# MODELING A RECOGNITION MEMORY TASK TO INVESTIGATE DIFFERENCES IN WORKING MEMORY

By

Ryan Buss

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Approved:

______________________________

Dr. Wayne D. Gray, Thesis Adviser

______________________________

Dr. Michael J. Schoelles, Thesis Adviser

______________________________

Dr. Michael J. Kalsher, Thesis Adviser

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## Abstract

Investigating the sources of individual differences in human working memory, Öztekin and McElree (2010) used subject performance in a recognition memory task to argue that the interplay between item familiarity information and episodic retrieval information marked an important difference between individuals with high and low working memory spans. However, they were unable to adjudicate between several hypotheses about the precise sources of those differences. We developed a computational cognitive model using the ACT-R (Anderson, 2007) architecture that performed a replication of (Öztekin & McElree, 2010) recognition memory task, and attempted to fit model performance to Öztekin and McElree's human data through parameter changes to the model and the addition of a new recognition memory module. The model was able to produce performance that approximated that of the high span subjects, but had limited success matching low span subject performance. Importantly, parameter changes that produced slower memory retrievals, which was among Öztekin and McElree's hypotheses, were insufficient to produce model performance matching that of low span subjects. This constitutes evidence that a primary difference between high and low span subjects lies in the conflict resolution between familiarity and episodic recall, as opposed to differences in episodic recall initiation or completion time.

# 1. Introduction

Measures of Working Memory (WM) correlate with a variety of valuable metrics of human performance, including performance on reasoning tasks (Kane & Engle, 2002; Engle & Kane, 2004), verbal comprehension (Daneman & Carpenter, 1980), and academic attainment (T. P. Alloway & R. G. Alloway, 2010). Given that WM tasks appear to at least partially measure meaningful individual differences in cognition, what variations in the cognitive system produce these differences? One hypothesis is that individuals who perform better on WM tasks simply have a *larger* WM, and we would expect the existence of a distinct store for recent events like that proposed by Atkinson and Shiffrin (1968), which varies in size between individuals. However, this explanation has generally not been supported by modern evidence (McElree, 2006), and a variety of other explanations of the contents and dynamics of WM have been proposed.

Confusingly, the term "working memory" has been applied to a variety of different concepts (Baddeley, 1992, 2010). According to Randall Engle, "Working memory is a system of domain-specific stores or formats for temporarily representing information along with a domain-general supervisory or executive attention mechanism" (Engle, 2010). Some researchers argue that the contents of working memory are activated long-term memory (LTM) representations, or pointers to those representations (Cowan, 1995; Engle, 2010; McElree, 2006; Öztekin, Davachi, & McElree, 2010). Another popular theory posits a multicomponent model with different specialized buffers: the phonological loop, episodic buffer, visuo-spatial sketch-pad, and a central executive (Baddeley & Hitch, 1975; Baddeley, 2000). There is no generally accepted explanation of the processes that underly the relationship between WM tasks and other performance measures (Baddeley, 2010).

Öztekin and McElree (2010) argue that individual differences in performance on WM tasks are a function of some, but not all, processes in memory. They attempted to identify some of these differences by contrasting performance of a high working memory span (HS) group and a low working memory span (LS) group, selected from the upper and lower quartiles, respectively, of performance on automated reading and operation span tasks (See Conway et al., 2005, for a review of WM span tasks). The two span groups, composed of nine HS and ten LS subjects, performed a word recognition task utilizing a response-signal speed-accuracy tradeoff procedure (SAT), described in detail later. Two important differences between HS and LS subjects emerged. First, given sufficient processing time (approximately one second), high span subjects reached a higher level of average accuracy than LS subjects, but at shorter processing times, the groups did not significantly differ in response accuracy. Second, HS and LS groups displayed differences in false-alarm rates on particular types of trials. These group differences in performance on the memory task led Öztekin and McElree to propose the following three hypotheses for a source of differential performance between HS and LS participants.

**A.** LS participants retrieve episodic memory information at a slower rate than HS participants.

**B.** LS and HS participants do not differ on episodic retrieval rates, but LS participants are slower to initiate episodic retrievals.

**C.** LS and HS participants do not differ on episodic retrieval rates or retrieval initiation time, but are slower to resolve the conflict between familiarity information and episodic retrieval information.

Based on their data, these researchers were unable to conclusively distinguish between these possibilities. The aim of the current research is to evaluate these alternatives by utilizing the ACT-R cognitive architecture (Anderson, 2007) to model HS subject performance, then manipulate the model's episodic retrieval parameters to test the slower retrieval hypotheses. The following sections will outline the original findings from Öztekin and McElree (2010), and discuss some of the current theory on recognition memory and its component processes. Within the methods section, there is a description of the task being modeled, then a discussion of the choice of ACT-R as a suitable architecture for this model. The methods section concludes with details about the human and model data and a description of the

ACT-R model. Next, the results section addresses the model performance in relation to the human data. Finally, the discussion section addresses the model results with respect to Öztekin and McElree's hypotheses, and the conclusion summarizes the findings.

## 1.1 Öztekin & McElree's 2010 Study

Öztekin and McElree (2010) used a contrast group design with high span and low span participants whose performance fell in the upper and lower quantiles, respectively, on automated reading span and operation span tasks. These high and low span subjects then performed a word recognition memory task utilizing the SAT procedure. The memory task was composed of trials in which six words were presented serially, followed by a visual mask, and finally a probe word. After an unpredictable delay, a tone sounded to cue the subject's response, with the time between probe onset and response cue ranging from almost simultaneous to several seconds. Subjects pressed one button to indicate if the probe was on the study list, or another button to indicate that the probe was not on the study list. For example, a study list of one trial might be composed of the words ”dog”, ”bear”, ”cow”, ”lemon”, ”mango”, ”peach” (Example from Öztekin and McElree, 2010). Words in the study list of each trial were grouped into two sets of three, with each set drawn from a single semantic category, and semantic categories always differed between consecutive trials.

Several varieties of trials were designed to test memory performance. Details relevant to the current work will be mentioned here, but see Öztekin and McElree (2010) for a full explanation of their trial generation procedure. The experimental trials can be classified into four categories: positive, novel negative, recent negative, and category distractor trials. Positive trials were ones in which the probe was, in fact, on the study list. Novel negative trials contained a probe word not on the study list, also was not on the previous trial, and was not within the same semantic categories used on the current or previous trial. Recent negative trials had one of the words from the previous trial as the current trial's probe, but importantly the probe was not from the same semantic category as words on the current trial. Category distractor trials were ones in which the probe word was not on the current trial, but was in the same semantic category as the the words on the current trial.

Öztekin and McElree found several interesting differences between the high span and low span subjects in their performance on the recognition memory task. Subjects who performed better on WM span tasks were able to achieve higher levels of recognition accuracy, correctly identifying previously seen stimuli and avoiding false positives on lures, as compared to subjects who had low performance on the span task. As shown in Figure 3.2, low span subjects had a significantly lower asymptotic accuracy than high span subjects. However, the two groups did not display significant differences in the rate at which they improved from chance performance with processing time, nor the intercept time at which their response accuracy diverged from chance. Öztekin and McElree argue that the data support a dual-process theory of recognition memory (e.g. Yonelinas, 2002), composed of a fast, automatic familiarity-based retrieval process, and a slower, controlled episodic retrieval process. Analysis of false alarm rates provides an even more nuanced distinction between higher and lower WM span subjects. Subject performance suggests that there exist differences in the controlled recollection of an item from memory between high and low WM span individuals, but not the familiarity-based retrieval process.

