

Encyclopedia of Cognitive Science

Computational Models of Episodic Memory

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Kenneth A. Norman

Department of Psychology

University of Colorado, Boulder

345 UCB

Boulder, CO 80309

phone: (303) 492-2269

fax: (303) 492-2967

email: norman@psych.colorado.edu

I. Headword

Computational Models of Episodic Memory

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III. Contents list

Abstract models of episodic memory

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IV. Article Definition

Computational models of episodic memory constitute mechanistically explicit theories of how we recall previously experienced events, and how we recognize stimuli as having been encountered previously. Because these models concretely specify the algorithms that govern recall and recognition, researchers can run computer simulations of these models to explore how (according to a particular model) different manipulations will affect recall and recognition performance.

V. Introduction

Episodic memory refers to our ability to remember specific, previously experienced events: We can *recall* (i.e., mentally re-create) previously experienced events, and we can *recognize* a stimulus as having been encountered previously. From a computational standpoint, the unifying feature of episodic memory tests is the need to isolate the memory trace corresponding to the to-be-remembered (*target*) event. Recall tests ask subjects to isolate the target event's memory trace in order to retrieve some missing detail, and recognition tests ask subjects to assess whether the target event is actually stored in

memory. On both recall and recognition tests, good performance is contingent on the system's ability to screen out the effects of non-target memory traces.

Computational models of episodic memory can be divided into two categories: *abstract* and *biological*. Abstract models make claims about the "mental algorithms" that support recall and recognition judgments, without addressing how these algorithms might be implemented in the brain. The primary goal of these models is to account for challenging patterns of behavioral recall and recognition data from list learning paradigms (where stimuli are presented as part of a well-defined "study episode"; then, subjects are asked to recall specific events from the study episode, or to discriminate between stimuli that were and were not presented during that episode). Biological models, like abstract models, make claims about the computations that support recall and recognition judgments; the main difference is that they also make specific claims about how the brain gives rise to these computations. This brain-model mapping provides an extra source of constraints on the model's behavior.

VI. Main Text

1. Abstract models

Abstract *global matching* memory models take a unified approach to recognition and recall. There are several different global matching models; this article will focus on a single, representative model (MINERVA 2; Hintzman, 1988; see Clark & Gronlund, 1996, for an explanation of differences between the various models). MINERVA 2 (M2) represents each study list item as a vector where each element equals 1, -1, or 0. Each element corresponds to a particular feature that may or may not be

present in that item; a 1 value indicates that the feature is present, a -1 value indicates that the feature is absent, and a 0 value indicates that the feature value is unknown. Thus, the vectors corresponding to different items will overlap (i.e., have the same value for a particular vector element) to the extent that they consist of the same features. M2 posits that the vectors corresponding to different studied items are stored separately in memory (but see Murdock, 1993, for an example of an abstract model that posits that memory traces are stored in a composite fashion; Murdock's TODAM model stores items by adding together vectors corresponding to different items). When an item is presented at test, M2 computes how well the test item vector matches all of the different vectors stored in memory. On recognition tests, M2 sums together all of these individual match scores to get a "global match" (*familiarity*) score; recognition decisions are made by comparing familiarity scores to a criterion value -- i.e., respond "studied" if an item's familiarity score exceeds the criterion value, respond "nonstudied" otherwise. M2 implements recall by computing a weighted average of all of the items stored in memory, where each item is weighted by its match to the test probe. Thus, M2 generates a *vector* output on recall tests and a *scalar* output on recognition tests, but both recall and recognition depend on the same underlying match computation.

1.1. How match is computed

In global match models like M2, the match computation weights multiple matches to the same trace more highly than the same total number of feature matches, spread across multiple memory traces (e.g., a test cue that matches two features of one item yields a higher familiarity signal than a test cue that matches one feature each of two items). Put another way: The match computation is sensitive to whether the features of the test probe were studied together (vs. separately). M2's match computation

achieves this *sensitivity to conjunctions* by first computing the dot product of the cue vector and each memory trace vector (this gives the proportion of matching features minus the proportion of mismatching features for each memory trace) and then cubing the dot product score for each trace; finally, M2 adds together the cubed match scores to get the familiarity score for that cue. This algorithm yields sensitivity to conjunctions insofar as matches spread across multiple stored traces are combined in an additive fashion, but -- because of the cube rule -- multiple matches to a single trace are combined in a positively accelerated fashion.

