the experimenter's demands and their own interest in quitting the experiment. Although this trade-off scenario is an ubiquitous feature of experimental research it is problematic when it directly affects and can partially explain the results obtained. For instance, when a participant assumes that the experimenter expects him or her to retrieve at least a certain number of items before they can terminate a task he or she could quit more rapidly after having retrieved a larger number of items—which is exactly the trend reported by Dougherty and Harbison (2007).

Another set of questions introduced by the sequential nature of a participant responding to multiple tasks within a session concern the nature of meta-knowledge, e.g., about the relative difficulty of the current and alternative tasks. Whereas previous questions may have set expectations, knowledge of later tasks may generate anticipations. In short, the fact that motivational and meta-cognitive issues can profoundly affect the results in an open-ended retrieval paradigm necessitates more careful experimental controls than with traditional paradigms.

Noting that the impact of stopping rules on memory retrieval dynamics has rarely been examined Harbison, Davelaar, and Dougherty (2008) compare the predictions of four stopping rule candidates in a theoretical framework based on a reduced SAM model. SAM stands for "Search of Associative Memory" and was proposed by Raaijmakers and Shiffrin (1981) to account for memory recall. The model assumes that recall is stopped after a number of unsuccessful retrieval attempts. Harbison et al. (2008) examine the data from an (yet unpublished) experiment using the open-ended retrieval paradigm (Dougherty & Harbison, 2007) in a delayed free recall task. The four candidate stopping rules considered terminate memory search as a function of

1. the total retrieval time T,

2. the time since the last retrieved item,

3. the last inter-retrieval time (IRT),

4. the number of retrieval failures (Raaijmakers & Shiffrin, 1980).

Only the last stopping rule could qualitatively reproduce a robust empirical pattern: As the number n of retrieved items increased, the total retrieval time T increased but the the corresponding exit latencies t_X decreased.[5] However, the authors acknowledge

[5]This pattern is the same as in Dougherty and Harbison (2007) and held both across and within subjects.

that there are many possible alternative stopping rules and they have not yet explored the consequences of some prominent ones (e.g., by Anderson & Milson, 1989; Anderson & Schooler, 1991).

A step towards analyzing the dynamics of multiple memory retrieval tasks (rather than a sequence of individual tasks) was taken by Young (2004). In an innovative study Young (2004) assesses the contributions of meta-knowledge to semantic retrieval of instances from natural categories. Based on a meta-cognitive framework she identifies the feeling-of-knowing and willingness to continue search as crucial components of any search termination decision. Participants had one minute of time to retrieve exemplars from two natural categories of various potencies.[6] Whereas participants could freely switch back and forth between both categories in part 1, they they were constrained to switch categories only once (i.e., could not go back to an abandoned task) in part 2.

As predicted, participants spent more time exhausting the first category when they were unable to switch back into it (in part 2). More importantly, they generally allocated more time to categories of high potency and took the relative potency of both categories into account from the very beginning. Young (2004) concludes that meta-knowledge plays a crucial role in search termination decisions.

Although the studies discussed so far document the influence of motivational and meta-cognitive factors on memory retrieval they also suffer from various shortcomings. Dougherty and Harbison (2007) emphasize motivational effects on memory search but study motivation as a measure of individual differences rather than manipulating it directly, e.g., by differentially rewarding certain tasks. The lack of baseline data and short task duration of Young (2004)'s study makes it difficult to judge whether participants' time-to-task allocations were adaptive or even optimal. In addition to lacking a normative standard, both studies fail to explicitly define what participants are trying to maximize (within each task and over the duration of the entire experimental session) and do not adequately address the issue of switch costs.[7] In short, the studies mentioned so far have made valuable methodological contributions, but have not yet substantially illuminated the mechanisms that lead to the termination of memory search.

[6]Category *potency* was defined as the number of items retrievable from a given category (i.e., the potential yield of a category) and manipulated according to the norms of Battig and Montague (1969) (see Van Overschelde, Rawson, & Dunlosky, 2004, for an updated version).

[7]For instance, it is possible that the mere effort to switch from one retrieval task to another in Young (2004)'s task rendered repeated category switches in one minute maladaptive. The fact that 86% of trials during Part 1 had less than 3 (i.e., 1 or 2) switches raises the question how different parts 1 and 2 really were.

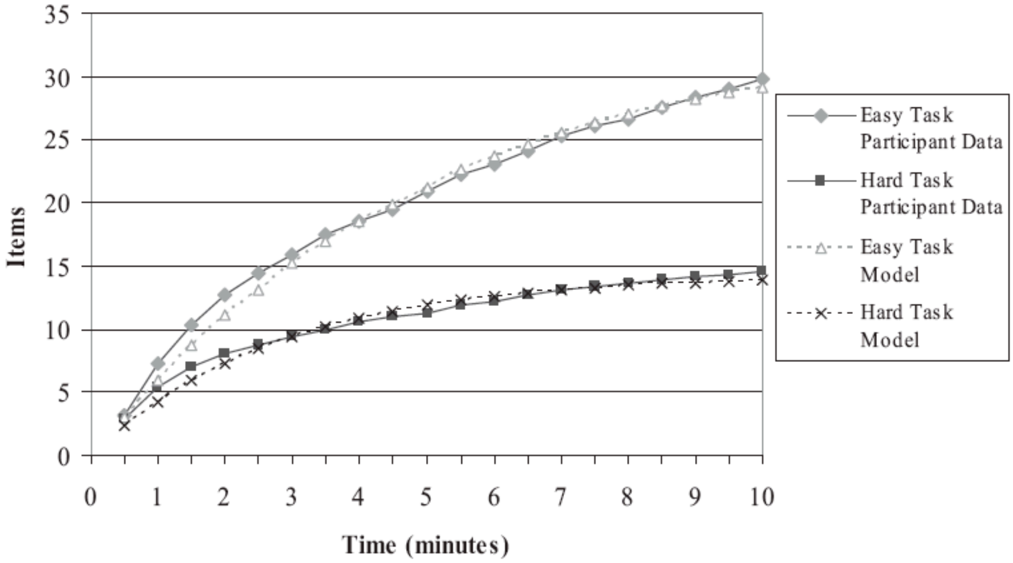


Figure 2.3: Cumulative gain of words found for two separate anagram tasks showing a typical diminishing-returns curve. (Image source from Payne et al., 2007, Figure 1, p. 374.)

2.2.2 Maximizing Multiple Tasks

Just as in the case of memory the literature on human multitasking is vast and multi-faceted, but offers few insights with regards to optimal task switching or stopping rules.[8]

Payne, Duggan, and Neth (2007) report a series of experiments that investigated the simultaneous completion of two independent tasks. In contrast to a psychological tradition that studies task switching and interruptions mainly in terms of costs their starting point is the observation that people habitually abandon one task to work on another before returning to resume the first task. How do people decide when to leave one task to work on another? And does such *discretionary interleaving* lead to the adaptive allocation of time to tasks?

To address this question, the authors first presented two anagram tasks (finding as many words as possible by using only the letters in the set 'LNAOIET' and 'ESI-FLCE', respectively) in isolation, each for a duration of 10 minutes. The cumulative function of words found by participants is shown in Figure 2.3 and displays a typical *diminishing-returns* profile, i.e., the rate of items per unit of time progressively diminishes throughout a trial.[9]

Figure 2.4 displays an integrated version of the two tasks included in Figure 2.3. By computing the time-weighted average of both individual curves it shows that an optimal overall allocation of time would be to spend approximately 20–30% of the total time on the harder task. Importantly, this curve is purely theoretical at this

[8]The exception is a general recommendation to switch tasks at sub-goal boundaries.
[9]The model data in Figure 2.3 approximates the empirical data by two exponential functions.

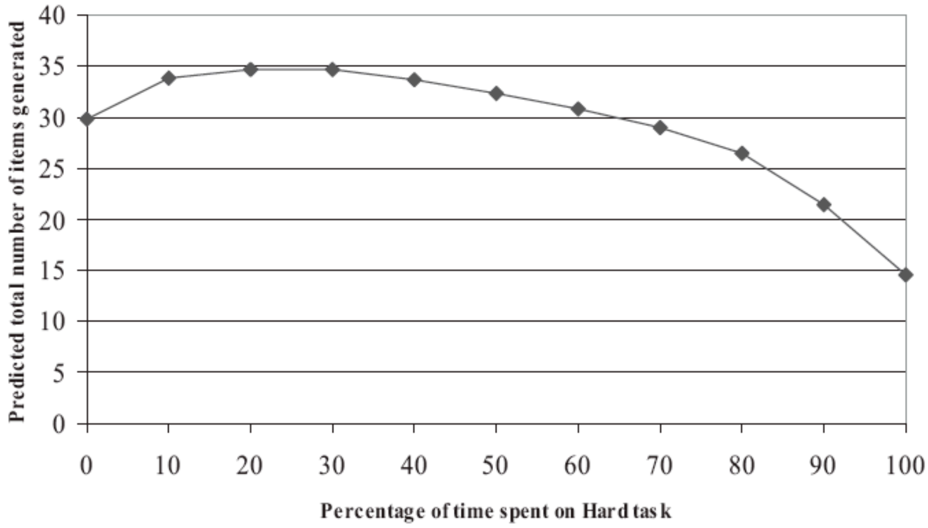


Figure 2.4: Expected amount of items found in two simultaneous anagram tasks of Figure 2.3 as a function of time spent in the harder task. (Image source from Payne et al., 2007, Figure 2, p. 375.)

point, as it is derived entirely without any details about the processes involved in multitasking and task switching.[10] Consequently, it can serve as an optimal prediction for the empirical study of time-to-task allocations.

What happens when both tasks are presented at once to participants? Payne et al. (2007) use a task-switching paradigm similar to Young (2004) to address this issue. Both tasks are presented simultaneously. Although only a single task is active at any moment, participants are free to switch back and forth between tasks at their discretion. As the tasks extend over several (10–15) minutes and require the visual display of an external stimulus the authors frame their discussion in terms of problem solving rather than memory search. Specifically, participants were presented with two anagram tasks or two word search puzzles at the same time. Both tasks contributed independently and entirely additively to the overall goal (of maximizing the number of words found) but the freedom to switch between tasks was experimentally manipulated to assess whether people spontaneously allocated their time in an adaptive manner.

