Memory in Chains: A Dual-Code Associative Model of Positional Uncertainty

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Abstract

Models like perturbation (Estes, 1997), primacy (Henson, Norris, Page, & Baddeley, 1996), and partial matching (Anderson & Matessa, 1997) reproduce uncertainty gradients in memory for order but fail to address how cognition might encode the underlying memory representation in the first place. This paper introduces a model of uncertainty gradients that explains the encoding as well as the reconstruction of order. The model is built on an integrated and computational cognitive theory (ACT-R/PM) that provides the central mechanisms: a dual-code representation of attended items, associative learning, and noise in activation levels. The model addresses the main structural objection to chaining models (over-predicting relative or "shift" error), fits experimental data better than the perturbation and partial-matching models, and makes strong serial-position predictions.

Introduction

An important test of theories of memory is whether they can explain "near-miss" errors, for example the uncertainty gradient in memory for order. The uncertainty gradient is the robust finding that an item recalled out of order is more likely recalled close to its original position than far away (e.g., Nairne, 1992). The finding is illustrated by the hypothetical gradient in Figure 1, for an item presented third a list of five. The modal response during reconstruction is to place that item correctly (third). A gradient arises because errors that place the item in positions two and four are more common than errors placing the item in positions one and five.

Existing models of positional uncertainty are only descriptive, in that they reproduce uncertainty gradients once the analyst has encoded the appropriate underlying memory representation. For example, the perturbation model takes as input an array of items indexed by time. Every so often, two cells in this array have some chance of swapping with one another. Over time, elements drift away from their original position and produce the uncertainty gradient. However, the assumption that memory is organized as an array is problematic. The perturbation model has been offered as an explanation of memory distortion along any dimension, with time as just one example (Estes, 1997). However, for this explanation to be accurate, memory would have to be an immense array with one dimension for each way in which memory can distort. A representation this complex would place a heavy burden on the encoding process that creates it, and yet the perturbation model fails to address encoding at all. Two other models of memory for order, the primacy model (Henson et al., 1996), and the partial matching model (Anderson & Matessa, 1997), also fail to address the encoding question.

This paper presents a model of memory for order that not only explains the encoding processes, but fits existing data better than the other models cited above.[1]

[1] The dual-code associative model is available http://hfac.gmu.edu/people/altmann/nairne-rpm.txt.

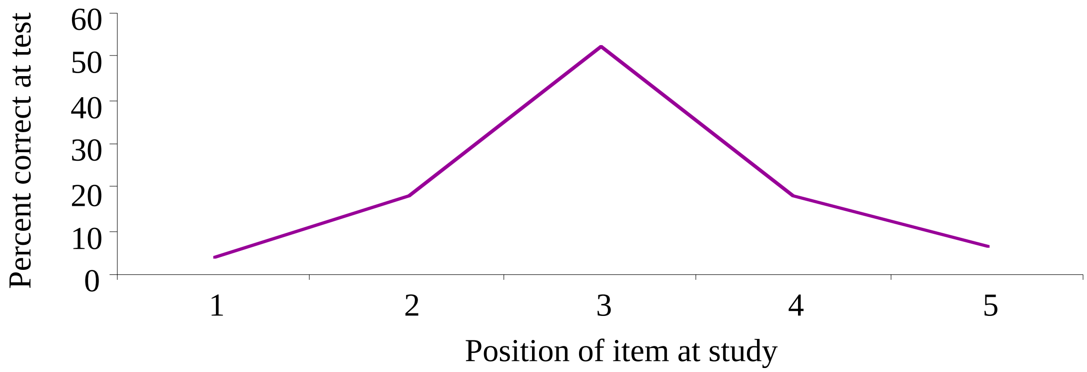

Figure 1: Hypothetical uncertainty gradient for the item presented third in a list of five. The modal response during reconstruction is to place the item in its correct position (3). If the item is placed incorrectly, it is more likely to be placed near its original position (2 or 4) than farther away (1 or 5).

Encoding Memory for Order

The model presented here is built on the ACT-R/PM cognitive theory, which combines constraints imposed by perceptual-motor systems (Byrne, 1998) with a rational-analysis of memory (Anderson, 1990). The three theoretical mechanisms underlying the model are a dual-code representation of objects, associative learning, and noisy memory retrieval.