Sensitivity to conjunctions ensures that one strong match outweighs the effects of several weak matches. Given the fact that different episodes share features to some extent, it is inevitable that test probes will match at least one feature from several memory traces other than the target trace. In models that lack sensitivity to conjunctions, these small matches -- in aggregate -- would swamp the one large match score associated with the target trace. Figure 1 illustrates how sensitivity to conjunctions (implemented using the cube rule) helps reduce interference in M2.

Insert Figure 1 about here

1.2. Modeling interference data

1.2.1 List length effects

While sensitivity to conjunctions minimizes interference caused by low amounts of cue-trace overlap, there is no way to completely eliminate interference caused by higher amounts of cue-trace overlap. There will always be non-target memory traces that, by chance, match the test probe strongly; these strong, spurious matches add noise to the global match signal and degrade performance. All global matching models predict that adding new items to the list (increasing *list length*) will impair both recognition and recall, by increasing the odds that a strong (but spurious) match will occur. In keeping with this prediction, a very large number of studies have obtained list length effects for recognition and recall, although it is becoming clear that list length effects are not always obtained for recognition (see Dennis & Humphreys, 2001, for discussion of this issue).

1.2.2 Modeling the null list strength effect

One finding that global match models initially failed to predict is the null list strength effect (*LSE*) for recognition: Ratcliff, Clark, & Shiffrin (1990) found that strengthening some list items, by presenting them repeatedly or for a longer duration, does not impair recognition of other (non-strengthened) list items. In models like M2, strengthening is operationalized by storing extra copies of an item to memory, or by increasing the probability of successful feature encoding. Both of these manipulations increase the global match score triggered by the strengthened item (thereby allowing the model to accommodate the finding that strengthening an item improves memory for that item). However, strengthening an item's memory trace also increases the mean and variance of the global match signal triggered by *other* items (intuitively: random, spurious match between the test probe and memory trace X has a larger effect on the global match signal when X is *strong* vs. when X is *weak*); this increase in variance leads to decreased recognition performance.

Researchers have been working from 1990 to the present to modify global matching models so they can accommodate the null recognition LSE obtained by Ratcliff et al. (1990). One promising approach to modeling the null LSE has been to posit that *differentiation* occurs as a consequence of strengthening (Shiffrin, Ratcliff, & Clark, 1990); the gist of differentiation is that -- as participants acquire experience with an item -- the item's representation becomes increasingly refined, making it less likely that it will spuriously match some other item at test.

One example of an abstract model that incorporates differentiation is the REM model described by Shiffrin & Steyvers (1997; see McClelland & Chappell, 1998, for a similar model). REM uses a "match" rule, based on Bayesian statistics, that computes the odds that the test probe and the stored trace are the *exact same item*. With this rule, a small amount of mismatch can have a very large effect; if you are certain that a memory trace contains a particular feature, and you are certain that the test probe does *not* contain that feature, the match value will be zero. In REM, strengthening a memory trace increases the number of encoded features; strong traces are less likely to trigger a spurious match because they are more likely to contain features that mismatch the test probe. Figure 2 illustrates this point.

Insert Figure 2 about here

1.2.3 Single-process vs. dual-process approaches

An important feature of abstract global match models is that they attempt to explain recognition performance entirely in terms of the scalar familiarity signal. This *single-process* approach contrasts with *dual-process* theories of recognition, which posit that both familiarity and recall contribute to

recognition performance (i.e., items can be called "old" because they trigger a nonspecific feeling of familiarity, or because the subject specifically recalls some detail from when the item was studied). Furthermore, the most prevalent dual-process theory (Jacoby, Yonelinas, & Jennings, 1997) posits that the operating characteristics of familiarity and recall are qualitatively distinct; according to this theory, familiarity is a signal-detection process (i.e., studied-item and lure familiarity are both normally distributed, and the two distributions overlap extensively) but recall is a high-threshold process (i.e., recall is all-or-none; studied items are sometimes called "old" based on recall, but lure items are never called "old" based on recall). Note that recall can be applied to recognition in abstract models like M2 (e.g., by cuing with the test item and the comparing the recalled vector to the test item -- if they match above a certain threshold, say "old"). However, recall-based recognition and familiarity-based recognition have very similar operating characteristics in abstract models, because they are based on the same underlying match computation; as such, adding a recall process typically does not affect these models' recognition predictions. The only time that adding recall affects these models' performance is on recognition tests where some kind of content has to be retrieved (e.g., an exclusion test, where subjects have to say "old" to studied words from one list and "new" to studied words from another list). Also, some models derive different predictions for recall and familiarity based on the assumption that subjects cue memory differently when they are trying to recall items (i.e., they are more likely to incorporate context into the retrieval cue; Shiffrin et al., 1990); however, this is not a difference between recall and familiarity per se.