The most basic result is that participants used the opportunity to switch tasks frequently (5–7 times on average) and this lead to an adaptive allocation of time to tasks. Figure 2.4 computes a prediction of this allocation on the basis of the curves for individual tasks in Figure 2.3. Based on this computation, it seems optimal to spend approx. 25% of one's task in the harder task, while devoting 75% of one's time to the easier one. That participants on average spent only 69% on the easier task points towards under-matching, but more investigations like this are needed to further investigate this claim. More specifically, the authors report a complex pattern

[10]As it assumes a between-task switch costs of zero the combination curve does not discriminate between different possible processes at arriving at a specific overall allocation.

of results that replicated across three experiments:

1. When switches are unconstrained participants allocate more time to easier tasks (that yielded higher rewards) than to harder tasks;
2. exit-latencies (giving-up times, GUTs) are higher for harder task;
3. on average, exit-latencies are preceded by longer between-item times.

In contrast to the meta-cognitive effects reported by Young (2004) people's decision to switch did not seem to be determined by the characteristics of the competing task.

To address the issue of optimality Payne et al. (2007) relate their research to a large body of theoretical and empirical work known as *foraging theory* (Stephens & Krebs, 1986). Four crucial variables that may contribute to the decision to abandon a task are:

1. current time on a task (analogous to T above),
2. number of items found (n),
3. giving-up time (GUT), or exit latency (t_X),
4. rate of item encounter (number of items per unit of time, i.e., n_i/t_i).

As none of these parameters can explain the complex pattern of results in a qualitatively and quantitatively satisfying manner, Payne et al. (2007) explain their results by extending Green's rule[11] (Green, 1984) by an independent p-subgoal parameter that specifies the probability of terminating a task directly after finding an item.

Hutchinson, Wilke, and Todd (2008) also explicitly relate cognition to animal foraging theory in studying human patch leaving decisions in an experimental fishing task (see also Wilke, 2006). Participants encountered a series of ponds in a serial fashion and had to maximize the number of fish caught over the duration of a 45 min experimental session. Prey items were gradually depleted by catching fish in a pond and distributed according to three different distributions (even, Poisson, and negative-binomial). Participants were free to abandon a given pond at any time, but switching to the next pond incurred a substantial time cost (of 15 or 25 s).

In their results Hutchinson et al. (2008) emphasize some maladaptive tendencies: Compared to the optimal strategy participants delayed their switch decisions for too long and spent too much time in ponds in which they had found more fish. The main cues predicting a switch decision were the current time interval without a capture

[11] According to Green (1984), the visit length V is a linear function of a minimum within-patch time T_{min} plus a gain G component that is added upon finding each item i: $V = T_{min} + iG$. This heuristic leads to an adaptive time allocation in patches for which the reward function is not known. (See Green, 2006, for a more general Bayesian analysis.)

(analogous to the exit latency t_X or giving-up time above), the interval preceding the last capture (last IRT), and the total time T spent at the current pond. In contrast to Payne et al. (2007) the authors attribute the observation of short exit latencies as a possible instance of the Concorde (or sunk cost) fallacy (Arkes & Ayton, 1999) rather than to a tendency to switch upon subgoal completion.

2.2.3 Foraging for Food and Information

Several of the preceding studies described aspects of human cognition in terms of biological theories of animal foraging. Analogies between human cognition and animal foraging are not new. As early as 1956 Simon described an idealized foraging agent that navigates environments in which food is distributed in different ways and argues that the the cognitive capacities of the agent are partially determined by the structure of the environment.

Foraging theory is essentially an economic approach to foraging behavior (see Stephens & Krebs, 1986, for an overview). Animals are assumed to inhabit a patchy environment in which energy gains by feeding on prey items are weighted against the costs of moving within and between patches (incurred through locomotion, prey handling, or the risk of predation). Optimal foraging theory (MacArthur & Pianka, 1966) assumes that organisms forage by allocating their resources in ways that maximize their energy intake per unit of time.

The analogy to animal foraging is attractive because foraging theory yields formal models on the basis of assumptions about environmental structure and an organism's capabilities. By assuming that animals have adapted optimally to their environments these models yield empirical predictions in which normative models serve as theoretical benchmarks with which the actual behavior of animals is compared.

An example of a productive formal model is the *marginal-value theorem* (MVT) by Charnov (1976) that directly addresses the issue when the currently visited patch ought to be deserted in favor of another one. It states that the optimal time to leave a patch (with a known prey distribution and diminishing returns) is when the marginal rate of return matches the the average rate of gain so far.

Figure 2.5 illustrates that the optimal patch leaving time t^* depends on the specific gain function $g(t_W)$ of the current patch and the travel time t_B between patches. The MVT predicts that the rate of optimal gain (shown as slope of the tangent line R^* in Figure 2.5) would increase if the between-patch travel time t_B decreased (Figure 2.6(a)) and if the gain function $g(t_W)$ of the current patch increased (Figure 2.6(b)). These predictions (of shorter patch-residence times, i.e., a reduction of t^*) were empirically confirmed for the foraging behavior of Great Tits in an artificial aviary (Cowie, 1977). Similar tests have been conducted for many species, including bumblebees (Pyke,

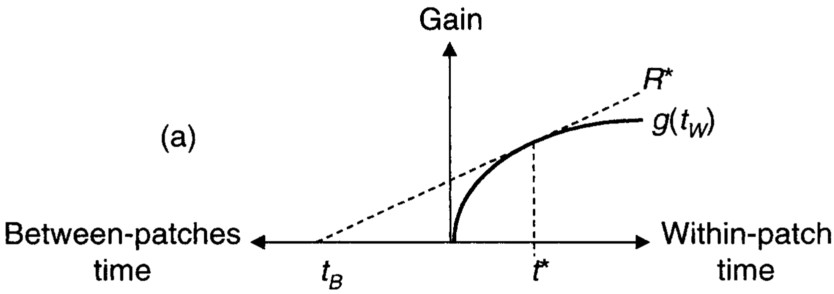
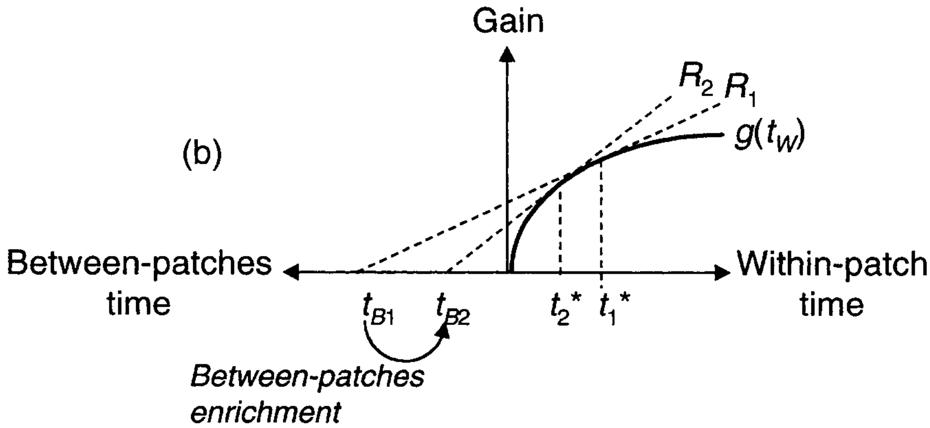
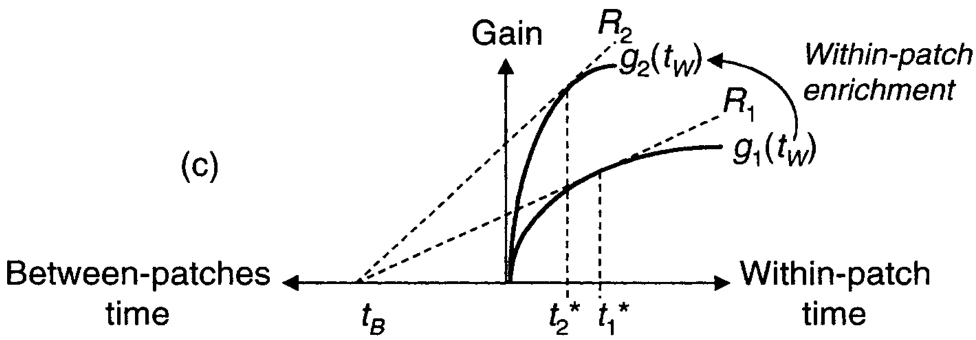


Figure 2.5: Optimal patch leaving time t^* according to the marginal value theorem of Charnov (1976). (Image source from Pirolli & Card, 1999, Figure 5a, p. 653.)



(a) Prediction 1: If t_B decreases t^* decreases.



(b) Prediction 2: If $g(t_W)$ increases t^* decreases.

Figure 2.6: Changes in optimal patch leaving time t^* due to between-patch enrichment (lower t_B) and within-patch enrichment (higher $g(t_W)$). (Images from Pirolli & Card, 1999, Figures 5b and 5c, p. 653.)

1978b; Zimmerman, 1981), hummingbirds (Pyke, 1978a) and woodpeckers (Lima, 1984) (see Pyke, 1984, for a review).

Importantly, Charnov's MVT provides an optimal solution to the problem of patch leaving times but not the mechanism by which organisms could actually derive this solution. Whereas the foraging models developed by ecologists address the questions "What is the optimal strategy?" (to exploit a patch, given some constraints) and "How are animals doing?" (relative to the normative benchmark) a major question for psychologists and cognitive scientists is "*How* are animals doing?" Addressing this latter question requires to consider various cue variables and simple heuristics that could potentially be used to approximate the optimal solution without the need for complex computations (e.g., Iwasa, Higashi, & Yamamura, 1981; Ydenberg, 1984; Nishimura, 1999; Green, 1984, 2006).