Dual-Code Representation

The main representational constraint on the model is that as an item is attended it is represented in memory by two codes. One code is locational (or positional) and the other object-based (or post-categorical). This dual-code representation is incorporated directly into the ACT-R/PM theory, rather than being an assumption I had to make independently. In general, dual-code representations like this have broad empirical and theoretical support (e.g., Anderson, Bothell, Lebiere, & Matessa, 1998; Logan, 1996; Paivio, 1971; Whiteman, Nairne, & Serra, 1994).

A complementary processing constraint is that the perceptual and attention systems use these two codes to communicate with cognition. Again, this constraint is imposed by ACT-R/PM directly. Below I illustrate how this constraint directs the model's performance in a generic serial-processing protocol. Each step is carried out by an ACT-R/PM production (or if-then rule). To summarize, the model processes the item's location (steps 1 and 2) and then its identity (steps 3 and 4), then uses these codes to carry out other processing is required by the task (step 5). The model repeats the procedure on the next item, when that is presented.

1. `Find-Location`
2. `Retrieve-Location`
3. `Move-Attention`
4. `Retrieve-Content`
5. `Other-Processing`

In detail, step 1 is for cognition to issue a command to the perceptual system to find the item's location. The perceptual system responds by pre-attentively finding the location (using features supplied top-down in the find-location command). When perception has found the location, it places a location code in memory. Step 2 is for cognition to retrieve the location code that perception just added to memory. Step 3 is for cognition to formulate a command to move attention to the retrieved location. This command instructs the attention system to create an object code for the attended item and place this code in memory. Step 4 is for cognition to retrieve this object code from memory. Step 5 is to carry out higher-level processing with the object code as input, for example categorizing the item and selecting a response. When this higher-level processing is complete, the cycle starts over again with the next item.

The procedure described above is a theory-based communication protocol for perceptual and attention mechanisms to exchange information with cognition. The next question is what kind of traces this protocol leaves behind in memory as it executes, and how such traces might allow reconstruction of the order in which items were processed.

Associative Learning

There is strong evidence from a variety of sources that associative information is acquired incidentally by the cognitive system. The incidental acquisition of episodic codes has been argued on grounds both empirical (Hasher & Zacks, 1979; Naveh-Benjamin, 1987; Naveh-Benjamin, 1990) and theoretical (Altmann & John, 1999; Logan, 1988). Moreover, there is evidence that such codes that neighbor each other in time are incidentally joined by associative links (Nairne, 1983; Nairne, 1992). This formal evidence may explain the phenomenal experience of being able to simulate past experiences in the mind's eye. For example, to answer a question like "Did I lock the door on the way out?", one might replay a sequence like putting on a coat, walking outside, then closing the door, to try to cue the event of locking the door.

ACT-R specifies an associative learning mechanism (Anderson & Lebiere, 1998) that explains the findings cited above. This mechanism creates a link between two codes if one code (the target) is retrieved from memory while the other code (the cue) is already in the focus of attention. As in Soar (Newell, 1990), this association is a new, permanent element of long-term memory. In future, if the cue again enters the focus of attention it will prime (spread activation to) the target, increasing the chance that the target will be the next item retrieved to the focus of attention. This representation allows chained retrieval, in which each retrieval cues the next.

Applied to the five-step procedure described above, the associative learning mechanism produces a linked structure in which location codes are interleaved with object codes. Figure 2A illustrates such a structure after a hypothetical scenario in which the model has studied and encoded three items (X, Y, and Z). An important assumption in the model is that each code remains in the focus of attention long enough to still be there when the next code is retrieved. The consequence is that the first code becomes the cue for the second code, and the associative-learning mechanism links the two codes permanently in memory.

Noise in Memory

In the absence of noise, the dual-code representation of attended items, combined with associative learning, produces a linked structure that allows perfect sequential retrieval of items in the future. However, a memory system without noise would be unrealistic (and, indeed, suboptimal; Anderson & Lebiere, 1998). In ACT-R, as in many memory theories, memory elements have activation levels that determine their availability – items high in activation are less vulnerable to interference by other items. Noise in the memory system is expressed as transient fluctuations in item activation, introducing the possibility of memory-retrieval error.