It would be possible to build an abstract model that uses different match rules for recall and familiarity-based recognition, in keeping with the idea that these systems have distinct operating characteristics. This has not occurred because, once recall and familiarity are allowed to use different match rules, it is unclear how to constrain these (separate) systems based purely on behavioral data.

Extant techniques for measuring the separate contributions of recall and familiarity to behavioral recognition performance are controversial because they rely on assumptions about the properties of recall and familiarity that can not be tested empirically (e.g., that recall and familiarity are stochastically independent; for more on these techniques, see Jacoby et al., 1997).

2. Biological models

One way to further constrain dual-process models is to incorporate information about how recall and familiarity are computed in the brain. Biological models of episodic memory, like abstract models, try to account for the widest possible range of behavioral findings; however, unlike abstract models, biological models incorporate explicit claims about how the brain gives rise to recognition. Biological models of episodic memory have focused largely on the hippocampus, because neuropsychological data unequivocally indicates that the hippocampus is necessary for recall.

2.1. Modeling hippocampal contributions to episodic memory

Over the past decade, several researchers have developed biologically detailed computational models of the hippocampus, with the goal of explaining how the hippocampus contributes to episodic memory (e.g., Norman & O'Reilly, under review; Hasselmo & Wyble, 1997). The aforementioned models all view the hippocampus as a machine that is specialized for rapidly storing patterns of cortical activity ("episodes") in a manner that minimizes interference and allows for *pattern completion*: subsequent recall of entire stored patterns in response to partial cues. Furthermore, these models make similar -- albeit not identical -- claims about how different hippocampal substructures contribute to this

process. This article will focus on the Norman & O'Reilly Complementary Learning Systems (*CLS*) neural network model, which has a hippocampal component (described in this section) and a cortical component (described in the next section); a schematic diagram of the CLS hippocampal network is shown in Figure 3.

Insert Figure 3 about here

In the CLS model, the hippocampal network binds together sets of co-occurring neocortical features (corresponding to a particular episode) by linking co-active units in entorhinal cortex (*EC* -- the neocortical region that serves as a gateway to the hippocampus) to a cluster of units in region CA3 of the hippocampus; these CA3 units serve as the hippocampal representation of the episode. Recurrent connections between active CA3 units are strengthened. To allow for recall, active CA3 units are linked back to the original pattern of cortical activity via region CA1. Learning in the model occurs according to a Hebbian rule whereby connections between units are strengthened if both the sending and receiving units are active, and connections are weakened if the receiving unit is active but the sending unit is not.

At test, when a partial version of a stored EC pattern is presented to the hippocampal model, the model is capable of reactivating the entire CA3 pattern corresponding to that item because of learning that occurred at study; activation then spreads from the item's CA3 back to the item's EC representation (via CA1). In this manner, the hippocampus manages to retrieve a complete version of the EC pattern in response to a partial cue.

To minimize interference between episodes, the hippocampus has a built-in bias to assign relatively non-overlapping (*pattern separated*) CA3 representations to different episodes. Pattern separation occurs because hippocampal units are sensitive to conjunctions of neocortical features; given two neocortical patterns with 50% feature overlap, the probability that a particular conjunction of features will be present in both patterns is much less than 50% (see O'Reilly & McClelland, 1994, for a much more detailed treatment of pattern separation in the hippocampus, and for discussion of the role of the dentate gyrus in facilitating pattern separation). The hippocampal model is sensitive to conjunctions because it uses *sparse* representations (where this sparseness is enforced by inhibitory competition); in the model, a given input pattern only activates about 4% of the units in CA3. Inhibitory competition forces units to compete to represent input patterns, and units that are sensitive to multiple features of a given input pattern (i.e., feature conjunctions) are more likely to win the competition than units that are only sensitive to single input features.