The predictions of foraging theory are not only attractive to researchers but also applicable to many real-world problems. In their explorations of *information foraging* Pirolli and Card (1999) have demonstrated that people's habitual interaction with information bears many characteristics of foraging.[12] As the internet is structured hierarchically (e.g., into pages, sites and domains) surfing and searching can be described as navigating between information patches. During online information search, e.g., for prices or medical facts, the data encountered often follows a diminishing returns curve in that a lot of useful information is encountered initially but the longer the search the harder it gets to uncover additional relevant information (Bhavnani, Jacob, Nardine, & Peck, 2003). This regularity is partially due to information being copied and distributed over multiple locations (Zipf, 1949) but is aggravated by the fact that search engines rank their results by assumed relevance.

Both in casual browsing and targeted information search web users constantly negotiate a resource allocation problem in which limited attention and time have to allocated to an abundance of information, often of varying degrees of quality and trustworthiness. Consequently, online navigation has been described both in terms of multitasking (Spink, Park, Jansen, & Pedersen, 2006) and the targeted pursuit of information scent (Fu & Pirolli, 2007).

Given that the web is structured in patches, it takes time and effort to locate and process information and the yield of information diminishes when too much time is spent in any one place it is not surprising that the foraging analogy has been a productive metaphor for the empirical research of online behavior (see Pirolli, 2007, for an overview).

In a simple empirical study, Browne, Pitts, and Wetherbe (2005) investigated the stopping rules reported by participants who were conducting online searches for information about digital cameras. Due to the high familiarity and well-structured nature of this task the authors hypothesized that participants would be more likely to use simple "mental list" or "single criterion" rules than more complex rules that incorporate thresholds (of total or marginal information gain) or a (rather vague) notion of "representational stability". While these predictions were confirmed, the results are based entirely on retrospective self-reports and are likely to suffer from issues of identifiability and the limits of introspection. In fact, the qualitative nature of such studies highlights the quantitative approach of animal foraging theory as a key advantage.

[12]See Banks, Vincent, and Phalp (2008) for an application of foraging theory to more general search scenarios in computer science.

2.2.4 Cognitive Foraging and Extended Cognition

Beyond the rather specialized task of web surfing many real-world tasks and activities (like the benefits derived from eating, sleeping or studying) are characterized by diminishing returns (Payne et al., 2007). Hills, Todd, and Goldstone (2008) hypothesize that goal-directed cognition is an evolutionary descendant of spatial foraging behavior, as both external and internal search processes require the organism to strike a balance between exploration and exploitation. By showing that participants' patch residence times in a cognitive (word search) task can be primed by a spatial foraging task the authors argue in favor of generalized cognitive search processes.

The idea that memory processes could resemble external navigation patterns is not new. Memory has figuratively been described as a mirror of the environment (Draaisma, 2000) and as early as 1890 William James compared memory retrieval to the search for an external object:

> "(...) we make search in our memory for a forgotten idea, just as we rummage our house for a lost object. In both cases we visit what seems to us the probable *neighborhood* of that which we miss. We turn over the things under which, or within which, or alongside of which, it may possibly be; and if it lies near them, it soon comes to view." James (1890, Ch. 16)

Complementary to this view of memory as an 'inner environment' the boundaries between within and outside the organism are frequently blurred in the context of memory. For instance, Newell and Simon (1972) refer to the external task environment during problem solving as "external working memory" and Simon (1996) characterizes memory as a part of the outer environment:

> "A thinking human being is an adaptive system; men's goals define the interface between their inner and outer environments, including in the latter their memory stores. To the extent that they are effectively adaptive, their behavior will reflect characteristics largely of the outer environment (in the light of their goals) and will reveal only a few limiting properties of the inner environment—of the physiological machinery that enables a person to think." Simon (1996, p. 53)

A potential caveat against a view of memory search as internal foraging is that cognitive representations and processing characteristics may differ significantly from external structures and navigation patterns. For instance, the foraging analogy would be seriously misguided if people could search more than a single memory patch in parallel. Although this possibility has been raised (e.g., Logan & Delheimer, 2001) two studies by Maylor, Chater, and Jones (2001) explicitly addressed this question and concluded that search in semantic and autobiographical memory search is exclusive to a single task at any one time.

Another indication of potential similarities between internal and external structures and processes is that researchers on cognitive representations frequently assume semantic knowledge to be organized in structured (quasi-spatial) representations of networks and maps (Steyvers & Tenenbaum, 2005).

A complementary view to cognitive processes as the traversal of some inner environment is the view of *extended cognition*, which claims to "radically reconfigure our image of rationality" (Clark, 2001, p. 121). The ubiquitous use of tools and gestures during cognition suggests that many elements of the external world (e.g., body parts, interactive devices and informational artifacts) can be viewed as integral parts of cognition, rather than mere media for modified inputs and outputs (Clark & Chalmers, 1998). Clark (2003) even claims that we are living cyborgs, routinely wearing and relying on cognitive prostheses.

Such views are no surprise to empiricists. In fact, most real-world problem solving recruits external tools and achieves its goals through an intricate process of interaction with the physical environment. When solving arithmetic problems, people spontaneously distribute memory demands over internal and external resources (e.g., Cary & Carlson, 2001) and spontaneously employ their hands and other available resources to rearrange, add and count items (Carlson, Avraamides, Cary, & Strasberg, 2007; Neth & Payne, 2001). Continued reliance of experienced pilots on external markers to track current control states (Hutchins, 1995) shows that external aids are not just cognitive crutches for novices. On a lower level, research on so-called 'active vision' (e.g., Findlay & Gilchrist, 2003) supports the view that agents continually sample their environments, rather than constructing complex internal representations.

To account for these phenomena, cognitive science has seen a recent upsurge in approaches that try to cross the traditional divide between thought and action by mapping the close connections between mental processes and the environments in which they are situated (e.g., Lave, 1988; Suchman, 1987; Hollan, Hutchins, & Kirsh, 2000; Neth et al., 2007). Despite differences in emphasis and labels, their common denominator is that cognition is fundamentally embodied and embedded and the boundaries between inner and outer environments tend to blur and are often rendered meaningless.

2.3 Planned Research

This section sketches a series of studies, each of which is likely to contain several iterations of empirical data collection, data analysis and mathematical or computational modeling. As the designs and experimental conditions of later studies partially depend on the results of earlier ones our descriptions will become increasingly generic. Before describing the details of specific studies we outline some objectives and characteristics that are shared by all our experiments in this series.

Encouraged by the co-evolution and mutual adaptation of cognition and the environment and the successful application of foraging analogies to other cognitive tasks we aim to explore the notion of *memory foraging*, i.e., the application of foraging theory to models of human memory.

Subscribing to the basic tenets of extended cognition we also propose to manipulate the *search space* by comparing and contrasting processes of human information search in two variants:

1. *Unaided cognition* or *in-the-head*: Humans answer queries by retrieving information from semantic memory.

2. *Extended cognition* or *in-the-head + on-the-web*: Humans answer queries from semantic memory, by conducting online information searches, or by some combination of both.

Under both conditions we will study the temporal characteristics of retrievals and the utility functions of the corresponding information. Although we intend to start by studying retrieval we will later incorporate other known factors of influence, like gradients of relevance changes. For instance, when the relevance of the information retrieved decreases it may become functional to stop even though retrieval still occurs at a fast rate.[13]

The *extended cognition* condition is of particular interest because it implicitly contains a dual-task paradigm: Humans can decide to answer a question from memory, or abandon this attempt and try to find information somewhere else. However, as background knowledge guides search strategies (e.g., Duggan & Payne, 2008) any information retrieved from consulting external sources cannot exclusively be attributed to the external source.

Throughout all experiments our main focus is on the strategies employed to answer queries for information retrieval and selection, as well as the cues and potential heuristics that humans use to terminate a search or switch between tasks. More specifically, our studies address the following research questions:

- Does the complex pattern of previous empirical results (e.g., of Young, 2004; Dougherty & Harbison, 2007; Payne et al., 2007; Hutchinson et al., 2008) replicate in a memory foraging scenario (in which participants aim to maximize their yield over the entire experimental session)?

- Are people allocating their time adaptively when engaging in individual or multiple memory retrievals? Specifically, do they respond strategically to the meta-

[13]A foraging analogy to this phenomenon would be that the energy obtained from certain prey items is too low to make their pursuit worthwhile.

cognitive manipulation of having knowledge of the next task? Do they respond strategically to manipulations of switch costs and differential benefits of retrieval?

- What cues are people using to terminate memory search? Are there simple heuristics for stopping tasks to allocate time adaptively to a sequence of individual or multiple simultaneous tasks?
- Does memory retrieval and processes of internal plus external information search share the same regularities, or are there systematic discontinuities between internal and extended cognition?
- Can the empirical findings be captured theoretically by simple heuristics and by enriching existing models of memory with elements of optimal foraging theory?

In short, a series of studies will adapt and combine the methodologies of earlier research and extends previous findings on information foraging and discretionary task interleaving to discover guidelines for fast and simple stopping and switching rules and heuristics and other processes that can approximate such idealized performance. We provide additional details on these studies in Appendix A.

2.4 Discussion

We have argued that the issue of appropriate stopping rules can fruitfully be addressed by applying insights and paradigms from multitasking and foraging theory to the study of human semantic memory. This section will show the generality of these issues and highlight the relevance of our research and eventual findings to the LarKC effort.

2.4.1 Generality

Despite our focus on memory recall we are confident that the findings of our experiments will generalize to other aspects of cognition and task domains.

Whenever resources are limited, the allocation of time and effort to different tasks constitutes a problem. Of particular importance are the rules used to stop certain processes to take up or switch to other ones.

