

Abstract

The mental contexts in which we interpret experiences are often person-specific, even when the experiences themselves are shared. We developed a geometric framework for mathematically characterizing the subjective conceptual content of dynamic naturalistic experiences. We model experiences and memories as ~~trajectories~~ “trajectories” through word embedding spaces whose coordinates reflect the universe of thoughts under consideration. Memory encoding can then be modeled as geometrically preserving or distorting the ~~shape~~ “shape” of the original experience. We applied our approach to data collected as participants watched and verbally recounted a television episode while undergoing functional neuroimaging. Participants’ recountings all preserved coarse spatial properties (essential narrative elements), but not fine spatial scale (low-level) details, of the episode’s trajectory. We also identified networks of brain structures sensitive to these trajectory shapes. Our work provides insights into how we preserve and distort our ongoing experiences when we encode them into episodic memories.

Introduction

What does it mean to ~~remember~~ remember something? In traditional episodic memory experiments e.g., ~~list-learning or trial-based experiments^{1,2}~~, (e.g., list-learning or trial-based experiments^{1,2}), remembering is often cast as a discrete, binary operation: each studied item may be separated from the rest of one’s experience and labeled as having been either recalled or forgotten. More nuanced studies might incorporate self-reported confidence measures as a proxy for memory strength, or ask participants to discriminate between recollecting the (contextual) details of an experience and having a general feeling of familiarity³. Using well-controlled, trial-based experimental designs, the field has amassed a wealth of information regarding human episodic memory ~~for review see⁴~~ ⁴. However, there are fundamental properties of the external world and our memories that trial-based experiments are not well suited to capture ~~for review, also see^{5,6}~~ ^{5,6}. First, our experiences and memories are continuous, rather than discrete—isolating a naturalistic event from the context in which it occurs can substantially change its meaning. Second, whether or not the rememberer has precisely reproduced a specific set of words in describing a given experience is nearly orthogonal

33 to how well they were actually able to remember it. In classic (e.g., list-learning) memory studies,
34 by contrast, the number or proportion of ~~exact~~ exact recalls is often considered to be a primary
35 metric for assessing the quality of participants' memories. Third, one might remember the essence
36 (or a general summary) of an experience but forget (or neglect to recount) particular low-level
37 details. Capturing the essence of what happened is often a main goal of recounting an episodic
38 memory to a listener, whereas the inclusion of specific low-level details is often less pertinent.

39 How might we formally characterize the ~~essence~~ "essence" of an experience, and whether it has
40 been recovered by the rememberer? And how might we distinguish an experience's overarching
41 essence from its low-level details? One approach is to start by considering some fundamental
42 properties of the dynamics of our experiences. Each given moment of an experience tends to
43 derive meaning from surrounding moments, as well as from longer-range temporal associations⁷⁻⁹.
44 Therefore, the timecourse describing how an event unfolds is fundamental to its overall meaning.
45 Further, this hierarchy formed by our subjective experiences at different timescales defines a ~~context~~
46 context for each new moment ~~e.g.,~~ e.g.,^{10,11}, and plays an important role in how we interpret that
47 moment and remember it later ~~for review see~~ see^{9,12}. Our memory systems can leverage these
48 associations to form predictions that help guide our behaviors¹³. For example, as we navigate
49 the world, the features of our subjective experiences tend to change gradually (e.g., the room
50 or situation we find ourselves in at any given moment is strongly temporally autocorrelated),
51 allowing us to form stable estimates of our current situation and behave accordingly^{14,15}.

52 Occasionally, this gradual drift of our ongoing experience is punctuated by sudden changes,
53 or shifts ~~e.g., when we walk through a doorway,~~ (e.g., when we walk through a doorway¹⁶).
54 Prior research suggests that these sharp transitions (termed ~~event boundaries~~ "event boundaries")
55 help to discretize our experiences (and their mental representations) into ~~events~~ "events"¹⁶⁻²¹. The
56 interplay between the stable (within-event) and transient (across-event) temporal dynamics of an
57 experience also provides a potential framework for transforming experiences into memories that
58 distills those experiences down to their essences. For example, prior work has shown that event
59 boundaries can influence how we learn sequences of items^{18,21}, navigate¹⁷, and remember and
60 understand narratives^{15,20}. This work also suggests a means of distinguishing the essence of an

61 experience from its low-level details: The overall structure of events and event transitions reflects
62 how the high-level experience unfolds (i.e., its essence), while subtler event-level properties reflect
63 its low-level details. Prior research has also implicated a network of brain regions (including the
64 hippocampus and the medial prefrontal cortex) in playing a critical role in transforming experiences
65 into structured and consolidated memories²².

66 Here, we sought to examine how the temporal dynamics of a naturalistic experience were later
67 reflected in participants' memories. We also sought to leverage the above conceptual insights into
68 the distinctions between an experience's essence and its low-level details to build models that ex-
69 plicitly quantified these distinctions. We analyzed an open dataset that comprised behavioral and
70 functional Magnetic Resonance Imaging (fMRI) data collected as participants viewed and then ver-
71 bally recounted an episode of the BBC television show *Sherlock*²³. We developed a computational
72 framework for characterizing the temporal dynamics of the moment-by-moment content of the
73 episode and of participants' verbal recalls. Our framework uses topic modeling²⁴ to characterize
74 the thematic conceptual (semantic) content present in each moment of the episode and recalls by
75 projecting each moment into a word embedding space. We then use hidden Markov models^{25,26}
76 to discretize this evolving semantic content into events. In this way, we cast both naturalistic ex-
77 periences and memories of those experiences as geometric ~~trajectories~~ "trajectories" through word
78 embedding space that describe how they evolve over time. Under this framework, successful
79 remembering entails verbally traversing the content trajectory of the episode, thereby reproducing
80 the shape (essence) of the original experience. Our framework captures the episode's essence in
81 the sequence of geometric coordinates for its events, and its low-level details by examining its
82 within-event geometric properties.

83 Comparing the overall shapes of the topic trajectories for the episode and participants' recalls
84 reveals which aspects of the episode's essence were preserved (or lost) in the translation into mem-
85 ory. We also develop two metrics for assessing participants' memories for low-level details: (1)
86 the ~~precision~~ "precision" with which a participant recounts details about each event, and (2) the
87 ~~distinctiveness~~ "distinctiveness" of their recall for each event, relative to other events. We examine
88 how these metrics relate to overall memory performance as judged by third-party human anno-

tators. We also compare and contrast our general approach to studying memory for naturalistic experiences with standard metrics for assessing performance on more traditional memory tasks, such as list-learning. Last, we leverage our framework to identify networks of brain structures whose responses (as participants watched the episode) reflected the temporal dynamics of the episode and/or how participants would later recount it.

