This thesis is about memory. More specifically, it is about memory for facts such as Amsterdam is the capital of the Netherlands, or The object I am looking at is called a computer screen. This type of memory will be referred to as declarative memory. Declarative memory is an interesting object of study because remembering facts is something humans continuously do; retrieving facts from declarative memory is at the core of cognitive functioning. For example, while typing this page I am continuously trying to remember words that are appropriate given the message I want to convey. At the same time I might remember that I have an appointment later on, and remember the name of the person I have the appointment with. Because declarative memory plays such a central role in human cognition, we can learn a great deal about human behavior if we understand the process by which declarative memory retrievals are driven. Therefore this thesis focuses at understanding the functional process of retrieving facts from declarative memory.

This thesis is also about information selection. Because of the over-abundance of information in modern society - caused by an increase in digital storage capacity coupled to an increased accessibility of digital sources - access to information has become cluttered (Brusilovsky & Tasso, 2004). Even though the likelihood that certain information is available is increased (because the amount of information is increased), finding the relevant information has become harder. Therefore, automated assistance to select relevant information out of the abundance of information sources seems a necessity. In a response to this demand, the research field of Information Retrieval has expanded rapidly in recent years (as witnessed for instance by the number of submissions to the annual international ACM SIGIR Conference on Research and Development in Information Retrieval, which is the most important conference in the Information Retrieval field. The number of submissions has expanded in the last decade from 135 in 1999 to 490 in 2007).

The approach we will take in this thesis is to study the similarities between declarative memory retrieval and information retrieval. Very superficially, declarative memory can be perceived as a storage capacity for information that has been encountered during a person’s lifetime. Consequently, remembering this information (these declarative facts) for current usage may be analogous to selecting currently relevant information. If we assume that the human cognitive system, through evolution and learning, has developed an optimal solution for this information-selection problem we can develop new information selection algorithms and assist people in handling the information glut (Schenk, 1997) by mimicking the retrieval process of facts from declarative memory.

Multiple researchers have stressed the similarities between information selection and human declarative-memory retrieval. For instance, Anderson (e.g., Anderson, 1989; Anderson & Milson, 1989) demonstrated the parallels between human declarative memory and artificial information-retrieval systems as introduced by Salton and McGill (1983). Salton and McGill characterize information-retrieval systems as systems that (1) consist of sets of files that contain the to-be-retrieved information, (2) have some sort of index of terms that can be used to retrieve the files, and (3) have the possibility to query the system using a subset of these terms. Anderson and colleagues noted that the human declarative memory system shares these characteristics with artificial information-retrieval systems. That is, human memory (1) contains facts (or cognitive chunks, in his terminology), (2) contains relations between these chunks, for instance semantic relations, and (3) has the possibility to retrieve chunks, based on these relations between chunks.
More recently, Griffiths and colleagues (Griffiths, Steyvers, & Firl, 2007) showed that also search-engine technology parallels human memory behavior. They argue that, given the similar structure of the web and the mind (Figure 1.1), algorithms that are optimized for finding relevant web pages can best predict associations in human declarative memory. Indeed, they show that Google’s PageRank algorithm (Page, Brin, Motwani, & Winograd, 1998) outperforms some other algorithms when predicting human responses on a fluency task. In this task, participants are presented with a letter and have to name the first word beginning with that letter that comes to mind. PageRank’s predictions map better onto human data than simpler algorithms, specifically word frequency norms and word co-occurrence frequency norms. The ultimate suggestion of this result might be that the way PageRank calculates the relevance of words, given a certain letter, is functionally equivalent to the way human declarative memory “calculates” the relevance of facts in a certain context. This example thus shows that it is useful to study information retrieval algorithms if you are interested in human memory. In this thesis, we will argue that also the opposite direction, that is, applying knowledge of the functional process of human declarative memory to information access, will be beneficial for information retrieval (Part II).

The work reported in this thesis may be separated into two distinct topics. In Part I (Theory) we will study the functional process of declarative memory retrieval, and in Part II (Applications) we will study how functional models of declarative memory retrieval may be applied in information retrieval systems. However, despite this apparent dichotomy both topics involve the concept of declarative memory retrieval, which is the unifying concept for this thesis. Also, both in Part I and in Part II we will argue that declarative memory retrievals are mediated by changes in the environment. That is to say, which declarative fact is retrieved from memory is determined by the personal environment of the cognitive agent. Aspects of the personal environment of the agent that we will study will be the history the agent has with a certain declarative fact and the current context in which the agent attempts to retrieve a certain facts. These two aspects will play an important role in the cognitive models reported in Part I as well as in the application-based studies reported in Part II.