A formal analogy of this allocation problem has appeared in the literature on animal foraging (for food, prey and mates) and successfully been formalized and addressed empirically. Previous analogies to animal foraging (e.g., Pirolli & Card, 1999; Pirolli, 2007; Payne et al., 2007; Hutchinson et al., 2008) have argued that the main requirement for the application of these models is that the problem in question has diminishing returns. This appears to be a fairly universal property of many task domains. Other domains of relevance include:

- *Information search*, e.g., knowing where to allocate one's limited amount of time and attention, given the abundance of information encountered during both casual web browsing and specific search.
- *Problem solving*, e.g., knowing when to interrupt a task or switch between tasks.
- *Decision making*, e.g., when gathering and evaluating cues in medical or financial contexts (e.g., see Wübben & Wangenheim, 2008, for an application to marketing).
- *Meta-cognition*, e.g., knowing which problem to tackle first, or when to continue or stop studying for an exam.

More generally, foraging models provide a formal framework where anthropologists, biologists, cognitive scientists, designers and engineers could meet (see Hutchinson & Gigerenzer, 2005, for an elaboration of this point).

2.4.2 Links to LarKC

In the context of LarKC, the question of appropriate stopping rules lurks in multiple locations:

- *Process termination*: The basic LarKC processing cycle includes many components that are subject to cost-benefit tradeoffs of speed vs. accuracy (or recall vs. precision). Specifically, the components of repository *selection*, *abstraction* (or transformation) and *reasoning* would benefit greatly by insights into successful, fast and frugal stopping rules.
- *Topography*: The web is a patchy environment. The semantic web will alter the current patch structure by enriching the current structures (e.g., by reducing the travel times between and increasing the productivity within patches). Our research will inform the issue how humans are likely to react to these topographical changes.
- *Evaluation*: LarKC essentially promises to generate more profitable patches of online information. This ought to have a measurable impact on human behavior when engaging in information search. Our methodology to study human information search can be adapted to compare traditional online search settings with setups aided by semantic web technology.

People often switch between tasks. Curiously, the psychological literature on task switching typically emphasizes the costs of doing so. In contrast, we emphasize the adaptive values of task switching and hypothesize that people have evolved or learned to select good switching opportunities. Consequently, finding out when and how people abandon one task to begin another may yield valuable heuristics for the search and reasoning processes of machines.

3 Human Heuristic Search in Problem Solving

3.1 Motivation and Links to LarKC

The major problem that LarKC focuses on is the huge scale requirement in Web and other IT areas caused by the explosion of information and knowledge (e.g., reasoning about 10 billion RDF triples in less than 100 ms) (Fensel and Harmelen, 2007). One of the central ideas to overcome this problem proposed by LarKC is limited rationality, including heuristic reasoning (Fensel et al., 2008).

The real world faced by human beings is also with distributed, incomplete, inconsistent, dynamic massive scale heterogeneous information sources. By evolution, human beings have developed sophisticated heuristic search skills in reasoning, problem solving and decision making.

Both human brain and Web reasoning systems are devices of information processing. Employing cognitively inspired approaches and techniques is one of the basic methodologies in LarKC. Hopefully with the help of deeper understanding of the heuristic search used in human problem solving, this Web-scale reasoning platform will be able to use heuristics more efficiently and effectively and will even be able to form better heuristics during reasoning and problem solving by itself.

Brain imaging technologies will offer much more detailed information than traditional behavior experiments on heuristic search. It may be able to reveal the processes of brain choosing and applying heuristics and therefore it may offer cues for us to organize and select heuristics better in LarKC. For many traditional problem solving tasks, however, it is difficult to directly run them in brain imaging experiments. Therefore, we developed a new paradigm, simplified 4x4 Sudoku, to investigate the brain activations and the information processing processes in brain during human heuristic searching. In general, the research in heuristic problem solving involves how people use heuristics in problem solving and how people form new heuristics during problem solving. As the first step, we will leave the research on the acquisition of new heuristics to the future and focus on the first problem, how people perform heuristic search in problem solving, with tow studies: (1) The retrieval and application of heuristics; (2) The selection of heuristics.

ACT-R is a computational cognitive architecture. We have seen the applications of the concept on spreading activation of ACT-R in retrieval and abstraction in Deliverable 2.1.1. In this proposal, we will use ACT-R to build the model of heuristic search and to predict the BOLD (Blood Oxygenation Level Dependent) effect recorded in fMRI scanning. This model may help us to improve the use of heuristics in LarKC.

The relation between LarKC and brain imaging can be in an opposite direction, the techniques developed in LarKC may advance the analysis of brain imaging data.

We will also explore this direction by using the pattern recognition, commonly used in machine learning and data mining, in the analysis of our brain imaging data.

In the following sections of this chapter, we will briefly review the research on heuristic search in human problem solving and give a short introduce to ACT-R in section 3.2, describe the design of the experiments and the methodologies of the data analysis of the two studies proposed above in section 3.3, and end with a discuss remarks including future studies in section 3.4.

3.2 Background

3.2.1 Problem Solving and Heuristics

Human problem solving has been researched from various aspects. One of the most fundamental approaches, and also most related to LarKC, is thinking it as searching a problem space, which consists of various states of the problem, to find a path from the initial state to the goal state, proposed by Newell and Simon (1972). Heuristics, rules of thumb, are often used in this searching to reduce the cost. There seem two kinds of heuristics. One kind is domain-independent, such as "means-end analysis" proposed in GPS (General Problem Solver) by Newell and Simon (1972, P. 416). The other kind of heuristics is domain-dependent, some "smart ways" specific to the problem. Sometimes it may not be easy to separate them clearly and people may combine both kinds of heuristics to solve the problems, but we will pay the major attention to the domain-dependent heuristics in our proposed studies.

Even though people may not solve any problem in the real world without the help of heuristics, heuristics may also cause various cognitive biases as pointed by Tversky and Kahneman (1974). How to use heuristics avoiding this possible drawback should be important to LarKC, but beyond the scope of this chapter.

Comparing with the behavioral data (the time the participants spend to solve a problem and the rate of correct answer), verbal protocol records, advocated by Newell and Simon (1972), usually carry much more detailed information on what the heuristic rule is, when it is used, and, in some circumstance, why the heuristics is selected. But, of course, it cannot offer the information on how the brain works to choose and apply the heuristics, which may offer cues for us to organize and select heuristics better in LarKC. Therefore, we plan to run fMRI experiments to explore the information processing processes in the brain when a human selects and applies heuristics in problem solving.

To get as detailed information as is possible in a laboratory setting, the problems used by Newell and Simon (1972, p. 3) were moderately difficult and lasted about half an hour. Half an hour might have been short to them, but it is too long for conducting fMRI experiments (that usually last between 10 or 20 seconds for a trial). Other traditional tasks used in the research of problem solving, such as the Tower of Hanoi task, are also too complex (the participants might use different strategies to solve it) and too long. For example, Fincham et al. (2002) used the Tower of Hanoi task in their fMRI experiment but they modified the task with unnatural restrictions. The Tower of Hanoi task used by Anderson, Albert, and Fincham (2005) was more natural, but they only performed a confirmation analysis on their data. To overcome this problem, we will introduce a simplified 4x4 Sudoku as a new paradigm for problem solving research in fMRI experiments with with both a confirmatory and exploratory analysis.

3.2.2 ACT-R

ACT-R (Adaptive Control of Thought–Rational) is a theory and computational model of human cognitive architecture (Anderson et al., 2004). As a theory, it proposes a systematical hypothesis on the basic structure of human cognitive system and functions of these structures in information processing to generate human cognitive behavior; as a computational model, it offers a computer software platform for the development of computational models to quantitatively simulate and predict the human behavior for a wide range of cognitive tasks.

There are two kinds of knowledge represented in ACT-R – *declarative* knowledge, with chunks as its basic units, and *procedural* knowledge, with production rules (condition-action pairs) as its units. In Deliverable 2.1.1, we employed the idea of spreading activation of chunks for retrieval and abstraction. To simulate and/or predict the behavior of human problem solving, however, we need to use the whole ACT-R system.

As shown in Figure 3.1, ACT-R consists of a set of modules with their own buffers, each devoted to processing a different kind of information. Besides the declarative memory module mentioned above, there is a visual module for identifying objects in the visual field, a manual module for controlling the hands, a goal module for keeping track of current goals and intentions and other modules. The information in these modules is largely encapsulated and the modules communicate only by firing the productions based on the chunks in their buffers. Within a module and among different modules, the information processing can go on in parallel and asynchronously. However, there are two sequential processing restrictions in ACT-R: Only one chunk can be in the buffer of any module at any time and there is only one production rule can be fire at each processing cycle.

The critical information processing cycle in ACT-R is one in which the buffers hold representations determined by the external world and internal modules, if the

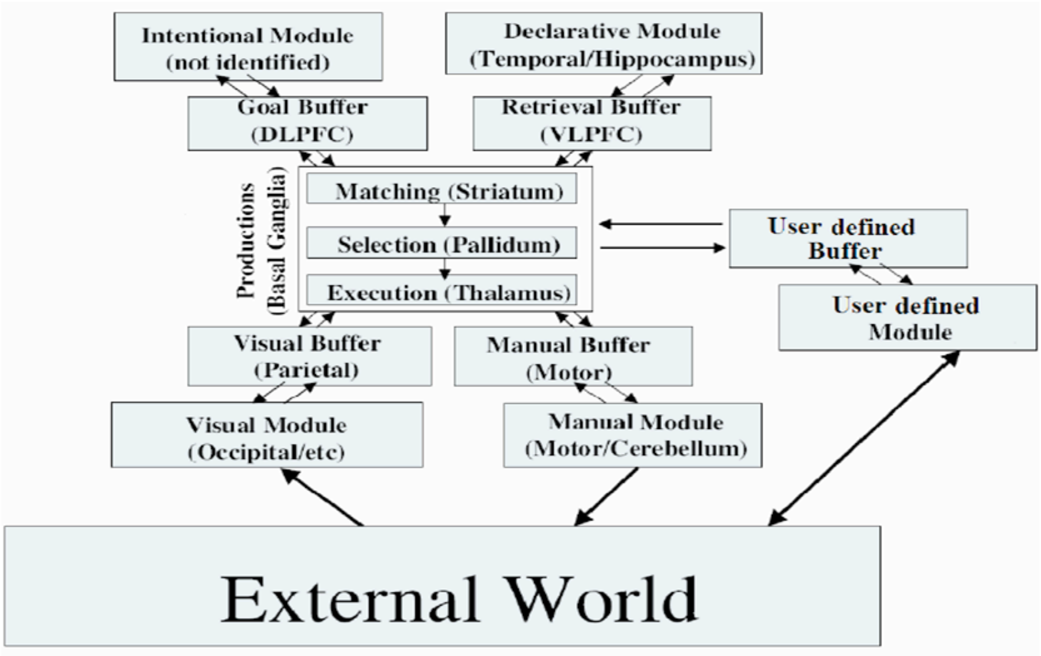


Figure 3.1: The organization of information in ACT-R. DLPFC = dorsolateral prefrontal cortex, VLPFC = ventrolateral prefrontal cortex from Figure 1 of Anderson, Bothell, Byrne, Douglass, Lebiere, and Qin (2004).

patterns in these buffers and the state of the modules match the condition part of a production, the production fires, and the buffers and/or the state of related modules are then updated for another cycle.

