CHAPTER 8

Models of Episodic Memory

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Abstract

Episodic memory refers to memory for specific episodes from one's life, such as working in the garden yesterday afternoon while enjoying the warm sun and chirping birds. In the laboratory, the study of episodic memory has been dominated by two tasks: single item recognition and recall. In single item recognition, participants are simply presented a cue and asked if they remember it appearing during the event in question (e.g., a specific flower from the garden) and in free recall they are asked to generate all aspects of the event. Models of episodic memory have focused on describing detailed patterns of performance in these and other laboratory tasks believed to be sensitive to episodic memory. This chapter reviews models with a focus on models of recognition with a specific emphasis on REM (Shiffrin & Steyvers, 1997) and models of recall with a focus on TCM (Howard & Kahana, 2002). We conclude that the current state of affairs, with no unified model of multiple memory tasks, is unsatisfactory and offer suggestions for addressing this gap.

Key Words: episodic memory, computational modeling, free recall, recognition

Tulving (1972, 1983, 2002) coined the term *episodic memory* to refer to the ability to vividly remember specific episodes from one's life. Episodic memory is often framed in contrast to other forms of memory which are not accompanied by the same experience. For instance, asking a subject "what did you have for breakfast?" usually elicits an episodic memory. In the process of answering the question, subjects will sometimes report re-experiencing the event as if they were present. They might remember being in their kitchen, with the morning sun shining in and the sound of the radio, the smell of the coffee in the process of retrieving the information that they had a bagel for breakfast. Other times, subjects may not have memory for all associated details, but instead have a fuzzy general memory for the event. Both vivid and fuzzy episodic memories are situated in a particular spatio-temporal context. The nature of these two types of episodic experiences is under debate (see Box 1). In contrast, subjects can frequently answer factual questions, such as "what is the capital of France?" without any knowledge about the specific moment when they learned that piece of information. The association of a memory with a specific spatial and temporal context is considered the hallmark of episodic memory.

This chapter is about mathematical and computational models of episodic memory. This is something of an unusual topic. One could argue that there are no mathematical models of episodic memory as defined here. To date, there are no quantitative models that have attempted to describe how or why the distinctive internal experience associated with episodic memory sometimes takes place and sometimes does not. In contrast, models of episodic memory have focused on describing detailed patterns of performance in a set of laboratory memory tasks believed to be sensitive

Box 1 Dual process models of recognition

You go to the grocery store and pass many other shoppers. You pass one shopper who seems familiar. You consider saying hello, but you can't quite figure out how you know this person. If you were asked to perform an item recognition test ("have you seen this person before?"), you would have been much more likely to say yes for this shopper than for one of the other shoppers. Perhaps you would even express high confidence that you had seen the familiar shopper before. After thinking about it for a while, you might later remember that you met this person at a meeting last semester. You might remember his or her name, position and even details of your interaction and be able to report these pieces of information.

The ability to distinguish this one familiar face from all the other unfamiliar faces you passed in the grocery store certainly requires some form of memory. Similarly, the ability to remember the details about your experience with that person also requires some form of memory. The question is whether those two abilities are best understood as points along a continuum or as distinct forms of memory, typically referred to as familiarity—a general sense of knowing that a probe is old—and recollection—the vivid recall of specific details about the probe.

This question has been a major source of disagreement. It has been actively pursued in mathematical modeling (e.g., Klauer & Kellen, 2010; DeCarlo, 2003), behavioral studies (e.g., Hintzman & Curran, 1994; Rotella, Macmillan, Reeder, & Wong, 2005), and a wide variety of cognitive neuroscience techniques (Fortin, Agster, & Eichenbaum, 2002; Rugg & Curran, 2007; Staresina, Fell Dunn. Axmacher, & Henson, 2013; Wilding, Doyle, & Rugg, 1995; Wixted & Squire, 2011). A major problem leading to this debate has been difficulty in extracting satisfactory measures of these two putative latent processes using observable data. Although signal detection approaches have been popular (Wixted, 2007; Yonelinas & Parks, 2007) in solving this problem, signal detection is by no means definitive (Malmberg, 2002; Province & Rouder, 2012).

to episodic memory. This is extremely important because the experimenter must have control over the stimuli the participant has experienced in order to evaluate the success or failure of memory retrieval.

In the laboratory, the study of episodic memory has been dominated by two tasks: *single item recognition* and *recall*. In both recognition and recall tasks, subjects are typically presented with a series of stimuli—a list—and then tested on their memory for that experience later. In recognition, participants discriminate between studied targets and unstudied foils. In recall, participants are asked to generate some member of the stimulus set. There exist successful process models for both individual tasks but no single model that captures a wide range of theoretically and empirically important data in both tasks. In part, this is because a number of variables differentially affect performance in these two tasks, and in part because the methodological details in the two domains often vary in ways that preclude direct comparison. The division of this chapter into recognition and recall sections reflects the fact that efforts to provide a common modeling framework have not been successful thus far. This is a major gap in our understanding—a unified model of episodic memory that provides a quantitative description of the data from the various paradigms would be much preferable. In this chapter, we first present an overview of the important data and models in each area.

Models of Recognition Memory

Recognition memory tests are among the most widely used experimental paradigms for the study of episodic memory. Here, a to-be-remembered event is created, typically in the form of a list of individually presented items (words, pictures, etc). After a delay ranging from a few seconds to 7 or more days, memory is tested by intermixing the studied items (from the to-be-remembered list) along with foils that did not occur during the study episode. In forced choice recognition, a target item is presented alongside a foil or foils and participants are instructed to select the target. In single item recognition, test items are presented one by one and the participant is asked to endorse studied items and reject foil items. Multiple measures describe performance: a hit is correctly endorsing a studied item, a correct rejection is correctly identifying a foil, a false alarm is incorrectly endorsing a foil as having been studied, and a miss is incorrectly rejecting a studied item. Although measuring accuracy in recognition memory is itself an active topic of research, in general, the larger the difference between the hit rate (proportion of hits to old probes) and the false alarm rate (the proportion of false alarms to new probes), the more accurate is episodic memory. In forced choice, the measurement of performance is simply percent correct. Based on these and other measures, such as the time for providing a response or the confidence associated with the response, a number of detailed mathematical models have been developed to explain episodic memory.

Global matching models

The global matching models were successful for decades (Gillund & Shiffrin, 1984; Hintzman, 1984; Humphreys, Bain, & Pike, 1989; Murdock, 1982). The premise of these models was that the search of episodic memory included a comparison to a relevant set of items and the memory decision was based on the overall or global match between the probe and the set to which it was compared.

THE MATCHED FILTER MODEL

The basic idea of global matching models is concisely illustrated by Anderson's matched filter model (Anderson, 1973). Let the list be composed of N unique items represented as vectors $\mathbf{f}_i$, where the subscript denotes which of the N vectors is referred to. Let the vectors be randomly chosen Gaussian deviates such that

$$E\left[\mathbf{f}_i{}^T\mathbf{f}_j\right] = \delta_{ij} \tag{1}$$

(where $\delta_{ij} = 1$ if $i = j$ and $\delta_{ij} = 0$ otherwise) and the similarity of the vectors to have variance given by

$$Var\left[\mathbf{f}_i{}^T\mathbf{f}_j\right] = \sigma^2.$$

We will treat σ as a free parameter but, in general, it will be specfied by the distribution of the features of $\mathbf{f}_i$. Now, in the matched filter model, the list is represented simply as the sum of the list items. At each time step, the sum $\mathbf{m}_i$ is updated according to

$$\mathbf{m}_i = \mathbf{m}_{i-1} + \mathbf{f}_i, \tag{2}$$

such that at the end of the list

$$\mathbf{m}_n = \sum_{i=1}^{N} \mathbf{f}_i. \tag{3}$$

To model recognition, we take the vector corresponding to a probe and match it against the list. Denoting the vector corresponding to the probe stimulus as $\mathbf{f}_p$ we have

$$D_p = \mathbf{f}_p{}^T\mathbf{m}_n = \sum_i \mathbf{f}_p{}^T\mathbf{f}_i. \tag{4}$$

Notice that this decision variable has different distributions depending on whether the probe was on the list. If the probe is old, then $\mathbf{f}_p$ should match one of the list items, resulting in

$$E\left[D_p\right] = \begin{cases} 1 & \text{old} \\ 0 & \text{new} \end{cases}. \tag{5}$$

Moreover, the variance of D_p is a function of the length of the list

$$Var\left[D_p\right] = N\sigma^2. \tag{6}$$

The matched filter model is an example of global matching model. It is a matching model because the similarity of the probe stimulus to the contents of memory is calculated and drives the decision process. It is a global matching model because the match is calculated not only to information stored about the probe stimulus during study; rather the match from other study items also contributes to the decision. This concept is perhaps best understood in contrast to direct access models (Dennis & Humphreys, 2001; Glanzer & Adams, 1990) that posit a direct comparison of the test item to its corresponding memory trace.

In global matching models, errors in memory result from similarity between the test item and memory traces with similar features. More formally, the probability that D_p is greater than some criterion is higher for old probes than for new probes; for a fixed criterion c, $P\left(D_p > c|\text{old}\right) > P\left(D_p > c|\text{new}\right)$. However, in order to correspond to performance in the task (which is typically far from perfect) the criterion (and the variances) must be chosen such that the match from some new probes exceeds the criterion. According to the matched filter model, and global matching models more generally, this happens because a particular new probe happens to match well with the study list.

We can generate several other predictions from global matching models from these expressions as well. First, Eq. 6 tells us that the the discriminability of the decision goes down with σ *and* with the length of the list N. If the vectors are chosen such that the similarity is a normal deviate, then the discriminability between the old and the new distributions is $d' = \frac{1}{\sqrt{N}\sigma}$. This makes a straightforward experimental prediction—that accuracy should go down as the length of the study list increases. This finding is typically observed in recognition memory experiments (Criss & Shiffrin, 2004; Ohrt & Gronlund, 1999; Shiffrin, Huber, & Marinelli, 1995 but see (21)).