A key property of neural network models is that some degree of structural interference between memory traces at storage is inevitable, assuming that there is overlap between memory traces (i.e., different items activate the same units). Whenever there is overlap, sensitivity to features that are shared across items increases, but sensitivity to features that are unique to specific items decreases. Pattern separation mechanisms in the hippocampus reduce structural interference (effectively preventing *catastrophic interference*, where studying new items totally wipes out stored memory traces) but do not eliminate interference entirely. The view that degradation is inevitable contrasts strongly with models like MINERVA 2 and REM, which posit that memory traces with overlapping features can be stored separately, with no structural degradation (but do not explain how this could come about).

The raw output of the CLS hippocampal model is a vector comprised of recalled information. Norman & O'Reilly (under review) apply the model to recognition by comparing the output vector

(recall) to the input vector. If recalled information matches the test probe, this constitutes evidence that the test probe was studied; if recalled information mismatches the test probe, this is evidence that the test probe was not studied; specifically, Norman & O'Reilly compute a recall score equal to the number of matching features minus the number of mismatching features. While the hippocampal model shows good recognition discrimination in standard list-learning paradigms, there are several findings in the recognition literature that the hippocampal model, taken by itself, can not explain. For example, the hippocampal model tends to underpredict false recognition. Because of pattern separation, test cues have to overlap strongly with studied patterns in order to activate the CA3 representations of these studied patterns (thereby triggering recall); as such, the hippocampal model predicts that the memory signal triggered by nonstudied lure items should be at floor, unless lures are highly similar to studied items. This prediction conflicts with the finding that false recognition rates are typically well above floor in list-learning experiments.

2.2. Modeling neocortical contributions to episodic memory

One way to accommodate these issues with the hippocampal model is to argue that the hippocampus is not the only structure that contributes to recognition memory. Consistent with this view, neuropsychological data indicates that *medial temporal neocortex* (MTLC) also contributes to recognition -- patients with hippocampal damage but spared MTLC perform well above chance on recognition tests. Norman & O'Reilly (under review) have also constructed a neural network model of MTLC to explore how this structure contributes to recognition memory. In keeping with the complementary learning systems view set forth by McClelland, McNaughton, & O'Reilly (1995), Norman & O'Reilly posit that the primary function of neocortex (including MTLC) is to integrate across

episodes to learn about the statistical structure of the environment. In contrast to the hippocampal model, which is biased to assign distinct representations to episodes and uses a large learning rate (thereby allowing it to quickly memorize individual episodes), the MTLC model assigns overlapping representations to similar episodes (thereby allowing it to represent what these episodes have in common) and uses a relatively small learning rate.

A schematic diagram of the MTLC model is shown in Figure 4. Because cortex uses a small learning rate, it is not capable of pattern completion (recall) following limited exposure to a stimulus. However, it is possible to extract a scalar signal from the MTLC model that reflects stimulus familiarity: In the MTLC model, as items are presented repeatedly, their representations in MTLC become *sharper*: Novel stimuli weakly activate a large number of MTLC units, whereas familiar (previously presented) stimuli strongly activate a relatively small number of units. Sharpening occurs because Hebbian learning specifically tunes some MTLC units to represent the stimulus. When a stimulus is first presented, some MTLC units, by chance, will respond more strongly to the stimulus than other units; these units get tuned by Hebbian learning to respond even more strongly to the item then next time it is presented; and these strongly active units start to inhibit units that are less strongly active. To index representational sharpness -- and through this, stimulus familiarity -- we measure the average activity of the MTLC units that win the competition to represent the stimulus. Because there is more overlap between representations in MTLC than in the hippocampus, the MTLC signal has very different operating characteristics than the hippocampal recall signal. Whereas lures rarely trigger hippocampal recall, Norman & O'Reilly (under review) showed that the MTLC signal tracks, in a graded fashion, how similar the test probe is to studied items.

Insert Figure 4 about here

2.3. Some predictions of the CLS model

2.3.1. Effects of hippocampal lesions

Because the CLS model maps clearly onto the brain, it is possible to use the model to address neuroscientific data in addition to (purely) behavioral data. For example, the model makes predictions about how different kinds of medial temporal lesions will affect episodic memory. One prediction is that hippocampal lesions should impair performance on yes-no recognition tests with *related lures* (i.e., lures that are similar to specific studied items) more so than on tests with *unrelated lures*. When lures are not highly similar to studied items, both systems (MTLC and hippocampus) discriminate well, but when lures are similar to studied items the hippocampus outperforms MTLC because of its ability to assign distinct representations to similar stimuli, and its ability to reject lures when they trigger recall that *mismatches* the test probe. For evidence in support of this prediction see Holdstock et al. (in press).