The output of an ACT-R model is a time course to show when and for how long time for each module actives when the model perform the tasks. With this time course, one can simulate/predict the participants' performance (Reaction time and accuracy). If we have the knowledge of the brain areas corresponding to the modules (see Figure 3.1 for example), one can simulate/predict the BOLD effect of fMRI experiment with the help of Gama function that describes the BOLD response. Figure 3.2 copied from Anderson, Albert, and Fincham (2005) to show the latency data in a Tower of Hanoi fMRI experiment and the fit to the data.

Figure 3.3 shows the observed and predicted BOLD response for three brain regions: the motor area (corresponding to the manual module of ACT-R, see Figure 3.1), the parietal cortex (corresponding to the visual buffer for the representation of problem states), and the ventrolateral prefrontal cortex (VLPFC) for declarative memory retrieval when the participant performs the Tower of Hanoi task.

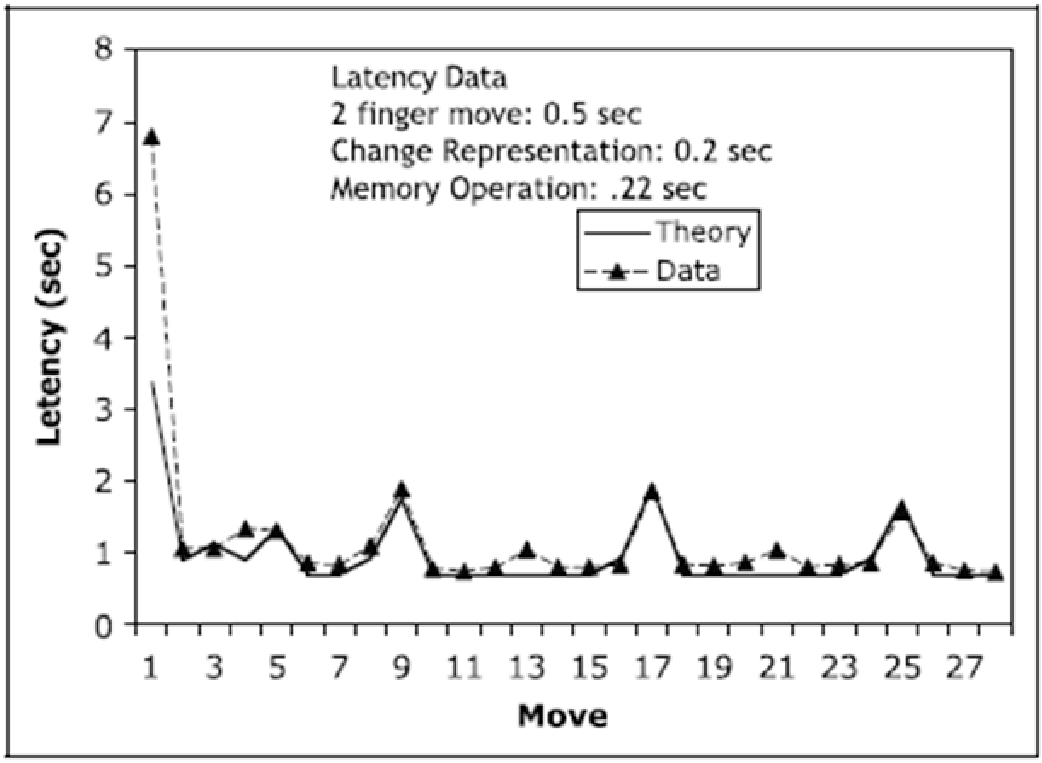


Figure 3.2: Mean observed and predicted times to make a move as a function of the position of the move in the problem sequence of a 5-disk TOH task from Figure 4 of Anderson, Albert, and Fincham (2005).

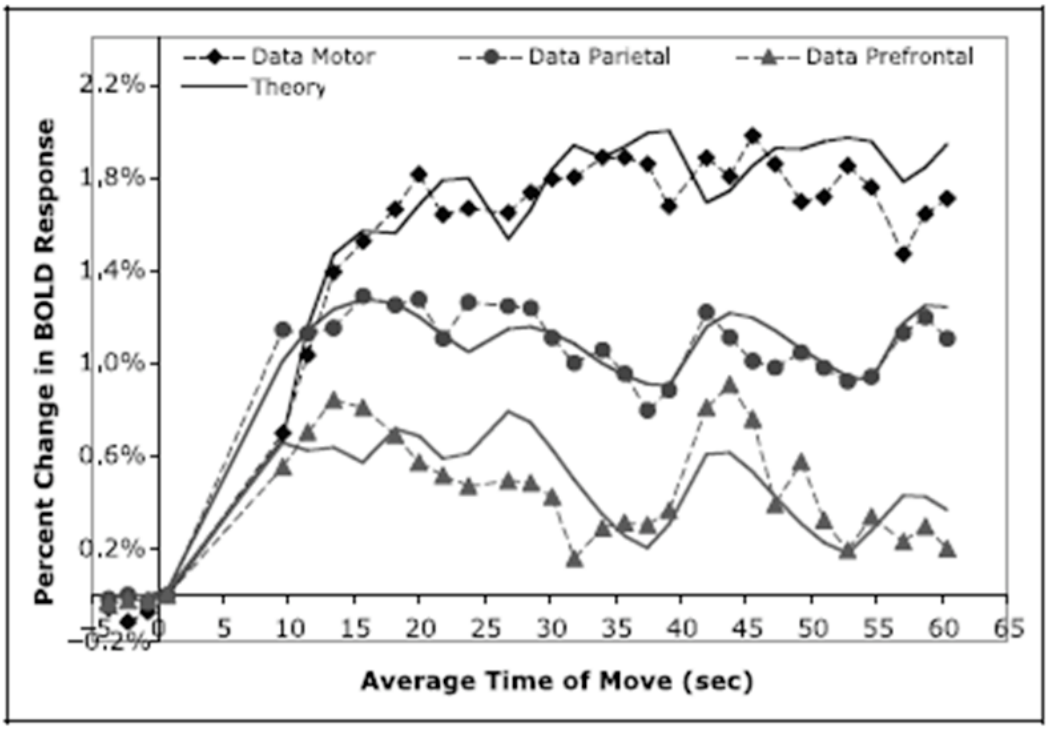


Figure 3.3: Mean observed and predicted BOLD response for three regions in Figure 3.1 as a function of mean time of move in the Tower of Hanoi problem solution. The BOLD response are calculated as percent change from the baseline established by the premove scans from Figure 5 of Anderson, Albert, and Fincham (2005).

3.3 Planned Research

3.3.1 Problem Solving and Heuristics

Cognitive psychology and AI have used different classical problem solving tasks, such as Tower of Hanoi, the savage and the missionary puzzle, eight-tile problem and so on, to investigate the information processing processes in problem solving. These tasks are somewhat complicated, and participants have to take relative long time to solve the problems. They may not be suited for the brain imaging study, which adds many limitations during scanning. A good task to investigate the heuristic search with brain imaging experiments should meet the following requirements:

- The problem can be solved in a short period, usually within 20 seconds, and never more than a few minutes;
- There exist clear heuristics that have to be used in searching the problem space;
- The processes of solving the problem are relatively consistent across the participants or can be manipulated so that all of the participants will follow the same strategy to solve the problem;
- The processes of solving the problems can be well controlled and easily manipulated for parametric design.

We found that the simplified 4x4 Sudoku is a good candidate task. A 4x4 Sudoku, as shown in Figure 3.4a, is a 4x4 matrix; two midlines divide the matrix into 4 sections, called boxes. Some cells have been provided with numbers. The task is to fill all of the empty cells so that every row, every column, and every 2x2 box contains the digits 1 through 4 only one time each, as shown in Figure 3.4b.

If enumeration is used, there will be many possible attempts, but only one is correct. If heuristic rules are employed, however, only a few steps will be needed to solve the problem.

4x4 Sudoku is much easier than the Tower of Hanoi task and can be solved in a shorter time period. Also we can produce abundant 4x4 Sudoku tasks with different constraints to study heuristic search systematically. The heuristic rules are simple, clear and easy to use. Furthermore, the appearance of 4x4 Sudoku can be easily be changed, e.g., by using figure symbols to replace the numbers. We are going to use 4x4 Sudoku to carry out a series of experiments on human heuristic problem solving. As the first step, we will perform two studies, (1) The retrieval and application of heuristics; (2) The selection of heuristics. While participants are solving the problems, BOLD signals and behavioral patterns will be recorded in an fMRI scanner. We will use these data to explore spatio-temporal characteristics of heuristics in the brain, and

1		2	
3		4	
			3

a. 4x4 Sudoku

1	3	2	4
4	2	3	1
3	1	4	2
2	4	1	3

b. Answer

Figure 3.4: An example of a Sudoku task and its answer.

to develop ACT-R models to predict where, when and how long the brain areas are active during processes of problem solving.

3.3.2 Study 1: The Retrieval and Application of Heuristics

As the first step, our ongoing research will focus on the basic processes of heuristic search in problem solving.