THE DEMISE OF GLOBAL MATCHING MODELS

Two observations contributed to the demise of the global matching models for recognition memory: the generality of the mirror effect and the null list strength effect. The mirror effect refers to the finding that when the hit rate is higher for a particular experimental variable, the false alarm rate is lower. This is a challenge for global matching models because the strength of target items appears to leapfrog the foil items. Suppose we perform an experiment in which we observe some hit rate and false alarm rate. Now, we change the experiment such that each studied item is presented five times rather than just once. Now, the mean of D_p for the old probes will be 5 rather than 1 but the mean of D_p for the new probes will still be zero. The variance of the distributions should also increase, to $5N\sigma^2$. If the criterion c is fixed across experiments, we would expect the hit rate, $P(D_p > c|\text{old})$ to be higher for the list with the repeated stimuli. However, the false alarm rate should also increase, in contrast to the experimental results. In order to account for the mirror effect in the context of the matched filter model, we would have to assume that the criterion, C, changes across experiments, which is akin to unprincipled curve-fitting. The mirror effect is quite general and is observed for a wide variety of experimental variables including repetition, changes in presentation time, and word frequency (e.g., Glanzer & Adams, 1985, 1990). Most global matching models did not attempt to account for the mirror effect at all and those that did relied on a changing criterion (Gillund & Shiffrin, 1984), which is largely inconsistent with the empirical data (e.g., Glanzer, Adams, Iverson, & Kim, 1993).

The null list strength effect posed a more fundamental challenge to global matching models. The null list strength effect is the finding that the strength of *other* study items does not affect recognition memory accuracy (Shiffrin, Ratcliff, Clark, 1990; Ratcliff, Clark & Shiffrin, 1990). To make this more concrete, consider two experiments. In one experiment, as before, we present all the items five times. We would expect accuracy to be much higher in this pure strong condition relative to the pure weak condition, where all the items are presented only once. But now consider a mixed list experiment in which half the list items are presented five times and half are presented only once. We refer to probes presented five times during study in the mixed list as mixed-strong probes and the probes presented only once as mixed-weak probes. Note that the mean of D_p for the pure-strong and mixed-strong probes should be identical. However, the variance should not be the same. The mixed-strong probes should be subject to less noise from the weak items in the mixed list and should thus have higher accuracy than the pure-strong probes. Following similar logic, we would expect accuracy to be lower for the mixed-weak probes than for the pure-weak probes due to additional interference from the strong items on the study list. In contrast to this very strong prediction, this pattern of results does not hold (Ratcliff et al., 1990; Shiffrin et al., 1990), reflecting a fundamental problem for global matching models.

The Retrieving Effectively from Memory (REM) Model

The pervasiveness of the mirror effect and the discovery of the null list strength effect created a paradigm shift wherein a new set of models incorporating Bayesian principles were developed to account for recognition memory.

The REM model (Shiffrin & Steyvers, 1997) is the most thoroughly explored of these approaches and we will focus on it extensively here. As in the global matching models, a probe is compared to each of the traces in memory. There are two key insights that allow REM to overcome the weaknesses of the global matching models. First, the comparison between the probe and the contents of memory incorporates both positive evidence of a match but also negative evidence for nonmatch. That is, rather than simply the absence of evidence, REM can incorporate positive evidence for absence. This is a powerful assumption. As a stimulus is studied more extensively, it means that this stimulus can provide both more positive evidence that the trace matches an old probe, but also more negative evidence that it doesn't match a new probe. This provides a mechanism for altering the new item distribution rather than assuming that encoding is restricted to altering the target distribution. Second, the decision rule takes into account the nature of the environment and expected memory evidence based on that prior knowledge.

REM is a Bayesian model with the core assumption that processes underlying memory are optimal given noisy information on which to base a decision. There are two types of memory traces in REM: lexical-semantic and episodic. Lexical-semantic traces are accumulated across the lifespan and are thus complete, accurate, and de-contextualized relative to episodic traces. Episodic traces are formed during a given episode and are updated with item, context, and sometimes associative features during each presentation in a given context. REM is a simulation model wherein a set of episodic and lexical-semantic traces are generated for each simulated subject as described next.

REPRESENTATION

A memory trace consists of multiple types of information. Item features represent a broad range of information about the stimulus including the meaning of the stimulus and orthographic-phonological units. Context represents the internal and external environment at the time of encoding. Associative features are sometimes generated and represent information relating multiple items (e.g., a stimulus-specific association formed during or prior to the experiment). All features are drawn from a geometric distribution with parameter g. The probability that a feature takes the value v is

$$P(v) = g\left(1-g\right)^{v-1}. \tag{7}$$

A geometric distribution assures that some features will be relatively common and others will be relatively rare. Evidence provided by a matching feature is a function of the base rate of that feature: matching a common feature provides less evidence than matching a rare feature.

STORAGE

During each experience with a stimulus, the lexical-semantic trace for a stimulus is retrieved from memory and updated with the current context features. In a typical recognition memory experiment the lexical-semantic traces are used solely for the purposes of generating and testing episodic traces. Therefore, the theoretical principle of updating lexical-semantic traces with current context is typically not implemented in a simulation (c.f., Schooler, Shiffrin, & Raaijmakers, 2001). An episodic memory trace is formed by storing each lexical-semantic feature and the context feature with some probability ($\overset{*}{u}$) per unit of time (t). Given that a feature is stored, the correct value is stored with some probability (c). Otherwise, a random value from the geometric distribution is stored. Features that are not stored during encoding are denoted by a zero indicating a lack of information. Thus, episodic memory is incomplete (i.e., some features are not stored), prone to error (i.e., an incorrect feature value may be stored), and context-bound (i.e., contains a set of features representing the context).

Study of a pair results in the concatenation of the two sets of item features and shared context features. Depending on the goals at encoding, associative features that capture relationships between the two stimuli may also be encoded in the vector (e.g., Criss & Shiffrin, 2004, 2005). Processes at retrieval are necessarily different for different tasks as they depend on the information provided as a cue and the required output. Next we only consider recognition memory, but note that REM has been applied to multiple memory tasks including judgments of frequency (Malmberg, Holden, & Shiffrin, 2004), free recall (Malmberg & Shiffrin, 2005), cued recall (Diller, Nobel, & Shiffrin, 2001), and associative recognition (Criss & Shiffrin, 2004, 2005).

RETRIEVAL

According to REM, there are an immense number of traces that have been laid down over an extremely long time. In order to restrict the comparison to the relevant event, reinstated context features identifying the context to be searched are used to define the activated set. In a typical experiment with a single study list, this step simply limits the comparisons of the test cue to the study list and is often implemented by assumption for simplicity, which we assume here. The basis for a memory decision in REM is the likelihood computation. The likelihood reflects evidence in favor of the test cue as the ratio of the probability that the cue matches a trace in memory given the data compared to the probability that the cue does not match an item in memory given the data. Here, data refer to the match between the cue and the contents of the activated subset of episodic memory. The item features from test cue j are retrieved from its lexical-semantic trace and compared to each item in the activated set, indexed by i. A likelihood ratio, indicating how well the test cue j matches memory trace i is computed using

$$\lambda_{ij} = (1-c)^{n_q} \prod_{v=1}^{\infty} \left[\frac{c + (1-c)\, g_{\text{sys}} \left(1-g_{\text{sys}}\right)^{v-1}}{g_{\text{sys}} \left(1-g_{\text{sys}}\right)^{v-1}} \right]^{n_m}. \tag{8}$$

The g_{sys} parameter is the long-run base rate. This is a fixed value, estimated by the system based on experience. This base rate value may differ from the g values in Eq. 7, which gives the value of the g parameter for the stimulus itself. The number of nonzero features that mismatch is n_q and the number of features that match and have the v is n_m. Missing features (value of zero) are ignored. Note that the amount of evidence provided by a matching feature depends on the feature value. This is one way in which prior knowledge contributes to the decision. Specifically, in a geometric distribution, low values are common and, therefore are likely to match by chance. These values provide little evidence when they match. In contrast, large values are uncommon and, therefore unlikely to match by chance, providing greater evidence when they match. Thus, knowledge about the statistics of the environment (i.e., rarity of features, estimated by g_{sys}) learned over the course of life contributes to the evidence of match between a test cue and the contents of each memory trace. For single item recognition the decision that test cue j was present during the relevant context is based on the average of the likelihood ratios. If the average exceeds a criterion, the item is endorsed as from the list, otherwise it is rejected.

Word Frequency and Null List Strength Effects in REM

REM can provide an account of the mirror effect based on properties of the words themselves, such as word frequency. The probability of a given feature value (g) and the expectation of feature values (g_{sys}) are both specified in REM. REM has used the g parameter to model the effects of normative word frequency. Specifically, low frequency words (LF) are assumed to have more uncommon features (i.e., a lower value of g is used to generate the stimuli). In contrast, high frequency (HF) words have relatively common features. The common features of HF words tend to match other features of memory traces by chance increasing the false alarm rate. Additionally, the likelihood ratio includes prior information by taking into account the base rate of features (g_{sys}) such that matching unexpected features contribute more evidence in favor of endorsing the test, increasing the hit rate for LF words. Together, the stimulus representation (g) and prior expectations (g_{sys}) generate a word frequency mirror effect, consistent with empirical data.

