

# Carryover effects in free recall reveal how prior experiences influence memories of new experiences

Jeremy R. Manning<sup>1,\*</sup>, Kirsten Ziman<sup>1,2</sup>, Emily Whitaker<sup>1</sup>,  
Paxton C. Fitzpatrick<sup>1</sup>, Madeline R. Lee<sup>1</sup>, Allison M Frantz<sup>1</sup>,  
Bryan J. Bollinger<sup>1</sup>, Campbell E. Field<sup>1</sup>, and Andrew C. Heusser<sup>1,3</sup>

<sup>1</sup>Dartmouth College

<sup>2</sup>Princeton University

<sup>3</sup>Akili Interactive

\*Corresponding author: [jeremy.r.manning@dartmouth.edu](mailto:jeremy.r.manning@dartmouth.edu)

## Abstract

We perceive, interpret, and remember ongoing experiences through the lens of our prior experiences. Inferring that we are one type of situation versus another can lead us to interpret the same physical experience differently. In turn, this can affect how we focus our attention, form expectations of what will happen next, remember what is happening now, draw on our prior related experiences, and so on. To study these phenomena, we asked participants to perform simple word list learning tasks. Across different experimental conditions, we held the set of to-be-learned words constant, but we manipulated the orders in which the words were studied. We found that these order manipulations affected not only how the participants recalled the ordered lists, but also how they recalled later randomly ordered lists. Our work shows how structure in our ongoing experiences can exert influence on how we remember unrelated subsequent experiences.

## 17 Introduction

18 Experience is subjective: different people who encounter identical physical experiences  
19 can take away very different meanings and memories. One reason is that our subjective  
20 experiences in the moment are shaped in part the idiosyncratic prior experiences, mem-  
21 ories, goals, thoughts, expectations, and emotions that we bring with us into the present  
22 moment. These factors collectively define a *context* for our experiences (Manning, 2020).

23 The contexts we encounter help us to construct *situation models* (Manning et al., 2015;  
24 Ranganath and Ritchey, 2012) or *schemas* (Baldassano et al., 2018; Masís-Obando et al.,  
25 2022) that describe how experiences are likely to unfold based on our prior experiences  
26 with similar contextual cues. For example, when we enter a sit-down restaurant, we might  
27 expect to be seated at a table, given a menu, and served food. Priming someone to expect a  
28 particular situation or context can also influence how they resolve potential ambiguities in  
29 their ongoing experiences, including ambiguous movies and narratives (Yeshurun et al.,  
30 2017).

31 Our understanding of how we form situation models and schemas, and how they  
32 interact with our subjective experiences and memories, is constrained in part by substantial  
33 differences in how we study these processes. Situation models and schemas are most often  
34 studied using “naturalistic” stimuli such as narratives and movies (Nastase et al., 2020;  
35 Zwaan et al., 1995; Zwaan and Radvansky, 1998). In contrast, our understanding of how  
36 we organize our memories has been most widely studied using more traditional paradigms  
37 like free recall of random word lists (Kahana, 2012). In free recall, participants study lists  
38 of items and are instructed to recall the items in any order they choose. The orders in  
39 which words come to mind can provide insights into how participants have organized  
40 their memories of the studied words. Because random word lists are unstructured by  
41 design, it is not clear if or how non-trivial situation models might apply to these stimuli.

42 Nevertheless, there are *some* commonalities between memory for word lists and memory  
43 for real-world experiences.

44 Like remembering real-world experiences, remembering words on a studied list re-  
45 quires distinguishing the current list from the rest of one's experience. To model this  
46 fundamental memory capability, cognitive scientists have posited the existence of a spe-  
47 cial representation, called *context*, that is associated with each list. According to early  
48 theories (e.g. Anderson and Bower, 1972; Estes, 1955) context representations are com-  
49 posed of many features which fluctuate from moment to moment, slowly drifting through  
50 a multidimensional feature space. During recall, this representation forms part of the  
51 retrieval cue, enabling us to distinguish list items from non-list items. Understanding the  
52 role of context in memory processes is particularly important in self-cued memory tasks,  
53 such as *free recall*, where the retrieval cue is "context" itself.

54 Over the past half-century, context-based models have enjoyed impressive success at  
55 explaining many stereotyped behaviors observed during free recall and other list-learning  
56 tasks (Estes, 1955; Glenberg et al., 1983; Howard and Kahana, 2002; Kimball et al., 2007;  
57 Polyn and Kahana, 2008; Polyn et al., 2009; Raaijmakers and Shiffrin, 1980; Sederberg et al.,  
58 2008; Shankar and Howard, 2012; Sirotin et al., 2005; ?). These phenomena include the  
59 well-known recency and primacy effects (superior recall of items from the end and, to  
60 a lesser extent, from the beginning of the study list), as well as semantic and temporal  
61 clustering effects (?). The contiguity effect is an example of temporal clustering, which is  
62 perhaps the dominant form of organization in free recall. This effect can be seen in the  
63 tendency for people to successively recall items that occupied neighboring positions in the  
64 study list. For example, if a list contained the sub-sequence "ABSENCE HOLLOW PUPIL" and  
65 the participant recalls the word "HOLLOW", it is far more likely that the next response will  
66 be either "PUPIL" or "ABSENCE" than some other list item (Kahana, 1996). In addition, there

67 is a strong forward bias in the contiguity effect: subjects make forward transitions (i.e.,  
68 “HOLLOW” followed by “PUPIL”) about twice as often as they make backward transitions,  
69 despite an overall tendency to begin recall at the end of the list. There are also striking  
70 effects of semantic clustering (Bousfield, 1953; Bousfield et al., 1954; Jenkins and Russell,  
71 1952; Manning and Kahana, 2012; Romney et al., 1993), whereby the recall of a given item  
72 is more likely to be followed by recall of a similar or related item than a dissimilar or  
73 unrelated one. In general, people organize memories for words along a wide variety of  
74 stimulus dimensions. As captured by models like the *Context Maintenance and Retrieval*  
75 *Model* (Polyn et al., 2009), the stimulus features associated with each word (e.g. the word’s  
76 meaning, font size, font color, location on the screen, size of the object the word represents,  
77 etc.) are incorporated into the participant’s mental context representation (Manning, 2020;  
78 Manning et al., 2015, 2011, 2012; Smith and Vela, 2001). During a memory test, any of  
79 these features may serve as a memory cue, which in turn leads the participant to recall in  
80 succession words that share stimulus features.

81 A key mystery is whether the sorts of situation models and schemas that people use to  
82 organize their memories of real-world experiences might map onto the clustering effects  
83 that reflect how people organize their memories for word lists. On one hand, situation  
84 models and clustering effects both reflect statistical regularities in ongoing experience.  
85 Our memory systems exploit these regularities when generating inferences about the  
86 unobserved past and yet-to-be-experienced future (Bower et al., 1979; Momennejad et al.,  
87 2017; Ranganath and Ritchey, 2012; Schapiro and Turk-Browne, 2015; Xu et al., 2022). On  
88 the other hand, the rich structure of real-world experiences and other naturalistic stimuli  
89 that enable people to form deep and meaningful situation models and schemas have no  
90 obvious analog in simple word lists. Often lists in free recall studies are explicitly *designed*  
91 to be devoid of exploitable temporal structure, for example by sorting the words in a

92 random order (Kahana, 2012).

93 We designed an experimental paradigm to explore how people organize their mem-  
94 ories for simple stimuli (word lists) whose temporal properties change across different  
95 “situations,” analogous to how the content of real-world experiences change across dif-  
96 ferent real-world situations. We asked participants to study and freely recall a series  
97 of word lists (Fig. 1). Across the different conditions in the experiment, we varied the  
98 lists’ presentation orders in different ways across lists. The studied items (words) were  
99 designed to vary along three general dimensions: semantic (word *category*, and physical  
100 *size* of the referent), lexicographic (word *length* and *first letter*), and visual (font *color* and  
101 the onscreen *location* of each word). In our main manipulation conditions, we asked par-  
102 ticipants to study and recall eight lists whose items were sorted by a target feature (e.g.,  
103 word category). Next, we asked them to study and recall an additional eight lists whose  
104 items had the same features, but that were sorted in a random temporal order. We were in-  
105 terested in how these order manipulations affected participants’ recall behaviors on early  
106 (sorted) lists, as well as how order manipulations on early lists affected recall behaviors  
107 on later (unsorted) lists. We used a series of control conditions as a baseline; in these  
108 control conditions all of the lists were sorted randomly, but we manipulated the presence  
109 or absence of the visual features. Finally, in an *adaptive* experimental condition we used  
110 participants’ recall behaviors on early lists to manipulate, in real-time, the presentation  
111 orders of subsequent lists. In this adaptive condition, we sought to identify potential  
112 commonalities within and across participants in how people organized their memories  
113 and how those organizational tendencies affect overall performance.

## 114 **Materials and methods**

### 115 **Participants**

116 We enrolled a total of 491 Dartmouth undergraduate students across 11 experimental  
117 conditions. The conditions included two primary controls (feature rich, reduced), two  
118 secondary controls (reduced (early), reduced (late)), six order manipulation conditions  
119 (category, size, length, first letter, color, and location), and a final adaptive condition. Each  
120 of these conditions are described in the *Experimental design* subsection below.

121 Participants received course credit for enrolling in our study. We asked each participant  
122 to fill out a demographic survey that included information about their self-reported age,  
123 gender, ethnicity, race, education, vision, reading impairments, medications or recent  
124 injuries, coffee consumption on the day of testing, and level of alertness at the time of  
125 testing. All components of the demographics survey were optional. One participant  
126 elected not to fill out any part of the demographic survey, and all other participants report  
127 some or all of their requested demographic information.