## 1.2 Recognition Memory

Yonelinas (2002) argues that recognition memory is based on the two separable memory processes: familiarity and recollection. Familiarity is considered to be the strength or activation of the item in memory, without relation to the context in which the memory was created. It is theorized to be an automatic process in that the judgment of degree of familiarity of an item is available without conscious effort and it is relatively fast compared to recollection. Recollection is considered to be a deliberate retrieval process that can succeed or fail, with successful retrievals providing contextual information about the memory. For example, the contextual information could include when the memory was created and some of the surrounding stimuli. This distinction is also supported by other lines of research, such as the "feeling-of-knowing" phenomena, where subjects are able to decide if the answer to a math problem is able to be quickly retrieved from memory faster than the actual answer can be retrieved (Reder & Ritter, 1992; Paynter, Reder, & Kieffaber, 2008). Reder and Ritter (1992) argue that such rapid familiarity judgment of a stimulus can be useful in strategy selection. Investigations employing electroencephalography (EEG) have also distinguished different timeframes and brain areas associated with familiarity and recollection processes (Rugg & Curran, 2007).

# 2. Methods

## 2.1 The Recognition Memory Task and Response-Signal Speed-Accuracy Trade-Off (SAT) Procedure

The SAT procedure is designed to experimentally control subject processing time in order to precisely measure performance for different processing durations. In this case, the procedure was applied to a recognition memory task that involved the sequential presentation of a six word study list, followed by a probe word and a response tone. Subjects were instructed to press one of two keys to indicate if the probe word was or was not in the study list. Further, subjects were instructed to only respond immediately after the response tone sounded, and given feedback that encouraged responses approximately 300ms after the onset of the response tone. Subjects received no feedback regarding the correctness of their identification of the probe. On each trial, the response tone occurred at one of seven intervals after the probe word appeared: 43, 200, 300, 500, 800, 1500 or 3000ms. An important feature of the procedure was that subjects were not free to select their own speed-accuracy trade-off level in making responses. This design permits the conjoint measure of accuracy and response time. The range of response cue times was designed to allow examination of response accuracy at processing times ranging from too short to perform above chance through enough time to reach asymptotic accuracy. In addition to the tighter experimenter control of response time, another important distinction that separates the current task from many other memory tasks is its use of a probe item. Unlike common working memory capacity tasks, such as reading span or operation span (see Conway et al., 2005 for a review), the current task does not require free-recall. Instead, the displayed probe word allows subjects to employ recognition memory processes (see the Recognition Memory section).

## 2.2 Why Use ACT-R?

There are several reasons why ACT-R is suitable for modeling the paradigm and phenomena under investigation, including previous successes of ACT-R in modeling memory and correspondence with theoretical assertions about humans' ability to access recent events. ACT-R has been used previously to model human performance in a variety of different list memory tasks, including free recall and recognition paradigms(Anderson, Bothell, Lebiere, & Matessa, 1998). Specifically, the declarative memory module in the architecture provides mechanisms for the basic memory operations of storage and retrieval, as well as more nuanced memory phenomena such as spreading activation among similar memories and incorrect retrievals, termed *partial matching*. Humans are more likely to incorrectly report recognition of a word that is semantically similar to previously studied words(Roediger & McDermott, 1995). Modeling this similarity between memories is important for Öztekin and McElree's task, as the trials were created to contain words from two categories, along with some lure probes from one of the presented semantic categories. The effect of semantic similarity between the study list and probe word is revealed by slightly lower average asymptotic accuracy on category distractor trials compared to novel negative trials, displayed in Figure 3.1. Lastly, the ACT-R architecture corresponds somewhat to the conceptualization of memory that posits two components: a focus of attention and long term memory, with no general purpose working memory store (McElree, 2006). In the architecture, the focus of attention is instantiated as specialized buffers, such as the retrieval buffer which holds the chunk most recently retrieved from memory, and is limited to contain only one chunk at a given time. The availability of memories (chunks) is determined by their activation, and the capacity limits often described in working memory tasks (i.e., Cowan 2010) arise from the properties of chunk activation and decay (Anderson, Reder, & Lebiere, 1996).

It should be noted that one limitation of the architecture is that it does not canonically possess any module that corresponds to human familiarity judgments. Considering that the interplay between familiarity and retrieval is the driving question behind this modeling effort, a module for ACT-R was developed to provide a recognition-like capability. In summary, ACT-R is a suitable architecture for the current modeling effort due to previous empirical support for its memory system, which implements many of the presently desired memory phenomena, and its approximate match with theoretical arguments about the relevant constituent components of human memory.

## 2.3 Human Data

The dataset from Öztekin and McElree (2010) was generously shared by Dr. Öztekin. It comprises the performance of 19 subjects on each trial of the recognition memory task, including response times. In the original study, subjects were assigned to one of two groups based on their performance on automated reading span and operation span tasks, resulting in nine HS and ten LS subjects. Following Öztekin and McElree's procedure, trials in which the subject took longer than 500ms after the tone to respond were excluded from the dataset. Due to this constraint, one subject in the high span group was left with only a single valid positive trial at the 43ms response cue time. As the subject responded correctly to this single trial, the subject's *d'* for that 43ms response interval was inflated, producing a modestly inflated average *d'* for the HS group at the .043ms interrupt time. Öztekin and McElree do not mention special treatment of this subject. In this case, accuracy at the shortest response deadline was of minimal relevance to the current argument and modeling conclusions, therefore the subject was retained.

## 2.4 Model Data

The model performed sets of 20 independent runs for parameter settings corresponding to High Span subjects, displayed as the blue line in Figure 3.2. In addition to this main High Span data set, nine other model runs were completed varying the latency exponent parameter, which manipulated the speed of the memory retrievals. Figure 3.4 displays the asymptotic model performance for each of these nine runs at the different parameter values. An individual run is intended to approximate the performance of a human subject. Each run consisted of 3024 trials, evenly split between positive trials, in which the probe was part of the study list, and negative trials in which the probe was not part of the study list. Although the model was provided equivalent stimuli to the human subjects for the task, unlike human subjects the model was designed to give one of three responses: *match*, *no-match*, or *unknown*. Human subjects were only permitted *match* or *no-match* responses. Designing the model to respond with *unknown* in particular circumstances significantly eased its creation and debugging. Unlike humans, the model was not vulnerable to Hick's Law, wherein the number of response options increases response time (Hick, 1952). For analysis, all model responses of *unknown* were stochastically replaced with *match* and *no-match* responses to enable straightforward comparison with human data. The *unknown* responses were generated only when the model was cued to respond before any retrieval or recognition requests finished (either successfully or unsuccessfully), and having the model produce *match* or *no-match* responses at that point would have been equivalent to the stochastic process done afterwards. In practice, the model responded with *unknown* mostly at shortest response cue interval of 43ms, where human performance is also close to chance.