The null list strength account in REM is based on differentiation. The Subjective Likelihood Model (SLiM) of McClelland and Chappell (1998) shares the mechanism of differentiation and for that reason also predicts a null list strength effect for recognition. Differentiation refers to the idea that the more that is known about an item, the less confusable that item is with any other randomly chosen item. Obvious applications are a bird expert or a radiologist, who have such knowledge in their area of expertise that they can quickly and accurately identify a Rusty Blackbird or a cancerous tumor, whereas a novice simply sees a bird or a blurry grayscale image. In episodic memory, an item becomes differentiated by being well practiced within a specific contextual episode, for example by repetition in an experiment. Within the differentiation models, an episodic memory trace is updated during repetition, which causes the memory trace to be more accurate and more complete. Note that updating was a departure from the standard assumption of storing additional exemplars or additional memory traces with repetition (e.g., Hintzman, 1986). In REM, differentiation is implemented by assuming that if an item is recognized as having been previously experienced in a given context, then the best matching trace is updated such that any missing (zero valued) features have the potential of being replaced in accordance with the encoding mechanism described earlier. If an item is not recognized as a repetition, then a new memory trace is stored. In the original REM model, updating only occurred during study for simplicity. However, more recent applications incorporate updating and encoding at test (Criss, Malmberg, & Shiffrin, 2010).

When a memory trace is stored with higher quality, that is when more features are stored, not only is it a better match to a later comparison with the lexical-semantic trace from which it was generated, but it is also a poorer match to other test items. In Eq. 8, note that the matching and mismatching features contribute to the overall evidence in favor of the test item. As the total number of stored features in a given memory trace increases, due to additional encoding, so too does the total number of features matching the target trace. Critically, the total number of mismatching features for any item other than the corresponding target trace also increases. The net result is that although a strengthened target item matches better and will be better remembered, it is not at the cost of the other studied items. Differentiation models correctly predict that recognition memory is not harmed by increasing the strength of the other items on the study list. In fact, in some cases, the models predict a small negative list strength effect such that, for a given item, memory may slightly improve as the strength of other studied items increases (see Shiffrin et al., 1990).

In summary the differentiation models were developed to address shortcomings of the global matching models, in particular their failure to capture the robust empirical findings of the word frequency (WF) mirror effect and the null-list strength effect. In REM, the WF effect is due to the assumed distribution of features along with a Bayesian decision rule that gives more weight to unexpected matches or alternatively downplays expected matches. The null-list strength effect is due to differentiation of well-learned items caused by updating memory traces.

The Empirical Consequences of Updating

The updating mechanism in REM was necessary to produce differentiation and to account for empirical data. Auspiciously, this same mechanism makes critical *a priori* predictions that appeared in the literature after the model was conceived. First, updating memory traces during the encoding of test items results in output interference. Output interference (OI) is the finding that memory accuracy decreases over the course of testing (Murdock & Anderson, 1975; Roediger & Schmidt, 1980; Tulving & Arbuckle, 1963, 1966; Wickens, Born, & Allen, 1963). Output interference is not a new finding, but a detailed understanding of the manifestation of OI in recognition memory is (Criss, Malmberg, & Shiffrin, 2011; Malmberg, Criss, Gangwani, & Shiffrin, 2012). Figure 8.1 shows a typical pattern of OI in recognition testing (left panel) along with predictions from REM. The middle panel shows predictions for REM where remembered items cause the best matching episodic trace to be updated, as described earlier. The right panel shows predictions for a version of REM where updating does not occur; instead, a new trace is added to memory for each test item. Both the predictions of REM with updating and the data show a dramatic decrease in the rate of endorsing target items as old as a function of test position and the nearly flat function for foils. In contrast, the multitrace version of REM in which additional traces are stored with each test item predicts a shallow decrease in the hit rate along with an increase in the false-alarm rate. Both implementations of REM predict output interference in the sense that overall accuracy (e.g., d-prime) decreases across test position. However, only the updating model predicts the precise pattern of observed data.

A second prediction that follows directly from the differentiation mechanism is a higher hit rate and lower false alarm rate following a strongly encoded list compared to a weakly encoded list. This finding is called the strength-based mirror effect (SBME) and has been widely replicated (Cary & Reder, 2003; Criss, 2006, 2009, 2010; Glanzer & Adams, 1985; Starns, White, & Ratcliff, 2010; Stretch & Wixted, 1998). The WF mirror effect is related to the nature of the stimuli, whereas the SBME is related to the encoding conditions. Both findings co-occur (Criss, 2010; Stretch & Wixted, 1998) and despite the shared label of mirror effect, they result from entirely different mechanisms in REM. Increasing the strength with which a study list is encoded via levels of processing, repetition, or study time increases the number of stored features and produces a distribution of λ that is higher for strongly than weakly encoded targets. The same fact—that strongly encoded memory traces contain more information—produces a distribution of lower λ for foil items. Foils match a strongly encoded memory trace less well than a weakly encoded memory trace. Thus, a list containing all strongly encoded targets will match any given foil poorly, reducing the false alarm rate. Not only are the HR and FAR patterns that make up the SBME well predicted by REM, but REM makes additional specific predictions that have been confirmed with behavioral experiments (see Criss & Koop, in press for a review). For one, the actual distribution of estimated memory strength follows the pattern predicted by REM (Criss, 2009). Further, the interaction between target-foil similarity and encoding strength presents just as predicted by REM (Criss, 2006; Criss, Aue, & Kilic, 2014). If one conceives of the λ values as the driving force behind a random walk or diffusion model, then the rate at which the walk reaches a boundary is consistent with REM, that is, targets and foils following a strongly encoded list have a steeper approach (e.g., larger drift rate) to the decision bound (Criss, 2010; Criss, Wheeler, & McClelland, 2013).

In summary, the global matching models were found to be inadequate on the basis of several findings, critically, the WF mirror effect and null-list strength effect. REM was developed to

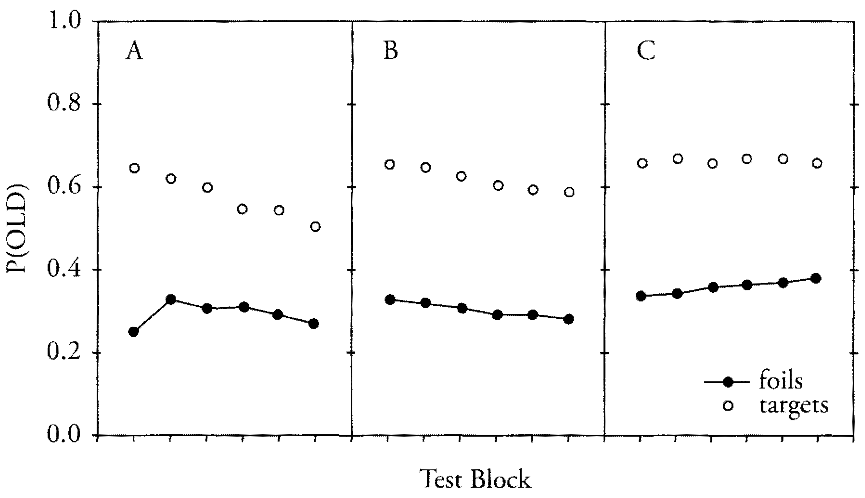

Fig. 8.1 Panel A shows data (Koop, Criss, & Malmberg, in press) that is representative of output interference. The panel gives the probability of endorsing old probes (targets) and new probes (foils) for several test blocks. The hit rate is P(OLD) for targets; the false-alarm rate is P(OLD) for foils. The data reveal a steep decline in the hit rate and flat false alarms across test position. Panel B shows the standard REM model where remembered items cause updating of an episodic memory trace. Updating produces patterns of data consistent with empirical findings. Panel C shows a version of REM where each test item causes the storage of a new memory trace (i.e., no updating). Such a model predicts a shallow decrease in the hit rate and increase in the false alarm rate, inconsistent with observed data.

account for these data and others. Two key features of REM are updating a single context-bound episodic trace and a Bayesian decision rule that takes into account positive and negative evidence from the stimulus as well as expectations based on the environment. These properties not only accounted for the problematic data but also lead to specific and fortuitous predictions. Differentiation, the same mechanism that was required to predict the data that lead to the demise of a whole class of models, predicted the observed pattern of output interference and strength-based mirror effects.

An Alternative Idea: Context-Noise Models

Context-noise models (Dennis & Humphreys, 2001) were also developed to account for data problematic for the global matching models. However, they took a very different approach. Context-noise models assume that memory evidence is based on the similarity between the test context and the previous contexts in which the test item was encountered. There is no comparison between the test item and any other studied item, in fact no other items from episodic memory enter the decision process. Briefly, the model works as follows. Each time a word is encoded, the current context is bound to the word. During test, the item causes retrieval of its prior contexts. Those contexts are compared to the context in question, the test context in a typical recognition experiment. The recognition decision is made based on how well the retrieved contexts of the test item match the test context. It should be clear that context information is the only factor that contributes to memory evidence and, thus, such models predict no effects of list composition per se. Neither the number nor strength of the other studied items affect the decision because those items are never compared to the test item, thus the model easily predicts a null list strength effect. The WF mirror effect is predicted on the assumption that common words have more prior contexts that interfere with the ability to isolate the tested context. Although the context noise models are limited—for example, they only apply to recognition and must generate post-hoc explanations for many findings including output interference and the SBME—they certainly advanced the field by making context a touchstone for models of recognition. Unlike models of recall that emphasize context, models of recognition have largely neglected context. The item-context-noise debate sparked by the introduction of the Dennis & Humphreys model of has brought to the forefront the fact that context must be taken seriously in recognition models but also raised questions about the nature of context.

Models of Episodic Recall

In recall tasks, subjects must report their memory for an event by producing a stimulus. Recall tasks most commonly use words as stimuli. In cued recall, subjects are given a probe stimulus as a cue to retrieve a particular word from the list. Most commonly, pairs of words are studied, with one member of the pair serving as a cue for recall of the other (but see Phillips, Shiffrin, & Atkinson, 1967; Nelson, McEvoy, & Schreiber, 1990; Tehan & Humphreys, 1996; for other possibiities). In free recall, subjects are presented with a list of words, typically one at a time and then asked to recall the words in the order they come to mind. In serial recall, subjects are asked to produce the stimuli in order, typically starting at the beginning of the list. Although there is a well-developed literature modeling serial recall, the serial recall task is most commonly described as a function of working memory rather than as a function of episodic memory,[1] and we will not discuss it here.