128 We aimed to run (to completion) at least 60 participants in each of the two primary  
129 control conditions and in the adaptive condition. In all other conditions we set a target  
130 enrollment of at least 30 participants. Because our data collection efforts were coordinated  
131 12 researchers and multiple testing rooms and computers, it was not feasible for individ-  
132 ual experimenters to know how many participants had been run in each experimental  
133 condition until the relevant databases were synchronized at the end of each working day.  
134 We also over-enrolled participants for each condition to help ensure that we met our min-  
135 imum enrollment targets even if some participants dropped out of the study prematurely  
136 or did not show up for their testing session. This led us to exceed our target enrollments  
137 for several conditions.

Participants were assigned to experimental conditions based loosely on their date of participation. (This aspect of our procedure helped us to more easily synchronize the experiment databases across multiple testing computers.) Of the 490 participants who opted to fill out the demographics survey, reported ages ranged from 17 to 31 years (mean: 19.1; standard deviation: 1.356). A total of 318 participants reported their gender as female, 170 as male, and 2 participants declined to report their gender. A total of 442 participants reported their ethnicity as “not Hispanic or Latino,” 39 as “Hispanic or Latino,” and 9 declined to report their ethnicity. Participants reported their races as White (345 participants), Asian (120 participants), Black or African American (31 participants), American Indian or Alaska Native (11 participants), Native Hawaiian or Other Pacific Islander (4 participants), Mixed race (3 participants), Middle Eastern (1 participant), and Arab (1 participant). A total of 5 participants declined to report their race. We note that several participants reported more than one of racial category. Participants reported their highest degrees achieved as “Some college” (359 participants), “High school graduate” (117 participants), “College graduate” (7 participants), “Some high school” (5 participants), “Doctorate” (1 participant), and “Master’s degree” (1 participant). A total of 482 participants reported no reading impairments, and 8 reported mild reading impairments such as mild dyslexia. A total of 489 participants reported having normal color vision and 1 participant reported that they were color blind. A total of 482 participants reported taking no prescription medications and having no recent injuries; 4 participants reported having ADHD, 1 reported having dyslexia, 1 reported having allergies, 1 reported a recently torn ACL/MCL, and 1 reported a concussion from several months prior. The participants reported consuming 0 – 3 cups of coffee prior to the testing session (mean: 0.32 cups; standard deviation: 0.58 cups). Participants reported their current level of alertness, and we converted their responses to numerical scores as follows: “very sluggish” (-2), “a little

163 sluggish" (-1), "neutral" (0), "a little alert" (1), and "very alert" (2). Across all partici-  
164 pants, the full range of alertness levels were reported (range: -2 – 2; mean: 0.35; standard  
165 deviation: 0.89).

166 We dropped from our dataset the 1 participant who reported abnormal color vision, as  
167 well as 39 participants whose data were corrupted due to technical failures while running  
168 the experiment or during the daily database merges. In total, this left usable data from  
169 452 participants, broken down by experimental condition as follows: feature rich (67  
170 participants), reduced (61 participants), reduced (late) (41 participants), reduced (early),  
171 (42 participants), category (30 participants), size (30 participants), length (30 participants),  
172 first letter (30 participants), color (31 participants), location (30 participants), and adaptive  
173 (60 participants). The participant who declined to fill out their demographic survey  
174 participated in the location condition, and we verified verbally that they had normal color  
175 vision.

## 176 **Experimental design**

177 Our experiment is a variant of the classic free recall paradigm that we term *feature-rich free*  
178 *recall*. In feature-rich free recall, participants study 16 lists, each comprised of 16 words that  
179 vary along a number of stimulus dimensions (Fig. 1). The stimulus dimensions include  
180 two semantic features related to the *meanings* of the words (semantic category, referent  
181 object size), two lexicographic features related to the *letters* that make up the words (word  
182 length in number of letters, identity of the word's first letter), and two visual features  
183 that are independent of the words themselves (text color, presentation location). Each  
184 list contains four words from each of four different semantic categories and two object  
185 sizes; all other stimulus features are randomized. After studying each list, the participant  
186 attempts to recall as many words as they can from that list, in any order they choose.



187 Because each individual word is associated with several well-defined (and quantifiable)  
188 features, and because each list incorporates a diverse mix of feature values along each  
189 dimension, this allows us to evaluate participants' memory fingerprints in rich detail.

## 190 **Stimuli**

191 Stimuli in our paradigm were 256 English words selected in a previous study (Ziman et al.,  
192 2018). The words all referred to concrete nouns, and were chosen from 15 unique semantic  
193 categories: body parts, building-related, cities, clothing, countries, flowers, fruits, insects,  
194 instruments, kitchen-related, mammals, (US) states, tools, trees, and vegetables. We  
195 also tagged each word according to the approximate size of the object the word referred  
196 to. Words were labeled as "small" if the corresponding object was likely able to "fit  
197 in a standard shoebox" or "large" if the object was larger than a shoebox. Semantic  
198 categories varied in how many object sizes they reflected (mean number of different sizes  
199 per category: 1.33; standard deviation: 0.49). The numbers of words in each semantic  
200 category also varied from 12 – 28 (mean number of words per category: 17.07; standard  
201 deviation number of words: 4.65). We also identified lexicographic features for each word,  
202 including the words' first letters and lengths (i.e., number of letters). Across all categories,  
203 all possible first letters were represented except for 'Q' (average number of unique first  
204 letters per category: 11; standard deviation: 2 letters). Word lengths ranged from 3 – 12  
205 letters (average: 6.17 letters; standard deviation: 2.06 letters).

206 We assigned the categorized words into a total of 16 lists with several constraints.  
207 First, we required that each list contained words from exactly 4 unique categories, each  
208 with exactly 4 exemplars from each category. Second, we required that (across all words  
209 on the list) at least one instance of both object sizes were represented. On average, each  
210 category was represented in 4.27 lists (standard deviation: 1.16 lists). Aside from these



**Figure 1: Feature-rich free recall.** After studying lists comprised of words that vary along several feature dimensions, participants verbally recall words in any order (microphone icon). Each experimental condition manipulates word features and/or presentation orders within and/or across lists. The rows display representative (illustrated) examples of the first lists participants might encounter in each condition. The rectangles during the “Presentation phase” show illustrated screen captures during a series of word presentations. Each word appeared onscreen for 2 seconds, followed by 2 seconds of blank screen. The red microphone icons during the “Recall” phase denote the one minute verbal recall interval. The labels on the right (and corresponding groupings on the left) denote experimental condition labels.

211 two constraints, we assigned each word to a unique list. After random assignment, each  
212 list contained words with an average of 11.13 unique starting letters (standard deviation:  
213 1.15 letters) and an average word length of 6.17 letters (standard deviation: 0.34 letters).

214 The above assignments of words to lists was performed once across all participants,  
215 such that every participant studied the same set of 16 lists. In every condition we random-  
216 ized the study order of these lists across participants. For participants in some conditions,  
217 on some lists, we also randomly varied two additional visual features to each word: the  
218 presentation font color, and the word’s onscreen location. These attributes were assigned  
219 independently for word (and for every participant) at the times the words were displayed  
220 onscreen. These visual features were varied for words in all lists and conditions except for  
221 the “reduced” condition (all lists), the first eight lists of the “reduced (early)” condition,  
222 and the last eight lists of the “reduced (late)” condition. In these latter cases, words were  
223 all presented in black at the center of the experimental computer’s display.

224 To assign a random font color to each word, we selected three integers uniformly  
225 and at random between 0 and 255, corresponding to the red (r), green (g), and blue (b)  
226 color channels for that word. To assign random presentation locations to each word, we  
227 selected two floating point numbers uniformly at random (one for the word’s horizontal  
228  $x$  coordinate and the other for its vertical  $y$  coordinate). The bounds of these coordinates  
229 were selected to cover the entire visible area of the display without cutting off any part of  
230 the words. The words were shown on 27 in (diagonal) Retina 5K iMac displays (resolution:  
231  $5120 \times 2880$  pixels).

232 Most of the experimental manipulations we carried out entailed presenting or sorting  
233 the presented words differently on the first eight lists participants studied (which we call  
234 *early* lists) versus on the final eight lists they studied (*late* lists). Since every participant  
235 studied exactly 16 lists, using this terminology every list was either “early” or “late”

236 depending on its order in the list study sequence.

### 237 **Real-time speech-to-text processing**

238 Our experimental paradigm incorporates the Google Cloud Speech API speech-to-text  
239 engine (Halpern et al., 2016) to automatically transcribe participants' verbal recalls into  
240 text. This allows recalls to be transcribed in real time– a distinguishing feature of the  
241 experiment; in typical verbal recall experiments the audio data must be parsed manually.  
242 In prior work, we used a similar experimental setup (equivalent to the “reduced” condition  
243 in the present study) to verify that the automatically transcribed recalls were sufficiently  
244 close to human-transcribed recalls to yield reliable data (Ziman et al., 2018). This real-time  
245 speech processing component of the paradigm plays an important role in the “adaptive”  
246 condition of the experiment, as described below.

### 247 **Random conditions (Fig. 1, top four rows)**

248 We used four “control” conditions to evaluate and explore participants' baseline behaviors.  
249 We also used performance on these control conditions to help interpret performance in  
250 other “manipulation” conditions. Two control conditions served as “anchorpoints.” In the  
251 first anchorpoint condition, which we call the *feature rich* condition, we randomly shuffled  
252 the presentation order (independently for each participant) of the words on each list. In  
253 the second anchorpoint condition, which we call the *reduced* condition, we randomized  
254 word presentations as in the feature rich condition. However, rather than assigning each  
255 word a random color and location, we instead displayed all of the words in black and at  
256 the center of the screen.

257 In the *reduced (early)* condition, we followed the “reduced” procedure (presenting each  
258 word in black at the center of the screen) for early lists, and followed the “feature rich”

259 procedure (presenting each word in a random color and location) for late lists. Finally, in  
260 the *reduced (late)* condition, we followed the feature rich procedure for earlylists and the  
261 reduced procedure for late lists.