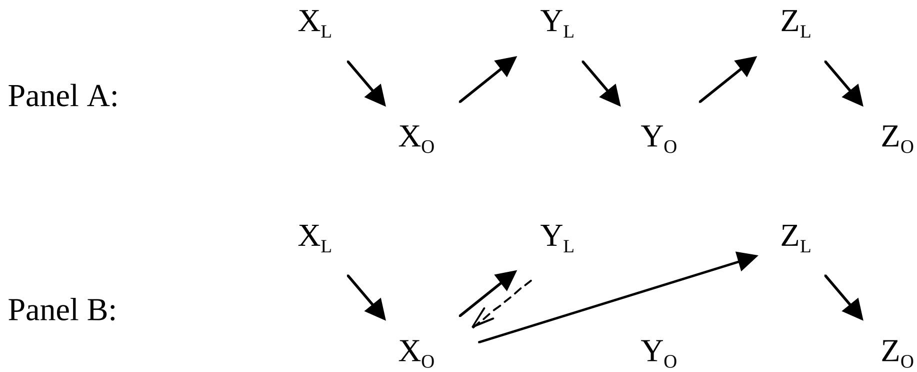

Figure 2: Memory representations encoded by the dual-code associative model at study time for items X, Y, and Z. Each item has a location code (subscript L) and an object code (subscript 0). Panel A: Error-free representation. Panel B: Representation with an incorrect link pointing from Y_L to X_O, created by a retrieval error on the object code in processing Y.

Noise can critically affect the encoding process described above and result in incorrect links between codes. For each item processed, the procedure carries out two memory retrievals, one of a location code and one of an object code. Both retrievals are subject to activation noise. Specifically, when cognition attempts to retrieve the location code most recently placed in memory, it may retrieve an old location code instead. Similarly, when cognition attempts to retrieve the object code most recently placed in memory, it may retrieve an old object code instead.[2] In terms of an everyday example, suppose that a newcomer is being introduced to a number of people, serially and perhaps too rapidly. While looking at the current person, the newcomer might “fall behind” and retrieve a previous, incorrect name. The result of such an error (to foreshadow) is that the newcomer will associate the wrong name with the wrong face.

The associative learning mechanism implies that a retrieval error during encoding produces an incorrect link in memory. This is illustrated in Figure 2B. In the scenario shown there, a retrieval error occurred as cognition was trying to retrieve the object code for item Y. This code (Y_O) was just placed in memory by the attention system. However, due to noise in activation levels, the previous object code (X_O) was transiently more active and hence was retrieved instead. An association was therefore encoded between the location code Y_L and the object code X_O. This link is shown as a dashed arrow to indicate that it represents an encoding error. Because of this encoding error, Y could be mistakenly placed in the first position at test time, producing a near-miss error. I explore this possibility below as I discuss the model’s order-reconstruction process.

When the model began processing Z (in Figure 2B), it correctly retrieved location code Z_L. However, object code X_O was still in the focus of attention, because of the retrieval error that just occurred. Therefore, a link was created from X_O to Z_L, bypassing object code Y_O completely. The consequence is that during reconstruction the model could follow the link from X_O to Z_L and produce the correct order, a possibility also explored below.

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[2] I assume that errors occur within a code type only, and that a retrieval attempt always produces an item. These assumptions imply, for example, that an attempt to retrieve a location code will always produce a location code, though it may produce the wrong location code.

A final but critical constraint on retrieval error is that interference by newer codes is more likely than interference by older codes. This constraint follows directly from the dynamics of activation in ACT-R. An item's activation depends on the lag since it was last retrieved – the longer the lag, the lower the activation. Therefore, each item will be more active than its predecessor (more precisely, each item's codes will be more active than its predecessor's codes), because the lag since presentation is smaller. The implication for encoding error is that most erroneous links will be like those in Figure 2B – near-misses, rather than far misses. This directly predicts the uncertainty gradient, as I describe next.

Reconstruction of Memory for Order

In order-memory experiments, items themselves are usually present at test as well as at study – participants are asked simply to reconstruct their original order. Because items and positions are available at test, I assume that people choose an initial item or position randomly to start the reconstruction process. This assumption means that the model can take many paths through the representation in Figure 2B. In particular, one of these paths produces a positional swap of the kind that underlies the uncertainty gradient, and a second path produces a correct reconstruction.