## 2.5 An ACT-R Model of the SAT Task

An ACT-R model was developed with the goal of replicating subject responses in the recognition SAT task. The model was presented equivalent trial stimuli to the human subjects: a six item study list, probe, and simulated response-cue tone. The productions of the model can be found in the Appendix and the pseudocode is presented below.

1. While in the study phase of a trial
    (a) For each word presented, retrieve the word chunk from memory
    (b) Create a new chunk with the retrieved word and a marker for the current trial
    (c) If the visual mask is seen, change to response phase.

2. While in the response phase of a trial, hold a pending answer and

    (a) Check if the probe word is familiar (once)

    (b) Attempt to retrieve a chunk from declarative memory matching the probe word (repeated)

    (c) If the probe word is familiar, change the pending answer to match

    (d) If the probe word is not familiar, change the pending answer to no-match

    (e) If the chunk retrieved from memory matches the probe word, and has a trial marker, change the pending answer to match, and attempt another retrieval

    (f) If the retrieved chunk matches the probe word, but does not have a trial marker, change the pending answer to no-match, and attempt another retrieval

    (g) If retrieval fails, or the retrieved chunk does not match the probe word, change the pending answer to no-match, and attempt another retrieval

    (h) If the response tone sounds, respond with the current pending answer

The precise sequence of events that precipitate the model's response are of particular interest. After the model encodes the probe word, it simultaneously attempts a recognition memory check and a declarative memory retrieval. For the recognition check, if the activation (subject to noise) of the chunk in memory is above the threshold parameter, then the word is recognized, and a production fires to change the model's pending answer to *match*. If the activation of the chunk is below threshold, the pending answer is changed to no-match. For the the memory retrieval, the model attempts to retrieve a chunk from memory that best matches the probed word, which could successfully retrieve the correct word, or if a competing chunk's activation is high enough, the model can incorrectly remember a related word. Mismatched chunks have penalized activation, and thus compete at a disadvantage, but memory activation noise can sometimes drop the activation of the matching word below a related word. If the word that is retrieved from memory matches the probe word, which is still visible, then the pending answer is updated to *match*. However, if the retrieved word does not match the probe, the probe is treated as a novel word, and the answer is updated to *no-match*. In either case, after the retrieval updates the pending answer, another retrieval of the probe word is attempted. Because these retrievals occur at different times, and the pending answer is updated after each retrieval, the model may repeatedly change its answer until cued to respond. This implementation means that short response cue intervals may force the model to respond before a recollection (declarative) retrieval completes, or at the shortest time interval, before even the relatively fast recognition (familiarity) retrieval completes.

To represent the association between words in shared semantic categories, the model employs ACT-R's partial matching mechanism, which allows the modeler to specify a similarity value between any two chunks. When a retrieval request is made by the model, the declarative memory module attempts to find a chunk in memory that matches the request attributes and has the highest activation. The similarity value is a mismatch penalty applied to the activation of chunks that have different attributes from the requested chunk attributes, thereby making the mismatched chunk less likely to be retrieved. However, due to transient noise in chunk activation, mismatched chunks can sometimes be retrieved. This process is intended to produce variability in memory retrievals analogous to the variability of memory retrieval in humans. Without this partial matching mechanism enabled, declarative memory chunk retrieval requests must be matched exactly or the retrieval fails. The semantic categories of the words are further used by the model's representation of spreading activation. When the model processes each word of the study list, for example *lemon*, it attempts to recall from memory the chunk of type word that possesses the name *lemon*. In addition, each word chunk also has a semantic category, in this example *fruit*. When a chunk is successfully retrieved, ACT-R's spreading activation mechanism provides additional activation to all word chunks that possess the same semantic category; continuing the example, the *pear* and *orange* word chunks would receive a slight boost in activation due to sharing the semantic category of *fruit*.

The purpose of employing this mechanism is to increase the speed and likelihood of retrieving chunks that are in the same semantic category as chunks that have already been retrieved, simulating a priming effect that subjects likely experienced in the task. As the memory task utilized English words in semantic categories with which subjects were presumably well acquainted, the model needed to enter the task with an equivalent vocabulary in its memory. In addition to this vocabulary, the semantic categories of the words were never given to subjects, but influenced performance as demonstrated by slightly increased error rates on category distractor trials (see Figure 3.1). To meet these requirements, the declarative memory of the model was seeded with word chunks containing two values: the name of the word and it's associated semantic category. The set of available words for use as trial stimuli was exactly the same as the set of seeded words. The model was also seeded with semantic category chunks that were utilized by ACT-R's spreading activation mechanism to increase the activation of chunks semantically related to those recently retrieved. For example, when the word *lemon* was retrieved as part of a trial's study list, the semantic category *fruit* was utilized to spread activation to all other *fruit* chunks in memory, such as the chunks for *mango* and *peach*.

## 3. Results: Comparison of Human and Model Performance

Evaluating the fit between the model and human performance is accomplished at two levels of detail. First, model and human estimated *d'* values for the range of response intervals are compared. The *d'* statistic measures the separation between the mean hit rate and false alarm rate, in terms of standard deviations. It is estimated with the equation *d'*=Z(hit rate) - Z(false alarm rate). Second, the correspondence between model accuracy and human accuracy will be examined for each of four trial types: *positive*, *category distractor*, *novel negative*, and *lures*. Good correspondence between model and human performance in these two evaluations supports the final level of analysis, in which the effects of slowing the model's memory retrievals are examined. Model and human *d'* measures are displayed in Figure 3.2. At this level, the model approximately matches the behavior of high span subjects, displaying a similar pattern of increasing accuracy with increasing processing time, up to an accuracy plateau.

Breaking apart the human and model data to examine performance at each trial type reveals several interesting features, which are presented in Figures 3.1 and 3.3. On lure trials, where the probed word was on the study list of the previous trial, both the human subjects and the model display a slower accuracy improvement at short response times, and a lower accuracy asymptote, compared to novel negative trials. Interestingly, the model's asymptotic accuracy on positive trials best corresponds to that of LS subjects, although the model's parameters were intended to replicate HS performance. This reflects an ambiguity bias in the model. Specifically, the model will only update its answer to *match* when it successfully retrieves the probed word, and there are several ways this can fail. Humans, it seems, have less stringent criteria for positive responses. In contrast to the relatively good model performance on lure trials, the model generally fails to capture the accuracy growth curves for category distractor and positive trials.