Results

To characterize the dynamic content of the *Sherlock* episode and participants’ subsequent recountings, we used a topic model²⁴ to discover the episode’s latent themes. Topic models take as inputs a vocabulary of words to consider and a collection of text documents, and return two output matrices. The first of these is a ~~topics matrix~~ “topics matrix” whose rows are ~~topics~~ “topics” (or latent themes) and whose columns correspond to words in the vocabulary. The entries in the topics matrix reflect how each word in the vocabulary is weighted by each discovered topic. For example, a detective-themed topic might weight heavily on words like “crime,” and “search.” The second output is a ~~topic proportions matrix~~ “topic proportions matrix” with one row per document and one column per topic. The topic proportions matrix describes the mixture of discovered topics reflected in each document.

²³Chen et al. (2017) collected hand-annotated information about each of ~~1,000~~ 1000 (manually delineated) time segments spanning the roughly 50 minute video used in their study²³. Each annotation included: a brief narrative description of what was happening, the location where the action took place, the names of any characters on the screen, and other similar details (for a full list of annotated features, see *Methods*). We took the union of all unique words (excluding stop words, such as “and,” “or,” “but,” etc.) across all features from all annotations as the vocabulary for the topic model. We then concatenated the sets of words across all features contained in overlapping sliding windows of (up to) 50 annotations, and treated each window as a single document for the purpose of fitting the topic model. Next, we fit a topic model with (up to) $K = 100$ topics to this collection of documents. We found that 32 unique topics (with non-zero weights) were sufficient

115 to describe the time-varying content of the episode (see *Methods*; ~~Figs~~Fig. 1, ~~Supp. Fig.~~Supp. Fig. 2). We
116 note that our approach is similar in some respects to Dynamic Topic Models²⁷ in that we sought
117 to characterize how the thematic content of the episode evolved over time. However, whereas
118 Dynamic Topic Models are designed to characterize how the properties of ~~collections~~ collections
119 of documents change over time, our sliding window approach allows us to examine the topic
120 dynamics within a single document (or video). Specifically, our approach yielded (via the topic
121 proportions matrix) a single ~~topic-vector~~ “topic vector” for each sliding window of annotations
122 transformed by the topic model. We then stretched (interpolated) the resulting windows-by-topics
123 matrix to match the time series of the 1,976 fMRI volumes collected as participants viewed the
124 episode.

125 [Figure 1 about here.]

126 The 32 topics we found were heavily character-focused (i.e., the top-weighted word in each
127 topic was nearly always a character) and could be roughly divided into themes centered around
128 Sherlock Holmes (the titular character), John Watson (Sherlock’s close confidant and assistant),
129 supporting characters (e.g., Inspector Lestrade, Sergeant Donovan, or Sherlock’s brother Mycroft),
130 or the interactions between various groupings of these characters (~~Supp.~~Supp. Fig. 2). This likely follows
131 from the frequency with which these terms appeared in the episode annotations. Several of the
132 identified topics were highly similar, which we hypothesized might allow us to distinguish between
133 subtle narrative differences if the distinctions between those overlapping topics were meaningful.
134 The topic vectors for each timepoint were also ~~sparse~~sparse, in that only a small number of topics
135 (typically one or two) tended to be “active” in any given timepoint (Fig. 2A). Further, the dynamics
136 of the topic activations appeared to exhibit ~~persistence~~ persistence (i.e., given that a topic was active
137 in one timepoint, it was likely to be active in the following timepoint) along with ~~occasional-rapid~~
138 ~~changes~~ occasional rapid changes (i.e., occasionally topic weights would change abruptly from one
139 timepoint to the next). These two properties of the topic dynamics may be seen in the block diagonal
140 structure of the timepoint-by-timepoint correlation matrix (Fig. 2B) and reflect the gradual drift
141 and sudden shifts fundamental to the temporal dynamics of many real-world experiences, as well

142 as television episodes. Given this observation, we adapted an approach devised by [Baldassano](#)
143 [et al. \(2017\)](#)²⁶, and used a hidden Markov model (HMM) to identify the *event boundaries* “*event*
144 *boundaries*” where the topic activations changed rapidly (i.e., the boundaries of the blocks in the
145 temporal correlation matrix; event boundaries identified by the HMM are outlined in yellow in
146 Fig. 2B). Part of our model fitting procedure required selecting an appropriate number of events
147 into which the topic trajectory should be segmented. To accomplish this, we used an optimization
148 procedure that maximized the difference between the topic weights for timepoints within an event
149 versus timepoints across multiple events (see *Methods*). We then created a stable summary of the
150 content within each episode event by averaging the topic vectors across the timepoints spanned
151 by each event (Fig. 2C).

152 [Figure 2 about here.]

153 Given that the time-varying content of the episode could be segmented cleanly into discrete
154 events, we wondered whether participants’ recalls of the episode also displayed a similar structure.
155 We applied the same topic model (already trained on the episode annotations) to each participant’s
156 recalls. Analogously to how we parsed the time-varying content of the episode, to obtain similar
157 estimates for each participant’s recall transcript, we treated each overlapping window of (up to)
158 10 sentences from their transcript as a document, and computed the most probable mix of topics
159 reflected in each timepoint’s sentences. This yielded, for each participant, a number-of-windows
160 by number-of-topics topic proportions matrix that characterized how the topics identified in the
161 original episode were reflected in the participant’s recalls. An important feature of our approach
162 is that it allows us to compare participants’ recalls to events from the original episode, despite
163 that different participants used widely varying language to describe the events, and that those
164 descriptions often diverged in content, quality, and quantity from the episode annotations. This
165 ability to match up conceptually related text that differs in specific vocabulary, detail, and length
166 is an important benefit of projecting the episode and recalls into a shared topic space. An example
167 topic proportions matrix from one participant’s recalls is shown in Figure 2D.