The model will make an order error if the first cue it uses is location code Y_L. This code was linked incorrectly to object code X_O at encoding time, because of a retrieval error then. The result now is that the model will infer that X_O was the object that originally appeared in location Y_L, producing an order error. Next, the model might use X_O as a cue for which location to focus on next, in which case it would focus on location Z_L. Using Z_L as a cue, the model would most likely retrieve Z_O, which is correct. Thus, of two items placed, one was placed incorrectly and one correctly. The environment now indicates one remaining position and one remaining item. (Participants are typically instructed in the one-to-one nature of the reconstruction task, namely that every item maps to one position, with no items or positions left over.) The model will therefore infer that object Y_O occurred at location X_L. That is, the model will have swapped the order of the neighboring items X and Y. This is precisely the swap assumed (but not explained) by the perturbation model (Estes, 1997; Nairne, 1992).

Despite the encoding error, the structure in Figure 2B can also produce a correct reconstruction. If the model begins with location code X_L, for example, then it will most likely retrieve object code X_O, which is correct. Used as a cue, X_O will then prime two location codes, Y_L and Z_L. Suppose, first, that Z_L is retrieved. Used as a cue, Z_L will likely retrieve Z_O, which is correct. At this point, because only one item and one position remain, the model can place Y_O at Y_L, and the reconstruction will be correct. Suppose, instead, that when X_O is the cue, Y_L is retrieved. Used as a cue, Y_L will likely retrieve X_O, but this is now a dead end – X_O has been placed. The model might now decide to place X_O elsewhere, but it might also decide simply to abandon Y_L as the cue and use Z_L instead. This would also produce a correct reconstruction.

It is critical to note how the model produces the hypothetical gradient illustrated in Figure 1. There are two features of this gradient to explain. First, there is the slope away from the modal response – that is, near misses are more likely than far misses. This effect is caused by the interaction of activation and error at encoding time. That is, items presented closer in time to the current item are more active and hence more likely to intrude on perception-cognition communication, producing an incorrect link. Thus, the closer together in time two items are presented, the closer their activation levels, and the more likely they are to be confused during reconstruction as a function of encoding error.

The second feature of the gradient is its symmetry – in both directions of the list, near misses are more likely than far misses. This effect follows directly from the model's dual-code representation. Figure 2B illustrates an error in which a location code (Y_L) incorrectly pointed backward (to X_O). However, a location code could incorrectly point forward as well.[3] Thus, the dual-code representation overcomes the main flaw attributed to chaining models of memory, which is that they predict "relative errors" (Henson et al., 1996) in which one bad link shifts all subsequent items off by one. The typical straw-man chaining model is required to infer order essentially by counting the links have been traversed so far.[4] The dual-code representation overcomes this difficulty by representing position information explicitly in memory.

Comparing Model and Data

To test the model, I simulated data from Nairne (1992). In that study, memory for order was tested implicitly; at study time, participants were asked simply to give speeded pleasantness ratings of five words presented in sequence. Participants (in the condition reported here) were distracted for 30 seconds after study, and then were given a surprise order-reconstruction test.

Empirical data from that study are shown in Figure 3. The model accurately reproduces positional uncertainty at all five list positions, accounting for 97% of the variance over 25 data points (RMSD = 4.1%). This is a better fit than both the perturbation (Nairne, 1992) and partial matching (Anderson & Matessa, 1997) models of the same data. The dual-code associative model also shows the shallow primacy and recency effects typical of memory for order, and goes beyond the perturbation and partial matching models to predict that primacy should be systematically greater than recency. (The logic of these predictions will be reported in future reports.) This close fit to complex data is strong support for the model's assumptions.