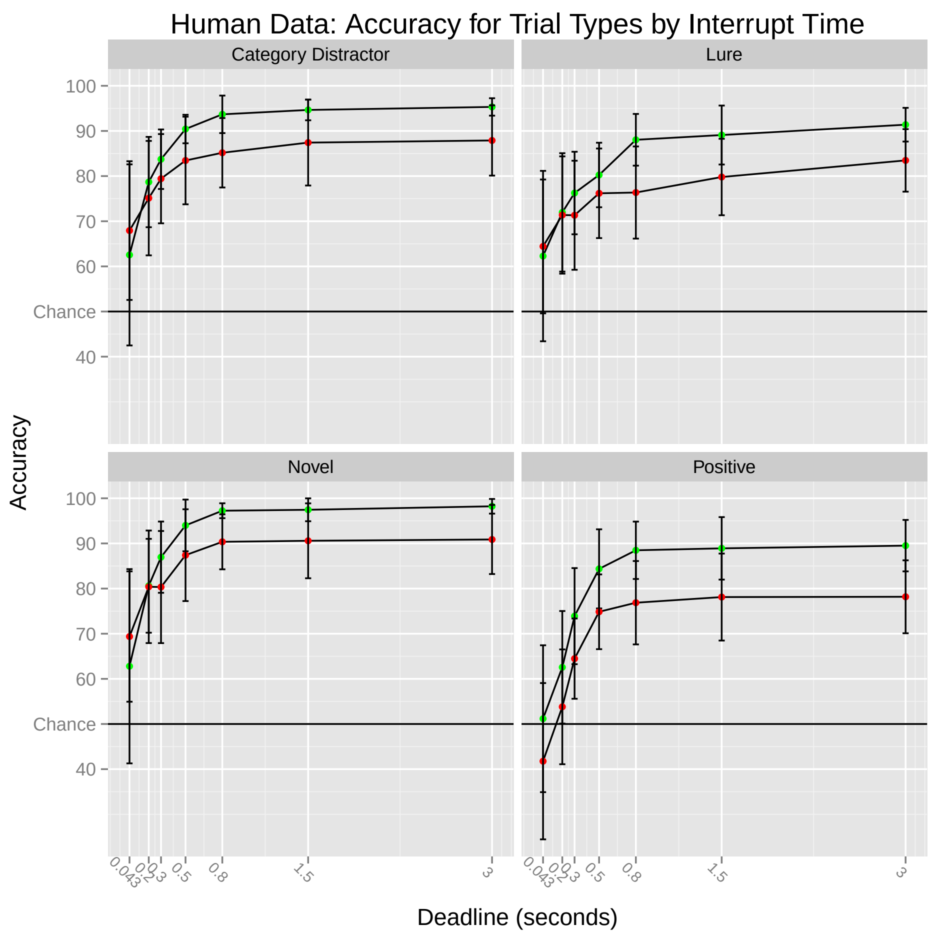


**Figure 3.1: Average accuracy for high span (green) and low span (blue) groups. Category distractor, lure and novel trial types are all variants of trials where the probe was not on the memory list. Positive trials are trials where the probe was one of the six to-be-remembered items. Bars represent 95 percent confidence intervals.**

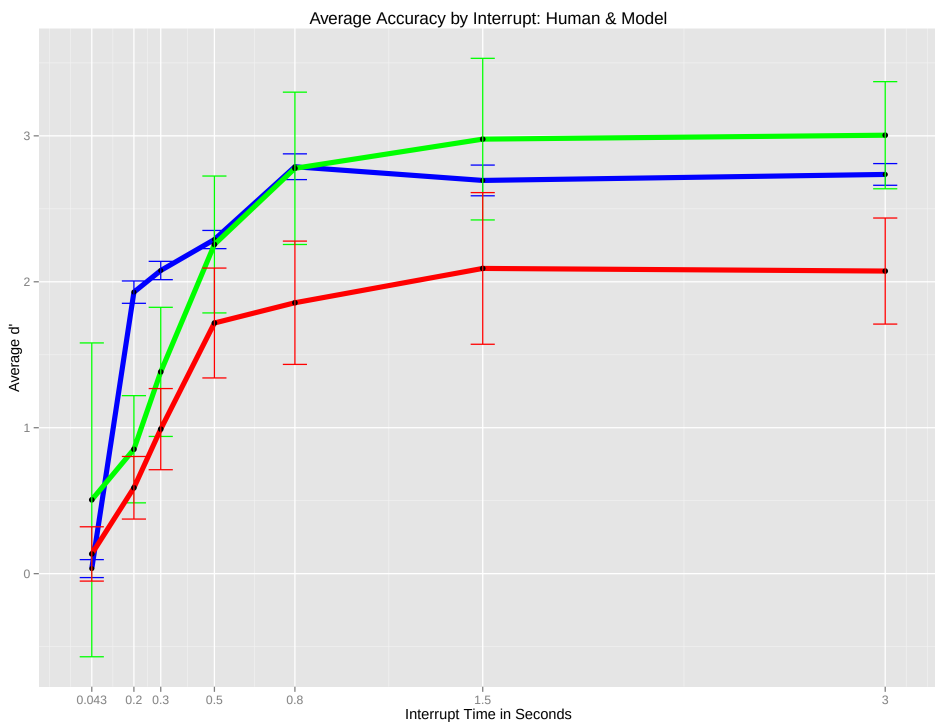


**Figure 3.2: Average *d'* accuracy on the recognition task. The green line represents high span subjects, low span subjects in red, and the model performance is the blue line. Bars represent 95 percent confidence intervals.**