#### 262 **Order manipulation conditions (Fig. 1, middle six rows)**

263 Each of six *order manipulation* conditions used a different feature-based sorting procedure  
264 to order words on early lists, where each sorting procedure relied on one relevant feature  
265 dimension. All of the irrelevant features varied freely across words on early lists, in  
266 that we did not consider irrelevant features in ordering the early lists. However, some  
267 features were correlated– for example, some semantic categories of words referred to  
268 objects that tended to be a particular size, which means that category and size are not  
269 fully independent. On late lists, the words were always presented in a randomized order  
270 (chosen anew for each participant). In all of the order manipulation conditions, we varied  
271 words’ font colors and onscreen locations, as in the feature rich condition.

272 **Defining feature-based distances.** Sorting words according to a given relevant feature  
273 requires first defining a distance function for quantifying the dissimilarity between each  
274 pair of features. This function varied according to the type of features. Semantic features  
275 (category and size) are *categorical*. For these features, we defined a binary distance function:  
276 two words were considered to “match” (i.e., have a distance of 0) if their labels are the  
277 same (i.e., both from the same semantic category or both of the same size). If two words’  
278 labels were different for a given feature, we defined the words to have a distance of 1 for  
279 that feature. Lexicographic features (length and first letter) are *discrete*. For these features  
280 we defined a discrete distance function. Specifically, we defined the distance between  
281 two words as either the absolute difference between their lengths, or the absolute distance  
282 between their starting letters in the English alphabet, respectively. For example, two

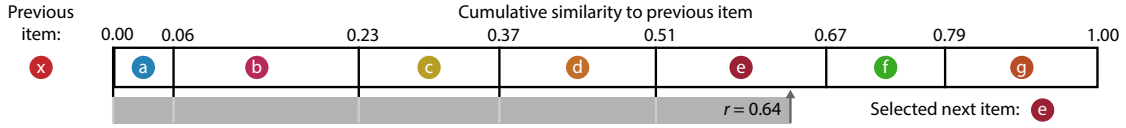
words that started with the same letter would have a “first letter” distance of 0, and words starting with ‘J’ and ‘A’ would have a first letter distance of 9. Because words’ lengths and letters’ positions in the alphabet are always integers, these discrete distances always take on integer values. Finally, the visual features (color and location) are *continuous* and *multivariate*, in that each “feature” takes on multiple (positive) real values. We defined the “color” and “location” distances between two words as the Euclidean distances between their  $(r, g, b)$  color or  $(x, y)$  location vectors, respectively. Therefore the color and location distance measures always take on positive real values (upper bounded at 441.67 for color, or 27 in for location, reflecting the distances between the corresponding maximally different vectors).

**Constructing feature-sorted lists.** Given a list of words, a relevant feature, and each word’s value(s) for that feature, we developed a stochastic algorithm for (noisily) sorting the words. First, we choose a word uniformly at random from the set of candidates. Next, we compute the distances between the chosen word’s feature(s) and the corresponding feature(s) of all yet-to-be-presented words. Third, we convert these distances (between the previously presented word’s feature values,  $a$ , and the candidate word’s feature values,  $b$ ) to similarity scores:

$$\text{similarity}(a, b) = \exp\{-\tau \cdot \text{distance}(a, b)\}, \quad (1)$$

where  $\tau = 1$  in our implementation. We note that increasing the value of  $\tau$  would amplify the influence of similarity on order, and decreasing the value of  $\tau$  would diminish the influence of similarity on order. Also note that this approach requires  $\tau > 0$ . Finally, we computed a set of normalized similarity values by dividing the similarities by their sum:

$$\text{similarity}_{\text{normalized}}(a, b) = \frac{\text{similarity}(a, b)}{\sum_{i=1}^n \text{similarity}(a, i)}, \quad (2)$$



**Figure 2: Generating stochastic feature-sorted lists.** For a given feature dimension (e.g., color), we compute the similarity (Eqn. 1) between the feature value(s) of the previous item,  $x$ , and all yet-to-be-presented items ( $a - g$ ). Next, we normalize these similarity scores so that they sum to one. We lay in sequence a set of “sticks,” one for each candidate item, whose lengths are equal to these normalized similarity scores. Note that the combined lengths of these sticks is one. To select the next to-be-presented item, we draw a random number,  $r$ , from the uniform distribution bounded between 0 and 1 (inclusive). The identity of the next item is given by the stick adjacent to an indicator that moves distance  $r$  (starting from 0) along the sequence of sticks. In this case, the next to-be-presented item is  $e$ . Note that each item’s chances of selection is proportional to its similarity to the previous item, along the given feature dimension.

304 where in the demoniator,  $i$  takes on each of the  $n$  feature values of the to-be-presented  
 305 words. The resulting set of normalized similarity scores sums to one.

306 As illustrated in Figure 2, we use these normalized similarity scores to construct a  
 307 sequence of “sticks” that we lay end to end in a line. Each of the  $n$  sticks corresponds  
 308 to a single to-be-presented word, and the stick lengths are proportional to the relative  
 309 similarities between each word’s feature value(s) and the feature value(s) of the just-  
 310 presented word. We choose the next to-be-presented word by moving an indicator along  
 311 the set of sticks, by a distance chosen uniformly at random on the interval  $[0, 1]$ . We  
 312 select the word associated with the stick lying next to the indicator to be presented next.  
 313 This process continues iteratively (re-computing the similarity scores and stochastically  
 314 choosing the next to-be-presented word using the just-presented word) until all of the  
 315 words have been presented. The result is an ordered list that tends to change gradually  
 316 along the selected feature dimension.

## 317 **Adaptive condition**

318 We designed the *adaptive* experimental condition to study the effect on memory for infor-  
319 mation that matched (or mismatched) the ways participants “naturally” organized their  
320 memories of the lists they studied. Like the other conditions, all participants in the adap-  
321 tive condition studied a total of 16 lists, in a randomized order. We varied the words’ colors  
322 and locations for every word presentation, as in the feature rich and order manipulation  
323 conditions.

324 All participants in the adaptive condition began the experiment by studying a set of  
325 four *initialization* lists. Words and features on these lists were presented in a randomized  
326 order (computed independently for each participant). These initialization lists were used  
327 to estimate each participant’s “memory fingerprint,” defined below. At a high level, a  
328 participant’s memory fingerprint describes how they prioritize different semantic, lexico-  
329 graphic, and/or visual features when they organize their memories.

330 Next, participants studied a sequence of 12 lists in three batches of 4 lists each. These  
331 batches came in three types: *random*, *stabilize*, and *destabilize*. The batch types determined  
332 how words on the lists in that batch were ordered. Lists in each batch were always  
333 presented consecutively (e.g., a participant might receive four random lists, followed  
334 by four stabilize lists, followed by four destabilize lists). The batch orders were evenly  
335 counterbalanced across participants: there are six possible orderings of the three batches,  
336 and 10 participants were randomly assigned to each ordering sub-condition.

337 Lists in the random batches were sorted randomly (as on the initialization lists and in  
338 the feature rich condition). Lists in the stabilize and destabilize batches were sorted in  
339 ways that either matched or mismatched each participant’s memory fingerprint, respec-  
340 tively. Our procedures for computing participants’ memory fingerprints and ordering the  
341 stabilize and destabilize lists are described next.



342 **Feature clustering scores (uncorrected).** Feature clustering scores describe participants’  
343 tendencies to recall similar presented items together in their recall sequences, where  
344 “similarity” considers one given feature dimension (e.g., category, color, etc.). We base  
345 our main approach to computing clustering scores on analogous temporal and semantic  
346 clustering scores developed by (Polyn et al., 2009). Computing the clustering score for  
347 one feature dimension starts by considering those feature values from the first word the  
348 participant recalled on the list. Next, we sort all not-yet-recalled words in ascending order  
349 according to their feature-based distance to the just-recalled item (see *Defining feature-based*  
350 *distances*). We then compute the percentile rank of the observed next recall. We averaged  
351 these percentile ranks across all of the participant’s recalls for the current list to obtain a  
352 single uncorrected clustering score for the list, for the given feature dimension. We repeat  
353 this process for each feature dimension in turn to obtain a single uncorrected clustering  
354 score for each list, for each feature dimension.

355 **Temporal clustering score (uncorrected).** Temporal clustering describes a participant’s  
356 tendency to organize their recall sequences by the learned items’ encoding positions. For  
357 instance, if a participant recalled the episode events in the exact order they occurred (or  
358 in exact reverse order), this would yield a score of 1. If a participant recalled the events in  
359 random order, this would yield an expected score of 0.5. For each recall-event transition  
360 (and separately for each participant), we sorted all not-yet-recalled events according to  
361 their absolute lag (that is, distance away in the episode). We then computed the percentile  
362 rank of the next event the participant recalled. We took an average of these percentile ranks  
363 across all of the participant’s recalls to obtain a single (uncorrected) temporal clustering  
364 score for the participant.

365 **Permutation-corrected feature clustering scores.** Suppose that two lists contain unequal  
366 numbers of items of each size. For example, suppose that list *A* contains all “large” items,  
367 whereas list *B* contains an equal mix of “large” and “small” items. For a participant  
368 recalling list *A*, any correctly recalled item will necessarily match the size of the previous  
369 correctly recalled item. In other words, successively recalling several list *A* items of the  
370 same size is essentially meaningless, since *any* correctly recalled list *A* word will be large.  
371 In contrast, successively recalling several list *B* items *could* be meaningful, since (early in  
372 the recall sequence) the yet-to-be-recalled items come from a mix of sizes. However, once  
373 all of the “small” items on list *B* have been recalled, the best possible next matching recall  
374 will be a large item. And all subsequent correct recalls must also be large items– so for  
375 those later recalls it becomes difficult to determine whether the participant is successively  
376 recalling “large” items because they are organizing their memories according to size, or  
377 (alternatively), whether they are simply recalling the yet-to-be-recalled items in a random  
378 order. In general, the precise order and blend of feature values expressed in a given list,  
379 the orders and numbers of correct recalls a participant makes, the number of intervening  
380 presentation positions between successive recalls, and so on, can all affect the range of  
381 clustering scores that are possible to observe for a given list. The uncorrected clustering  
382 score therefore conflates participants’ actual memory organization with other “nuisance”  
383 factors.