168 Although the example participant’s recall topic proportions matrix has some visual similarity

to the episode topic proportions matrix, the time-varying topic proportions for the example participant's recalls are not as sparse as those for the episode (compare Figs. 2A and D). Similarly, although there do appear to be periods of stability in the recall topic dynamics (i.e., most topics are active or inactive over contiguous blocks of time), the changes in topic activations that define event boundaries appear less clearly delineated in participants' recalls than in the episode's annotations. To examine these patterns in detail, we computed the timepoint-by-timepoint correlation matrix for the example participant's recall topic proportions matrix (Fig. 2E). As in the episode correlation matrix (Fig. 2B), the example participant's recall correlation matrix has a strong block diagonal structure, indicating that their recalls are discretized into separated events. We used the same HMM-based optimization procedure that we had applied to the episode's topic proportions matrix (see *Methods*) to estimate an analogous set of event boundaries in the participant's recounting of the episode (outlined in yellow). We carried out this analysis on all 17 participants' recall topic proportions matrices (Supp. Fig. 5).

Two clear patterns emerged from this set of analyses. First, although every individual participant's recalls could be segmented into discrete events (i.e., every individual participant's recall correlation matrix exhibited clear block diagonal structure; Supp. Fig. 5), each participant appeared to have a unique ~~recall-resolution~~, "recall resolution," reflected in the sizes of those blocks. While some participants' recall topic proportions segmented into just a few events (e.g., Participants P4, P5, and P7), others' segmented into many shorter-duration events (e.g., Participants P12, P13, and P17). This suggests that different participants may be recalling the episode with different levels of detail—i.e., some might recount only high-level essential plot details, whereas others might recount low-level details instead (or in addition). The second clear pattern present in every individual participant's recall correlation matrix was that, unlike in the episode correlation matrix, there were substantial off-diagonal correlations. ~~Whereas~~ One potential explanation for this finding is that the topic models, trained only on episode annotations, do not capture topic proportions in participants' "held-out" recalls as accurately. A second possibility is that, whereas each event in the original episode was (largely) separable from the others (Fig. 2B), in transforming those separable events into memory, participants appeared to be integrating across multiple events,

197 blending elements of previously recalled and not-yet-recalled content into each newly recalled
198 event ~~Figs. 2E, 5; also see ^{8,28,29}~~ (Fig. 2E, Supp. Fig. 5) ^{8,28,29}.

199 The above results demonstrate that topic models capture the dynamic conceptual content
200 of the episode and participants' recalls of the episode. Further, the episode and recalls exhibit
201 event boundaries that can be identified automatically using HMMs to segment the dynamic
202 content. Next, we asked whether some correspondence might be made between the specific
203 content of the events the participants experienced while viewing the episode, and the events
204 they later recalled. We labeled each recall event as matching the episode event with the most
205 similar (i.e., most highly correlated) topic vector (~~Figs~~Fig. 2G, Supp. Fig. 6). This yielded a se-
206 quence of "presented" events from the original episode, and a (potentially differently ordered)
207 sequence of "recalled" events for each participant. Analogous to classic list-learning studies, we
208 can then examine participants' recall sequences by asking which events they tended to recall first
209 ~~probability of first recall; Fig. 3A; ³⁰⁻³²~~ (probability of first recall ³⁰⁻³²; Fig. 3A); how participants
210 most often transitioned between recalls of the events as a function of the temporal distance be-
211 tween them ~~lag-conditional response probability; Fig. 3B; ²~~ (lag-conditional response probability ²
212 ; Fig. 3B); and which events they were likely to remember overall ~~serial position recall analyses; Fig. 3C; ¹~~
213 ~~(serial position recall analyses ¹; Fig. 3C)~~. Some of the patterns we observed appeared to be similar
214 to classic effects from the list-learning literature. For example, participants had a higher proba-
215 bility of initiating recall with early events (Fig. 3A) and a higher probability of transitioning to
216 neighboring events with an asymmetric forward bias (Fig. 3B). However, unlike what is typically
217 observed in list-learning studies, we did not observe patterns comparable to the primacy or recency
218 serial position effects (Fig. 3C). We hypothesized that participants might be leveraging meaningful
219 narrative associations and references over long timescales throughout the episode.

220 [Figure 3 about here.]

221 Clustering scores are often used by memory researchers to characterize how people organize
222 their memories of words on a studied list ~~for review, see ^{33,33}~~. We defined analogous measures
223 to characterize how participants organized their memories for episodic events (see *Methods* for

224 details). Temporal clustering refers to the extent to which participants group their recall responses
 225 according to encoding position. Overall, we found that sequentially viewed episode events tended
 226 to appear nearby in participants' recall event sequences (mean clustering score: 0.732, SEM: 0.033).
 227 Participants with higher temporal clustering scores tended to exhibit better overall memory for the
 228 episode, according to both [Chen et al. \(2017\)](#)²³'s hand-counted numbers of recalled scenes from
 229 the episode (Pearson's $r(15) = 0.49, p = 0.046$ ~~$r(15) = 0.49, p = 0.046$~~ $r(15) = 0.49, p = 0.046, 95\% CI = [0.25, 0.76]$) and the
 230 numbers of episode events that best-matched at least one recall event (i.e., model-estimated number
 231 of events recalled; Pearson's $r(15) = 0.59, p = 0.013$ ~~$r(15) = 0.59, p = 0.013$~~ $r(15) = 0.59, p = 0.013, 95\% CI = [0.31, 0.80]$).
 232 Semantic clustering measures the extent to which participants cluster their recall responses ac-
 233 cording to semantic similarity³⁴. We found that participants tended to recall semantically similar
 234 episode events together (mean clustering score: 0.650, SEM: 0.032), and that semantic clustering
 235 score was also related to both hand-counted (Pearson's $r(15) = 0.65, p = 0.005$ ~~$r(15) = 0.65, p = 0.005$~~ $r(15) = 0.65, p = 0.004, 95\% CI = [0.31, 0.85]$)
 236 and model-estimated (Pearson's $r(15) = 0.58, p = 0.015$ ~~$r(15) = 0.58, p = 0.015$~~ $r(15) = 0.58, p = 0.015, 95\% CI = [0.10, 0.83]$)
 237 numbers of recalled events.

238 [Figure 4 about here.]