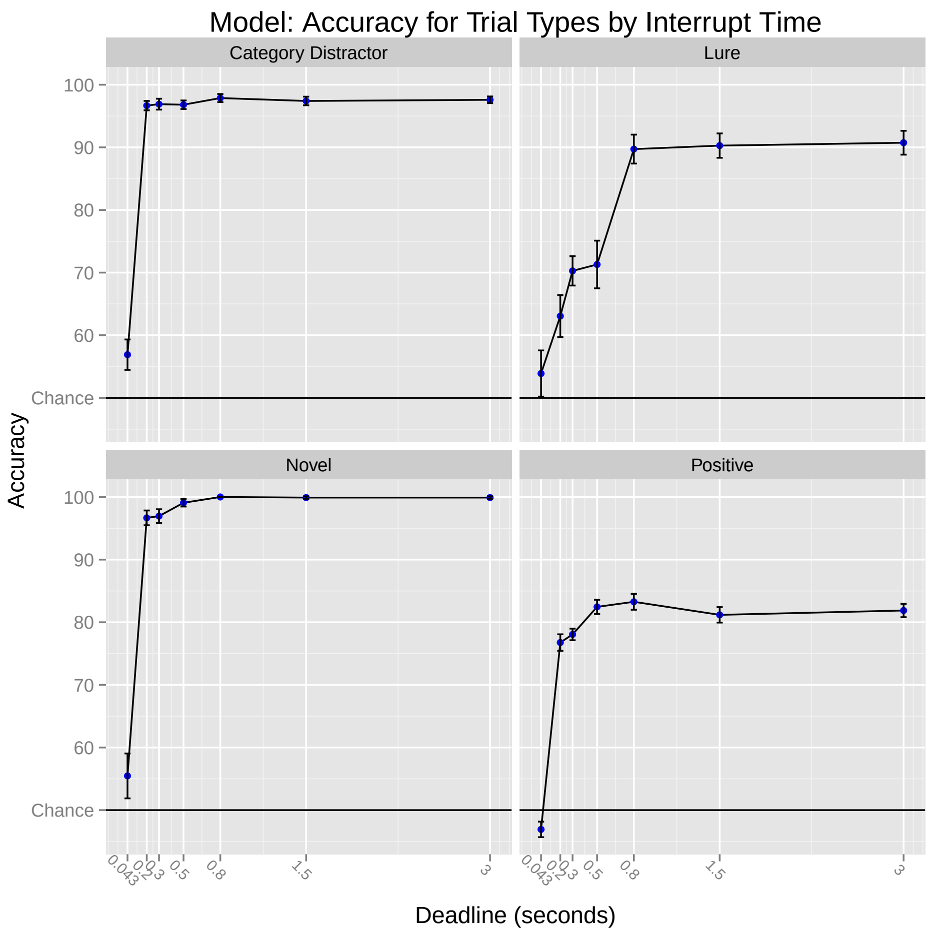


**Figure 3.3: Average Model Accuracy for each Trial Type. Bars represent 95 percent confidence intervals.**

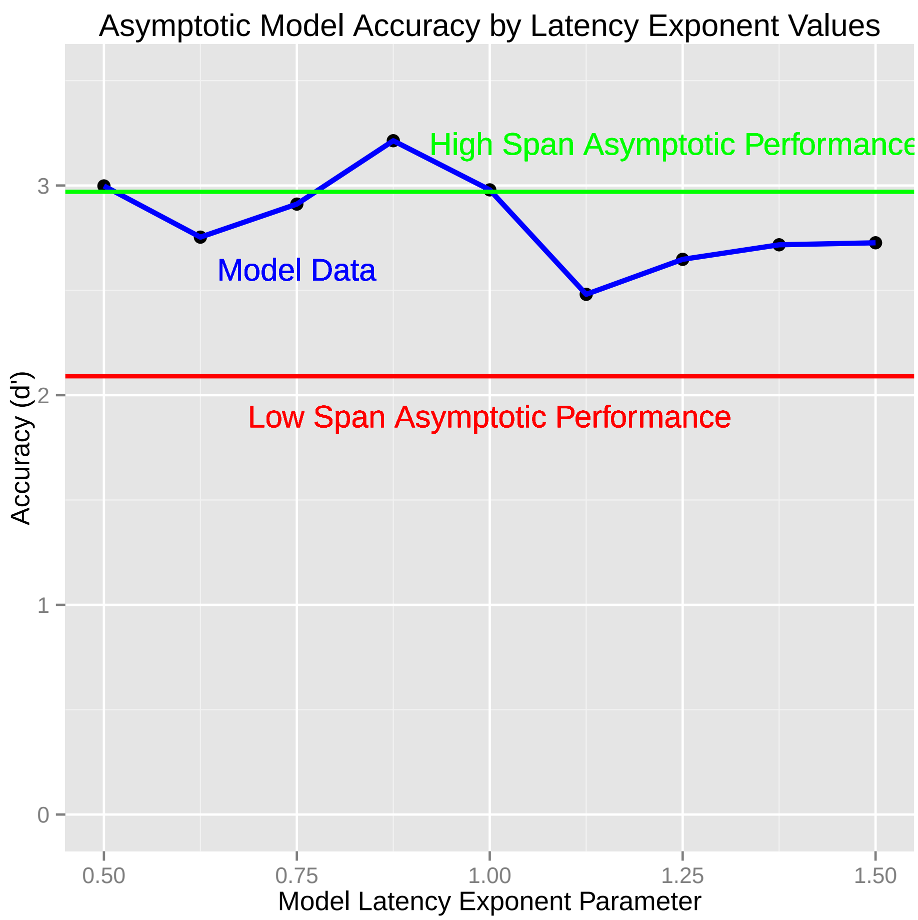


**Figure 3.4: Asymptotic model accuracy for different Latency Exponent parameter values. The blue line displays the asymptotic accuracy of the model at increasing Latency Exponent parameter settings. The green and red lines represents the average asymptotic accuracy for high span and low span subjects, respectively.**

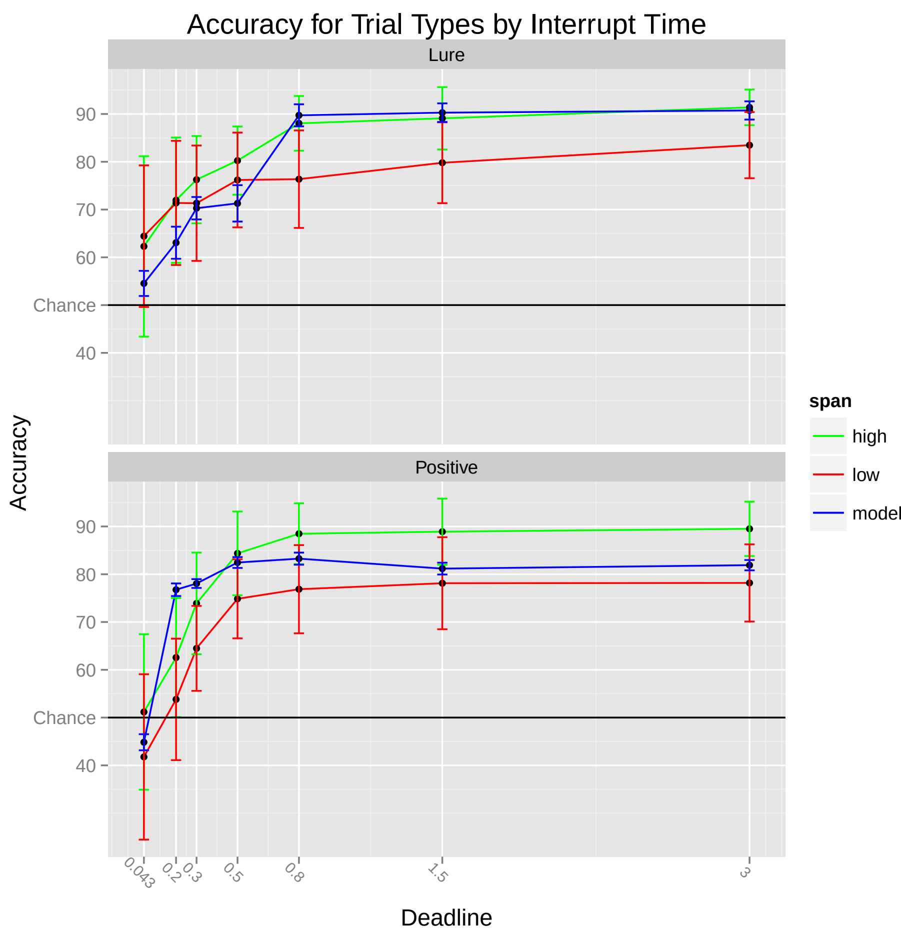


**Figure 3.5: Average human and model accuracy for Lure and Positive type trials. Bars represent 95 percent confidence intervals.**