The fundamental question in episodic recall is to determine what constitutes the cue. In cued recall, this might seem like an obvious question. Given the pair DOG-QUEEN the subject is presented DOG as a cue at test and correctly recalls QUEEN. Is it not sufficient to understand this as a simple, almost Pavlovian, association between some distributed representation of the word DOG and the word QUEEN? This is not sufficient. If the subject is asked instead to recall the first word that comes to mind when hearing the word DOG it is likely the subject would recall CAT. If asked to recall a word that rhymes with dog the subject would likely recall LOG. If asked to remember a specific event from their life that involved a dog (or the word DOG) it is unlikely that the subject would recall QUEEN. All these tasks take the same nominal cue but result in very different responses. From this we conclude that the cue stimulus itself is not enough to account for the subjects' responses. In free recall the problem is even more acute; in free recall there is no external cue whatsoever. Free recall must proceed solely on the basis of some set of internal cues. Several concepts—fixed-list context, variable context, short-term memory, and temporally varying context—have been introduced to detailed models of recall tasks to attempt to solve these problems.

Cued recall

In cued recall, subjects are presented with pairs of stimuli, such as ABSENCE-HOLLOW, PUPIL-RIVER, and so forth. At test, the subject is given one of the stimuli, such as ABSENCE and asked to produce the corresponding member of the pair, i.e., say (or write) HOLLOW. One way to approach cued recall is to form an association between the stimuli composing a pair. We will see that this assumption is ultimately limited for recall more broadly, but illustrates several important properties of models of recall. For that reason, we will spend some time examining an extremely simple model of association in memory.

SIMPLE LINEAR ASSOCIATION

In the matched filter model we constructed a memory vector that was the sum of the vectors corresponding to the list items. In a linear associator, we again form a sum, but now of a set of outer product matrices. Each matrix provides the outer product of the first members of a pair with the second members of a pair. These associations can be understood as changing the synaptic weights between two vector spaces according to a Hebbian rule. Such associations between distinct items are referred to as *heteroassociative*.

Here we follow the heteroassociative model of J. A. Anderson, Silverstein, Ritz, and Jones (1977). Let us refer to vector corresponding to the first member of the ith studied pair as $\mathbf{f}_i$ and the second member as $\mathbf{g}_i$. Now, the matrix storing the associations between each stimulus and each response can be described by

$$\mathbf{M}_i = \mathbf{M}_{i-1} + \mathbf{f}_i \mathbf{g}_i^{\,T}. \tag{9}$$

To model the association, we can probe the matrix with a probe stimulus, $\mathbf{Mg}_p$. Here we find this to be

$$\mathbf{M}_i \mathbf{g}_p = \sum_i \mathbf{f}_i \left(\mathbf{g}_i^{\,T} \mathbf{g}_p \right). \tag{10}$$

That is, the output is a combination of the vector for each first member $\mathbf{f}_i$ weighted by the degree to which the paired stimulus g_i stimulus matches the probe vector. Equations 9 and 10 can be understood as describing a simple neural network connecting $\mathbf{f}$ and $\mathbf{g}$, with $\mathbf{M}$ understood as a simple Hebbian matrix describing the connections between them (see Figure 8.2).

In recall tasks, subjects report one word at a time, rather than a mixture of words. This can be reconciled with a deblurring mechanism in which one takes an ambiguous stimulus and perceives one of several possibilities. This is somewhat analogous to the problem of perception in which one identifies a particular stimulus from a blurry input. One can imagine a number of physical processes that could be used to accomplish this

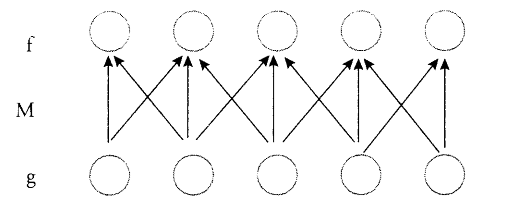

Fig. 8.2 Schematic of a neural network interpretation of Eq. 9. Two sets of "neurons," **f** and **g** are connected by a weight matrix **M**. As each pair is presented, the values of the elements in **f** and **g** are set to the values corresponding to the stimulus in that pair. The connections between an individual element in **g** and an individual element in **f** are strengthened according to the product of those two elements, that is, the corresponding element of the outer product of the two patterns.

deblurring (e.g., J. A. Anderson et al., 1977; Sederberg, Howard, & Kahana, 2008), but in many applications, researchers simply assume that the probability of recalling a particular word is some phenomenological function of its activation relative to the activation of competing words (e.g., Howard & Kahana, 2002a) or a sampling and recovery process (e.g., Raaijmakers & Shiffrin, 1980).

A series of models can be developed that can be thought of as variations on the basic theme illustrated by Eq. 10. These models differ in the associative mechanism but are similar in that they store the associations between each of the members of the pairs and provide a noisy output when given a probe. TODAM utilizes a convolution/correlation associative mechanism rather than the outer product (e.g., Murdock 1982). The matrix model (Humphreys et al., 1989) utilizes a triple association between the two members of the pair and a fixed-list context vector to form a three tensor that can be probed with the conjunction of a probe item and a test context.

Free recall

Free recall raises two computational problems that are probably central to the question of episodic memory. First, how do subjects initiate recall in the absence of a particular cue? Second, how do those cues change across the unfolding process of retrieval? Models of free recall have not focused on differences in associative mechanisms, nor detailed assumptions about how items are represented, but on representations that are used to initiate recall and how those representations change across retrieval attempts. These two problems can be concisely summarized by two classes of empirically observable phenomena: the probability that subjects initiate recall with a particular word and the probability of transitions between stimuli after recall has been initiated.

EMPIRICAL PROPERTIES OF RECALL INITIATION IN FREE RECALL

The finding that subjects can direct their recall to a specific region of time has also had a large effect on hypotheses about the cue used to initiate free recall. Shiffrin (1970) gave subjects a series of lists of varying lengths for free recall. However, rather than having subjects recall the most recent list, he had subjects direct their recall to the list before the most recent list. Remarkably, the probability of recall depended on the length of the target list rather than the length of the intervening list. This suggested a representation of the list *per se* that was used to focus the subjects' retrieval attempts.[2]

But the most dramatic effect in the initiation of free recall is the recency effect manifest in the probability of first recall. The probability of first recall gives the probability that the first word the subject recalls came from each of the positions within the list. When the test is immediate, this measure shows a dramatic advantage for the last items in the list (Figure 8.3a). This, combined with the fact that the recency effect is reduced when a delay intervenes between presentation of the last word and the test (Glanzer & Cunitz, 1966; Postman & Phillips, 1965) led many researchers to attribute the recency effect in immediate free recall to the presence of a short-term memory buffer (e.g., Atkinson & Shiffrin, 1968). However, the recency effect measured in the probability of first recall is present even when the time between the last item in the list and the test is much longer. Similarly, when subjects make errors in free recall by recalling a word from a previous list, the intrusions are more likely for recent lists (Zaromb et al., 2006). The debate among researchers modeling free recall in the last several years has focused on whether these longer-term recency effects depend on a different memory store than the short-term effects (Davelaar, Goshen-Gottstein, Ashkenazi, Haarmann, & Usher, 2005; Lehman & Malmberg, 2012) or if recency effects across time scales reflect a common retrieval mechanism (Sedcrberg et al., 2008; Shankar & Howard, 2012).

CONTEXT AS A CUE FOR RECALL

To solve the problem of initiating recall researchers have appealed to a representation of "context," some information that is not identical to

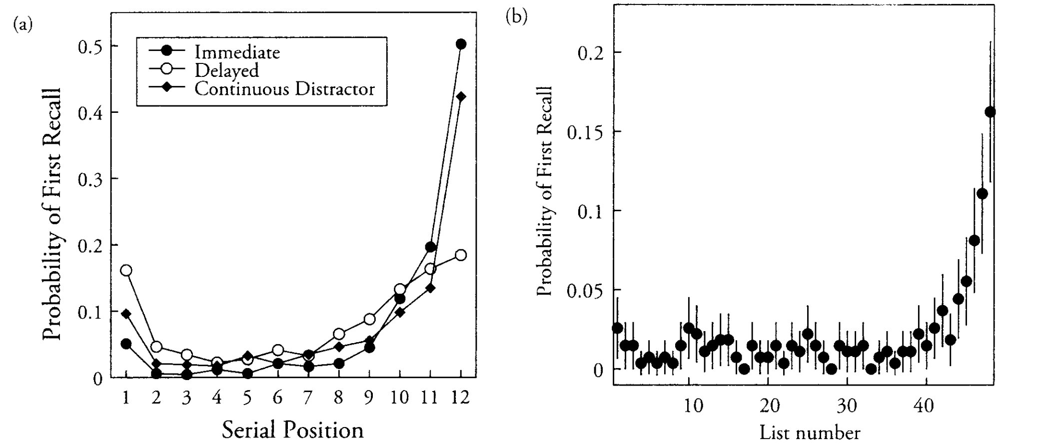

Fig. 8.3 The recency effect in recall initiation across time scales. The probability of first recall gives the probability that the first word the subject free recalls came from each position within the list. **a.** In immediate free recall, the test comes immediately after presentation of the last list item. A dramatic recency effect results. In delayed free recall, a distractor task intervenes after presentation of the last word in the list. The recency effect is sharply attenuated. In continuous distractor free recall, a distractor is presented after the last item, but also between presentation of each item in the list. The recency effect in the probability of first recall recovers. Here the distractor interval was approximately 16 s. After Howard & Kahana (1999). **b.** Subjects studied and recalled 48 lists of words. At the end of the experiment, they recalled all the words they could remember from all lists. Probability of first recall is shown as a function of the list the word came from. Here the recency effect extends over a few hundred seconds. After Howard, Youker, & Venkatadass (2008).

the stimuli composing the list but that nonetheless enables the subject to focus their memory search on a subset of the stimuli that could potentially be generated. Context can function as a cue for retrieval of items from the appropriate list if it is associated to the list stimuli during learning. We can think of a straightforward extension of Eq. 9:

$$\mathbf{M}_i = \mathbf{M}_{i-1} + \mathbf{f}_i \mathbf{c}_i^T, \tag{11}$$

where $\mathbf{c}_i$ the state of the context vector at time step i. The "context" available at the time of test can be used as a probe for recall from memory (Figure 8.4). In much the same way that words in memory were activated to the extent that they were paired with the probe word in Eq. 10, the words in memory will be activated to the extent that the cue context resembles the state of context available when they were encoded.

$$\mathbf{M}_i \mathbf{c} = \sum_i \mathbf{f}_i \left(\mathbf{c}_i^T \mathbf{c} \right), \tag{12}$$

where $\mathbf{c}$ is the context available at the time of test. We can see the power of proposing a context representation from Eq. 12: each studied item $\mathbf{f}_i$ is activated to the extent that its encoding context $\mathbf{c}_i$ overlaps with the probe context.