384 Following our prior work (Heusser et al., 2017), we used a permutation-correction  
385 procedure to help isolate the behavioral aspects of clustering that we were most interested  
386 in. After computing the uncorrected clustering score (for the given list and observed  
387 recall sequence), we compute a “null” distribution of  $n$  additional clustering scores after  
388 randomly shuffling the recall order (we use  $n = 500$  in the present study). This null  
389 distribution represents an approximation of the range of clustering scores one might expect

390 to observe by “chance,” given that a hypothetical participant was *not* truly clustering their  
391 recalls, but where the hypothetical participant studied and recalled exactly the same items  
392 (with the same features) as the true participant. We define the permutation-corrected  
393 clustering score as the percentile rank of the observed uncorrected clustering score in this  
394 estimated null distribution. In this way, a corrected score of 1 indicates that the observed  
395 score was greater than any clustering score one might expect by chance; in other words,  
396 good evidence that the participant was truly clustering their recalls along the given feature  
397 dimension. We applied this correction procedure to all of the clustering scores (feature  
398 and temporal) reported in this paper.

399 **Memory fingerprints.** We define each participant’s *memory fingerprint* as the set of their  
400 permutation-corrected clustering scores across all dimensions we tracked in our study,  
401 including their six feature-based clustering scores (category, size, length, first letter, color,  
402 and location) and their temporal clustering score. Conceptually, this memory fingerprint  
403 describes the participant’s tendencies to order (and, presumably, organize in memory)  
404 the studied words along each dimension. To obtain stable estimates of these fingerprints  
405 for each participant, we averaged clustering scores across lists. We also tracked and  
406 characterized how participants’ fingerprints changed across lists (e.g., Figs. 6, S8).

407 **Online “fingerprint” analysis.** The presentation orders of some lists in the adaptive  
408 condition of our experiment (see *Adaptive condition*) were sorted according to participants’  
409 *current* memory fingerprint, estimated using all of the lists they had studied up to that point  
410 in the experiment. Because our experiment incorporated a speech-to-text component, all  
411 of the behavioral data for each participant could be analyzed just a few seconds after the  
412 conclusion of the recall intervals for each list. We used the Quail Python package (Heusser  
413 et al., 2017) to apply speech-to-text algorithms to the just collected data, aggregate the data

414 for the given participant, and estimate the participant’s memory fingerprint using all of  
415 their available data up to that point in the experiment. Two aspects of our implementation  
416 are worth noting. First, because memory fingerprints are averaged across lists, the already-  
417 computed memory fingerprints for earlier lists could be cached and loaded as needed  
418 in future computations. This meant that our computations pertaining to updating our  
419 estimates of a participant’s memory fingerprint only needed to consider data from the  
420 most recent list. Second, each element of the null distributions of uncorrected fingerprint  
421 scores (see *Permutation-corrected feature clustering scores*) could be estimated independently  
422 from the others. This enabled us to make use of the testing computers’ multi-core CPU  
423 architectures by elements of the null distributions in batches of eight (i.e., the number  
424 of CPU cores on each testing computer). Taken together, we were able to compress  
425 the fingerprint computations into just a few seconds of computing time. The combined  
426 processing time for the speech-to-text algorithm and fingerprint computations easily fit  
427 within the inter-list intervals, where participants typically paused before moving on to the  
428 next list.

429 **Ordering “stabilize” and “destabilize” lists by an estimated fingerprint.** In the adap-  
430 tive condition of our experiment, the presentation orders for *stabilize* and *destabilize* lists  
431 were chosen to either maximally or minimally (respectively) comport with participants’  
432 memory fingerprints. Given a participant’s memory fingerprint and a to-be-presented set  
433 of items, we designed a permutation-based procedure for ordering the items. First, we  
434 dropped from the participant’s fingerprint the temporal clustering score. For the remain-  
435 ing feature dimensions, we arranged the clustering scores in the fingerprint into a template  
436 vector,  $f$ . Second, we computed  $n = 2500$  random permutations of the to-be-presented  
437 items. These permutations served as prospective presentation orders. We sought to select  
438 the specific order that most (or least) matched  $f$ . Third, for each random permutation, we

439 computed the (permutation-corrected) “fingerprint,” treating the permutation as though  
 440 it were a potential “perfect” recall sequence. (We did not include temporal clustering  
 441 scores in these fingerprints.) This yielded a “simulated fingerprint” vector,  $\hat{f}_p$  for each per-  
 442 mutation  $p$ . We used these simulated fingerprints to select a specific permutation,  $i$ , that  
 443 either maximized (for stabilized lists) or minimized (for destabilize lists) the correlation  
 444 between  $\hat{f}_i$  and  $f$ .

### 445 **Computing low-dimensional embeddings of memory fingerprints**

446 Following some of our prior work (Heusser et al., 2018), we use low-dimensional em-  
 447 beddings to help visualize how participants’ memory fingerprints change across lists  
 448 (Figs. 6A, S8A). To compute a shared embedding space across participants and experimen-  
 449 tal conditions, we concatenated the full set of fingerprints (across all lists, participants,  
 450 and experimental conditions) to create a large matrix with number-of-lists  $\times$  number-of-  
 451 participants rows and seven columns (one for each word feature dimension’s clustering  
 452 scores, plus an additional temporal clustering score column). We used principal compo-  
 453 nents analysis to project the seven-dimensional observations into a two-dimensional space  
 454 (using the two principal components that explained the most variance in the data). For  
 455 two visualizations (Figs. 6B, and S8B) we computed an additional set of two-dimensional  
 456 embeddings for participants’ *average* fingerprints (i.e., across lists within a given group of  
 457 lists— early or late). For those visualizations we averaged each participant’s rows (for the  
 458 given group of lists) in the combined fingerprint matrix prior to projecting it into the shared  
 459 two-dimensional space. This yielded a single two-dimensional coordinate for each *partic-*  
 460 *ipant* and *list group*, rather than for each individual list. We used these embeddings solely  
 461 for visualization. All statistical tests were carried out in the original (seven-dimensional)  
 462 feature spaces.

## 463 **Analyses**

### 464 **Probability of $n^{\text{th}}$ recall curves**

465 Probability of first recall curves (Atkinson and Shiffrin, 1968; Postman and Phillips, 1965;  
466 Welch and Burnett, 1924) reflect the probability that an item will be recalled first, as a  
467 function of its serial position during encoding. To carry out this analysis, we initialized  
468 (for each participant) a number-of-lists (16) by number-of-words-per-list (16) matrix of  
469 zeros. Then, for each list, we found the index of the word that was recalled first, and we  
470 filled in that position in the matrix with a 1. Finally, we averaged over the rows of the  
471 matrix to obtain a 1 by 16 array of probabilities, for each participant. We used an analogous  
472 procedure to compute probability of  $n^{\text{th}}$  recall curves for each participant. Specifically,  
473 we filled in the corresponding matrices according to the  $n^{\text{th}}$  recall on each list that each  
474 participant made. When a given participant had made fewer than  $n$  recalls for a given  
475 list, we simply excluded that list from our analysis when computing that participant's  
476 curve(s).

### 477 **Lag-conditional response probability curve**

478 The lag-conditional probability (lag-CRP) curve (Kahana, 1996) reflects the probability of  
479 recalling a given item after the just-recalled item, as a function of their relative encoding  
480 positions (lag). In other words, a lag of 1 indicates that a recalled item was presented  
481 immediately after the previously recalled item, and a lag of 3 indicates that a recalled item  
482 came 3 items before the previously recalled item. For each recall transition (following the  
483 first recall), we computed the lag between the just-recalled word's presentation position  
484 and the next-recalled word's presentation position. We computed the proportions of  
485 transitions (between successively recalled words) for each lag, normalizing for the total  
486 numbers of possible transitions. In carrying out this analysis, we excluded all incorrect

487 recalls and successive repetitions (e.g., recalling the same word twice in a row). This  
488 yielded, for each list, a 1 by number-of-lags (–15 to +15; 30 lags in total, excluding lags of  
489 0) array of conditional probabilities. We averaged these probabilities across lists to obtain  
490 a single lag-CRP for each participant.

### 491 **Serial position curve**

492 Serial position curves (Murdock, 1962) reflect the proportion of participants who remember  
493 each item as a function of the item’s serial position during encoding. For each participant,  
494 we initialized a number-of-lists (16) by number-of-words-per-list (16) matrix of zeros.  
495 Then, for each correct recall, we identified the presentation position of the word and  
496 entered a 1 into that position (row: list; column: presentation position) in the matrix.  
497 This resulted in a matrix whose entries indicated whether or not the words presented at  
498 each position, on each list, were recalled by the participant (depending on whether the  
499 corresponding entires were set to one or zero). Finally, we averaged over the rows of the  
500 matrix to yield a 1 by 16 array representing the proportion of words at each position that  
501 the participant remembered.

### 502 **Identifying event boundaries**

503 We used the distances between feature values for successively presented words (see *Defin-*  
504 *ing feature-based distances*) to estimate “event boundaries” where the feature values changed  
505 more than usual (DuBrow and Davachi, 2016; Ezzyat and Davachi, 2011; Manning et al.,  
506 2016; Radvansky and Copeland, 2006; Swallow et al., 2011, 2009). For each list, for each  
507 feature dimension, we computed the distribution of distances between the feature values  
508 for successively presented words. We defined event boundaries (e.g., Fig. 3B) as occurring  
509 between any successive pair of words whose distances along the given feature dimension

were greater than one standard deviation above the mean for that list. Note that, because event boundaries are defined for each feature dimension, each individual list may contain several sets of event boundaries, each at different moments in the presentation sequence (depending on the feature dimension of interest).