To control the strategies participants may take, we will simplify the puzzle and only ask the participants to find the value in one cell that is marked by "?". The basic heuristics to solve the problem are as follows:

1. Row heuristics, as shown in Figure 3.5a: If the row with the question mark "?" has been provided with 3 digits, fill in the missing one;

2. Column heuristics, as shown in Figure 3.5b: If the column with the question mark "?" has been provided with 3 digits, fill in the missing one;

3. Box heuristics, as shown in Figure 3.5c: If the box with the question mark "?" has been provided with 3 digits, fill in the missing one;

4. Row and column heuristics, as shown in Figure 3.5d: If the row and column with the question mark "?" has been provided with 3 digits, fill in the missing one;

5. Row and box heuristics, as shown in Figure 3.5e: If the row and box with the question mark "?" has been provided with 3 digits, fill in the missing one;

6. Column and box heuristics, as shown in Figure 3.5f: If the column and box with the question mark "?" has been provided with 3 digits, fill in the missing one;

7. Row, column and box heuristics, as shown in Figure 3.5g: If the row, column and box with the question mark "?" has been provided with 3 digits, fill in the missing one;

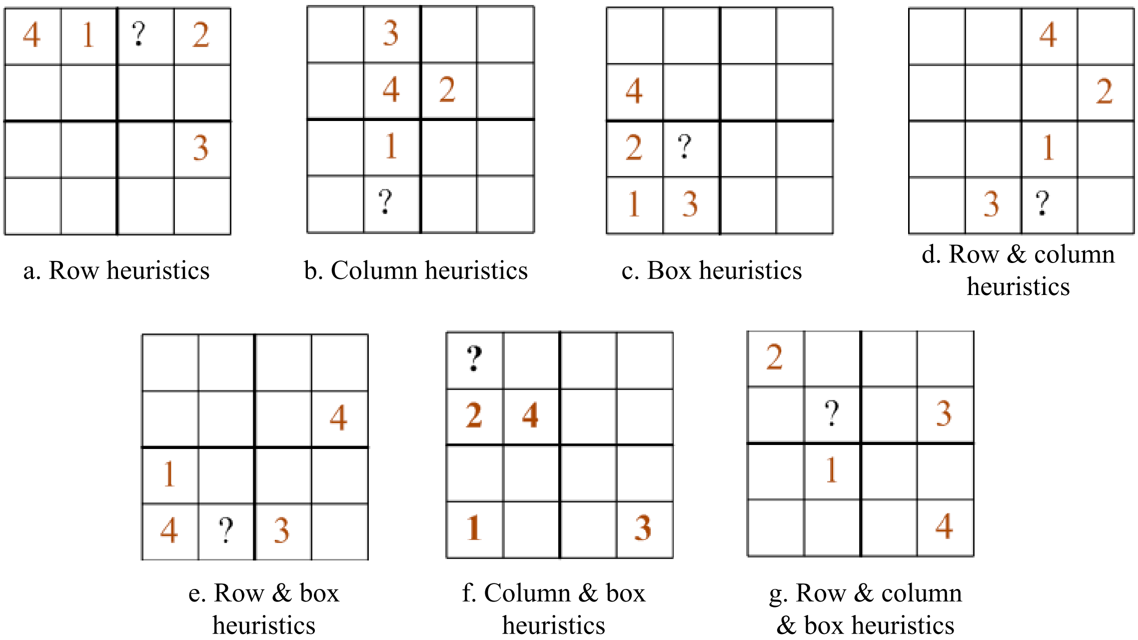


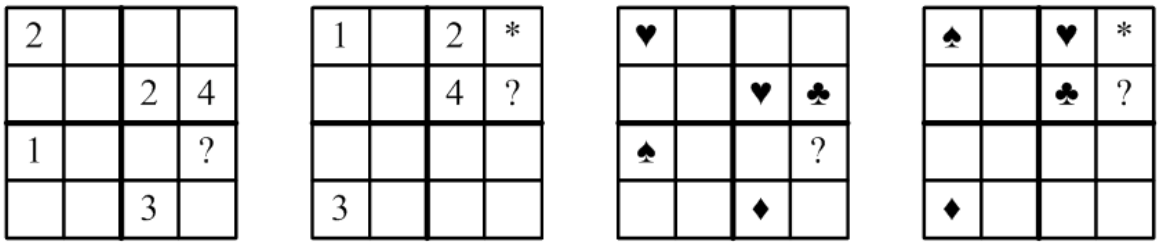
Figure 3.5: Basic heuristics in 4x4 Sudoku.

The heuristics 1 to 3 are called simple heuristics because the participants only need to check one dimension to choose the heuristics. The heuristics 4 to 7 are called complex heuristics because the participants need to check more than one dimension to choose the heuristics.

Pilot Experiment Pilot experiment showed that after training, the participants used these heuristics consistently.

Experiment Design In this basic experiment, the participants will only need to retrieve and apply the heuristics. To these relatively easy problems, after training, the same sequence of heuristics will be used by all of the participants to solve the problems. We will take an event-related parametric designed fMRI experiment with three 2-level factors:

- Steps needed to solve the problem: 1-step vs. 2-steps. In the 1-step condition, the cell marked with "?" can be solved directly; in the 2-step condition, however, the participants have to find the value of cell marked with "*" first, and then the value of the cell with "?";
- Difficulty to solve the problem, simple vs. complex. In simple condition, only one simple heuristic rule needed to solve a step of the problem; in complex condition, the complex heuristics will be needed to solve the problem;
- Mode, number vs. symbol. Half of the problems are with digit of 1 to 4, and the other half of problems are with 4 kinds of symbols.



a. 1-step number b. 2-step number c. 1-step symbol d. 2-step symbol

Figure 3.6: Examples in study 1.

The hypotheses behind the design of this experiment are: (a) The difference in the input mode (number vs. symbol) may only be involved in the perception and early information processing stages, but not in higher level cognition, such as applying the heuristics in the problem solving (Anderson, et al., 2007); (b) If a brain area is related to the heuristic search in problem solving, the more effort needed to apply the heuristics (e.g. 2-step and/or complex condition), the higher activation will be observed, which will be reflected by the BOLD effect recorded during the fMRI scanning (Anderson, et al., 2008).

Materials According to the design, there are 8 types of Sudoku problems. If a problem is with digits and can be solved with one of the first three heuristics above, it is a 1-step, simple, number problem (examples are not shown). Figure 3.6a is an example of 1-step, complex, number problem. Figure 3.6b is an example of 1-step, complex, symbol problem. Figures 3.6c and Figure 3.6d are examples for 2-step, complex problems.

Participants 20 healthy graduate and undergraduate students from Beijing University of Technology will participate in the experiment and will be paid for their participation. All participants are right-handed, native Chinese speakers, and have normal or corrected-to-normal vision.

Experiment Procedure This experiment will take two days. All participants will be trained on the day before the scan day to get familiar with heuristic rules. As shown in Fig 3.7, for each trial, a red asterisk for fixation will appear 2 s in the screen first, and then a 4x4 Sudoku will be presented and ask participants to find the value of the cell marked by "?". When participants find the value of the cell marked by "?", they need to press a button (to record the reaction time) and speak out the value (to check the accuracy) during the 2 s vocal time interval. In the 1-step condition, participants only need to find the value of the cell with a mark "?". In the 2-step condition, to avoid that different strategies are being used, participants have to first find the value

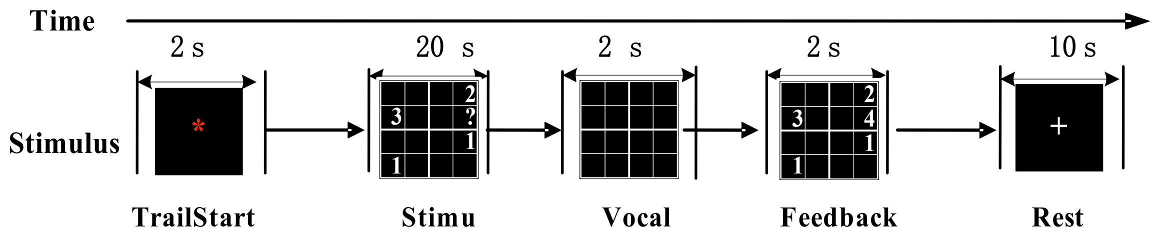


Figure 3.7: Procedure of a trial in study 1.

of the cell marked by "*", before finding the value of the cell marked by "?". They need to press the button once but speak out two values. A Sudoku with the correct answer will appear on the screen for 2 s to provide feedback and motivate participants. After a 10 s rest interval (which ensures that the BOLD signal returns to the baseline) the next trail will begin. There are 5 sessions in all and each session involves 48 trials (6 trials for each of 8 types of conditions). Participants are encouraged to finish the problem as accurately and quickly as possible. Both behavioral patterns and BOLD signals are recorded and analyzed.

The Protocol of the fMRI Scanning and fMRI Data Analysis The scanning will be performed on a Siemens Magnetom Trio Tim 3.0 T system using a standard whole-head coil. Functional data are acquired using a gradient echo planar pulse sequence (TR = 2 s, TE = 31 ms, 32 axial slices (with AC-PC through the 23rd slice from the top of the brain), 3.125 mm x 3.125 mm x 3.2 mm voxels, 0 mm inter-slice gap, 90 flip angle, 64 x 64 matrix size in 200 mm x 200 mm field of view). The imaging sequence will be optimized for detection of the BOLD effect including local shimming and 14 s of scanning prior to data collection to allow the MR signal to reach equilibrium. To minimize head motion, bi-temporal pressure pads will be employed. The scanner is synchronized with the presentation of every trial.

We will perform two kinds of data analysis. The first one is called confirmation analysis, in which the major ROIs (Regions of interest) involved in the problem solving found by ACT-R group (Anderson, et al, 2008) will be checked, an ACT-R model will be developed to predict the BOLD effects in these ROIs (Anderson, et al, 2004). The second one is called exploratory analysis in which the ROIs will be defined based on the activations. Pattern recognition techniques may be used in this analysis. The general conclusions and remarks will be generated based on the results of both analyses.