239 The above analyses illustrate how our framework for characterizing the dynamic conceptual
 240 content of naturalistic episodes enables us to carry out analyses that have traditionally been
 241 applied to much simpler list-learning paradigms. However, perhaps the most interesting aspects
 242 of memory for naturalistic episodes are those that have no list-learning analogs. The nuances of
 243 how one's memory for an event might capture some details, yet distort or neglect others, is central
 244 to how we use our memory systems in daily life. Yet when researchers study memory in highly
 245 simplified paradigms, those nuances are not typically observable. We next developed two novel,
 246 continuous metrics, termed ~~precision and distinctiveness~~"precision" and "distinctiveness," aimed at
 247 characterizing distortions in the conceptual content of individual recall events, and the conceptual
 248 overlap between how people described different events.

249 ~~Precision~~ Precision is intended to capture the "completeness" of recall, or how fully the presented
 250 content was recapitulated in a participant's recounting. We define a recall event's precision as the

251 maximum correlation between the topic proportions of that recall event and any episode event
252 (Fig. 4). In other words, given that a recall event best matches a particular episode event, more
253 precisely recalled events overlap more strongly with the conceptual content of the original episode
254 event. When a given event is assigned a blend of several topics, as is often the case (Fig. 2), a high
255 precision score requires recapitulating the relative topic proportions during recall.

256 ~~Distinctiveness~~ Distinctiveness is intended to capture the “specificity” of recall. In other words,
257 distinctiveness quantifies the extent to which a given recall event reflects the most similar episode
258 event over and above other episode events. Intuitively, distinctiveness is like a normalized variant
259 of our precision metric. Whereas precision solely measures how much detail about an episode was
260 captured in someone’s recall, distinctiveness penalizes details that also pertain to other episode
261 events. We define the distinctiveness of an event’s recall as its precision expressed in standard
262 deviation units with respect to other episode events. Specifically, for a given recall event, we
263 compute the correlation between its topic vector and that of each episode event. This yields a
264 distribution of correlation coefficients (one per episode event). We subtract the mean and divide
265 by the standard deviation of this distribution to z-score the coefficients. The maximum value in
266 this distribution (which, by definition, belongs to the episode event that best matches the given
267 recall event) is that recall event’s distinctiveness score. In this way, recall events that match one
268 episode event far better than all other episode events will receive a high distinctiveness score. By
269 contrast, a recall event that matches all episode events roughly equally will receive a comparatively
270 low distinctiveness score.

271 In addition to examining how precisely and distinctively participants recalled individual events,
272 one may also use these metrics to summarize each participant’s performance by averaging across
273 a participant’s event-wise precision or distinctiveness scores. This enables us to quantify how pre-
274 cisely a participant tended to recall subtle within-event details, as well as how specific (distinctive)
275 those details were to individual events from the episode. Participants’ average precision and dis-
276 tinctiveness scores were strongly correlated (~~$r(15) = -0.90, p < 0.001$~~ $r(15) = 0.90, p < 0.001, 95\% CI = [0.66, 0.96]$).
277 This indicates that participants who tended to precisely recount low-level details of episode events
278 also tended to do so in an event-specific way (e.g., as opposed to detailing recurring themes that

279 were present in most or all episode events; this behavior would have resulted in high precision but
 280 low distinctiveness). We found that, across participants, higher precision scores were positively cor-
 281 related with the numbers of both hand-annotated scenes ($r(15) = 0.60, p = 0.010, 95\% \text{ CI} = [0.02, 0.98]$)
 282 and model-estimated events ($r(15) = 0.90, p < 0.001, 95\% \text{ CI} = [0.54, 0.96]$) that
 283 participants recalled. Participants' average distinctiveness scores were also marginally correlated
 284 with both the hand-annotated ($r(15) = 0.45, p = 0.068, 95\% \text{ CI} = [-0.21, 0.79]$)
 285 and model-estimated ($r(15) = 0.71, p = 0.001, 95\% \text{ CI} = [-0.07, 0.90]$) num-
 286 bers of recalled events.

287 [Figure 5 about here.]

288 Examining individual recalls of the same episode event can provide insights into how the above
 289 precision and distinctiveness scores may be used to characterize similarities and differences in how
 290 different people describe the same shared experience. In Figure 5, we compare recalls for the same
 291 episode event from the participants with the highest (P17) and lowest (P6) precision scores. From
 292 the HMM-identified episode event boundaries, we recovered the set of annotations describing the
 293 content of a single episode event (event 21; Fig. 5C), and divided them into different color-coded
 294 sections for each action or feature described. Next, we used an analogous approach to identify
 295 the set of sentences comprising the corresponding recall event from each of the two example
 296 participants (Fig. 5D). We then colored all words describing actions and features in the transcripts
 297 shown in Panel D according to the color-coded annotations in Panel C. Visual comparison of these
 298 example recalls reveals that the more precise recall captures more of the episode event's content,
 299 and in greater detail.

300 Figure 5 also illustrates the differences between high and low distinctiveness scores. We
 301 extracted the set of sentences comprising the most distinctive recall event (P9) and least distinctive
 302 recall event (P6) corresponding to the example episode event shown in Panel C (event 21). We
 303 also extracted the annotations for all episode events whose content these participants' single recall
 304 events described. We assigned each episode event a unique color (Fig. 5E), and colored each
 305 recalled sentence (Panel F) according to the episode events they best matched. Visual inspection

306 of Panel F reveals that the most distinctive recall’s content is tightly concentrated around event
307 21, whereas the least distinctive recall incorporates content from a much wider range of episode
308 events.

309 The preceding analyses sought to characterize how participants’ recountings of individual
310 episode events captured the low-level details of each event. Next, we sought to characterize how
311 participants’ recountings of the full episode captured its high-level essence—i.e., the shape of
312 the episode’s trajectory through word embedding (topic) space. To visualize the essence of the
313 episode and each participant’s recall trajectory³⁵, we projected the topic proportions matrices for the
314 episode and recalls onto a shared two-dimensional space using Uniform Manifold Approximation
315 and Projection ~~UMAP~~; ³⁶UMAP³⁶. In this lower-dimensional space, each point represents a
316 single episode or recall event, and the distances between the points reflect the distances between
317 the events’ associated topic vectors (Fig. 6). In other words, events that are nearer to each other in
318 this space are more semantically similar, and those that are farther apart are less so.

319 [Figure 6 about here.]