## Results

We sought to manipulate two aspects of how participants memorized sequences of word lists. First, we added two additional sources of visual variation to the individual word presentations: font color and onscreen location. Importantly, these visual features were independent of the meaning or semantic content of the words (e.g., word category, size of the referent) and of the lexicographic properties of the word (e.g., word length, first letter). We wondered whether this additional word-independent information might facilitate recall (e.g., by providing new potential ways of organizing or retrieving memories of the studied words) or impair recall (e.g., by distracting participants). Second, our primary experimental manipulations entailed manipulating the orders in which words were studied (and how those orderings changed over time). We wondered whether presenting the same list of words in different orders (e.g., sorted along one feature dimension versus another) might serve to influence how participants organized their memories of the words. We also wondered whether some order manipulations might be temporally “sticky” by influencing how *future* lists were remembered.

To obtain a clean preliminary estimate of the consequences on memory of randomly varying the font colors and locations of presented words (versus holding the font color fixed at black, and holding the display locations fixed at the center of the display) we compared participants’ performance on the *feature rich* and *reduced* experimental conditions (see *Random conditions*, Fig. S1). In the feature rich condition the words’ colors and



locations varied randomly across words, and in the reduced condition words were always presented in black, at the center of the display. Aggregating across all lists for each participant, we found no difference in recall accuracy for feature rich versus reduced lists ( $t(126) = -0.290, p = 0.772$ ). However, participants in the feature rich condition clustered their recalls substantially more along every dimension we examined (temporal clustering:  $t(126) = 10.624, p < 0.001$ ; category clustering:  $t(126) = 10.077, p < 0.001$ ; size clustering:  $t(126) = 11.829, p < 0.001$ ; word length clustering:  $t(126) = 10.639, p < 0.001$ ; first letter clustering:  $t(126) = 7.775, p = 0.000$ ; see *Permutation-corrected feature clustering scores* for more information about how we quantified each participant’s clustering tendencies.) Taken together, these comparisons suggest that adding new features changes how participants organize their memories of studied words, even when those new features are independent of the words themselves and even when the new features vary randomly across words. We found no evidence that those additional uninformative features were distracting (in terms of their impact on memory performance), but they did affect participants’ recall dynamics (measured via their clustering scores).

We also wondered whether adding these irrelevant visual features to later lists (after the participants had already studied impoverished lists), or removing the visual features from later lists (after the participants had already studied visually diverse lists) might affect memory performance. In other words, we sought to test for potential effects of changing the “richness” of participants’ experiences over time. All participants studied and recalled a total of 16 lists; we defined *early* lists as the first eight lists and *late* lists as the last eight lists each participant encountered. To help interpret our results, we compared participants’ memories on early versus late lists in the above feature rich and reduced conditions. Participants in both conditions remembered more words on early versus late lists (feature rich:  $t(66) = 4.553, p < 0.001$ ; reduced:  $t(60) = 2.434, p = 0.018$ ). Participants in the feature

rich (but not reduced) conditions exhibited more temporal clustering on early versus late lists (feature rich:  $t(66) = 2.318, p = 0.024$ ; reduced:  $t(60) = 0.929, p = 0.357$ ). And participants in both conditions exhibited more semantic (category and size) clustering on early versus late lists (feature rich, category:  $t(66) = 3.805, p < 0.001$ ; feature rich, size:  $t(66) = 2.190, p = 0.032$ ; reduced, category:  $t(60) = 2.856, p = 0.006$ ; reduced, size:  $t(60) = 2.947, p = 0.005$ ). Participants in the reduced (but not feature rich) conditions exhibited more lexicographic clustering on early versus late lists (feature rich, word length:  $t(66) = 0.161, p = 0.872$ ; feature rich, first letter:  $t(66) = 0.410, p = 0.683$ ; reduced, word length:  $t(60) = 3.528, p = 0.001$ ; reduced, first letter:  $t(60) = 2.275, p = 0.026$ ). Taken together, these comparisons suggest that even when the presence or absence of irrelevant visual features is stable across lists, participants still exhibit some differences in their performance and memory organization tendencies for early versus late lists.

With these differences in mind, we next compared participants' memories on early versus late lists for two additional experimental conditions (see *Random conditions*, Fig. S1). In a *reduced (early)* condition, we held the irrelevant visual features constant on early lists, but allowed them to vary randomly on late lists. In a *reduced (late)* condition, we allowed the irrelevant visual features to vary randomly on early lists, but held them constant on late lists. Given our above findings that (a) participants tended to remember more words and exhibit stronger clustering effects on feature rich (versus reduced) lists, and (b) participants tended to remember more words and exhibit stronger clustering effects on early (versus late) lists, we expected these early versus late differences to be enhanced in the reduced (early) condition and diminished in the reduced (late) condition. However, to our surprise, participants in *neither* condition exhibited reliable early versus late differences in accuracy (reduced (early):  $t(41) = 1.499, p = 0.141$ ; reduced (late):  $t(40) = 1.462, p = 0.152$ ), temporal clustering (reduced (early):  $t(41) = 0.998, p = 0.324$ ; reduced (late):

584  $t(40) = 1.099, p = 0.278$ ), nor feature based clustering (reduced (early), category:  $t(41) =$   
 585  $0.753, p = 0.456$ ; reduced (early), size:  $t(41) = 0.721, p = 0.475$ ; reduced (early), length:  
 586  $t(41) = 0.493, p = 0.625$ ; reduced (early), first letter:  $t(41) = 0.780, p = 0.440$ ; reduced (late),  
 587 category:  $t(40) = -0.086, p = 0.932$ ; reduced (late), size:  $t(40) = 0.746, p = 0.460$ ; reduced  
 588 (late), length:  $t(40) = 1.476, p = 0.148$ ; reduced (late), first letter:  $t(40) = 0.966, p = 0.340$ ).

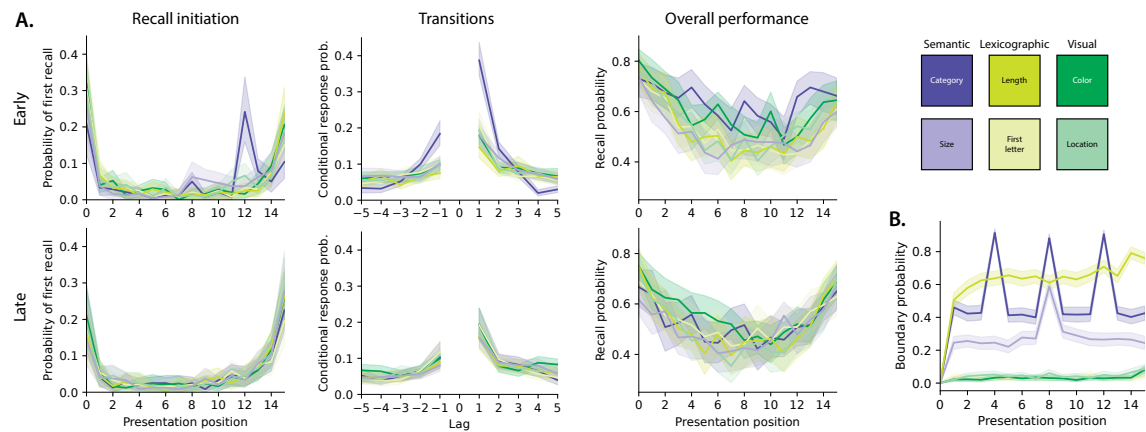
589 We hypothesized that adding or removing the irrelevant features was acting as a sort  
 590 of “event boundary” between early and late lists. In prior work, we (and others) have  
 591 found that memories formed just after event boundaries can be enhanced (e.g., due to less  
 592 contextual interference between pre- and post-boundary items; Manning et al., 2016).

593 We found that *adding* irrelevant visual features on later lists that had not been present  
 594 on early lists (as in the reduced (early) condition) served to enhance recall performance  
 595 relative to conditions where all lists had the same blends of features (accuracy for feature  
 596 rich versus reduced (early):  $t(107) = -2.230, p = 0.028$ ; reduced versus reduced (early):  
 597  $t(101) = -2.045, p = 0.043$ ; also see Fig. S3A). However, *subtracting* irrelevant visual fea-  
 598 tures on later lists that *had* been present on early lists (as in the reduced (late) condition) did  
 599 not appear to impact recall performance (accuracy for feature rich versus reduced (late):  
 600  $t(106) = -0.638, p = 0.525$ ; reduced versus reduced (late):  $t(100) = -0.407, p = 0.685$ ).  
 601 These comparisons suggest that recall accuracy has a directional component (i.e., accu-  
 602 racy is affected differently by removing features later that had been present earlier versus  
 603 adding features later that had *not* been present earlier). In contrast, we found that partic-  
 604 ipants exhibited more temporal and feature-based clustering when we added irrelevant  
 605 visual features to *any* lists (comparisons of clustering on feature rich and reduced lists  
 606 are reported above; temporal clustering in reduced versus reduced (early) and reduced  
 607 versus reduced (late) conditions:  $t_s \leq -9.780, p_s < 0.001$ ; feature based clustering in re-  
 608 duced versus reduced (early) and reduced versus reduced (late) conditions:  $t_s \leq -5.443, p_s$

609 < 0.001). Temporal and feature-based clustering were not reliably different in the feature  
610 rich, reduced (early), and reduced (late) conditions (temporal clustering in feature rich  
611 versus reduced (early) and feature rich versus reduced (late) conditions:  $t_s \geq -1.434$ ,  $p_s$   
612  $\geq 0.154$ ; feature based clustering in feature rich versus reduced (early) and feature rich  
613 versus reduced (late) conditions:  $t_s \geq -1.359$ ,  $p_s > 0.177$ ).