**APPROACH**

The models of declarative memory we have developed in the context of this thesis are computational cognitive models within the cognitive architecture ACT-R (Anderson, 2007a; Anderson, Bothell, Byrne, Douglass, Lebiere, & Qin, 2004).

The concept of a cognitive architecture was introduced by Allen Newell as a way of dealing with the plurality of cognitive dichotomies (Newell, 1973). He reasoned that psychological phenomena should not be explained only in terms of unrelated hypotheses that were either
confirmed or rejected but rather that psychological phenomena should be explained in each other’s context. For instance, for an explanation of visual search tasks, in which participants are asked to search an array of stimuli for a previously presented target stimulus, it is also important to have a theory of decision processes, and of declarative memory. During the task, the participant has to decide whether he or she has found the target stimulus based on his or her memory of the previous presentation of the stimulus.

Therefore, it makes sense to study different cognitive phenomena within one framework, so that one theory (for instance on visual search) stays consistent with others (for instance on decision making or declarative memory). More recently, Anderson defined the concept of a cognitive architecture as

“a specification of the structure of the brain at a level of abstraction that explains how it achieves the function of the mind” (Anderson, 2007a p. 7).

This definition also takes into account that ultimately the brain is what generates behavior. However, in the context of this thesis this aspect will only play a minor role.

There are three major advantages of cognitive modeling within the constraints posed by a cognitive architecture. The first is that the modeler is constrained in the freedom he or she has in developing cognitive models. Because the architecture consists of a set of central assumptions on cognitive functioning, all models should adhere to these in order to be part of the architecture’s body of work (R. P. Cooper, 2007). Cognitive models within an architecture support each other by applying the same central assumptions, thus providing more evidence that a cognitive model might be the correct functional specification of a certain behavior.

The second advantage is that a cognitive architecture gives the modeler the possibility to develop integrated cognitive models. Integrated cognitive models are meant to span multiple aspects of cognition (Gray, 2007b). Ideally, this would comprise models that capture human behavior in a certain task from stimulus perception to response action. For example, an integrated model of the visual search task mentioned before should account for the perception of the target stimulus, temporary storage of the target stimulus, perception of the stimulus array, matching of the stimuli in the array to the stored representation of the target, and issuing a motor command to respond (for instance by a button press). An integrated model can provide quantitative predictions of human behavior. If the model is successful it will accurately predict the behavior of participants engaging in the same task the model was designed for, for instance in terms of response times or accuracy scores.

The third advantage relates to the second. If it is possible to develop integrated models of human behavior in a certain task, then these models can also be deployed as predictors of human behavior in certain applied settings. Examples of these include cognitive models as intelligent agents in computer games (e.g., Shah, Rajaguru, St. Amant, & Ritter, 2003) or serious games (e.g., C. P. Janssen, Van Rijn, Van Liempd, & Van der Pompe, 2007), cognitive models as simulated users of interfaces (Ritter & Young, 2001), and cognitive models as control models to track a user’s attentive state (e.g., Grootjen, Neerincx, & Veltman, 2006).

All three major advantages of a cognitive architecture are utilized in this thesis. The models that appear in Part I take advantage of the central assumptions of the cognitive architecture we use (ACT-R), and are able to provide quantitative predictions of human behavior. The models that appear in Part II can be thought of as integrated models that serve as intelligent agents in information selection tasks.
Since the cognitive architecture ACT-R (Anderson, 2007a; Anderson et al., 2004) is at the core of the work presented in this thesis, we will now turn to a brief exposition of the central assumptions of ACT-R.

**ACT-R**

ACT-R is a hybrid cognitive architecture that consists of a set of modules that each process one kind of information. For instance, visual perception is handled by the visual module and motor commands are executed by the motor module. The declarative module is used for storing and retrieving information from declarative memory, the speech module handles the speech output, the aural module handles auditory perception, and the goal and imaginal are used modules for keeping track of sub goals and intentions (Figure 1.2).

Behavior in an ACT-R model emerges from the selection and subsequent execution of production rules. The production rule system communicates with the different modules through a set of buffers that can all contain one chunk of information. If the information that is present in the buffers matches the conditions of a production rule, that rule may be selected to execute its actions. If multiple production rules match, than the rule with the highest utility will be selected (this is referred to as conflict resolution). Production rule actions can be thought of as operations on the buffer contents, such as a request for a new chunk of information from declarative memory, or a request for pressing a button on a keyboard.

Chunks in ACT-R represent simple facts about the world, such as *Amsterdam is the capital of the Netherlands*, or *The object I am looking at is called a computer screen*. Both these example chunks are declarative facts, but the first example can typically be found in the retrieval buffer, and thus represents a fact retrieved from declarative memory, whereas the second example represents a visually observable fact of the world and might be present in the visual buffer. Because information does not occur in isolation chunks also have relations to other chunks. To this end, each chunk may have slots which indicate which other chunks are related.