2.3.2. Interference: A challenge for biological models

While the biological approach to episodic memory modeling has led to new insights into episodic memory (and the brain basis thereof), this approach faces several challenges. One major challenge is accounting for the effects of *interference* (e.g., list length, list strength) on recognition and

recall. As discussed above, biological models generally predict some degree of structural interference between memory traces at study -- i.e., learning about one item degrades the memory traces associated with other items. Several researchers have questioned whether models that posit structural interference at storage could account for the null list strength effect on recognition sensitivity, because of this pervasive tendency towards trace degradation. However, Norman & O'Reilly (under review) showed that biologically realistic neural network models with overlapping representations are, in fact, capable of accommodating the null list strength finding. The CLS cortical model predicts a null list strength effect for recognition sensitivity, given low-to-moderate levels of input pattern overlap, because (initially) the model's responding to lures decreases as much as its responding to studied items as a function of interference; as such, the distance between the studied-item and lure-item familiarity distributions stays relatively constant, and discriminability does not decrease.

Importantly, the CLS model also predicts that list strength effects should be obtained for the hippocampal recall process. In the hippocampal model, interference degrades the model's ability to recall studied items, and recall of lures tends to be at floor; because of this floor effect on lure recall, interference has the effect of pushing together the studied-item and lure-item recall distributions, leading to decreased discriminability. For evidence in support of the CLS model's list strength predictions, see Norman & O'Reilly (under review).

3. Summary

Abstract episodic memory models like M2 provide an elegant account, at the algorithmic level, of our ability to recall and recognize specific events from our personal past. These models posit that recall and familiarity rely on the same "match" rule and thus have similar operating characteristics. A

potential weakness of abstract models is that they do not consider the *neural plausibility* of these algorithms; it is very difficult to see how features of some abstract models (e.g., the total absence of structural interference between traces at study in M2 and REM) could be implemented in the brain.

Recently developed biological episodic memory models seek to remedy this by establishing a clear isomorphism between parts of the model and parts of the brain that have been implicated in episodic memory (e.g., in neuropsychological studies). The Norman & O'Reilly CLS model posits that recall and familiarity have different operating characteristics, insofar as they rely on distinct neural structures -- the hippocampus and medial temporal neocortex -- that differ in their architecture and connectivity. The hippocampus is more sensitive to feature conjunctions than cortex, which in turn leads to less overlap between representations. Low overlap makes it possible for the hippocampus to rapidly memorize patterns without catastrophic interference (although interference still occurs), and it also decreases the probability of false recognition, relative to what occurs in cortex.

VII. References

Clark SE and Gronlund SD (1996). Global matching models of recognition memory: How the models match the data. *Psychonomic Bulletin & Review* **3**: 37-60.

Dennis S and Humphreys MS (2001). A context noise model of episodic word recognition. *Psychological Review* **108**: 452-478.

Hasselmo ME and Wyble BP (1997). Free recall and recognition in a network model of the hippocampus: Simulating effects of scopolamine on human memory function. *Behavioural Brain Research* **89**: 1-34.

Hintzman D (1988). Judgments of frequency and recognition memory in a multiple-trace memory model. *Psychological Review* **95**: 528-551.

Holdstock JS, Mayes AR, Roberts N, Cezayirli E, Isaac CL, O'Reilly RC, & Norman KA (in press). Under what conditions is recognition relatively spared following selective hippocampal lesions? *Hippocampus*.

Jacoby LL, Yonelinas AP, and Jennings JM (1997). The relation between conscious and unconscious (automatic) influences: A declaration of independence. In Cohen JD and Schooler JW (eds), *Scientific Approaches to Consciousness*, pp. 13-47. Mahwah, NJ: Erlbaum.

McClelland JL and Chappell M (1998). Familiarity breeds differentiation: A Bayesian approach to the effects of experience in recognition memory. *Psychological Review* **105**: 724-760.

McClelland JL, McNaughton BL, and O'Reilly RC (1995). Why there are complementary learning systems in the hippocampus and neocortex. Insights from the successes and failures of connectionist models of learning and memory. *Psychological Review* **102**: 419-457.