614 Taken together, our findings thus far suggest that adding item features that change  
615 over time, even when they vary randomly and independently of the items, can enhance  
616 participants' overall memory performance and can also enhance temporal and feature-  
617 based clustering. To the extent that the number of item features that vary from moment  
618 to moment approximates the "richness" of participants' experiences, our findings sug-  
619 gest that participants remember "richer" stimuli better and organize richer stimuli more  
620 reliably in their memories. Next, we turn to examine the memory effects of varying the  
621 temporal ordering of different stimulus features while holding the features themselves  
622 constant. We hypothesized that changing the order in which participants were exposed  
623 to the words on a given list might enhance (or diminish) the relative influence of different  
624 features. For example, presenting a set of words alphabetically might enhance partici-  
625 pants' attention to the studied items' first letters, whereas sorting the same list of words by  
626 semantic category might instead enhance participants' attention to the words' semantic  
627 attributes. Importantly, we expected these order manipulations to hold even when the  
628 variation in the total set of features (across words) was held constant across lists (e.g.,  
629 unlike in the reduced (early) and reduced (late) conditions, where visual features were  
630 added or removed from a subset of the lists participants studied).

631 Across six order manipulation conditions, we sorted early lists by each feature dimen-  
632 sion but randomly ordered the items on late lists (see *Order manipulation conditions*; features:  
633 category, size, length, first letter, color, and location). Participants in the category-ordered

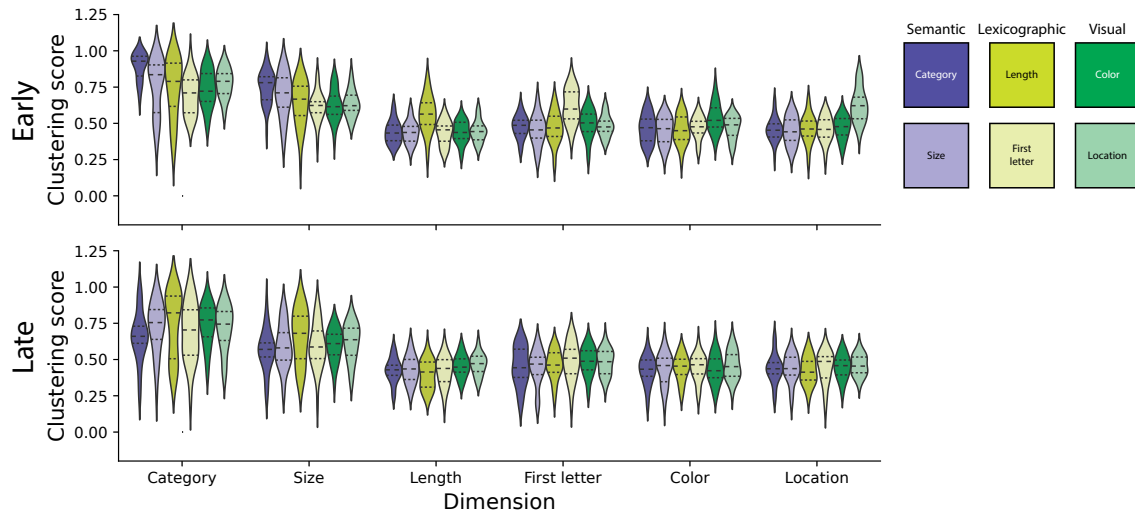


**Figure 3: Recall dynamics in feature rich free recall (order manipulation conditions).** **A.** Behavioral plots. **Left panels.** The probabilities of initiating recall with each word are plotted as a function of presentation position. **Middle panels.** The conditional probabilities of recalling each word are plotted as a function of the relative position (Lag) to the words recalled just-prior. **Right panels.** The overall probabilities of recalling each word are plotted as a function of presentation position. **All panels.** Error ribbons denote bootstrap-estimated 95% confidence intervals (calculated across participants). Top panels display the recall dynamics for early (order manipulation) lists in each condition (color). Bottom panels display the recall dynamics for late (randomly ordered) lists. See Figures S1 and S2 for analogous plots for the random (control) and adaptive conditions. **B.** Proportion of event boundaries (see *Methods*) for each condition's feature of focus, plotted as a function of presentation position.

condition showed an increase in memory performance on early lists (accuracy, relative to  
 early feature rich lists;  $t(95) = 3.034, p = 0.003$ ). Participants in the color-ordered condition  
 also showed a trending increase in memory performance on early lists (again, relative to  
 early feature rich lists:  $t(96) = 1.850, p = 0.067$ ). Participants' performance on early lists  
 in all of the other order manipulation conditions was indistinguishable from performance  
 on the early feature rich lists ( $|t|s < 1.013, ps > 0.314$ ). Participants in both of the se-  
 mantically ordered conditions exhibited stronger temporal clustering on early lists (versus  
 early feature rich lists; category:  $t(95) = 8.508, p < 0.001$ ; size:  $t(95) = 2.429, p = 0.017$ ).  
 Participants in the length-ordered condition tended to exhibit *less* temporal clustering  
 on early lists relative to early feature rich lists ( $t(95) = -1.666, p = 0.099$ ), whereas par-  
 ticipants in the first letter-ordered condition exhibited stronger temporal clustering on  
 early lists ( $t(95) = 2.587, p = 0.011$ ). Participants in the visually ordered conditions ex-  
 hibited more similar performance on early lists, relative to early feature rich lists (color:  
 $t(96) = -1.064, p = 0.290$ ; we found a trending enhancement for participants in the location-  
 ordered condition:  $t(95) = 1.682, p = 0.096$ ). We also compared feature-based clustering  
 on early lists across the order manipulation and feature rich conditions. Since results were  
 similar across both semantic conditions (category and size), both lexicographic conditions  
 (length and first letter), and both visual conditions (color and location), here we aggre-  
 gate data from conditions that manipulated each of these three feature groupings in our  
 comparisons to simplify the presentation. On early lists, participants in the semantically  
 ordered conditions exhibited stronger semantic clustering relative to participants in the  
 feature rich condition (category:  $t(125) = 2.524, p = 0.013$ ; size:  $t(125) = 3.510, p = 0.001$ ),  
 but showed no reliable differences in lexicographic (length:  $t(125) = 0.539, p = 0.591$ ; first  
 letter:  $t(125) = -0.587, p = 0.558$ ) or visual (color:  $t(125) = -0.579, p = 0.564$ ; location:  
 $t(125) = -0.346, p = 0.730$ ) clustering. Similarly, participants in the lexicographically or-

659 dered conditions exhibited stronger (relative to feature rich participants) lexicographic  
 660 clustering (length:  $t(125) = 3.426, p = 0.001$ ; first letter:  $t(125) = 3.236, p = 0.002$ ) on early  
 661 lists, but showed no reliable differences in semantic (category:  $t(125) = -1.078, p = 0.283$ ;  
 662 size:  $t(125) = -0.310, p = 0.757$ ) or visual (color:  $t(125) = -0.209, p = 0.835$ ; location:  
 663  $t(125) = -0.004, p = 0.997$ ) clustering. And participants in the visually ordered condi-  
 664 tions exhibited stronger visual clustering (again, relative to feature rich participants, and  
 665 on early lists; color:  $t(126) = 2.099, p = 0.038$ ; location:  $t(126) = 4.392, p = 0.000$ ), but  
 666 showed now reliable differences in semantic (category:  $t(126) = 0.204, p = 0.839$ ; size:  
 667  $t(126) = -0.093, p = 0.926$ ) or lexicographic (length:  $t(126) = 0.714, p = 0.476$ ; first letter:  
 668  $t(126) = 0.820, p = 0.414$ ) clustering. Taken together, these order manipulation results sug-  
 669 gest several broad patterns (Figs. 3, 4). First, most of the order manipulations we carried  
 670 out did *not* reliably affect overall recall performance. Second, most of the order manipula-  
 671 tions increased participants' tendencies to temporally cluster their recalls. Third, all of the  
 672 order manipulations enhanced participants' clustering of each condition's target feature  
 673 (i.e., semantic manipulations enhanced semantic clustering, lexicographic manipulations  
 674 enhanced lexicographic clustering, and visual manipulations enhanced visual clustering)  
 675 while leaving clustering along other feature dimensions roughly unchanged (i.e., semantic  
 676 manipulations did not affect lexicographic or color clustering, and so on).

677 The above comparisons between memory performance on early lists in the order ma-  
 678 nipulation versus feature rich conditions highlight how sorted lists are remembered differ-  
 679 ently from random lists. We also wondered how sorting lists along each feature dimension  
 680 influenced memory relative to sorting lists along the other feature dimensions. Participants  
 681 trended towards remembering early lists that were sorted semantically better than lexico-  
 682 graphically sorted lists ( $t(118) = 1.936, p = 0.055$ ). Participants also remembered visually  
 683 sorted lists better than lexicographically sorted lists ( $t(119) = 2.145, p = 0.034$ ). However,



**Figure 4: Memory “fingerprints” (order manipulation conditions).** The across-participant distributions of clustering scores for each feature type ( $x$ -coordinate) are displayed for each experimental condition (color), separately for order manipulation (early, top) and randomly ordered (late, bottom) lists. See Figures S5 and S6 for analogous plots for the random (control) and adaptive conditions.