Modeling The model developed in the confirmation analysis will be used to explain the information processing process in the brain during using the heuristics.

3.3.3 Study 2: The Selection of Heuristics

In study 1, we only investigate the retrieval and application of the heuristic rules when participants only need to find the value of the cell marked with a "?". In that study, the marked cell provides a way to guide the use of heuristic rules, and participants do not need to consider the whole problem situation. In study 2, we will investigate how participants decide their searching orientation and select between available heuristics.

Experiment Design An event-related parametric designed fMRI experiment with two 2-level factors will be taken:

- Task type: with mark vs. without mark. The task with mark is similar to the 1-step condition in study 1, in which Sudoku problems appeared with a mark "?" in the cell. While in the task without mark, no such a mark appeared and participants had to search the whole problem representation to find out a best and easiest cell.
- Difficulty to solve the problem: simple vs. complex. This factor is manipulated similarly as in study 1. In the simple condition, only one simple heuristic rule will be needed to solve the problem; in the complex condition, a complex heuristic rule will be needed to solve the problem.

The hypotheses behind the design of this experiment are that, in contrast to the task with a mark, in the task without mark brain areas related to visual attention and heuristic selection will be involved more and will show different activations, while there is no difference in the areas related to the retrieval and application of the heuristics between the two types of tasks.

Materials According to the design, there are 4 types of Sudoku problems. Figure 3.8a is an example of simple with mark task, Figure 3.8b is an example of complex,

	1		
	?		
	2		3
	4		

a. With mark & easy

2	?	3	
			4
	1		

b. With mark & difficult

	1		
	2		3
	4		

c. Without mark & easy

2		3	
			4
	1		

d. Without mark & difficult

Figure 3.8: Examples of tasks to be used in study 2.

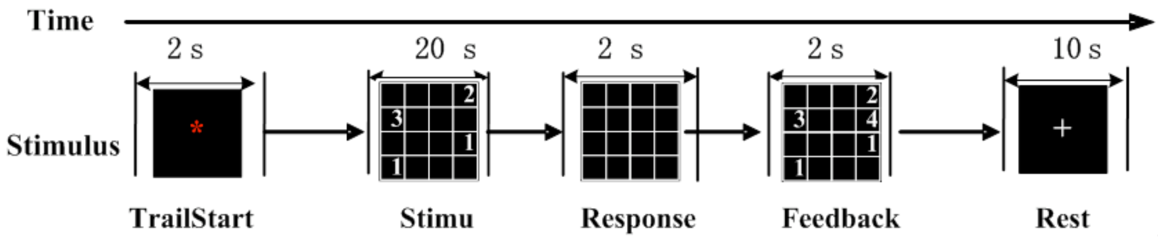


Figure 3.9: Procedure of a trial in study 2.

with mark task. Figure 3.8c and Figure 3.8d are examples for task without mark and the participants have to find out the cell easiest to be solved. They are examples to simple and complex conditions respectively.

Participants 20 healthy graduate and undergraduate students from Beijing University of Technology, who have not taken part in study 1, will participate in the experiment and will be paid for their participation. All participants will be right-handed, native Chinese speakers, and have normal or corrected-to-normal vision.

Experiment Procedure This experiment will take three stages. The first stage consists in training participants to become familiar with the heuristic rules, as shown in Figure 3.5; The second stage consists in training participants to become familiar with responding system; The third stage will be used for scanning. During scanning, the experimental procedure is similar to study 1, as shown in Figure 3.9, after the 2 s fixation, a Sudoku will be appeared in the screen. In the task condition with a mark, participants are required to find the value of the marked cell; in the task condition without a mark, participants are required to find the value of the cell that is the easiest to solve. Participants press the thumb button (to record the reaction time) and provide their answer by using the data glove. The buttons of the data glove are mapped to the numbers 1 through 4—index finger to 1, middle finger to 2, ring finger to 3 and little finger to 4. For the tasks with a mark, participants are instructed to report the value of the marked cell by pressing the corresponding button twice; for the tasks without a mark, participants are instructed to report the cell they think can be solved by pressing two fingers in sequence, with the first finger indicating the row and the second indicating the column of the cell. This is followed a 2 s feedback and 10 s rest interval.

The Protocol of the fMRI Scanning and fMRI Data Analysis The protocol of the fMRI scanning is similar to study 1. We will also perform both confirmation and exploratory analysis in study 2. The general conclusions and remarks will be generated based on the results of both analyses.

Modeling The model developed in the confirmation analysis will be used to explain the information processing processes in the brain during selecting and using heuristics.

3.4 Discussion

Through study 1 and study 2, we will measure the brain activations in retrieving and applying the heuristics, and in selecting the heuristics. Hopefully, our results will make contributions towards understanding the processes of human heuristic search in problem solving and offer some cues to improve the performance of LarKC.

According to 32 participants' oral protocol of 4x4 Sudoku (without simplification), participants did not search randomly for the correct values. Instead, they used heuristic strategies to solve the problem. At the very beginning of the experiment, most participants just tried in various ways. After several trials, however, they learned the heuristic rules gradually and increased the speed of the problem solving process. Forming new heuristics during problem solving is an important capability of human beings and should be of great significance to large scale integrated reasoning and Web search systems, such as LarKC. This is our further research direction.

4 Conclusion

Why would insights into human cognition provide any guidance for designing a technological system? One of our basic tenets is that humans are adaptive organisms that have evolved or learned to deal efficiently and effectively with the demands of a fundamentally risky and uncertain world. Although humans habitually perceive and process large amounts of information there is increasing evidence that they tend to develop fast and frugal heuristics that abandon any attempt at comprehensive analysis and can be particularly successful by ignoring information (Gigerenzer & Goldstein, 1996; Gigerenzer, Todd, & the ABC research group, 1999).

Insights into the strategies used by humans are applicable to the design of technological systems whenever the underlying problem is subject to the same basic constraints. In the case of stopping rules both humans and machines are facing the fundamental dilemma that limited resources (of time and effort) have to be allocated to tasks to arrive at a satisfying solution. How this can be accomplished in an effective and efficient manner depends on many aspects of the system (e.g., its available resources) and the task (e.g., its importance). On a more abstract level, the problem of giving up on a given task can be characterized in terms of the benefits and costs involved in continuing versus abandoning a task. Regardless whether the agent is a human or a machine, solving such resource allocation problems can involve negotiating complex tradeoffs by applying simple heuristics that capitalize on environmental regularities to come up with satisfying solutions. As the amount of time spent on a task is a basic currency of expenditure for both humans and machines, we believe that insights into the mechanisms that govern human decisions to give-up information search will provide valuable guidance to inform the design of LarKC's semantic web framework.

Similarly, insights into the basic mechanisms by which people learn and apply heuristics during problem solving can inform the design and development of technological systems. Both humans and machines routinely operate in environments in which comprehensive analysis, consistent knowledge sources and complete solutions are impossible or practically implausible. Early theories of human problem solving (e.g., Newell, Shaw, & Simon, 1958; Newell & Simon, 1972) have taken these limitations into account and discovered various ways in which people satisfice, i.e., find solutions that are non-optimal but satisfy some threshold criterion (Simon, 1956). The study of heuristics used by humans and other animals has yielded not just computational shortcuts, but often discovered solution strategies that are as good or even superior to computationally more expensive algorithms (see e.g., Gigerenzer et al., 1999; Gigerenzer, 2000; Gigerenzer & Selten, 2001; Gigerenzer, 2008).

Historically, many theories in the sub-disciplines of Cognitive Science (particularly Artificial Intelligence, Cognitive Psychology, Linguistics, and Neuroscience) have fruitfully been inspired by the computer analogy of the human mind, e.g., when comparing human memory to the data storage and retrieval systems implemented in digital computers. The LarKC project (Fensel et al., 2008) offers a platform that promises some influence in the other direction: As human beings are capable of coping with vast amounts of information in a timely manner discovering the rules and heuristics governing human cognition may help to inform and constrain the technical design process towards more robust and successful systems. The research proposed in this report aims to contribute to this goal.

References

Anderson, J. R., Albert, M. V., & Fincham, J. M. (2005). Tracing problem solving in real time: fMRI analysis of the subject-paced tower of hanoi. *Journal of Cognitive Neuroscience*, *17*(8), 1261–1274.

Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y. (2004). An integrated theory of the mind. *Psychological Review*, *111*(4), 1036–1060.

Anderson, J. R., Fincham, J. M., Qin, Y., & Stocco, A. (2008). A central circuit of the mind. *Trends in Cognitive Sciences*, *12*(4), 136–143.

Anderson, J. R., & Milson, R. (1989). Human memory: An adaptive perspective. *Psychological Review*, *96*(4), 703–19.

Anderson, J. R., Qin, Y., Jung, K. J., & Carter, C. S. (2007). Information-processing modules and their relative modality specificity. *Cognitive Psychology*, *54*(3), 185–217.

Anderson, J. R., & Schooler, L. J. (1991). Reflections of the environment in memory. *Psychological Science*, *2*(6), 396–408.

Arkes, H. R., & Ayton, P. (1999). The sunk cost and Concorde effects: Are humans less rational than lower animals? *Psychological Bulletin*, *125*, 591–600.

Banks, A., Vincent, J., & Phalp, K. (2008). Natural strategies for search. *Natural Computing*.

Battig, W. F., & Montague, W. E. (1969). Category norms for verbal items in 56 categories: a replication and extension of the Connecticut category norms. *Journal of Experimental Psychology Monographs*, *80*(3, Pt. 2).

Bhavnani, S., Jacob, R., Nardine, J., & Peck, F. (2003). Exploring the distribution of online healthcare information. *Proceedings of the SIGCHI conference on Human factors in computing systems*, 816–817.

Browne, G. J., Pitts, M. G., & Wetherbe, J. C. (2005). *Stopping rule use during web-based search.*

Carlson, R. A., Avraamides, M. N., Cary, M., & Strasberg, S. (2007). What do the hands externalize in simple arithmetic? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(4), 747–756.

Cary, M., & Carlson, R. A. (2001). Distributing working memory resources during problem solving. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(3), 836–848.