Obviously, the choice of how context varies has a tremendous effect on the behavioral model that results. One choice is to have the state of context be constant within a list but completely different from the state of context that obtains when one studies the next list. Models that exploit a fixed list context have been successful in describing many detailed aspects of free recall performance (Raaijmakers & Shiffrin, 1980, 1981). If there is a binary difference between the context of each list, then it is not possible to describe recency effects across lists (Glenberg, Bradley, Stevenson, Kraus, Tkachuk, & Gretz, 1980; Howard et al., 2008; Zaromb et al., 2006). Similarly, if the context is constant within a list, then fixed list context cannot be utilized to account for recency effects within the list.

Another choice is to have context change gradually across lists (J. R. Anderson & Bower, 1972), or across time *per se*. Following Estes (1955), Mensink and Raaijmakers (1988) introduced a model of interference effects in paired associate learning where the state of context gradually changed over intervals of time. The state of context at test is the cue for retrieval of words from the list. If the state changes gradually during presentation of the list items, then the state at the time of test will be a better cue for words from the end of the list than for words presented earlier. As a consequence, this produces a recency effect. This approach has been applied to describing the recency effect in free

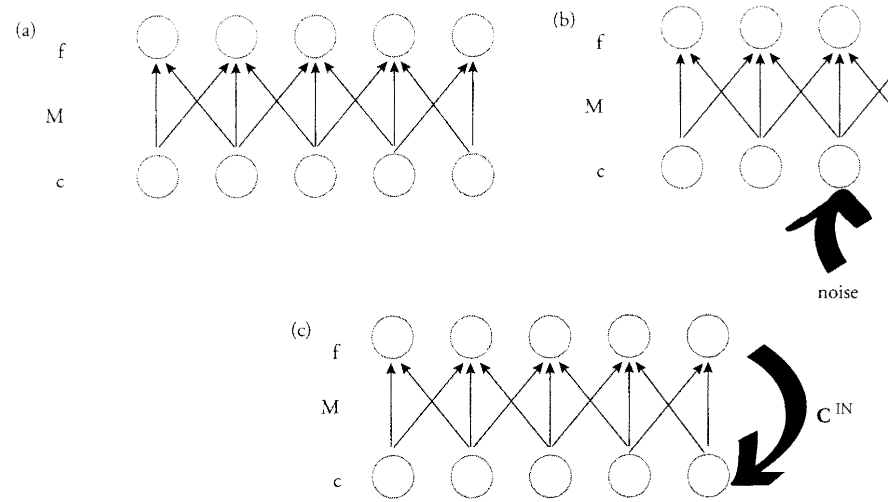

Fig. 8.4 Context as an explanatory concept. **a.** Stimuli **f** are associated to states of context **c**. Compare to Figure 8.2, Eqs. 9, 11. **b.** In contextual variability models, context changes gradually from moment to moment by integrating a source of external noise. See Eq. 13. **c.** In retrieved context models, the changes in context from moment to moment are caused by the input stimuli themselves. Repeating an item can also cause the recovery of a previous state of temporal context. See Eqs. 15, 16.

recall both within and across lists (Davelaar et al., 2005; Howard & Kahana, 1999; Sirotin, Kimball, & Kahana, 2005). If one can arrange for the state of context to change gradually over long periods of time, recency effects can be observed over similarly long periods of time.

Murdock (1997) used a particularly tractable model of variable context that illustrates this idea. At time step *i*, the context representation is updated as

$$\mathbf{c}_i = \rho \mathbf{c}_{i-1} + \sqrt{1-\rho^2}\,\boldsymbol{\eta}_i. \qquad (13)$$

where $\boldsymbol{\eta}_i$ is a vector of random features chosen at time step *i* (Figure 8.4b).

The noise vectors are chosen such that the expectation value of the inner product of any two vectors is zero and the expectation value of the inner product of a noise vector with itself is 1. Now, it is easy to verify that the expectation of the inner product of states of context falls off exponentially:

$$E\left[\mathbf{c}_i{}^T \mathbf{c}_j\right] = \rho^{|i-j|}. \qquad (14)$$

Here we can see that the parameter ρ controls the rate at which context drifts in this formulation. As a consequence, Eq. 13, coupled with Eq. 12 results in an exponentially decaying activation for list items.

EMPIRICAL PROPERTIES OF RECALL TRANSITIONS IN FREE RECALL

After the first recall is generated, transitions from one word to the next also show lawful properties. Broadly speaking, recall transitions show sensitivity both to the study context of the presented words as well as similarities between the words themselves. For instance, given that the subject has just recalled some word from the list, the next word recalled is more likely to be from a nearby position within the list than from a distant position within the list, showing a sensitivity to relationships induced by the study context. Similarly, the subject is more likely to recall a word from the list that is semantically related to the just-recalled word than to recall an unrelated word from the list, showing a sensitivity to the properties of the words themselves.

The tendency to recall words from nearby serial positions in sequence is referred to as the contiguity effect (Kahana, 1996; Sederberg, Miller, Howard, & Kahana, 2010). The contiguity effect is manifest not only in free recall, but in a wide variety of other episodic memory tasks as well (see Kahana, Howard, & Polyn, 2008 for a review). Like the recency effect, the contiguity effect is also manifest across time scales as well (Howard & Kahana, 1999; Howard et al., 2008; Kiliç, Criss, & Howard, 2013). In addition to the sensitivity to the temporal context in which words are studied, subjects' recall transitions also reflect the spatial context in which words were studied. Miller, Lazarus, Polyn, and Kahana (2013) had subjects study a list of objects while traveling on a controlled path within a virtual reality environment

to navigate to different locations where stimuli were experienced. After exploration, free recall of the stimuli was tested. Because the sequence of locations was chosen randomly, the sequential contiguity of the stimuli and the spatial contiguity of the stimuli were decorrelated. At test, the recall transitions that subjects exhibited reflected not only the temporal proximity along the path, but also the spatial proximity within the environment. Moreover, Polyn, Norman, and Kahana (2009a, 2009b) had subjects study concrete nouns using one of two orienting tasks. For some words, subjects would make a rating of its size ("Would this object fit in a shoebox?"); for other words subjects would rate its animacy. Polyn et al. (2009a, 2009b) found that recall transitions between words studied using the same orienting task were more common than transitions between words studied using different orienting tasks.

Because the words in the list are randomly assigned, the preceding effects must reflect new learning during the study episode. In addition, participants' memory search also reflects properties of the words themselves acquired from learning prior to the experimental session. It has long been known that, given that a list including pairs of associated words (TABLE, CHAIR) randomly assigned to serial positions, the pairs are more likely to be recalled together (Bousfield, 1953). This effect generalizes to lists chosen from several categories—when the words are presented randomly, subjects nonetheless organize them into categories during recall (e.g., Cofer, Bruce, & Reicher, 1966). Interestingly, the time taken to retrieve words within a category is faster than the retrieval time necessary to transition from one category to another (Pollio, Kasschau, & DeNise, 1968; Pollio, Richards, & Lucas, 1969). Semantic relatedness is also a major factor affecting recall errors (e.g., Deese, 1959; Roediger & McDermott, 1995). The effect of semantic relatedness on memory retrieval can even be seen when the words do not come from well-defined semantic categories. Semantic similarity can be estimated between arbitrary pairs of words using automatic computational methods such as latent semantic analysis (Landauer & Dumais, 1997) or the word association space (Steyvers, Shiffrin, & Nelson, 2004). There are elevated transition probabilities even between words with relatively low values of semantic similarity (Howard & Kahana, 2002b; Sederberg et al., 2010).

RETRIEVED CONTEXT MODELS

In the previous subsection we saw that many researchers have appealed to a representation of "context" that is distinct from the representations of the words in the list to explain free-recall initiation. We also saw that properties of context could be used to account for recency effects within and across lists if the states of context changed gradually. But a context that is independent of the list items seems like a poor choice to account for transitions between subsequent recalls, which seem to reflect the properties of the items themselves, both learned and pre-experimental.

One approach is to have multiple cues contribute to retrieval. That is, analogous to the Humphreys et al. (1989) model discussed earlier, one could have both direct item-to-item associations, as in Eq. 9, and context-to-item associations, as in Eq. 11. When an item is available, either because it is provided as an experimental cue or because it has been successfully retrieved in free recall, one can use both the item and the context to focus retrieval. These two sources of information can then be combined, perhaps multiplicatively, to select candidate words for recall (Raaijmakers & Shiffrin, 1980, 1981). This approach could readily account for semantic associations if the similarity of the vectors corresponding to different words reflects the semantic similarity between the meaning of those two words (Kimball, Smith, & Kahana, 2007; Sirotin et al., 2005).