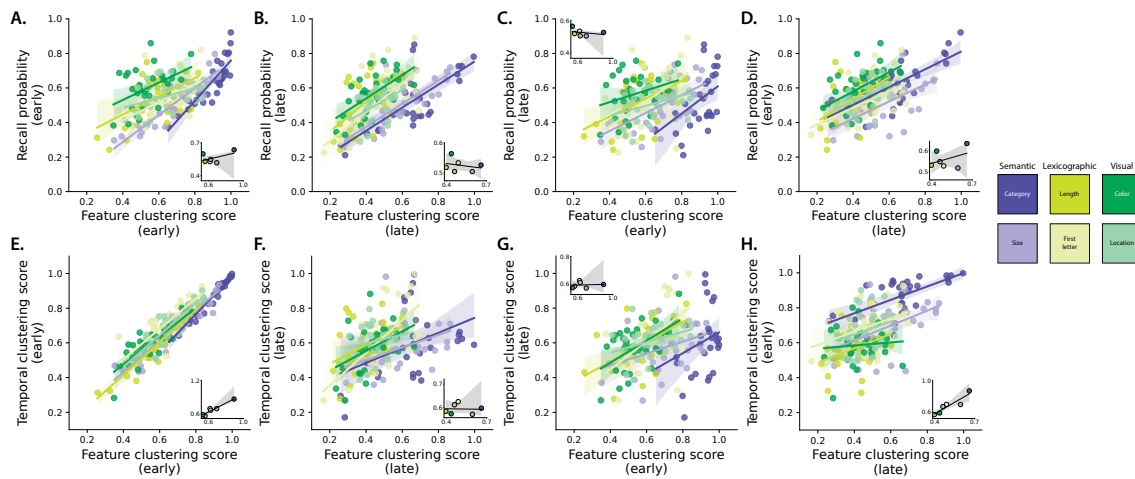
684 participants showed no reliable differences in recall performance on semantically versus  
 685 visually sorted lists ( $t(119) = 0.113, p = 0.910$ ). Participants temporally clustered semanti-  
 686 cally sorted lists more strongly than either lexicographically ( $t(118) = 5.572, p < 0.001$ ) or  
 687 visually ( $t(119) = 6.215, p < 0.001$ ) sorted lists, but did not show reliable differences in tem-  
 688 poral clustering on lexicographically versus visually sorted lists ( $t(119) = 0.189, p = 0.850$ ).  
 689 Participants also showed reliably more semantic clustering on semantically sorted lists  
 690 than lexicographically (category:  $t(118) = 3.492, p = 0.001$ , size:  $t(118) = 3.972, p < 0.001$ )  
 691 or visually (category:  $t(119) = 2.702, p = 0.008$ , size:  $t(119) = 4.230, p < 0.001$ ) sorted  
 692 lists; more lexicographic clustering on lexicographically sorted lists than semantically  
 693 (length:  $t(118) = 3.112, p = 0.002$ ; first letter:  $t(118) = 3.686, p = 0.000$ ) or visually (length:  
 694  $t(119) = 3.024, p = 0.003$ ; first letter:  $t(119) = 2.644, p = 0.009$ ) sorted lists; and more visual  
 695 clustering on visually sorted lists than semantically (color:  $t(119) = -2.659, p = 0.009$ ;



696 location:  $t(119) = -4.604, p = 0.000$ ) or lexicographically (color:  $t(119) = -2.366, p = 0.020$ ;  
697 location:  $t(119) = -4.265, p < 0.001$ ) sorted lists. In summary, sorting lists by different  
698 features appeared to have slightly different effects on overall memory performance and  
699 temporal clustering, and people tended to cluster their recalls along a given feature di-  
700 mension more when the studied lists were (versus were not) sorted along that dimension.

701 Beyond affecting how we process and remember *ongoing* experiences, what is happen-  
702 ing to us now can also affect how we process and remember *future* experiences. Within  
703 the framework of our study, we wondered: if early lists are sorted along different feature  
704 dimensions, might this affect how people remember later (random) lists? In exploring this  
705 question, we considered both group-level effects (i.e., effects that tended to be common  
706 across individuals) and participant-level effects (i.e., effect that were idiosyncratic across  
707 individuals).

708 At the group level, there seemed to be almost no lingering impact of sorting early  
709 lists on memory for later lists. To simplify the presentation, we report these null results  
710 in aggregate across the three feature groupings. Relative to memory performance on  
711 late feature rich lists, participants' memory performance in all six order manipulation  
712 conditions showed no reliable differences (semantic:  $t(125) = 0.487, p = 0.627$ ; lexico-  
713 graphic:  $t(125) = 0.878, p = 0.382$ ; visual:  $t(126) = 1.437, p = 0.153$ ). Nor did we observe  
714 any reliable differences in temporal clustering on late lists (relative to late feature rich  
715 lists; semantic:  $t(125) = 0.146, p = 0.884$ ; lexicographic:  $t(125) = 0.923, p = 0.358$ ; visual:  
716  $t(126) = 0.525, p = 0.601$ ). Aside from a slightly increased tendency for participants to  
717 cluster words by their length on late visual order manipulation lists (more than late fea-  
718 ture rich lists;  $t(126) = 2.199, p = 0.030$ ), we observed no reliable differences in any type of  
719 feature clustering on late order manipulation condition lists versus late feature rich lists  
720 ( $|t| \leq 1.234, p \geq 0.220$ ).



**Figure 5: Interactions between feature clustering, recall probability, and contiguity.** **A.** Recall probability versus feature clustering scores for order manipulation (early) lists. **B.** Recall probability versus feature clustering for randomly ordered (late) lists. **C.** Recall probability on late lists versus feature clustering on early lists. **D.** Recall probability on early lists versus feature clustering on late lists. **E.** Temporal clustering scores (contiguity) versus feature clustering scores on early lists. **F.** Temporal clustering scores versus feature clustering scores on late lists. **G.** Temporal clustering scores on late lists versus feature clustering scores on early lists. **H.** Temporal clustering scores on early lists versus feature clustering scores on late lists. **All panels.** Each dot in the main scatterplots denotes the average scores for one participant. The colored regression lines are computed across participants. The inset displays condition-averaged results, where each dot reflects a single condition and the regression line is computed across experimental conditions. All error ribbons denote bootstrap-estimated 95% confidence intervals.

721 Figure S3.

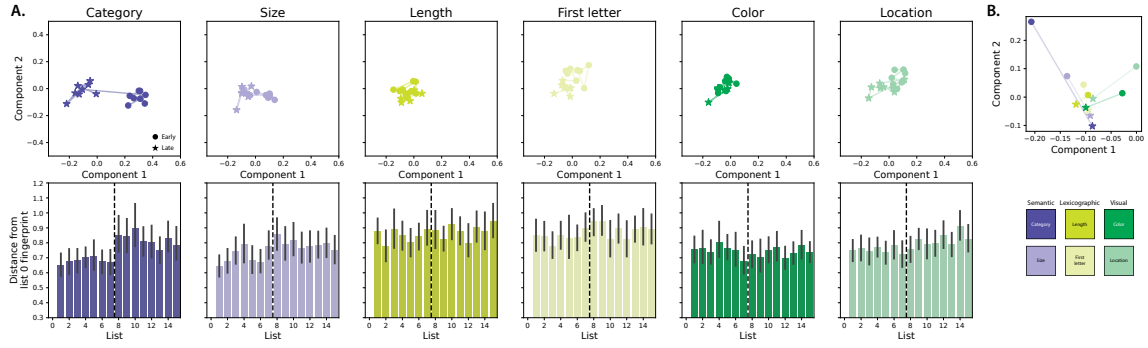
722 Figure S7.

723 Figure S4.

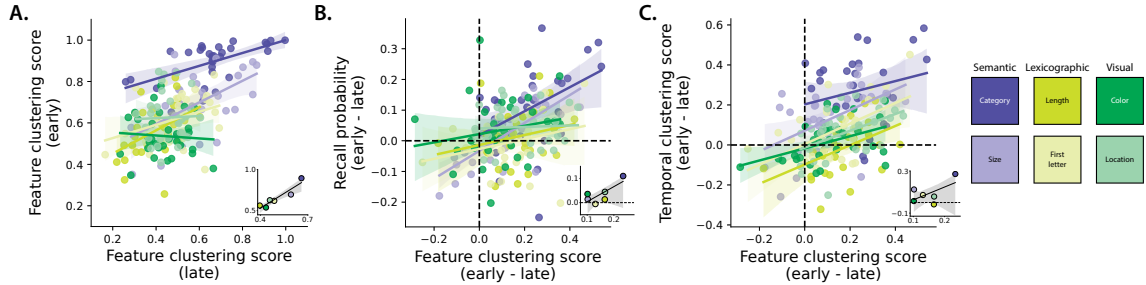
## 724 Discussion

## 725 References

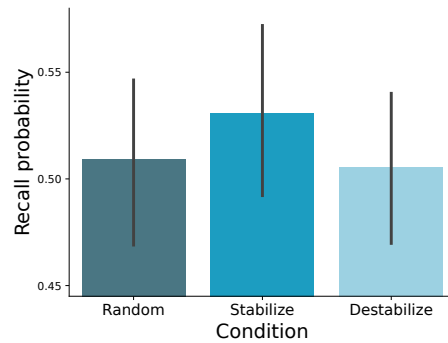
726 Anderson, J. R. and Bower, G. H. (1972). Recognition and retrieval processes in free recall.  
727 *Psychological Review*, 79(2):97–123.



**Figure 6: Memory fingerprint dynamics (order manipulation conditions).** **A.** Each column (and color) reflects an experimental condition. In the top panels, each marker displays a 2D projection of the (across-participant) average memory fingerprint for one list. Order manipulation (early) lists are denoted by circles and randomly ordered (late) lists are denoted by stars. All of the fingerprints (across all conditions and lists) are projected into a common space. The bar plots in the bottom panels display the Euclidean distances of the per-list memory fingerprints to the list 0 fingerprint, for each condition. Error bars denote bootstrap-estimated 95% confidence intervals. The dotted vertical lines denote the boundaries between early and late lists. **B.** In this panel, the fingerprints for early (circle) and late (star) lists are averaged across lists and participants before projecting the fingerprints into a (new) 2D space. See Figure S8 for analogous plots for the random (control) conditions.



**Figure 7: Feature clustering carryover effects.** **A.** Feature clustering scores for order manipulation (early) versus randomly ordered (late) lists. **B.** Accuracy differences (on early versus late lists) versus feature clustering “carryover” (defined as the differences between the average clustering scores on early and late lists). **C.** Temporal clustering differences (on early versus late lists) versus feature clustering carryover. **All panels.** Each dot in the main scatterplots denotes the average scores for one participant. The colored regression lines are computed across participants. The inset displays condition-averaged results, where each dot reflects a single condition and the regression line is computed across experimental conditions. All error ribbons denote bootstrap-estimated 95% confidence intervals.



**Figure 8: Recall performance (adaptive conditons).** The bars display the average probability of recall (taken across words, lists, and participants) for lists from each adaptive condition. Error bars denote bootstrap-estimated 95% confidence intervals. For additional details about participants' behavior and performance during the adaptive conditions, see Figure S2.