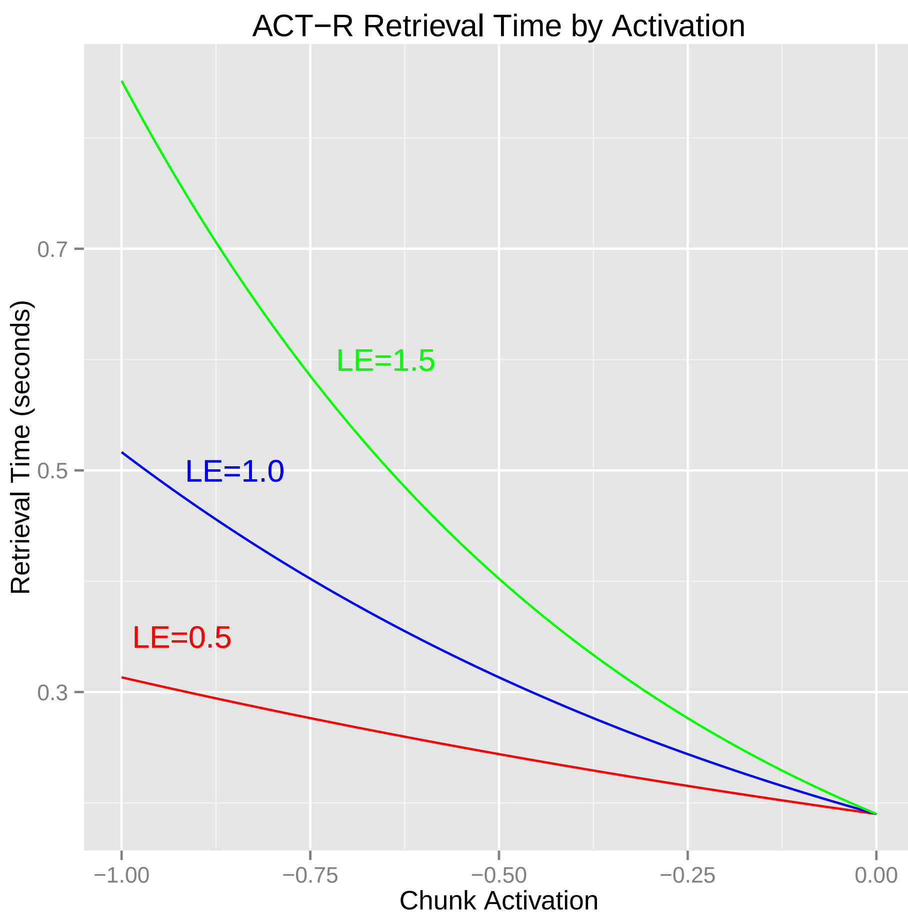


**Figure 3.6: Three curves display the declarative memory retrieval times for different Latency Exponent values used in separate runs of the model.**

# 4. Discussion

## 4.1 Hypothesis 1 and 2: Slower Memory Retrievals

Öztekin and McElree (2010) posit that a principle difference that produces lower asymptotic accuracy in LS subjects compared to HS subjects is either a slower initiation of memory retrieval, or longer retrieval times. The parameters for $F$ (latency factor) and $f$ (latency exponent) in equation (4.1) alter the function that is used to determine retrieval time for chunks in declarative memory.

$$RT = Fe^{f*A_i} \tag{4.1}$$

Asymptotic accuracy for nine model runs varying the latency exponent parameter was measured to evaluate this hypothesis, and is displayed as the blue line in Figure 3.4. The influence of different values for this parameter on retrieval times is displayed in Figure 3.6. Smaller values of the latency exponent decrease the average memory retrieval times in the model. Therefore, it is predicted that models with a larger latency exponent would show poorer asymptotic accuracy. Although the parameter manipulation succeeded in increasing retrieval times for the model, it did not have a consistent impact on the average *d'* values over multiple model runs. The primary reason this manipulation made little difference in the model's performance is that retrieval speed is most influential at the early response times smaller than 800ms. This is where the model is primarily reliant on the familiarity assessment. While slowing retrievals may have an impact on the accuracy growth curve, it has little impact on the asymptotic accuracy, which was the primary difference between HS and LS subjects in the data. Lastly, increasing instantaneous activation noise in the model produced degraded asymptotic performance, which at first appeared promising, but closer inspection revealed that activation noise had a strong impact solely on positive trials, and negligible impact on negative trials. While the average performance decreased for higher noise values, the decrease was almost entirely due to increases in error rates on positive trials, for which the model's performance already approximately matched that of the LS group.

## 4.2 Hypothesis 3: Familiarity and Recall Conflict Resolution

The third of Öztekin and McElree's (2010) hypotheses was that LS subjects are slower to resolve the conflicting signals from familiarity and recollection. The delay caused by this slower conflict resolution favors a response based on stimulus familiarity at the shortest time intervals, as familiarity judgments are completed faster than the memory retrievals (Yonelinas, 2002). Unfortunately, creating a model to implement a more advanced competition than the current "the most recent retrieval wins" would require alterations to both the established declarative memory module, and the newly created familiarity module. There are other more nuanced models of recognition memory than the one here implemented in ACT-R, such as the dual-process Source Activation Confusion model (Reder et al., 2000; Diana, Reder, Arndt, & Park, 2006), which would be a good candidate for a framework with which to test the conflict resolution hypothesis. Another potential candidate framework would be the Decision Field Theory proposed by Busemeyer and Townsend (1993, 2002), which allows detailed modeling of competing processes.

Lastly, increasing instantaneous activation noise in the model produced less accurate asymptotic performance, which at first appeared promising, but upon closer inspection we found that activation noise had a strong impact solely on positive trials, and negligible impact on negative trials. While the average performance decreased for higher noise values, the decrease was almost entirely due to increases in error rates on positive trials, for which the model's performance already approximately matched that of the LS group.

# 5. Conclusions

Working memory tasks appear to measure an important aspect of the cognitive system. Individual differences in working memory have been found to correlate with a variety of measures of cognitive performance and academic attainment (e.g. Kane & Engle, 2002; T. P. Alloway & R. G. Alloway, 2010). The aim of this research was to investigate the sources of individual differences in working memory. Specifically, we tested two hypotheses regarding the source of individual differences that were proposed by Öztekin and McElree (2010). These hypotheses were that a key difference modulating working memory performance was the initiation and speed of episodic memory retrievals, with high working memory span subjects able to complete episodic retrievals faster than low working memory span subjects. In principle, one way to test this would be to procure high working memory span subjects, manipulate their cognitive functioning so as to systematically delay only episodic memory retrievals, then evaluate their working memory performance. The prediction from the hypotheses would be that, with a suitable level of episodic memory delay, the modified high span subjects would perform similarly to low span subjects. Such an experiment would be challenging based on current knowledge of the brain, and further, would probably not be ethically permissible. However, a computational cognitive model is not limited by these factors. Therefore, to evaluate the influence of episodic memory retrieval time on memory performance we developed a cognitive model of a subject performing the task used by Öztekin and McElree (2010).

The cognitive model was created using the ACT-R architecture (Anderson, 2007). ACT-R features a well established episodic memory retrieval system called the declarative memory module. Despite its many useful attributes, the architecture does not canonically possess a mechanism for capturing the fast familiarity judgments that humans appear to make (see Yonelinas, 2002). Familiarity has been distinguished from recollection in that familiarity judgments are relatively fast, automatic, but coarser and less informative than slower, deliberately controlled episodic memory retrievals. Because such familiarity judgments are almost certainly present for humans performing Öztekin and McElree's recognition task, a module was created and added to ACT-R to supply the model with familiarity-like judgments.

When developing the model and adjusting its parameters, the aim was to produce performance approximating that of the high span subjects in Öztekin and McElree's data. In particular, the model should reach roughly the same level of asymptotic accuracy as the high span subjects. In addition to meeting this qualification, the model shows good correspondence with the human data patterns on *positive* and *lure* trial types (see Figure 3.5). Having a cognitive model that approximates high span subject performance in the recognition task permits the previously mentioned manipulation that would be problematic to perform on human subjects, namely increasing episodic memory retrieval times. Based on the Öztekin and McElree's slower retrieval hypotheses, this manipulation should systematically decrease asymptotic performance of the model to levels approximating that of low span subjects. The results, displayed in Figure 3.3, do not show model performance systematically declining to that of low span subjects as retrieval times are, on average, increased. This constitutes evidence against the slower episodic retrieval hypotheses.