Charnov, E. (1976). Optimal foraging: The marginal value theorem. *Theoretical Population Biology*, *9*, 129–136.

Clark, A. (2001). Reasons, robots and the extended mind. *Mind and Language*, *16*(2), 121–145.

Clark, A. (2003). *Natural-born cyborgs. Minds, technologies, and the future of human intelligence.* Oxford, UK: Oxford University Press.

Clark, A., & Chalmers, D. (1998). The Extended Mind. *Analysis*, *58*(1), 7–19.

Cowie, R. (1977). Optimal foraging in great tits (Parus major). *Nature*, *268*(5616), 137–139.

Dougherty, M. R., & Harbison, J. I. (2007). Motivated to retrieve: How often are you willing to go back to the well when the well is dry? *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *33*(6), 1108–1117.

Draaisma, D. (2000). *Metaphors of memory: A history of ideas about the mind.* Cambridge, UK: Cambridge University Press.

Duggan, G. B., & Payne, S. J. (2008). Knowledge in the head and on the web: Using topic expertise to aid search. In *Proceedings of the CHI 2008 Conference on Human Factors in Computing Systems.* New York, NY: ACM.

Fensel, D., & Harmelen, F. van. (2007). Unifying reasoning and search to web scale. *IEEE Internet Computing*, 94–96.

Fensel, D., Harmelen, F. van, Andersson, B., Brennan, P., Cunningham, H., Valle, E. D., Fischer, F., Huang, Z., Kiryakov, A., Lee, T. K. il, Schooler, L. J., Tresp, V., Wesner, S., Witbrock, M., & Zhong, N. (2008, 8). *Towards LarKC: a platform for web-scale reasoning.* IEEE Computer Society Press Los Alamitos, CA, USA.

Fincham, J. M., Carter, C. S., Veen, V. van, Stenger, V. A., & Anderson, J. R. (2002). Neural mechanisms of planning: A computational analysis using event-related fMRI. *Proceedings of the National Academy of Sciences*, *99*(5), 3347–3351.

Findlay, J. M., & Gilchrist, I. D. (2003). *Active Vision: The psychology of looking and seeing.* Oxford University Press.

Fu, W.-T., & Pirolli, P. (2007). SNIF-ACT: A cognitive model of user navigation on the World Wide Web. *Human-Computer Interaction*, *22*(4), 355–412.

Gigerenzer, G. (2000). *Adaptive thinking: Rationality in the real world.* New York, NY: Oxford University Press.

Gigerenzer, G. (2008). *Rationality for mortals: Risk and rules of thumb.* New York, NY: Oxford University Press.

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*, 650–669.

Gigerenzer, G., & Selten, R. (2001). *Bounded rationality: The adaptive toolbox.* Boston, MA: MIT Press.

Gigerenzer, G., Todd, P. M., & the ABC research group. (1999). *Simple heuristics that make us smart.* New York, NY: Oxford University Press.

Green, R. F. (1984). Stopping rules for optimal foragers. *The American Naturalist*, *123*(1), 30.

Green, R. F. (2006). A simpler, more general method of finding the optimal foraging strategy for Bayesian birds. *Oikos*, *112*(2), 274–284.

Harbison, J. I., Davelaar, E. J., & Dougherty, M. R. (2008). Stopping Rules and Memory Search Termination Decisions. In *Proceedings of the 30th annual conference of the cognitive science society* (pp. 565–570). Austin, TX: Cognitive Science Society.

Hills, T., Todd, P., & Goldstone, R. (2008). Search in External and Internal Spaces: Evidence for Generalized Cognitive Search Processes. *Psychological Science*, *19*(8), 802–808.

Hollan, J., Hutchins, E., & Kirsh, D. (2000). Distributed cognition: toward a new foundation for human-computer interaction research. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *7*(2), 174–196.

Hutchins, E. (1995). How a cockpit remembers its speeds. *Cognitive Science*, *19*(3), 265–288.

Hutchinson, J. M. C., & Gigerenzer, G. (2005). Simple heuristics and rules of thumb: Where psychologists and behavioural biologists might meet. *Behavioural Processes*, *69*(2), 97–124.

Hutchinson, J. M. C., Wilke, A., & Todd, P. M. (2008). Patch leaving in humans: Can a generalist adapt its rules to dispersal of items across patches? *Animal Behaviour*, *75*, 1331–1349.

Iwasa, Y., Higashi, M., & Yamamura, N. (1981). Prey distribution as a factor determining the choice of optimal foraging strategy. *The American Naturalist*, *117*(5), 710–723.

James, W. (1890). *The principles of psychology, Vols. 1 & 2.* New York, NY: Holt.

Kahana, M. J., & Miller, J. F. (submitted). What makes recall stop? *?*

Lave, J. (1988). *Cognition in practice. mind, mathematics and culture in everyday life.* Cambridge, UK: Cambridge University Press.

Lima, S. L. (1984). Downy woodpecker foraging behavior: Efficient sampling in simple stochastic environments. *Ecology*, *65*(1), 166–174.

Logan, G. D., & Delheimer, J. A. (2001). Parallel memory retrieval in dual-task situations: II. Episodic memory. *Journal of experimental psychology. Learning, memory, and cognition*, *27*(3), 668–685.

MacArthur, R. H., & Pianka, E. R. (1966). On optimal use of a patchy environment. *The American Naturalist*, *100*(916), 603–609.

Maylor, E. A., Chater, N., & Jones, G. V. (2001). Searching for two things at once: Evidence of exclusivity in semantic and autobiographical memory retrieval. *Memory & Cognition*, *29*, 1185–1195.

Neth, H., Carlson, R. A., Gray, W. D., Kirlik, A., Kirsh, D., & Payne, S. J. (2007). Immediate Interactive Behavior: How embodied and embedded cognition uses and changes the world to achieve its goals. In D. S. McNamara & J. G. Trafton (Eds.), *Proceedings of the Twenty-Ninth Annual Conference of the Cognitive Science Society* (pp. 33–34). Austin, TX: Cognitive Science Society.

Neth, H., & Payne, S. J. (2001). Addition as Interactive Problem Solving. In J. D. Moore & K. Stenning (Eds.), *Proceedings of the Twenty-Third Annual Conference of the Cognitive Science Society* (pp. 698–703). Mahwah, NJ: Lawrence Erlbaum Associates.

Newell, A., Shaw, J. C., & Simon, H. A. (1958). Elements of a theory of human problem solving. *Psychological Review*, *65*, 151–166.

Newell, A., & Simon, H.-A. (1972). *Human problem solving.* Englewood Cliffs, NJ: Prentice Hall.

Nishimura, K. (1999). Exploration of optimal giving-up time in uncertain environment: a sit-and-wait forager. *Journal of Theoretical Biology*, *199*(3), 321–327.

Payne, S., Duggan, G., & Neth, H. (2007). Discretionary task interleaving: Heuristics for time allocation in cognitive foraging. *Journal of Experimental Psychology: General*, *136*(3), 370–380.

Pirolli, P. (2007). *Information foraging theory: Adaptive interaction with information.* New York, NY: Oxford University Press.

Pirolli, P., & Card, S. (1999). Information foraging. *Psychological Review*, *106*, 643–675.

Pyke, G. H. (1978a). Optimal foraging in hummingbirds: Testing the marginal value theorem. *Integrative and Comparative Biology*, *18*(4), 739–752.

Pyke, G. H. (1978b). Optimal foraging: Movement patterns of bumblebees between inflorescences. *Theoretical Population Biology*, *13*(1), 72–98.

Pyke, G. H. (1984). Optimal foraging theory: A critical review. *Annual Reviews in Ecology and Systematics*, *15*(1), 523–575.

Raaijmakers, J. G. W., & Shiffrin, R. M. (1980). SAM: A theory of probabilistic search of associative memory. *The psychology of learning and motivation: Advances in research and theory*, *14*, 207–262.

Raaijmakers, J. G. W., & Shiffrin, R. M. (1981). Search of associative memory. *Psychological Review*, *88*(2), 93–134.

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, *63*(2), 129–138.

Simon, H. A. (1996). *The sciences of the artificial* (3rd ed.). Cambridge, MA: The MIT Press.

Spink, A., Park, M., Jansen, B. J., & Pedersen, J. (2006). Multitasking during Web search sessions. *Information Processing and Management*, *42*(1), 264–275.

Stephens, D. W., & Krebs, J. R. (1986). *Foraging theory.* Princeton, NJ: Princeton University Press.

Steyvers, M., & Tenenbaum, J. B. (2005). The large-scale structure of semantic networks: Statistical analyses and a model of semantic growth. *Cognitive Science*, *29*(1), 41–78.

Suchman, L. A. (1987). *Plans and situated actions: The problem of human-machine communication*. Cambridge, UK: Cambridge University Press.

Tulving, E., & Craik, F. I. M. (2000). *The Oxford Handbook of Memory*. New York, NY: Oxford University Press.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131.

Van Overschelde, J. P., Rawson, K. A., & Dunlosky, J. (2004). Category norms: An updated and expanded version of the Battig and Montague (1969) norms. *Journal of memory and language*, *50*(3), 289–335.

Wilke, A. (2006). *Evolved responses to an uncertain world*. Unpublished doctoral dissertation, Freie Universität Berlin.

Wübben, M., & Wangenheim, F. (2008). Instant customer base analysis: Managerial heuristics often "Get it Right". *Journal of marketing*, *72*(3), 82.

Ydenberg, R. C. (1984). Great tits and giving-up times: Decision rules for leaving patches. *Behaviour*, *90*(1-3), 1–24.

Young, C. J. (2004). Contributions of metaknowledge to retrieval of natural categories in semantic memory. *Journal of Experimental Psychology: Learning, Memory and Cognition*, *30*(4), 7.

Zimmerman, M. (1981). Optimal foraging, plant density and the marginal value theorem. *Oecologia*, *49*(2), 148–153.

Zipf, G. K. (1949). *Human behavior and the principle of least effort: An introduction to human ecology*. Cambridge, MA: Addison-Wesley.