One could account for the contiguity effect over shorter time scales *via* direct item-to-item associations if associations are formed in a short-term memory during study of the list. That is, rather than having the two simultaneously presented members of a pair be associated to one another in Eq. 9, one could form associations between all the words simultaneously active in short-term memory. At any one moment during study of the list, the last several items are likely to remain active in short-term memory. As a consequence, a particular word in the list is likely to have strengthened associations to words from nearby positions within the list. Recall of that item would provide a boost in accessibility of other words from nearby in the list. However, in much the same way that short-term memory has difficulty accounting for the recency effect across long time scales, this still leaves the question of how to account for contiguity effects across longer time scales.

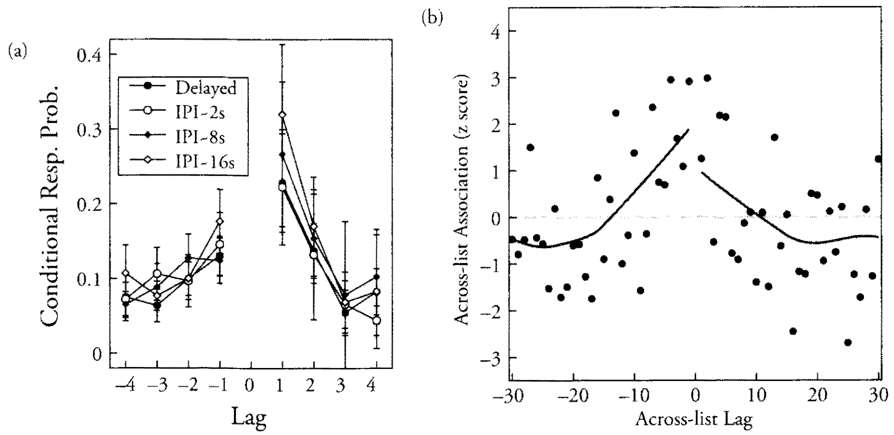

Fig. 8.5 Transitions between words in free recall are affected by the order in which the words were presented. Here the probability of a recall transition from one word to the next is estimated as a function of the distance between the two words. Suppose that the 10th word in the study list has just been recalled. The lag-CRP at position +2 estimates the probability that the next word recalled will be from position 12; the lag-CRP at position −3 estimates the probability that instead the next word recalled will be from position 7. **a.** The lag-CRP is shown for four conditions of a delayed free recall. There was always approximately 16 s between the presentation of the last word and the time of test. The duration of the distractor interval between words (the IPI) was manipulated across conditions. After Howard & Kahana (1999). **b.** Subjects studied and recalled 48 lists of words. At the end of the experiment, they recalled all the words they could remember from all lists. This plot estimates the excess probability of a transition between lists, expressed as a z-score, as a function of the distance between the lists. That is, given that the just-recalled word came from list 10, a list lag of −3 corresponds to a transition to a word from list 7. Here the contiguity effect extends over a few hundred seconds. After Howard et al. (2008).
a. After Howard & Kahana (1999), ©2008, Elsevier; b. After Howard, Youker, & Venkatadass (2008); With kind permission from Springer Science and Business Media.

Retrieved context models address this problem by postulating a coupling between words and a gradually changing state of context. Rather than contextual drift resulting from random fluctuations, context is driven by the presented items. Each word i provides some input $\mathbf{c}_i^{IN}$:

$$\mathbf{c}_i = \rho \mathbf{c}_{i-1} + \sqrt{1-\rho^2}\mathbf{c}_i^{IN}. \qquad (15)$$

For a random list of once-presented words, these inputs are uncorrelated, resulting in contextual drift analgous to Eq. 14. However, because the inputs are caused by the stimuli, the model is able to account for contiguity effects (Figure 8.4c). The key idea enabling the contiguity effect is the assumption that retrieving a word also results in recovery of the state of context in which that word was encoded. That is, if the word presented at time step i is repeated at some later time step r, then

$$\mathbf{c}_r^{IN} = \gamma\, \mathbf{c}_{i-1} + (1-\gamma)\mathbf{c}_i^{IN}. \qquad (16)$$

In addition to the input that stimulus caused when it was initially presented, it also enables recovery of the state of context present when it was presented, $\mathbf{c}_{i-1}$. Because this state resembles the context when neighboring items were presented, a contiguity effect naturally results. If context changes gradually over long periods of time, the contiguity effect naturally persists over those same periods of time (Howard & Kahana, 2002a; Sederberg et al., 2008). Computational models describing details of free recall dynamics, including semantic transition effects have been developed (Sederberg et al., 2008; Polyn et al., 2009a).

AUTONOMOUS SEARCH MODELS

In retrieved context models, retrieval of an item causes recovery of a previous state of temporal context, resulting in the contiguity effect. This is not the only possibility, however. Consider a brief thought experiment. Try to recall as many of the 50 United States as possible (if the reader is unfamiliar with U.S. geography, the experiment should work just as well with any well-learned geographical region with more than a dozen or so entities). Most subjects recall geographically contiguous states (MAINE, VERMONT, NEW HAMPSHIRE ...).[3] Examining the recall protocols, we would observe a spatial analog of a contiguity effect—if the subject has just recalled a word from a particular spatial location, the next word the subject retrieves would also tend to be from a nearby spatial location. However, it is not necessarily the case that remembering one state (Michigan) *caused* recovery of a nearby state (Wisconsin). Rather, both words might have been recalled because the search

happened to encounter a part of the map containing both of those states (the Great Lakes region).

Autonomous search models provide an account of the temporal contiguity effect that is similar in spirit to that described above. In the Davelaar et al. (2005) account of the contiguity effect, retrieving a word has no effect on the state of memory used as a cue for the next retrieval. Rather, a state of context evolves according to some dynamics during study. It is reset to the state at the beginning of the list during recall and evolves according to the same dynamics during recall. Because it tends to revisit states in a similar order, the sequence of retrievals is correlated with the study order. Similarly, Farrell (2012) described temporal contiguity effects as resulting from the retrieval dynamics of hierarchical groups of chunked contexts (see also Ezzyat & Davachi, 2011).

Autonomous search models have difficulty in accounting for genuinely associative contiguity effects. For instance, in cued recall, the experimenter chooses the cue—the fact that the correct pair is retrieved cannot be attributed to autonomous retrieval dynamics. Rather, the cue is utilized to recover the correct trace. The contiguity effect is observed under circumstances where the cue is randomized, eliminating the possibility that correlations between study and retrieval cause the contiguity effect (Kiliç et al., 2013; Howard, Venkatadass, Norman, & Kahana, 2007; Schwartz, Howard, Jing, & Kahana, 2005). The strong form of autonomous models—that memory search is independent of the products of previous memory search—must be false. Nonetheless, the geographical search thought experiment is compelling. A challenge going forward is to mechanistically describe the representations that could support a temporally defined search through memory analogous to the spatial search in the geography thought experiment.

Summary and Conclusions

- A variety of detailed process models of performance have been developed in a variety of episodic memory tasks.
- In recognition, differentiation and Bayesian decision rules have been important steps in advancing our understanding of recognition.
- The major driver of models in recall has been an attempt to understand the nature of the context representation—more broadly what constitutes the cue in free-recall tasks.

Open Problems and Future Directions

- If nothing else, the diversity of models demonstrates that behavioral data alone is not sufficient to result in a consensus model of any of the tasks we have considered, let alone a general theory of episodic memory. Going forward, early steps to use neurobiological constraints on process models of memory (e.g., Criss, Wheeler, & McClelland, 2013; Howard, Viskontas, Shankar, & Fried, 2012; Manning, Polyn, Litt, Baltuch, & Kahana, 2011) must be expanded. The results of these experiments must also affect the hypothesis space of models going forward.
- The textbook definition of episodic memory is the experience of a "jump back in time" such that the subject vividly reexperiences a particular moment from his life. One of the major limitations in constructing models of episodic memory is that we do not have a coherent idea about how to represent time—context in the models we have discussed here may change gradually over time but is nonetheless ahistorical. Richer representations of temporal history (Shankar & Howard, 2012) may be able to provide a more unified approach to episodic memory (Howard, Shankar, Aue, & Criss, in press).
- It is frustrating that there are so many differences between the item recognition models we have discussed and the recall models. The contiguity effect may provide a point of contact that could lead to the unification of these classes of models. Successful recognition of a list item during test seems to leave neighboring items in an elevated state of availability. Schwartz et al. (2005) presented travel scenes for item recognition testing. They systematically manipulated the lag between successively tested old probes. That is, after presenting old item i, they tested old item $i+\text{lag}$. They found that when $|\text{lag}|$ was small, memory for the second old probe was enhanced, but only when subjects endorsed the first probe with high confidence. The recovery of previous states given an old probe has been the focus of connectionist models of recall and recognition (Norman & O'Reilly, 2003; Hasselmo & Wyble, 1997) suggesting a point of contact between mathematical models of memory and connectionist modeling, perhaps *via* dual process assumptions (see Box 1).

Acknowledgments

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Notes

1. For instance amnesia patients with essentially complete loss of episodic memory are typically unimpaired at serial recall of a short list of digits.

2. Recent studies have significantly elaborated this empirical story (Jang & Huber, 2008; Unsworth, Spillers, & Brewer, 2012; Ward & Tan, 2004).

3. Occassionally, subjects will try to recall in alphabetical order (ALABAMA, ALASKA, ARIZONA ...) or according to some other idiosyncratic retrieval strategy, but that is not central to the point.

References

Anderson, J. A. (1973). A theory for the recognition of items from short memorized lists. *Psychological Review, 80(6),* 417–438.

Anderson, J. A., Silverstein, J. W., Ritz, S. A. & Jones, R. S. (1977). Distinctive features, categorical perception, and probability learning: Some applications of a neural model. *Psychological Review, 84,* 413–451.

Anderson, J. R., & Bower, G. H. (1972). Recognition and retrieval processes in free recall. *Psychological Review, 79*(2), 97–123.

Atkinson, R. C., Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. K. W. Spence J. T. Spence (Eds.), *The psychology of learning and motivation* (Vol. 2, p. 89–105). New York, NY: Academic.