Investigating the behavior of the model at different episodic memory retrieval times illuminates why the asymptotic accuracy of the model is minimally affected. Familiarity judgments are completed relatively quickly, and thus the model's response at early time intervals, below 800ms, is mostly dictated by familiarity. When episodic retrievals are adjusted to occur quickly, they slightly improve the model's accuracy at the shorter response deadlines from 200ms to 500ms, because some percentage of the time an episodic retrieval will complete before the response cue. Conversely, slowing retrievals makes the model slightly less accurate at the short response time intervals by minimizing the retrievals that can complete before those deadlines. Notably, in neither case is asymptotic accuracy substantially impacted. Given response deadlines of 1500ms or longer, the model is almost always able to complete at least one episodic retrieval and achieves asymptotic accuracy.

The remaining hypothesis posited by Öztekin and McElree is that a key difference between high and low span subjects resides in their ability to resolve conflicts between familiarity and episodic retrieval. One important stipulation is that the current evidence against Öztekin and McElree's slower retrieval hypotheses does not constitute direct evidence for their third conflict-resolution hypothesis. It is probable that there are other cognitive factors that influence the differences between high and low working memory span subjects, and it is even possible that the conflict-resolution hypothesis is incorrect. Future research into identifying the sources of individual differences in working memory may profit from testing such a conflict-resolution mechanism, both in cognitive models and laboratory experiments.