320 Visual inspection of the episode and recall topic trajectories reveals a striking pattern. First,
321 the topic trajectory of the episode (which reflects its dynamic content; Fig. 6A) is captured nearly
322 perfectly by the averaged topic trajectories of participants’ recalls (Fig. 6B). To assess the consis-
323 tency of these recall trajectories across participants, we asked: given that a participant’s recall
324 trajectory had entered a particular location in the reduced topic space, could the position of their
325 ~~next~~ next recalled event be predicted reliably? For each location in the reduced topic space, we
326 computed the set of line segments connecting successively recalled events (across all participants)
327 that intersected that location (see *Methods*, Supp. Fig. 4). We then computed (for each location)
328 the distribution of angles formed by the lines defined by those line segments and a fixed reference
329 line (the x -axis). Rayleigh tests revealed the set of locations in topic space at which these across-
330 participant distributions exhibited reliable peaks (blue arrows in Fig. 6B reflect significant peaks at
331 $p < 0.05$, corrected). We observed that the locations traversed by nearly the entire episode trajectory
332 exhibited such peaks. In other words, participants’ recalls exhibited similar trajectories to each

other that also matched the trajectory of the original episode (Fig. 6C). This is especially notable when considering the fact that the number of HMM-identified recall events (dots in Fig. 6C) varied considerably across people, and that every participant used different words to describe what they had remembered happening in the episode. Differences in the numbers of recall events appear in participants' trajectories as differences in the sampling resolution along the trajectory. We note that this framework also provides a means of disentangling classic "proportion recalled" measures (i.e., the proportion of episode events described in participants' recalls) from participants' abilities to recapitulate the episode's essence (i.e., the similarity between the shapes of the original episode trajectory and that defined by each participant's recounting of the episode).

In addition to enabling us to visualize the episode's high-level essence, describing the episode as a geometric trajectory also enables us to drill down to individual words and quantify how each word relates to the memorability of each event. This provides another approach to examining participants' recall for low-level details beyond the precision and distinctiveness measures we defined above. The results displayed in Figures 3C and 5A suggest that certain events were remembered better than others. Given this, we next asked whether the events that were generally remembered precisely or imprecisely tended to reflect particular content. Because our analysis framework projects the dynamic episode content and participants' recalls into a shared space, and because the dimensions of that space represent topics (which are, in turn, sets of weights over known words in the vocabulary), we are able to recover the weighted combination of words that make up any point (i.e., topic vector) in this space. We first computed the average precision with which participants recalled each of the 30 episode events (Fig. 7A; note that this result is analogous to a serial position curve created from our precision metric). We then computed a weighted average of the topic vectors for each episode event, where the weights reflected how precisely each event was recalled. To visualize the result, we created a "wordle" image³⁷ where words weighted more heavily by more precisely-remembered topics appear in a larger font (Fig. 7B, green box). Across the full episode, content that weighted heavily on topics and words central to the major foci of the episode (e.g., the names of the two main characters, "Sherlock" and "John," and the address of a major recurring location, "221B Baker Street") was best remembered. An analogous

analysis revealed which themes were less-precisely remembered. Here, in computing the weighted average over events' topic vectors, we weighted each event in ~~inverse~~ inverse proportion to its average precision (Fig. 7B, red box). The least precisely remembered episode content reflected information that was extraneous to the episode's essence, such as the proper names of relatively minor characters (e.g., "Mike," "Molly," and "Lestrade") and locations (e.g., "St. Bartholomew's Hospital").

[Figure 7 about here.]

A similar result emerged from assessing the topic vectors for individual episode and recall events (Fig. 7C). Here, for each of the three most and least precisely remembered episode events, we have constructed two wordles: one from the original episode event's topic vector (left) and a second from the average recall topic vector for that event (right). The three most precisely remembered events (circled in green) correspond to scenes integral to the central plot-line: a mysterious figure spying on John in a phone booth; John meeting Sherlock at Baker St. to discuss the murders; and Sherlock laying a trap to catch the killer. Meanwhile, the least precisely remembered events (circled in red) reflect scenes that comprise minor plot points: a video of singing cartoon characters that participants viewed in an introductory clip prior to the main episode; John asking Molly about Sherlock's habit of over-analyzing people; and Sherlock noticing evidence of Anderson's and Donovan's affair.

The results thus far inform us about which aspects of the dynamic content in the episode participants watched were preserved or altered in participants' memories. We next carried out a series of analyses aimed at understanding which brain structures might facilitate these preservations and transformations between the participants' shared experience of watching the episode and their subsequent memories of the episode. In the first analysis, we sought to identify brain structures that were sensitive to the dynamic unfolding of the episode's content, as characterized by its topic trajectory. We used a searchlight procedure to identify clusters of voxels whose activity patterns displayed a proximal temporal correlation structure (as participants watched the episode) matching that of the original episode's topic proportions (Fig. 8A; see *Methods* for additional details).

388 In a second analysis, we sought to identify brain structures whose responses (during episode
389 viewing) reflected how each participant would later structure their ~~recounting~~ recounting of the
390 episode. We used a searchlight procedure to identify clusters of voxels whose proximal temporal
391 correlation matrices matched that of the topic proportions matrix for each participant's recall tran-
392 script (Figs. 8B; see *Methods* for additional details). To ensure our searchlight procedure identified
393 regions ~~specifically~~ specifically sensitive to the temporal structure of the episode or recalls (i.e.,
394 rather than those with a temporal autocorrelation length similar to that of the episode and recalls),
395 we performed a phase shift-based permutation correction (see *Methods*). As shown in Figure 8C,
396 the episode-driven searchlight analysis revealed a distributed network of regions that may play a
397 role in processing information relevant to the narrative structure of the episode. The recall-driven
398 searchlight analysis revealed a second network of regions (Fig. 8D) that may facilitate a person-
399 specific transformation of one's experience into memory. In identifying regions whose responses
400 to ongoing experiences reflect how those experiences will be remembered later, this latter analysis
401 extends classic ~~subsequent-memory effect analyses e.g.,~~ ³⁸ "subsequent memory effect analyses" ³⁸ to
402 the domain of naturalistic experiences.

403 [Figure 8 about here.]

404 The searchlight analyses described above yielded two distributed networks of brain regions
405 whose activity timecourses tracked with the temporal structure of the episode (Fig. 8C) or par-
406 ticipants' subsequent recalls (Fig. 8D). We next sought to gain greater insight into the structures
407 and functional networks our results reflected. To accomplish this, we performed an additional,
408 exploratory analysis using Neurosynth³⁹. Given an arbitrary statistical map as input, Neurosynth
409 performs a massive automated meta-analysis, returning a ~~ranked~~ frequency-ranked list of terms
410 ~~frequently~~ used in neuroimaging papers that report similar statistical maps. We ran Neurosynth
411 on the (unthresholded) permutation-corrected maps for the episode- and recall-driven searchlight
412 analyses. The top ten terms with maximally similar meta-analysis images identified by Neurosynth
413 are shown in Figure 8.