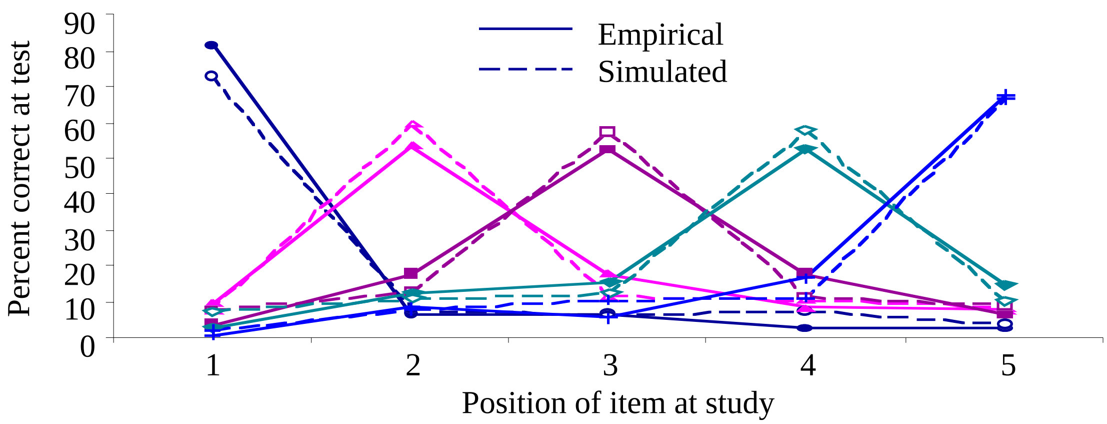

Figure 3: Accuracy data for order memory. Empirical data are from Nairne (1992), and simulation data are from the dual-code associative model.

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[3] Assume, again, a single retrieval error at study, but now place this error on the retrieval of the location code when Y_O is in the focus of attention. The correct location code is Z_L, but suppose Y_L intrudes and is now in the focus of attention. The next step is to retrieve an object code, and Z_O is retrieved correctly. This will encode a link from Y_L to Z_O, a forward-pointing encoding error. If the model happens to use Y_L as an initial cue during reconstruction, it will most likely retrieve Z_O, and thus move the third object backwards.

[4] A variety of other hypothetical chaining models have been proposed and had their putative shortcomings laid bare (Brown, 1997; Henson et al., 1996). Unfortunately, in the absence of a precise computational representation, such shortcomings are essentially impenetrable to anyone but the analyst who cites them.

Discussion

This paper presented a model of positional uncertainty that goes beyond existing models to explain encoding as well as reconstruction of order information. Of existing models, the perturbation model is the most discussed and has been advanced as a generalized model of memory loss and distortion (Estes, 1997). Although elegantly simple, the perturbation model says nothing about how the underlying memory representation is initially encoded, and thereby fails to address a critical aspect of memory distortions. The model presented here begins to fill this explanatory gap. Its dual-code representation of attended items and its incidental associative learning are low-level and generic enough that one might expect them to be part of any kind of processing of sequential stimuli, whether spatial, temporal, or semantic. Moreover, because the model is embedded in a larger cognitive theory, its mechanisms should transfer to models of higher-order cognitive behavior.

Another contribution of this work is a simplification of ACT-R theory. Much has been made of the partial matching mechanism layered on top of ACT-R's memory theory (Anderson & Lebiere, 1998). However, partial matching fails one of the critical constraints adopted by ACT-R's developers. The item similarities that the analyst must input to partial matching, like the array that must be input to the perturbation model, cannot be learned by ACT-R itself. Partial matching thus violates the constraint that all representations used by the system must be learnable by the system (Anderson & Lebiere, 1998). Because of this fundamental flaw, partial matching arguably falls outside ACT-R theory, despite being cited as an ACT-R explanation of positional uncertainty (Anderson & Matessa, 1997). The model presented here uses mechanisms clearly within theory to explain the target phenomena, producing better fits in the process.

The problems with ACT-R's partial matching mechanism extend beyond its application to memory for order. The mechanism has been invoked to explain near-miss errors in cognitive arithmetic (Lebiere & Anderson, 1998), but the link between mechanism and data is tenuous. To test whether partial matching accounted for any variance in the data, I removed it from one cognitive arithmetic model (Anderson & Lebiere, 1998, Chapter 4). The result was a slightly <u>improved</u> fit to data[5]. Thus, beyond being ad hoc, partial matching appears to be unnecessary for fitting the data it was developed to fit. Indeed, partial matching appears to be a programming convenience for the analyst interested in engineering particular kinds of memory errors. The problem with such programming conveniences is that they can mask deeper questions about representation and process (Altmann & Trafton, 1999).

In conclusion, the model presented here offers theory-based encoding and retrieval processes that explain near-miss error in memory for order. Because the processes themselves are domain independent, I hope that they provide a basis and an incentive to examine near-miss error in other domains, within a unified theory of cognition rather than with ad hoc mechanisms.

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[5] Modified model and fits to data are available at http://hfac.gmu.edu/people/altmann/siegler-ema.{txt, xl}

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