So far, we have only discussed the symbolic level of ACT-R. Being a hybrid cognitive architecture ACT-R also has a subsymbolic level. The subsymbolic equations of ACT-R govern the activation dynamics of the chunks and utility dynamics of the production rules. We will first briefly discuss the concept of utility in ACT-R before turning to the - in the context of this thesis much more important - concept of activation.

If multiple production rules match the buffer contents this means that ACT-R’s central cognition has multiple options that might be executed in order to achieve the current goal. In that case, the best choice is the production rule that has proven to be the most successful.
one in the past. In other words, the production rule with the highest utility will be selected, following Equation 1.1 (Anderson, 2007a).

\[ P_i = \frac{e^{U_i/s}}{\sum_j e^{U_j/s}} \]  

(equation 1.1)

Equation 1.1 denotes the probability that a certain production rule (rule \( i \)) will be selected.\(^2\)

The probability that a production rule is selected if multiple rules are applicable is determined by the utility of all applicable rules (\( U_i \)). The parameter \( s \) plays an important role in this mechanism, because it determines the trade-off between trying new strategies (exploration) and using strategies that have already been applied successfully (exploitation). A low value of \( s \) means a high probability of re-applying production rules that have been successful in the past; A high value if \( s \) means a high probability of selecting other production rules, and thus a higher chance of exploring new strategies.

For the chunks in ACT-R a similar system has been developed. All chunks have an activation level that represents the likelihood that a chunk will be needed in the near future. The likelihood is partly determined by a component describing the history of usage of a chunk called the base-level activation (\( B_i \) in Equation 1.2).

\[ B_i = \ln \left( \sum_j e^{-d_j} \right) \]  

(equation 1.2)

In this equation, \( t_j \) represents the time since the \( j \)th presentation of a memory chunk and \( d \) is the parameter that controls decay, which in most ACT-R models is fixed at 0.5 (Anderson et al., 2004). The idea is that the activation of a chunk decays over time unless attention is shifted to that chunk and its memory trace is strengthened (Figure 1.3). This way, the base-level activation can be used to model both forgetting and learning effects (Anderson & Schooler, 1991).

Figure 1.3. The base-level activation of a chunk. The activation decays over time, unless the chunk is being used (indicated by the grey vertical lines), in which case the activation is increased.

The total activation is the sum of the base-level activation, noise (\( \varepsilon \) in Equation 1.3), and another component describing the influence of the current context (spreading activation, Equation 1.3). The spreading activation component is composed of the associative values of other chunks, which are referred to in the slots of a chunk (chunks \( j \) in Equation 1.3) to chunk \( i \), weighed by \( W_{kJ} \), representing the importance of various buffers (\( k \)) and the importance of associated chunks (\( j \)).

\[ A_i = B_i + \sum_k \sum_j W_{kJ} S_{j\beta} + \varepsilon \]  

(equation 1.3)

Since in ACT-R it is assumed that the probabilities that chunks will be retrieved from memory are independent the activation values - which have an infinite range - can be scaled
to a probability of retrieval according to Equation 1.4 (Anderson, 2007a).

\[ P_i = \frac{1}{1 + e^{-(A_i - \tau)/s}} \]  
\[ \text{Equation 1.4} \]

That is to say that if the activation of a chunk \( i \) \( (A_i) \) goes to infinity the probability of it being retrieved goes to 1. Likewise, the probability of a chunk with activation going to minus infinity will go to 0. Two parameters play a role in determining whether a chunk will be retrieved or not. The retrieval threshold \( \tau \) sets the lower bound for memory retrievals. Chunks with an activation smaller than the retrieval threshold will not be retrieved. Similar to the production selection equation (Equation 1.1), there is a parameter \( s \) associated with this equation that controls the trade-off between exploration and exploitation in declarative memory retrievals.

Besides the probability that a chunk will be retrieved from declarative memory ACT-R also predicts the time it will take to retrieve it. If a chunk has a low activation value, indicating that it is not likely that this particular chunk will be needed right now, it is harder to remember, which will be reflected by a long retrieval time. This observation is captured by Equation 1.5, which determines the latency of retrieval, given a certain activation value, with \( F \) a scaling parameter:

\[ RT = Fe^{-A_i} \]  
\[ \text{Equation 1.5} \]

In the context of this thesis it is important to note that Equation 1.4 and 5 constitute a ballistic model of declarative memory retrieval. If the actions of the production rule that is selected require a chunk being retrieved from memory, the probability of that chunk being retrieved and the time it takes to retrieve it are deterministic (Brown & Heathcote, 2005). This assumptions will be challenged by the data presented in Part I.