Bousfield, W. A. (1953). The occurrence of clustering in the recall of randomly arranged associates. *Journal of General Psychology, 49,* 229–240.

Cary, M., Reder, L. M. (2003). A dual-process account of the list-length and strength-based mirror effects in recognition. *Journal of Memory and Language, 49*(2), 231–248.

Cofer, C. N., Bruce, D. R. & Reicher, G M. (1966). Clustering in Free Recall as a Function of Certain Methodological Variations. *Journal of Experimental Psychology, 71,* 858–866.

Criss, A. H. (2006). The consequences of differentiation in episodic memory: Similarity and the strength based mirror effect. *Journal of Memory and Language, 55*(4), 461–478.

Criss, A. H. (2009). The distribution of subjective memory strength: list strength and response bias. *Cognitive Psychology, 59*(4), 297–319. doi: 10.1016/j.cogpsych.2009.07.003

Criss, A. H. (2010). Differentiation and response bias in episodic memory: evidence from reaction time distributions., *Journal of Experimental Psychology: Learning, Memory, and Cognition, 36*(2), 484–499.

Criss, A. H., Aue, W. R., & Kılıç, A. (2014). Age and response bias: Evidence from the strength based mirror effect. Quarterly *Journal of Experimental Psychology, 67*(10), 1910–1924

Criss. A. H. & Koop, G. J. (in press). Differentiation in Episodic Memory. In Raaijmakers, J., Criss, A. H., Goldstone, R., Nosofsky, R., & Steyvers, M. (Eds.). *Cognitive Modeling in Perception and Memory: A Festschrift for Richard M. Shiffrin.* Psychology Press.

Criss, A. H., Malmberg, K. J. & Shiffrin, R. M. (2011). Output interference in recognition memory. *Journal of Memory and Language, 64,* 316–326.

Criss, A. H., & Shiffrin, R. M. (2004). Context noise and item noise jointly determine recognition memory: a comment on Dennis and Humphreys (2001). *Psychological Review, 111*(3), 800–807.

Criss, A. H., & Shiffrin, R M. (2005). List discrimination in associative recognition and implications for representation, *Journal Experimental Psychology: Learning, Memory and Cogntion, 31*(6), 1199–1212. doi: 10.1037/0278-7393.31.6.1199.

Criss, A. H., Wheeler, M. E., McClelland, J. L. (2013). A differentiation account of recognition memory: evidence from fmri. *Journal of Cognitive Neuroscience, 25*(3), 421–35. doi: 10.1162/jocn_a_00292

Davelaar, E. J., Goshen-Gottstein, Y., Ashkenazi, A., Haarmann, H. J., & Usher, M. (2005). The demise of short-term memory revisited: empirical and computational investigations of recency effects. *Psychological Review, 112*(1), 3–42.

DeCarlo, L. T. (2003). Source monitoring and multivariate signal detection theory, with a model for selection. *Journal of Mathematical Psychology, 47,* 292–303.

Deese, J. (1959). On the prediction of occurrence of particular verbal intrusions in immediate recall. *Journal of Experimental Psychology, 58,* 17–22.

Dennis, S., & Humphreys, M. S. (2001). A context noise model of episodic word recognition. *Psychological Review, 108*(2), 452–478.

Dennis, S., Lee, M. D., & Kinnell, A. (2008). Bayesian analysis of recognition memory: The case of the list-length effect. *Journal of Memory and Language, 59*(3), 361–376.

Diller, D. E., Nobel, P. A., & Shiffrin, R. M. (2001). An ARC-REM model for accuracy and response time in recognition and recall. *Journal Experimental Psychology: Learning, Memory and Cogntion, 27*(2), 414–35.

Estes, W. K. (1955). Statistical theory of spontaneous recovery and regression. *Psychological Review, 62,* 145–154.

Ezzyat, Y., & Davachi, L. (2011). What constitutes an episode in episodic memory?. *Psychological Science, 22*(2), 243–52. doi: 10.1177/0956797610393742

Farrell, S. (2012). Temporal clustering and sequencing in short-term memory and episodic memory. *Psychological Review, 119*(2), 223–71. doi: 10.1037/a0027371

Fortin, N. J., Agster, K. L. & Eichenbaum, H. B. (2002). Critical role of the hippocampus in memory for sequences of events. *Nature Neuroscience, 5*(5), 458–62.

Gillund, G. & Shiffrin, R. M. (1984), A retrieval model for both recognition and recall. *Psychological Review, 91,* 1–67.

Glanzer, M., & Adams, J. K. (1985). The mirror effect in recognition memory. *Memory & Cognition, 13*(1), 8–20.

Glanzer, M., & Adams, J K. (1990). The mirror effect in recognition memory: data and theory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*(1), 5–16.

Glanzer, M., & Cunitz, A. R. (1966). Two storage mechanisms in free recall. *Journal of Verbal Learning and Verbal Behavior, 5,* 351–360.

Glanzer, M., Adams, J. K., Iverson, G. J., & Kim, K. (1993). The regularities of recognition memory. *Psychological Review, 100,* 546–567.

Glenberg, A. M., Bradley, M. M., Stevenson, J. A., Kraus, T. A., Tkachuk, M. J., & Gretz, A. L. (1980). A two-process account of long-term serial position effects. *Journal of Experimental Psychology: Human Learning and Memory, 6,* 355–369.

Hasselmo, M. E., & Wyble, B. P. (1997). Free recall and recognition in a network model of the hippocampus: simulating effects of scopolamine on human memory function. *Behavioural Brain Research, 89*(1–20 1–34.

Hintzman, D. L. (1984). MINERVA 2: A simulation model of human memory. *Behavior Research Methods, Instruments & Computers, 16*(2), 96–101.

Hintzman, D. L. (1986). "Schema abstraction" in a multiple-trace memory model. *Psychological Review, 93,* 411–428.

Hintzman, D. L., & Curran, T. (1994). Retrieval dynamics of recognition and frequency judgements: Evidence for separate processes of familiarity and recall. *Journal of Memory and Language, 33,* 1–18.

Howard, M. W., & Kahana, M. J. (1999). Contextual variability and serial position effects in free recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25,* 923–941.

Howard, M. W., & Kahana, M. J. (2002a). A Distributed Representation of Temporal Context. *Journal of Mathematical Psychology, 46*(3), 269–299.

Howard, M. W., & Kahana, M. J. (2002b). When does semantic similarity help episodic retrieval?. *Journal of Memory and Language, 46*(1), 85–98.

Howard, M. W., Shankar, K. H., Aue, W., & Criss, A H. (in press). A distributed representation of internal time. *Psychological Review.* doi: 10.1037/a0037840

Howard, M. W., Venkatadass, V., Norman, K. A., & Kahana, M. J. (2007). Associative processes in immediate recency. *Memory & Cognition, 35,* 1700–1711.

Howard, M. W., Viskontas, I. V., Shankar, K. H., & Fried, I. (2012). A neural signature of mental time travel in the human MTL. *Hippocampus, 22*(PMC3407826), 1833–1847.

Howard, M. W., Youker, T. E., & Venkatadass, V. (2008). The persistence of memory: Contiguity effects across several minutes. *Psychonomic Bulletin & Review, 15,* 58–63.

Humphreys, M. S., Bain, J. D., & Pike, R. (1989). Different ways to cue a coherent memory system: A theory for episodic, semantic, and procedural tasks. *Psychological Review, 96,* 208–233.

Jang, Y., & Huber, D. E. (2008). Context retrieval and context change in free recall: recalling from long-term memory drives list isolation. *Journal Experimental Psychology: Learning, Memory and Cogntion, 34*(1), 112–127. doi: 10.1037/0278-7393.34.1.112

Kahana, M. J. (1996). Associative retrieval processes in free recall. *Memory & Cognition, 24,* 103–109.

Kahana, M. J., Howard, M., & Polyn, S. (2008). Associative Processes in Episodic Memory. In H. L. Roediger III (Ed.), *Cognitive psychology of memory, Vol. 2 of Learning and Memory – A Comprehensive Reference (J. Byrne, Editor)* (p. 476–490). Oxford Elsevier.

Kili c, A., Criss, A. H., & Howard, M. W. (2013). A causal contiguity effect that persists across time scales. *Journal Experimental Psychology: Learning, Memory and Cogntion, 39*(1), 297–303. doi: 10.1037/a0028463

Kimball, D. R., Smith, T. A. & Kahana, M. J. (2007). The fSAM model of false recall. *Psychological Review, 114*(4), 954–993.

Klauer, K. C., & Kellen, D. (2010). Toward a complete decision model of item and source recognition: A discrete-state approach. *Psychonomic Bulletin & Review, 17* 465–478.

Koop, G. J., Criss, A. H., & Malmberg, K. J. (in press). The role of mnemonic processes in pure-target and pure-foil recognition memory. *Psychonomic Bulletin & Review.*

Landauer, T. K., Dumais, S. T. (1997). Solution to Plato's problem : The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review, 104,* 211–240.

Lehman, M., & Malmberg, K. J. (2012). A Buffer Model of Memory Encoding and Temporal Correlations in Retrieval. *Psychological Review.* doi: 10.1037/a0030851

Malmberg, K. J. (2002). On the form of ROCs constructed from confidence ratings. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 28*(2), 380–387.

Malmberg, K. J., Criss, A. H., Gangwani, T. H., & Shiffrin, R. M. (2012). Overcoming the negative consequences of interference from recognition memory testing. *Psychological Science, 23*(2), 115–119. doi: 10.1177/0956797611430692

Malmberg, K. J., Holden, J. E., & Shiffrin, R. M. (2004). Modeling the effects of repetitions, similarity, and normative word frequency on old-new recognition and judgments of frequency. *Journal Experimental Psychology: Learning, Memory and Cogntion, 30*(2), 319–331.

Malmberg, K. J., & Shiffrin, R. M. (2005). The "one-shot" hypothesis for context storage. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31*(2), 322–336.