Murdock BB (1993). TODAM2: A model for the storage and retrieval of item, associative, and serial-order information. *Psychological Review* **100**: 183-203.

Norman KA and O'Reilly RC (under review). Modeling hippocampal and neocortical contributions to recognition memory: A complementary learning systems approach. *Psychological Review*.

O'Reilly RC and McClelland JL (1994). Hippocampal conjunctive encoding, storage, and recall: Avoiding a tradeoff. *Hippocampus* **4**: 661-682.

Ratcliff R, Clark SE, and Shiffrin RM (1990). The list-strength effect: I. Data and discussion. *Journal of Experimental Psychology: Learning, Memory, and Cognition* **16**: 163-178.

Shiffrin RM, Ratcliff R, and Clark SE (1990). The list strength effect: II. Theoretical mechanisms. *Journal of Experimental Psychology: Learning, Memory, and Cognition* **16**, 179-195.

Shiffrin RM and Steyvers, M (1997). A model for recognition memory: REM: Retrieving effectively from memory. *Psychonomic Bulletin and Review* **4**: 145-166.

VIII. Bibliography

Gillund G and Shiffrin RM (1984). A retrieval model for both recognition and recall. *Psychological Review* **100**: 546-567.

Grossberg S and Stone GO (1986). Neural dynamics of word recognition and recall: Attentional priming, learning, and resonance. *Psychological Review* **93**: 46-74.

Hasselmo ME and McClelland JL (1999). Neural models of memory. *Current Opinion in Neurobiology* **9**: 184-188.

Hintzman DL (1990). Human learning and memory: Connections and dissociations. *Annual Review of Psychology* **41**: 109-139.

Howard MW and Kahana MJ (in press). A distributed representation of temporal context. *Journal of Mathematical Psychology*.

Humphreys MS, Bain JD, and Pike R (1989). Different ways to cue a coherent memory system: A theory for episodic, semantic, and procedural tasks. *Psychological Review* **96**: 208-233.

Mensink G and Raaijmakers JG (1988). A model for interference and forgetting. *Psychological Review* **95**: 434-455.

Murnane K and Shiffrin RM (1991). Interference and the representation of events in memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition* **17**: 855-874.

Nobel PA and Huber DE (1993). Modeling forced-choice associative recognition through a hybrid of global recognition and cued-recall. *Proceedings of the 15th Annual Conference of the Cognitive Science Society*: 783-788.

Raaijmakers & Shiffrin (1992). Models for recall and recognition. *Annual Review of Psychology* **43**: 205-234.

Ratcliff R (1990). Connectionist models of recognition memory: Constraints imposed by learning and forgetting functions. *Psychological Review* **97**: 285-308.

Ratcliff R, Van Zandt T, and McKoon G (1995). Process dissociation, single-process theories, and recognition memory. *Journal of Experimental Psychology: General* **124**: 352-374.

Ratcliff R and McKoon G (2000). Memory models. In Tulving E and Craik FIM (eds), *The Oxford Handbook of Memory*, pp. 571-581. New York: Oxford University Press.

Rolls ET and Treves A (1998). *Neural Networks and Brain Function*. New York: Oxford University Press.

IX. Glossary

Hippocampus#A structure located in the medial temporal lobe that supports recall of patterns of neocortical activity.

Medial temporal neocortex#A subregion of neocortex (consisting of the entorhinal, perirhinal, and parahippocampal cortices) that serves as the interface between the rest of neocortex and the hippocampus.

Neocortex#A sheet of neurons that covers the cerebral hemispheres, consisting of a hierarchy of subregions that represent regularities in the environment at different levels of abstraction.

X. Figure captions

NOTE: Figures are attached as separate files:

444.Figure1.eps

444.Figure2.eps

444.Figure3.eps

444.Figure4.eps

Figure 1#Illustration of how MINERVA 2 (M2) computes global match. For each of the two traces stored in memory, M2 computes a match value = (number of matching features - number of mismatching features) / (total number of nonzero features); then, M2 cubes these match values and adds them together to get a familiarity score for that cue. In this example, if match values are summed prior to cubing, the summed match values are equivalent for the studied item and the nonstudied item. However, if match values are summed after cubing, the studied item generates a much larger summed match score than the nonstudied item. Cubing benefits discrimination by minimizing the effect of weak (partial) matches on the summed match score, relative to the effect of more complete matches.