- 728 Atkinson, R. C. and Shiffrin, R. M. (1968). Human memory: A proposed system and its  
 729 control processes. In Spence, K. W. and Spence, J. T., editors, *The Psychology of Learning*  
 730 *and Motivation*, volume 2, pages 89–105. Academic Press, New York, NY.
- 731 Baldassano, C., Hasson, U., and Norman, K. A. (2018). Representation of real-world event  
 732 schemas during narrative perception. *The Journal of Neuroscience*, 38(45):9689–9699.
- 733 Bousfield, W. A. (1953). The occurrence of clustering in the recall of randomly arranged  
 734 associates. *Journal of General Psychology*, 49:229–240.
- 735 Bousfield, W. A., Sedgewick, C. H., and Cohen, B. H. (1954). Certain temporal character-  
 736 istics of the recall of verbal associates. *American Journal of Psychology*, 67:111–118.
- 737 Bower, G. H., Black, J. B., and Turner, T. J. (1979). Scripts in memory for text. *Cognitive*  
 738 *Psychology*, 11(2):177–220.
- 739 DuBrow, S. and Davachi, L. (2016). Temporal binding within and across events. *Neurobi-*  
 740 *ology of Learning and Memory*, 134:107–114.

- 741 Estes, W. K. (1955). Statistical theory of spontaneous recovery and regression. *Psychological*  
742 *Review*, 62:145–154.
- 743 Ezzyat, Y. and Davachi, L. (2011). What constitutes an episode in episodic memory?  
744 *Psychological Science*, 22(2):243–252.
- 745 Glenberg, A. M., Bradley, M. M., Kraus, T. A., and Renzaglia, G. J. (1983). Studies of the  
746 long-term recency effect: support for a contextually guided retrieval theory. *Journal of*  
747 *Experimental Psychology: Learning, Memory, and Cognition*, 12:413–418.
- 748 Halpern, Y., Hall, K. B., Schogol, V., Riley, M., Roark, B., Skobeltsyn, G., and Bäuml,  
749 M. (2016). Contextual prediction models for speech recognition. In *Interspeech*, pages  
750 2338–2342.
- 751 Heusser, A. C., Fitzpatrick, P. C., Field, C. E., Ziman, K., and Manning, J. R. (2017). Quail:  
752 a Python toolbox for analyzing and plotting free recall data. *Journal of Open Source*  
753 *Software*, 10.21105/joss.00424.
- 754 Heusser, A. C., Ziman, K., Owen, L. L. W., and Manning, J. R. (2018). HyperTools: a  
755 Python toolbox for gaining geometric insights into high-dimensional data. *Journal of*  
756 *Machine Learning Research*, 18(152):1–6.
- 757 Howard, M. W. and Kahana, M. J. (2002). A distributed representation of temporal context.  
758 *Journal of Mathematical Psychology*, 46:269–299.
- 759 Jenkins, J. J. and Russell, W. A. (1952). Associative clustering during recall. *Journal of*  
760 *Abnormal and Social Psychology*, 47:818–821.
- 761 Kahana, M. J. (1996). Associative retrieval processes in free recall. *Memory and Cognition*,  
762 24:103–109.

- 763 Kahana, M. J. (2012). *Foundations of human memory*. Oxford University Press, New York,  
764 NY.
- 765 Kimball, D. R., Smith, T. A., and Kahana, M. J. (2007). The fSAM model of false recall.  
766 *Psychological Review*, 114(4):954–993.
- 767 Manning, J. R. (2020). Context reinstatement. In Kahana, M. J. and Wagner, A. D., editors,  
768 *Handbook of Human Memory*. Oxford University Press.
- 769 Manning, J. R., Hulbert, J. C., Williams, J., Piloto, L., Sahakyan, L., and Norman, K. A.  
770 (2016). A neural signature of contextually mediated intentional forgetting. *Psychonomic*  
771 *Bulletin and Review*, 23(5):1534–1542.
- 772 Manning, J. R. and Kahana, M. J. (2012). Interpreting semantic clustering effects in free  
773 recall. *Memory*, 20(5):511–517.
- 774 Manning, J. R., Norman, K. A., and Kahana, M. J. (2015). The role of context in episodic  
775 memory. In Gazzaniga, M., editor, *The Cognitive Neurosciences*, pages 557–566. MIT Press.
- 776 Manning, J. R., Polyn, S. M., Baltuch, G., Litt, B., and Kahana, M. J. (2011). Oscillatory pat-  
777 terns in temporal lobe reveal context reinstatement during memory search. *Proceedings*  
778 *of the National Academy of Sciences, USA*, 108(31):12893–12897.
- 779 Manning, J. R., Sperling, M. R., Sharan, A., Rosenberg, E. A., and Kahana, M. J. (2012).  
780 Spontaneously reactivated patterns in frontal and temporal lobe predict semantic clus-  
781 tering during memory search. *The Journal of Neuroscience*, 32(26):8871–8878.
- 782 Masís-Obando, R., Norman, K. A., and Baldassano, C. (2022). Scheme representations in  
783 distinct brain networks support narrative memory during encoding and retrieval. *eLife*,  
784 11:e70445.

- 785 Momennejad, I., Russek, E. M., Cheong, J. H., Botvinick, M. M., Daw, N. D., and Gershman,  
786 S. J. (2017). The successor representation in human reinforcement learning. *Nature*  
787 *Human Behavior*, 1:680–692.
- 788 Murdock, B. B. (1962). The serial position effect of free recall. *Journal of Experimental*  
789 *Psychology: General*, 64:482–488.
- 790 Nastase, S. A., Goldstein, A., and Hasson, U. (2020). Keep it real: rethinking the primacy  
791 of experimental control in cognitive neuroscience. *NeuroImage*, 15(222):117254–117261.
- 792 Polyn, S. M. and Kahana, M. J. (2008). Memory search and the neural representation of  
793 context. *Trends in Cognitive Sciences*, 12:24–30.
- 794 Polyn, S. M., Norman, K. A., and Kahana, M. J. (2009). Task context and organization in  
795 free recall. *Neuropsychologia*, 47:2158–2163.
- 796 Postman, L. and Phillips, L. W. (1965). Short-term temporal changes in free recall. *Quarterly*  
797 *Journal of Experimental Psychology*, 17:132–138.
- 798 Raaijmakers, J. G. W. and Shiffrin, R. M. (1980). SAM: A theory of probabilistic search of  
799 associative memory. In Bower, G. H., editor, *The Psychology of Learning and Motivation: Advances in Research and Theory*, volume 14, pages 207–262. Academic Press, New York,  
800 NY.  
801
- 802 Radvansky, G. A. and Copeland, D. E. (2006). Walking through doorways causes forgetting:  
803 situation models and experienced space. *Memory and Cognition*, 34(5):1150–1156.
- 804 Ranganath, C. and Ritchey, M. (2012). Two cortical systems for memory-guided behavior.  
805 *Nature Reviews Neuroscience*, 13:713–726.

- 806 Romney, A. K., Brewer, D. D., and Batchelder, W. H. (1993). Predicting clustering from  
807 semantic structure. *Psychological Science*, 4:28–34.
- 808 Schapiro, A. and Turk-Browne, N. (2015). Statistical learning. *Brain Mapping: An Encyclo-*  
809 *pedic Reference*, 3:501–506.
- 810 Sederberg, P. B., Howard, M. W., and Kahana, M. J. (2008). A context-based theory of  
811 recency and contiguity in free recall. *Psychological Review*, 115(4):893–912.
- 812 Shankar, K. H. and Howard, M. W. (2012). A scale-invariant internal representation of  
813 time. *Neural Computation*, 24:134–193.
- 814 Sirotin, Y. B., Kimball, D. R., and Kahana, M. J. (2005). Going beyond a single list: modeling  
815 the effects of prior experience on episodic free recall. *Psychonomic Bulletin and Review*,  
816 12(5):787–805.
- 817 Smith, S. M. and Vela, E. (2001). Environmental context-dependent memory: a review and  
818 meta-analysis. *Psychonomic Bulletin and Review*, 8(2):203–220.
- 819 Swallow, K. M., Barch, D. M., Head, D., Maley, C. J., Holder, D., and Zacks, J. M. (2011).  
820 Changes in events alter how people remember recent information. *Journal of Cognitive*  
821 *Neuroscience*, 23(5):1052–1064.
- 822 Swallow, K. M., Zacks, J. M., and Abrams, R. A. (2009). Event boundaries in perception  
823 affect memory encoding and updating. *Journal of Experimental Psychology: General*,  
824 138(2):236–257.
- 825 Welch, G. B. and Burnett, C. T. (1924). Is primacy a factor in association-formation. *American*  
826 *Journal of Psychology*, 35:396–401.



- 827 Xu, X., Zhu, Z., and Manning, J. R. (2022). The psychological arrow of time drives  
828 temporal asymmetries in retrodicting versus predicting narrative events. *PsyArXiv*,  
829 page doi.org/10.31234/osf.io/yp2qu.
- 830 Yeshurun, Y., Swanson, S., Simony, E., Chen, J., Lazaridi, C., Honey, C. J., and Hasson, U.  
831 (2017). Same story, different story: the neural representation of interpretive frameworks.  
832 *Psychological Science*, 28(3):307–319.
- 833 Ziman, K., Heusser, A. C., Fitzpatrick, P. C., Field, C. E., and Manning, J. R. (2018).  
834 Is automatic speech-to-text transcription ready for use in psychological experiments?  
835 *Behavior Research Methods*, 50:2597–2605.
- 836 Zwaan, R. A., Langston, M. C., and Graesser, A. C. (1995). The construction of situation  
837 models in narrative comprehension: an event-indexing model. *Psychological Science*,  
838 6(5):292–297.
- 839 Zwaan, R. A. and Radvansky, G. A. (1998). Situation models in language comprehension  
840 and memory. *Psychological Bulletin*, 123(2):162–185.