A detailed description of the ACT-R cognitive architecture is provided in (Anderson, 2007a; Anderson et al., 2004).

OVERVIEW

In Part I of this thesis a new mechanism for chunk retrieval will be proposed. The new chunk retrieval mechanism, Retrieval by ACcumulating Evidence in an Architecture or RACE/A, can be thought of as a more fine-grained process-model than the current, deterministic, chunk retrieval model in ACT-R (Equations 1.4 and 1.5 above). RACE/A provides a prediction of the activation dynamics during the retrieval process, instead of a ballistic prediction of the retrieval latency and the probability of retrieval. From certain experimental paradigms (for instance, tasks with varying stimulus onsets, e.g., M. O. Glaser & Glaser, 1982; or subliminal perception, e.g., Merikle, Smilek, & Eastwood, 2001), it becomes clear that the default activation equation in ACT-R is not capable of explaining the mechanism by which chunks are retrieved from declarative memory. Chapter 2 will present a general account of the model of memory retrieval processes put forth in this thesis. In addition, it will present experimental evidence that some tasks cannot be modeled within the constraints of the cognitive architecture ACT-R without using RACE/A. The focus of this chapter will be on the interplay between repetition priming (one of the effects successfully modeled by ACT-R) and semantic priming (one of the effects successfully modeled by RACE/A) (Van Maanen, Van Rijn, & Taatgen, submitted).

In Chapter 3, we will validate RACE/A by showing how it accounts for a range of benchmark phenomena. First, Section 3.1 demonstrates how RACE/A accounts for a set of common finding in the lexical decision literature (e.g., Wagenmakers et al., 2008; Wagenmakers, Steyvers, Raaijmakers, Shiffrin, Van Rijn, & Zeelenberg, 2004a). Second, we will present a model of a picture-word interference (PWI) task in which two stimuli dimensions are presented at various
onset asynchronies (Section 3.2). The model is able to account for the PWI typical latencies (see also Van Maanen & Van Rijn, 2007b). Third, Section 3.3 shows that RACE/A can also account for effects caused by partially available information, such as in the subliminal priming paradigm (Merikle, Smilek, & Eastwood, 2001; see also Van Maanen & Van Rijn, 2007a).

In Chapter 4 we will present a cognitive model that explains both response times in the Stroop task and response times in a PWI task. By adjusting one parameter, the model can account for the recent finding that the PWI effect is located early in the mental processing stream, while the Stroop effect is late (Dell’Acqua et al., 2007). The chapter demonstrates that RACE/A is not just a theoretical novelty, but can also lead to new insights. The RACE/A enhancement to the ACT-R model described in this chapter was necessary to explain the difference between Stroop and picture-word interference (Van Maanen & Van Rijn, 2008; Van Maanen, Van Rijn, & Borst, submitted).

Part II of this thesis explores the possibility of developing recommender systems based on cognitive models of declarative memory. Recommender systems are applications that assist users in finding relevant or useful information. Often, recommender systems incorporate some form of personalization. This means that by tracking the cognitive state of a user (user modeling), a recommender system can offer recommendations that are relevant or useful for the individual user. By creating user models that predict the declarative memory behavior of individual users, we will be able to predict which facts will be personally relevant or useful. Chapter 5 will show how the ACT-R declarative memory model can be applied for personalized information retrieval in the cultural heritage domain. It will focus on how the roles of the visitor and the museum can both be appreciated in an online museum. By providing cognitive models that take the role of a museum guide, we will study which aspects of the museum guide's behavior are important for successful artwork recommendations, and we will provide a framework for an online artwork recommender (the Virtual Museum Guide or VMG). This chapter is an extended version of Van Maanen (2007).

In Chapter 6, we will discuss how eye gaze can be used as an input device for such an online artwork recommender. Because the eyes are an important input modality for humans, the point of gaze of museum visitors might express the museum visitor's current interest. In this chapter, we will study how this insight can be used to develop recommender systems that provide personalized information on a specific artwork. We will present results that indicate that gaze and user interest are closely related in the cultural heritage domain. We will conclude by presenting a framework for a complete automated museum guide that may be capable of recommending relevant art and highlighting relevant aspects of the artwork, based on the visitor’s point of gaze.

In Chapter 7, we will describe how the declarative memory model of ACT-R can be used for personalized information retrieval of (scientific) abstracts from an indexed database of publications (Van Maanen, Van Rijn, Van Grootel, Kemna, Klomp, & Scholtens, in press), and in Chapter 8, we will provide the results of a competition between the activation-based recommender developed in the previous chapter and other models developed for the same task (Van Maanen & Marewski, 2009).