Figure 2#Illustration of how strengthening -- operationalized as more complete feature encoding -- can reduce spurious matches. Question marks indicate features that were not encoded at study. Prior to strengthening (upper two panels), the studied item and the nonstudied item match stored traces equally well; for both items, there is one trace that appears to match the test cue, i.e., there are some matching features, and no mismatching features. After strengthening (lower two panels), it is apparent that the nonstudied item does not exactly match either of the stored traces.

Figure 3#Diagram of the CLS hippocampal network. The hippocampal network links input patterns in entorhinal cortex (EC) to relatively non-overlapping (*pattern-separated*) sets of units in region CA3; recurrent connections in CA3 bind together all of the units involved in representing a particular EC pattern; the CA3 representation is linked back to EC via region CA1. Learning in the CA3 recurrent connections, and in projections linking EC to CA3 and CA3 to CA1, makes it possible to recall entire stored EC patterns based on partial cues. The dentate gyrus (DG) serves to facilitate pattern separation in region CA3; see O'Reilly & McClelland (1994) for details.

Figure 4#Diagram of the CLS cortical network. The cortical network consists of two layers, an input layer (corresponding to "lower" cortical regions that represent basic features of input patterns) and a hidden layer (corresponding to MTLN). Units in the hidden layer compete to encode (via Hebbian learning) regularities that are present in the input layer.

XI. Cross references to other articles

573 -- Memory Models

571 -- Memory: Long-Term Memory

332 -- Neural Basis of Memory: Systems Level

96 -- Catastrophic Interference in Connectionist Networks

311 -- Hippocampus

XII. Suggestions for multimedia features

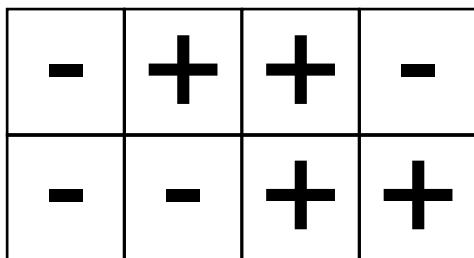
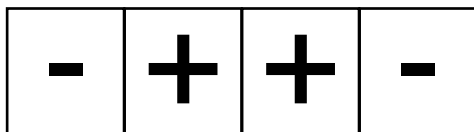
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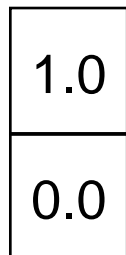
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The figures were composed using Adobe Illustrator on a PC. They are saved in Encapsulated PostScript (EPS) format.

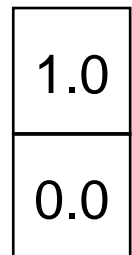
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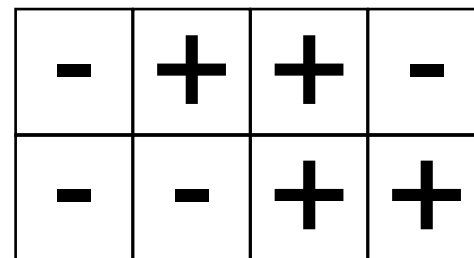
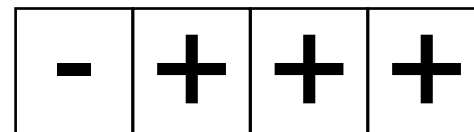
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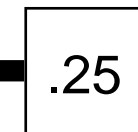
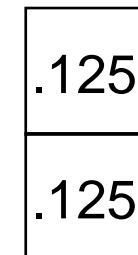
match cubed



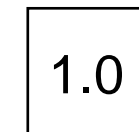
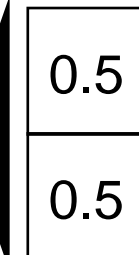
nonstudied item



match cubed



match



studied item

-	+	+	-
---	---	---	---

▼

-	?	?	-
?	?	+	+

match mis-match

▶

2	0
1	1

nonstudied item

-	+	+	+
---	---	---	---

match mis-match

▶

1	1
2	0

▼

-	?	?	-
?	?	+	+

studied item

-	+	+	-
---	---	---	---

▼

-	+	+	-
-	-	+	+

match mis-match

▶

4	0
2	2

nonstudied item

-	+	+	+
---	---	---	---

match mis-match

▶

3	1
3	1

▼

-	+	+	-
-	-	+	+