Discussion

Explicitly modeling the dynamic content of a naturalistic stimulus and participants' memories enabled us to connect the present study of naturalistic recall with an extensive prior literature that has used list-learning paradigms to study memory ~~for review see~~⁴⁴, as in Figure 3. We found some similarities between how participants in the present study recounted a television episode and how participants typically recall memorized random word lists. However, our broader claim is that word lists miss out on fundamental aspects of naturalistic memory more like the sort of memory we rely on in everyday life. For example, there are no random word list analogs of character interactions, conceptual dependencies between temporally distant episode events, the sense of solving a mystery that pervades the *Sherlock* episode, or the myriad other features of the episode that convey deep meaning and capture interest. Nevertheless, each of these properties affects how people process and engage with the episode as they are watching it, and how they remember it later. The overarching goal of the present study is to characterize how the rich dynamics of the episode affect the rich behavioral and neural dynamics of how people remember it.

Our work casts remembering as reproducing (behaviorally and neurally) the topic trajectory, or "shape," of an experience, thereby drawing implicit analogies between mentally navigating through word embedding spaces and physically navigating through spatial environments⁴⁰⁻⁴². When we characterized memory for a television episode using this framework, we found that every participant's recounting of the episode recapitulated the low spatial frequency details of the shape of its trajectory through topic space (Fig. 6). We termed this narrative scaffolding the episode's ~~essence~~essence. Where participants' behaviors varied most was in their tendencies to recount specific low-level details from each episode event. Geometrically, this appears as high spatial frequency distortions in participants' recall trajectories relative to the trajectory of the original episode (Fig. 7). We developed metrics to characterize the precision (recovery of any and all event-level information) and distinctiveness (recovery of event-specific information). We also used word cloud visualizations to interpret the details of these event-level distortions.

The neural analyses we carried out (Fig. 8) also leveraged our geometric framework for char-

acterizing the shapes of the episode and participants' recountings. We identified one network of regions whose responses tracked with temporal correlations in the conceptual content of the episode (as quantified by topic models applied to a set of annotations about the episode). This network included orbitofrontal cortex, ventromedial prefrontal cortex, and striatum, among others. As reviewed by [Ranganath and Ritchey \(2012\)](#)¹³, several of these regions are members of the *anterior temporal system*, "*anterior temporal system*," which has been implicated in assessing and processing the familiarity of ongoing experiences, emotions, social cognition, and reward. A second network we identified tracked with temporal correlations in the idiosyncratic conceptual content of participants' subsequent recountings of the episode. This network included occipital cortex, extrastriate cortex, fusiform gyrus, and the precuneus. Several of these regions are members of the *posterior medial system*, "*posterior medial system*"¹³, which has been implicated in matching incoming cues about the current situation to internally maintained *situation models*, "*situation models*" that specify the parameters and expectations inherent to the current situation *also see*^{14,15 14,15}. Taken together, our results support the notion that these two (partially overlapping) networks work in coordination to make sense of our ongoing experiences, distort them in a way that links them with our prior knowledge and experiences, and encodes those distorted representations into memory for our later use. [Our work also provides a potential framework for modeling and elucidating "memory schemas"—i.e., cognitive abstractions that may be applied to multiple related experiences](#)^{43,44}. [For example, the event-level geometric scaffolding of an experience \(e.g., Fig. 6A\) might reflect its underlying schema, and experiences that share similar schemas might have similar shapes. This could also help explain how brain structures including the ventromedial prefrontal cortex](#)⁴³ [\(Fig. 8\) might acquire or apply schema knowledge across different experiences \(i.e., by learning patterns in the schema's shape\).](#)

Our general approach draws inspiration from prior work aimed at elucidating the neural and behavioral underpinnings of how we process dynamic naturalistic experiences and remember them later. Our approach to identifying neural responses to naturalistic stimuli (including experiences) entails building an explicit model of the stimulus dynamics and searching for brain regions whose responses are consistent with the model *also see*^{45,46}. [Building an explicit model of](#)

469 these dynamics also enables us to match up different people’s recountings of a common shared
470 experience, despite individual differences ⁴⁷. In prior work, a series of studies from Uri Hasson’s
471 group^{7,23,26,48,49} have presented a clever alternative approach: rather than building an explicit
472 stimulus model, these studies instead search for brain responses to the stimulus that are reliably
473 similar across individuals. So called ~~inter-subject-correlation~~ “inter-subject correlation” (ISC) and
474 ~~inter-subject functional connectivity~~ “inter-subject functional connectivity” (ISFC) analyses effectively
475 treat other people’s brain responses to the stimulus as a “model” of how its features change over
476 time ~~also see~~ ^{50,50}. These purely brain-driven approaches are well suited to identifying which brain
477 structures exhibit similar stimulus-driven responses across individuals. Further, because neural
478 response dynamics are observed data (rather than model approximations), such approaches do
479 not require a detailed understanding of which stimulus properties or features might be driving
480 the observed responses. However, this also means that the specific stimulus features driving those
481 responses are typically opaque to the researcher. Our approach is complementary. By explicitly
482 modeling the stimulus dynamics, we are able to relate specific stimulus features to behavioral and
483 neural dynamics. However, when our model fails to accurately capture the stimulus dynamics that
484 are truly driving behavioral and neural responses, our approach necessarily yields an incomplete
485 characterization of the neural basis of the processes we are studying.

486 Other recent work has used HMMs to discover latent event structure in neural responses
487 to naturalistic stimuli²⁶. By applying HMMs to our explicit models of stimulus and memory
488 dynamics, we gain a more direct understanding of those state dynamics. For example, we found
489 that although the events comprising each participant’s recalls recapitulated the episode’s essence,
490 participants differed in the ~~resolution~~ resolution of their recounting of low-level details. In turn,
491 these individual behavioral differences were reflected in differences in neural activity dynamics as
492 participants watched the television episode.