Manning, J. R., Polyn, S. M., Litt, B., Baltuch, G., & Kahana, M. J. (2011). Oscillatory patterns in temporal lobe reveal context reinstatement during memory search. *Proceedings of the National Academy of Science, USA, 108*(31), 12893–12897.

McClelland, J. L., & Chappell, M. (1998). Familiarity breeds differentiation: a subjective-likelihood approach to the effects of experience in recognition memory. *Psychological Review, 105*(4), 724–760.

Mensink, G. J. M., Raaijmakers, J. G. W. (1988). A model for interference and forgetting. *Psychological Review, 95,* 434–55.

Miller, J. F., Lazarus, E. M., Polyn, S. M., & Kahana, M. J. (2013). Spatial clustering during memory search. *Journal Experimental Psychology: Learning, Memory and Cogntion, 39*(3), 773–781. doi: 10.1037/a0029684

Murdock, B. B. (1982). A theory for the storage and retrieval of item and associative information. *Psychological Review, 89,* 609–626.

Murdock, B. B. (1997). Context and mediators in a theory of distributed associative memory (TODAM2). *Psychological Review, 104*(2), 839–862.

Murdock, B. B., & Anderson, R. E. (1975). Encoding, storage and retrieval of item information. R L. Solso (Ed.), *Information Processing and Cognition: The Loyola Symposium* (p. 145–194). Hillsdale, New Jersey: Erlbaum.

Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (1990). Encoding context and retrieval conditions as determinants of the effects of natural category size. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*(1), 31–41.

Norman, K. A., & O'Reilly, R. C. (2003). Modeling hippocampal and neocortical contributions to recognition memory: a complementary-learning-systems approach. *Psychological Review, 110*(4), 611–646.

Ohrt, D. D., & Gronlund, S. D. (1999). List-length Effects and Continuous memory: Confounds and Solutions. C. Izawa (Ed.), *On Human Memory: Evolution, Progress, and Reflections on the 30th Anniversary of the Atkinson-Shiffrin Model* (p. 105–125). Mahwah, NJ: Erlbaum.

Phillips, J. L., Shiffrin, R. J., & Atkinson, R. C. (1967). The effects of list length on short-term memory. *Journal of Verbal Learning and Verbal Behavior, 6,* 303–311.

Pollio, H. R., Kasschau, R. A., & DeNise, H. E. (1968). Associative structure and the temporal characteristics of free recall. *Journal of Verbal Learning and Verbal Behavior, 10,* 190–197.

Pollio, H. R., Richards, S., & Lucas, R. (1969). Temporal properties of category recall. *Journal of Verbal Learning and Verbal Behavior, 8,* 529–536.

Polyn, S. M., Norman, K. A., & Kahana, M. J. (2009a). A context maintenance and retrieval model of organizational processes in free recall. *Psychological Review, 116,* 129–156.

Polyn, S. M., Norman, K. A., & Kahana, M. J. (2009b). Task context and organization in free recall. *Neuropsychologia, 47*(11), 2158–2163.

Postman, L., & Phillips, L. W. (1965). Short-term temporal changes in free recall. *Quarterly Journal of Experimental Psychology, 17,* 132–138.

Province, J. M., & Rouder, J. N. (2012). Evidence for discrete-state processing in recognition memory. *Proceedings of the National Academy of Sciences USA, 109*(36), 14357–14362. doi: 10.1073/pnas.1103880109

Raaijmakers, J. G. W., & Shiffrin, R. M. (1980). SAM: A theory of probabilistic search of associative memory. G H. Bower (Ed), The psychology of learning and motivation: Advances in research and theory (Vol. 14, p. 207–262). New York: Academic.

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

Ratcliff, R., Clark, S. E., & Shiffrin, R. M. (1990). List-strength effect: I. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16,* 163–178.

Roediger, H. L., & McDermott, K. B. (1995). Creating false memories: remembering words not presented in lists. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21,* 803–814.

Roediger, H. L., & Schmidt, S. R. (1980). Output interference in the recall of categorized and paired-associate lists. *Journal of Experimental Psychology: Human Learning and Memory, 6*(1), 91–102.

Rotello, C. M., Macmillan, N. A., Reeder, J. A., & Wong, M. (2005). The remember response: subject to bias, graded, and not a process-pure indicator of recollection. *Psychonomic Bulletin & Review, 12*(5), 865–873.

Rugg, M. D., & Curran, T. (2007). Event-related potentials and recognition memory. *Trends in Cognitive Science, 11*(6), 251–257.

Schooler, L. J., Shiffrin, R. M., & Raaijmakers, J. G. (2001). A Bayesian model for implicit effects in perceptual identification. *Psychological Review, 108*(1), 257–272.

Schwartz, G., Howard, M. W., Jing, B., & Kahana, M. J. (2005). Shadows of the past: Temporal retrieval effects in recognition memory. *Psychological Science, 16*(11), 898–904.

Sederberg, P. B., Howard, M. W., & Kahana, M. J. (2008). A context-based theory of recency and contiguity in free recall. *Psychological Review, 115,* 893–912.

Sederberg, P. B., Miller, J. F., Howard, M. W., & Kahana, M. J. (2010). The temporal contiguity effect predicts episodic memory performance. *Memory & Cognition, 38,* 689–699.

Shankar, K. H., & Howard, M. W. (2012). A scale-invariant representation of time. *Neural Computation, 24,* 134–193.

Shiffrin, R. M. (1970). Forgetting: Trace erosion or retrieval failure?. *Science, 168,* 1601–1603.

Shiffrin, R. M., Huber, D. E., & Marinelli, K. (1995). Effects of category length and strength on familiarity in recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*(2), 267–287.

Shiffrin, R. M., Ratcliff, R., & Clark, S. E. (1990). List-strength effect: II. Theoretical mechanisms. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*(2), 179–195.

Shiffrin, R. M. & Steyvers, M. (1997). A Model for Recognition Memory: REM — Retrieving Effectively From Memory. *Psychonomic Bulletin and Review, 4,* 145–166.

Sirotin, Y. B., Kimball, D. R., Kahana, M. J. (2005). Going beyond a single list: Modeling the effects of prior experience on episodic free recall. *Psychonomic Bulletin & Review, 12,* 787–805.

Staresina, B. P., Fell, J., Dunn, J. C., Axmacher, N., & Henson, R. N. (2013). Using state-trace analysis to dissociate the functions of the human hippocampus and perirhinal cortex in recognition memory. *Proceedings of the National Academy of Sciences, 110*(80), 3119–24. doi: 10.1073/pnas.1215710110

Starns, J. J., White, C. N., & Ratcliff, R. (2010). A direct test of the differentiation mechanism: REM, BCDMEM, and the strength-based mirror effect in recognition memory. *Journal of Memory and Language, 63*(1), 18–34.

Steyvers, M., Shiffrin, R. M., Nelson, D. L. (2004). Word association spaces for predicting semantic similarity effects in episodic memory. A. Healy (Ed.), *Experimental Cognitive Psychology and its Applications: Festschrift in Honor of Lyle Bourne, Walter Kintsch and Thomas Landauer* (pp. 237–249). Washington, D.C.: American Psychological Association.

Stretch, V., & Wixted, J T. (1998). On the difference between strength-based and frequency-based mirror effects in recognition memory. Journal Experimental Psychology: Learning, Memory and Cogntion, *24*(6), 1379–1396.

Tehan, G., & Humphreys, M. S. (1996). Cuing effects in short-term recall. *Memory & Cognition, 24*(6), 719–732.

Tulving, E. (1972). Episodic and semantic memory. E. Tulving & W. Donaldson (Ed.), Organization of Memory. (pp. 381–403). New York: Adademic.

Tulving, E. (1983). *Elements of episodic memory*. New York, NY: Oxford University Press.

Tulving, E. (2002). Episodic memory: from mind to brain. *Annual Review of Psychology, 53,* 1–25.

Tulving, E., & Arbuckle, T. (1963). Sources of intratrial interference in immediate recall of paired associates. *Journal of Verbal Learning and Verbal Behavior, 1*(5), 321–334.

Tulving, E., & Arbuckle, T Y. (1966). Input and output interference in short-term associative memory. *Journal of Experimental Psychology, 72,* 145–150.

Unsworth, N., Spillers, G. J., & Brewer, G. A. (2012). Evidence for noisy contextual search: examining the dynamics of list-before-last recall. *Memory, 20*(1), 1–13. doi: 10.1080/09658211.2011.626430

Ward, G., & Tan, L. (2004). The effect of the length of to-be-remembered lists and intervening lists on free recall: a reexamination using overt rehearsal. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30*(6), 1196–1210.

Wickens, D. D., Born, D. G. & Allen, C. K. (1963). Proactive inhibition and item similarity in short-term memory. *Journal of Verbal Learning and Verbal Behavior, 2*(5), 440–445.

Wilding, E. L., Doyle, M. C., & Rugg, M. D. (1995). Recognition memory with and without retrieval of context: an event-related potential study. *Neuropsychologia, 33*(6), 743–767.

Wixted, J. T. (2007). Spotlighting the Probative Findings: Reply to Parks and Yonelinas (2007). *Psychological Review, 114,* 203–209.

Wixted, J. T., & Squire, L. R. (2011). The familiarity/recollection distinction does not illuminate medial temporal lobe function: response to Montaldi and Mayes. *Trends in Cognitive Sciences, 15*(8), 340–1. doi: 10.1016/j.tics.2011.06.006

Yonelinas, A. P., & Parks, C. M. (2007). Receiver operating characteristics (ROCs) in recognition memory: a review. *Psychological Bulletin, 133*(5), 800–832.

Zaromb, F. M., Howard, M. W., Dolan, E. D., Sirotin, Y. B., Tully, M., Wingfield, A., & Kahana, M. J. (2006). Temporal associations and prior-list intrusions in free recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 32,* 792–804.