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# Appendix A
# Appendix: Model Code

```
(define-model SAT-memory-model

  (sgp :v nil :show-focus t :needs-mouse nil :trace-detail
     low)
  (sgp :visual-movement-tolerance 10) ;should allow model to
       skip productions when new words appear
  (sgp :sim-hook sim-sat) ;the default similarity
     calculation is replaced to accommodate similarity
     between seen text and declarative chunks

  (chunk-type word name category trial) ;each word has a
     name (the word), a category it is drawn from, and the
     trial (current/previous)
  (chunk-type category name)
  (chunk-type answer value)
  (chunk-type goal state trial numeric-trial category)
  (chunk-type number value next)


  (define-chunks (start isa chunk) (attending isa chunk) (
     question isa chunk)
     (respond isa chunk) (rehearse isa chunk) (end isa chunk
        ) (next-trial isa chunk))

  (set-memory-parameters)
```

```
 ;read the screen
(p encode-text
   =goal>
   isa goal
   state start
   =visual-location>
   isa visual-location
   ;?visual-location>
   ;attended new
   ?visual>
   state free

   ==>
   =visual-location> ;attempt to make rehearsal
      productions work correctly
   =goal>
   state attending
   +visual>
   isa move-attention
   screen-pos =visual-location)
   ;+imaginal> ;this sets up the imaginal buffer to hold
      the current trial's answer
   ;isa answer ;this is causing problems when relocating
      to new words - putting imaginal clear on fixation
      cross
   ;value "u"

; if there is a fixation cross, ignore it
(p catch-fixation-cross
   =goal>
   isa goal
```

```
    state attending
    ;numeric-trial =trial
    ;trial =prevTrial
    ;!bind! =currentTrial (1+ trial)

   =visual>
    isa text
    value =plus
    !eval! (equal =plus "+")

   ==>
    ;!output! (Incrementing trial current trial is =
       currentTrial)
   =goal>
    state start
    ;numeric-trial =currentTrial
   -visual-location>
   -visual>
   +imaginal>
    isa answer
    value "u"
    )

(p catch-response-prep
   =goal>
    isa goal
    state attending
   =visual>
    isa text
    value =mask
    !eval! (equal =mask "%%%%%")
```

```
==>
=goal>
state respond
-visual>
-visual-location>
-retrieval> ;clear retrieval buffer to prepair for
    probe retrievals
)

(p change-state-for-new-text
  ;after first letter, visual buffer is stuffed due to
    stimulus changing - change goal
  =goal>
  isa goal
  state start
  =visual>
  isa text
  value =word
  !eval! (not (equal =word "%%%%"))
  !eval! (not (equal =word "+"))
  =imaginal>
  isa answer
  ?visual>
  buffer unrequested

  ==>
  =goal>
  state attending
  =imaginal>
  =visual>
```

```
)

(p recall-word
   =goal>
   isa goal
   state attending
   ?retrieval>
   state free
   buffer empty
   =visual>
   isa text
   - value "+"
   - value "%%%%%" ;this the correct way to do this? will
      this work?
   value =newWord

   ==>
   !output! (Actual word seen =newWord)
   =goal>
   state rehearse
   +retrieval>
   isa word
   name =newWord
   =visual> ;retain visual buffer while attempting to
      rehearse
   ;-visual-location> ; clear this buffer so that if a new
      word pops up, retrievals will stop?
   )
```

```
(p recall-next-word ;this production should fire if there
   is already a word in the retrieval buffer - makes sure
   it doesn't recall the just-remembered word
   =goal>
   isa goal
   state attending
   ?retrieval>
   state free
   =retrieval>
   isa word
   name =wordName
   =visual>
   isa text
   - value "+"
   - value "%%%%%"
   value =newWord

   ==>
   !output! (Actual word seen =newWord)
   =goal>
   state rehearse
   +retrieval>
   isa word
   - name =wordName
   name =newWord
   =visual>)

;; need production to handle recall-word retrieval failure
;- What happens if this fails to retrieve a chunk? Try
   again
(p try-to-recall-again
```

```
=goal>
isa goal
state rehearse
=visual>
isa text
- value "+"
- value "%%%%"
value =newWord
?retrieval>
- state busy
state error
;; visual location should be empty? not a new item -
   Not sure if this will work right with visual buffer
   stuffing
;?visual-location>
;attended t
?visual>
state free
!bind! =bll *model-param-bll*
!bind! =rt *model-param-rt*

==>
!output! ("Warning: Model failed recall a categorized
   word. This probably should not happen.~%Params:~% bll
   :~a~%rt:~a~%~a" =bll =rt (
   set-flag-word-recall-failure t))
+retrieval>
isa word
name =newWord
=goal>
state rehearse
```

```
)


(p rehearse-word-trial-binding
   =goal>
   isa goal
   state rehearse
   trial =currentTrial
   =retrieval>
   isa word
   ;name =wordChunk
   category =cat
   =visual> ;need visual for this production to prevent
      trying to "resee" the word again
   isa text
   ;value =wordName
   ;?visual-location>  ;stop rehearsal if a new item pops
      on the screen
   ;attended t

   ==>
   -visual> ;clear visual to eliminiate loop; retain
      visual for checking end-rehearsal
   -visual-location>

   =retrieval> ;hold retrieval buffer
   trial =currentTrial
   ;-retrieval>
   =goal>
   state start
```

```
    category =cat ;put the category in the goal buffer for
        spreading activation to related words ?
    ;-visual-location>
    )

(p catch-retrieval-failure-at-binding
    =goal>
    isa goal
    state rehearse
    ?retrieval>
    state error
    - state busy

    ==>
    !output! ("Failed word rehearsal because no chunk was 
        retrieved")
    =goal>
    state start
    )
;; to slow down the model's retrievals, it re-encodes the
    probe after each retreival attempt

(p encode-probe
    =goal>
    isa goal
    state respond
    =visual-location>
    isa visual-location
    ?visual>
    buffer empty
    state free
```

```
==>
=visual-location>
+visual>
isa move-attention
screen-pos =visual-location)



(p try-to-recall-probe ; should involve partial matching ;
  added familiarity
=goal>
isa goal
state respond
trial =currentTrial
=visual>
isa text
value =probe
?retrieval>
buffer empty
- state busy
- state error ;prevents this production from competing
    with probe-recall-failure
?recognition>
busy nil ;avoid recognition buffer jamming

==>
!output! (Trying to recall probed word =probe)
+recognition>   ; familiarity check
isa word
name =probe
```

```
- trial 9999 ; force trial to not be LTM trial number

+retrieval>
isa word
name =probe
trial =currentTrial
=visual> ;; visual not harvest on first recall? ;
    harvested to slow repeated model retrievals
)

;;; familiar stimulus handling productions - if the probe is
    familiar, change response to yes, if unfamiliar, change
   response to no
 (p probe-familiar-success
   =goal>
   isa goal
   state respond
   ?recognition>
   familiar t
   busy nil
   =imaginal>
   isa answer
   value "u" ;should only happen when answer is unknown -
      if the answer is already set, this shouldn't
      override

   ==>
   !output! (Probe is familiar changing answer to yes)
   =imaginal>
   value "y"
   !output! (Updating imaginal answer to YES)
```

```
    )

(p probe-familiar-failure
    =goal>
    isa goal
    state respond
    ?retrieval>
    state busy ;familiar failure has to be during a
        retrieval - otherwise fails as soon as probe arrives
    ?recognition>
    familiar nil
    busy nil
    =imaginal>
    isa answer
    value "u" ;should only change answer if it has not
        already been set

    ==>
    !output! (Probe is unfamiliar changing answer to no)
    =imaginal>
    value "n"
    !output! (Updating imaginal answer to NO)
    )

(p probe-recall-failure
    ;this should fire if try-to-recall-probe fails to
        retrieve anything
    ;changes the imaginal answer to "n"
    =goal>
    isa goal
    state respond
```

```
 trial =currentTrial
=imaginal>
 isa answer
=visual>
 isa text
 value =probe
?retrieval>
 buffer empty
- state busy
 state error

==>
-visual> ;harvest visual to slow repeated retrievals
=imaginal>
 value "n"
 !output! (Updating imaginal answer to NO)
+retrieval>
 isa word
 name =probe
 trial =currentTrial
 )


;if the state is responding, and the retrieved word
   matches the current probe & trial, change anticipated
   answer to yes, and try to retrieve it again - this will
    be interrupted by the auditory tone, but will continue
    until then
(p probe-recall-perfect-match  ;affected by partial
   matching
=goal>
```

```
   isa goal
   state respond
   trial =currentTrial
   =visual>
   isa text
   value =wordName
   =retrieval>
   isa word
   name =wordName
   trial =currentTrial ;turning this check on or off will
      cause the model to make mistakes about what trial
      the retrieved word is from
;might even eliminate this check to have the model make more
   mistakes
   =imaginal>
   isa answer
   ?retrieval>
   - state busy
   ;!bind! =probe-chunk-activation (get-base-level =
      wordName)

   ==>

   -visual> ;harvest visual to slow repeated retrievals
   =imaginal>
   value "y"
   !output! (Updating imaginal answer to YES)
   +retrieval>
   isa word
   name =wordName
   trial =currentTrial
```

```
    )

(p probe-recall-word-not-seen  ;affected by partial matching
   ;this production attempts to overcome the familiarity
      limitation
   ;effectively says "if the probe is a word that I know,
      but I know I haven't seen it, change answer to no"
     =goal>
     isa goal
     state respond
     trial =currentTrial
     =visual>
     isa text
     value =wordName
     =retrieval>
     isa word
     name =wordName
     trial 9999
;might even eliminate this check to have the model make more
     mistakes
     ;trial =currentTrial ;turning this check on or off will
          cause the model to make mistakes about what trial
        the retrieved word is from
     =imaginal>
     isa answer
     ?retrieval>
     - state busy
     ;!bind! =probe-chunk-activation (get-base-level =
        wordName)

     ==>
```

```
;!output! (Probe chunk activation is =
    probe-chunk-activation)
-visual> ;harvest visual to slow repeated retrievals
=imaginal>
value "n"
!output! (Updating imaginal answer to NO)
+retrieval>
isa word
name =wordName
trial =currentTrial
)

(p probe-recall-word-name-mismatch ;affected by partial
    matching
=goal>
isa goal
state respond
trial =currentTrial
=visual>
isa text
value =wordName
=retrieval>
isa word
name =retrievedWord
- name =wordName ; the retrieved word is not the probe
    word - happens due to partial matching
=imaginal>
isa answer
?retrieval>
- state busy
```

```
    ==>
    -visual> ;harvested to slow repeated retrievals
    =imaginal>
    value "n"
    !output! (Updating imaginal answer to NO)
    +retrieval>
    isa word
    - name =retrievedWord  ;if we recalled a different word
        than the probe word, do not retrieve that word
       again
    name =wordName
    trial =currentTrial)

(p attend-tone
    =goal>
    isa goal
    ;state respond
    =aural-location>
    isa audio-event
    ?aural>
    state free

    ==>
    =goal>
    state end
    +aural>
    isa sound
    event =aural-location
    )

(p respond-to-tone
```

```
=goal>
isa goal
;state end
;trial =currentTrial
numeric-trial =numTrial
=aural>
isa sound
=imaginal>
isa answer
value =key
?manual>
state free
!bind! =nextNumericTrial (wrap-trial-number =numTrial)
!bind! =externalTrial *trial*

==>
!output! (model trial is =numTrial)
!output! (actual trial is =externalTrial)
=goal>
state next-trial
+manual>
isa press-key
key =key
-imaginal>
+retrieval> ;after responding to tone, fire productions
    to increment the trial chunk
isa number
value =nextNumericTrial
-visual-location>
-visual>
)
```

```
(p next-trial-update
   =goal>
   isa goal
   state next-trial
   =retrieval>
   isa number
   next =nextTrial
   value =numericTrial
   ;!bind! =nextNumericTrial (1+ =numericTrial)
   ==>
   +goal>
   isa goal
   state start
   trial =nextTrial
   numeric-trial =numericTrial
   -retrieval>)

(p trial-number-retrieval-failure
   ;This production is to catch a retrieval error - should
       not fire normally
   =goal>
   isa goal
   state next-trial
   trial =currentTrial
   ?retrieval>
   - state busy
   state error
   ==>
```

```
    !output! (Warning Failed to retrieve the trial chunk =
      currentTrial - Probably need to adjust baselevel
      activation)
    +retrieval>
    isa number
    value =currentTrial)

  (setf *actr-enabled-p* t)
)
```