493 Our approach also draws inspiration from the growing field of word embedding models. The
494 topic models²⁴ we used to embed text from the episode annotations and participants’ recall tran-
495 scripts are just one of many models that have been studied in an extensive literature. The earliest
496 approaches to word embedding, including latent semantic analysis⁵¹, used word co-occurrence

497 statistics (i.e., how often pairs of words occur in the same documents contained in the corpus) to
498 derive a unique feature vector for each word. The feature vectors are constructed so that words
499 that co-occur more frequently have feature vectors that are closer (in Euclidean distance). Topic
500 models are essentially an extension of those early models, in that they attempt to explicitly model
501 the underlying causes of word co-occurrences by automatically identifying the set of themes or
502 topics reflected across the documents in the corpus. More recent work on these types of semantic
503 models, including word2vec⁵², the Universal Sentence Encoder⁵³, [and Generative Pre-trained](#)
504 [Transformers \(e.g., GPT-2⁵⁴ and GTP-3⁵⁵\)](#) use deep neural networks to attempt to identify the
505 deeper conceptual representations underlying each word. Despite the growing popularity of these
506 sophisticated deep learning-based embedding models, we chose to prioritize interpretability of
507 the embedding dimensions (e.g., Fig. 7) over raw performance (e.g., with respect to some pre-
508 defined benchmark). Nevertheless, we note that our general framework is, in principle, robust
509 to the specific choice of language model as well as other aspects of our computational pipeline.
510 For example, the word embedding model, timeseries segmentation model, and the episode-recall
511 matching function could each be customized to suit a particular question space or application.
512 Indeed, for some questions, interpretability of the embeddings may not be a priority, and thus
513 other text embedding approaches (including the deep learning-based models described above)
514 may be preferable. Further work will be needed to explore the influence of particular models on
515 our framework's predictions and performance.

516 ~~Our work has~~ [Speculatively, our work may have](#) broad implications for how we characterize
517 and assess memory in real-world settings, such as the classroom or physician's office. For example,
518 the most commonly used classroom evaluation tools involve simply computing the proportion of
519 correctly answered exam questions. Our work ~~indicates~~ [suggests](#) that this approach is only loosely
520 related to what educators might really want to measure: how well did the students understand
521 the key ideas presented in the course? Under this typical framework of assessment, the same
522 exam score of 50% could be ascribed to two very different students: one who attended to the full
523 course but struggled to learn more than a broad overview of the material, and one who attended
524 to only half of the course but understood the attended material perfectly. Instead, one could apply

our computational framework to build explicit dynamic content models of the course material and exam questions. This approach ~~would~~^{might} provide a more nuanced and specific view into which aspects of the material students had learned well (or poorly). In clinical settings, memory measures that incorporate such explicit content models might also provide more direct evaluations of patients' memories, and of doctor-patient interactions.

Methods

Paradigm and data collection

Data were collected by ²³[Chen et al. \(2017\)](#)²³. In brief, participants ($n = 22$) viewed the first 48 minutes of "A Study in Pink," the first episode of the BBC television show *Sherlock*, while fMRI volumes were collected (TR = 1500 ms). Participants were pre-screened to ensure they had never seen any episode of the show before. The stimulus was divided into a 23 min (946 TR) and a 25 min (1030 TR) segment to mitigate technical issues related to the scanner. After finishing the clip, participants were instructed to ~~quoting from~~²³ "describe what they recalled of the [episode] in as much detail as they could, to try to recount events in the original order they were viewed in, and to speak for at least 10 minutes if possible but that longer was better. They were told that completeness and detail were more important than temporal order, and that if at any point they realized they had missed something, to return to it. Participants were then allowed to speak for as long as they wished, and verbally indicated when they were finished (e.g., 'I'm done')." ²³ Five participants were dropped from the original dataset due to excessive head motion (2 participants), insufficient recall length (2 participants), or falling asleep during stimulus viewing (1 participant), resulting in a final sample size of $n = 17$. For additional details about the testing procedures and scanning parameters, see [Chen et al. \(2017\)](#)²³. The testing protocol was approved by Princeton University's Institutional Review Board.

After preprocessing the fMRI data and warping the images into a standard (3 mm³ MNI) space, the voxel activations were z-scored (within voxel) and spatially smoothed using a 6 mm (full width

550 at half maximum) Gaussian kernel. The fMRI data were also cropped so that all episode-viewing
551 data were aligned across participants. This included a constant 3 TR (4.5 s) shift to account for the lag
552 in the hemodynamic response. ~~All of these preprocessing steps followed²³ where additional details may be found.~~
553 All of these preprocessing steps followed Chen et al. (2017)²³, where additional details may be
554 found.

555 The video stimulus was divided into ~~1,000-1000~~ fine-grained “time segments” and annotated
556 by an independent coder. For each of these ~~1,000-1000~~ annotations, the following information
557 was recorded: a brief narrative description of what was happening, the location where the time
558 segment took place, whether that location was indoors or outdoors, the names of all characters
559 on-screen, the name(s) of the character(s) in focus in the shot, the name(s) of the character(s)
560 currently speaking, the camera angle of the shot, a transcription of any text appearing on-screen,
561 and whether or not there was music present in the background. Each time segment was also tagged
562 with its onset and offset time, in both seconds and TRs.

563 **~~Data and code availability~~**

564 ~~The fMRI data we analyzed are available online . The behavioral data and all of our analysis code~~
565 ~~may be downloaded.~~

566 **Statistics**

567 All statistical tests performed in the behavioral analyses were two-sided. All statistical tests per-
568 formed in the neural data analyses were two-sided, except for the permutation-based thresholding,
569 which was one-sided. In this case, we were specifically interested in identifying voxels whose acti-
570 vation time series reflected the temporal structure of the episode and recall topic proportions matri-
571 ces to a ~~greater~~ greater extent than that of the phase-shifted matrices. The 95% confidence intervals
572 we reported for each correlation were estimated by generating 10000 “bootstrap” distributions of
573 correlation coefficients by sampling (with replacement) from the observed data.

Modeling the dynamic content of the episode and recall transcripts

Topic modeling

The input to the topic model we trained to characterize the dynamic content of the episode comprised 998 hand-generated annotations of short (mean: 2.96s) time segments spanning the video clip ([Chen et al., 2017](#)²³ generated 1000 annotations total; we removed two annotations referring to a break between the first and second scan sessions, during which no fMRI data were collected). We concatenated the text for all of the annotated features within each segment, creating a “bag of words” describing its content, and performed some minor preprocessing (e.g., stemming possessive nouns and removing punctuation). We then re-organized the text descriptions into overlapping sliding windows spanning (up to) 50 annotations each. In other words, we estimated the “context” for each annotated segment using the text descriptions of the preceding 25 annotations, the present annotations, and the following 24 annotations. To model the context for annotations near the beginning of the episode (i.e., within 25 of the beginning or end), we created overlapping sliding windows that grew in size from one annotation to the full length. We also tapered the sliding window lengths at the end of the episode, whereby time segments within fewer than 24 annotations of the end of the episode were assigned sliding windows that extended to the end of the episode. This procedure ensured that each annotation’s content was represented in the text corpus an equal number of times.

We trained our model using these overlapping text samples with `scikit-learn` ~~version 0.19.1~~,⁵⁶ [version 0.19.1](#)⁵⁶, called from our high-dimensional visualization and text analysis software, HyperTools³⁵. Specifically, we used the `CountVectorizer` class to transform the text from each window into a vector of word counts (using the union of all words across all annotations as the “vocabulary,” excluding English stop words); this yielded a number-of-windows by number-of-words ~~word-count~~ “word count” matrix. We then used the `LatentDirichletAllocation` class (topics=100, method=‘batch’) to fit a topic model²⁴ to the word count matrix, yielding a number-of-windows (1047) by number-of-topics (100) ~~topic-proportions~~ “topic proportions” matrix. The topic proportions matrix describes the gradually evolving mix of topics (latent themes) present in

each annotated time segment of the episode. Next, we transformed the topic proportions matrix to match the 1976 fMRI volume acquisition times. We assigned each topic vector to the timepoint (in seconds) midway between the beginning of the first annotation and the end of the last annotation in its corresponding sliding text window. By doing so, we warped the linear temporal distance between consecutive topic vectors to align with the inconsistent temporal distance between consecutive annotations (whose durations varied greatly). We then rescaled these timepoints to 1.5x TR units, and used linear interpolation to estimate a topic vector for each TR. This resulted in a number-of-TRs (1976) by number-of-topics (100) matrix.

We created similar topic proportions matrices using hand-annotated transcripts of each participant’s verbal recall of the episode ~~annotated by~~^{23,23}. We tokenized the transcript into a list of sentences, and then re-organized the list into overlapping sliding windows spanning (up to) 10 sentences each, analogously to how we parsed the episode annotations. In turn, we transformed each window’s sentences into a word count vector (using the same vocabulary as for the episode model), then used the topic model already trained on the episode scenes to compute the most probable topic proportions for each sliding window. This yielded a number-of-windows (range: 83–312) by number-of-topics (100) topic proportions matrix for each participant. These reflected the dynamic content of each participant’s recalls. ~~Note: for~~ For details on how we selected the episode and recall window lengths and number of topics, see ~~Supporting Supplementary~~ Supporting Supplementary Information and Supplementary Figure 1.

Segmenting topic proportions matrices into discrete events using hidden Markov Models

We parsed the topic proportions matrices of the episode and participants’ recalls into discrete events using hidden Markov Models ~~HMMs;~~²⁵ (HMMs)²⁵. Given the topic proportions matrix (describing the mix of topics at each timepoint) and a number of states, K , an HMM recovers the set of state transitions that segments the timeseries into K discrete states. Following Baldassano et al. (2017)²⁶, we imposed an additional set of constraints on the discovered state transitions that ensured that each state was encountered exactly once (i.e., never repeated). We used the BrainIAK toolbox⁵⁷ to implement this segmentation.

628 We used an optimization procedure to select the appropriate K for each topic proportions
629 matrix. Prior studies on narrative structure and processing have shown that we both perceive
630 and internally represent the world around us at multiple, hierarchical timescales^{e.g., 7,23,26,44,58,59}
631 ^{7,23,26,44,58,59}. However, for the purposes of our framework, we sought to identify the single
632 timeseries of ~~event representations that is emphasized most heavily~~ event representations that was
633 emphasized most heavily in the temporal structure of the episode and of each participant’s recall.
634 We quantified this as the set of K states that maximized the similarity between topic vectors
635 for timepoints comprising each state, while minimizing the similarity between topic vectors for
636 timepoints across different states. Specifically, we computed (for each matrix)

$$\operatorname{argmax}_K [W_1(a, b)],$$

637 where a was the distribution of within-state topic vector correlations, and b was the distribution
638 of across-state topic vector correlations. We computed the first Wasserstein distance (W_1 ^{17,4} also
639 known as ~~Earth-mover’s distance;~~ ^{60,61} “Earth mover’s distance” ^{60,61}) between these distributions
640 for a large range of possible K -values (range [2, 50]), and selected the K that yielded the maximum
641 value. Figure 2B displays the event boundaries returned for the episode, and Supplementary
642 Figure 5 displays the event boundaries returned for each participant’s recalls. See Supplementary
643 Figure 7 for the optimization functions for the episode and recalls. After obtaining these event
644 boundaries, we created stable estimates of the content represented in each event by averaging the
645 topic vectors across timepoints between each pair of event boundaries. This yielded a number-of-
646 events by number-of-topics matrix for the episode and recalls from each participant.

647 **Naturalistic extensions of classic list-learning analyses**

648 In traditional list-learning experiments, participants view a list of items (e.g., words) and then
649 recall the items later. Our episode-recall event matching approach affords us the ability to analyze
650 memory in a similar way. The episode and recall events can be treated analogously to studied and
651 recalled “items” in a list-learning study. We can then extend classic analyses of memory perfor-

652 mance and dynamics (originally designed for list-learning experiments) to the more naturalistic
653 episode recall task used in this study.

654 Perhaps the simplest and most widely used measure of memory performance is ~~accuracy~~ “accuracy” —
655 i.e., the proportion of studied (experienced) items (in this case, episode events) that the participant
656 later remembered. [Chen et al. \(2017\)](#)²³ used this method to rate each participant’s memory
657 quality by computing the proportion of (50 ~~manually~~ manually identified) scenes mentioned in their re-
658 call. We found a strong across-participants correlation between these independent ratings and
659 the proportion of 30 HMM-identified episode events matched to participants’ recalls (Pearson’s
660 ~~$r(15) = 0.71, p = 0.002$~~ $r(15) = 0.71, p = 0.002, 95\% \text{ CI} = [0.39, 0.88]$). We further considered a num-
661 ber of more nuanced memory performance measures that are typically associated with list-learning
662 studies. We also provide a software package, Quail, for carrying out these analyses⁶².

663 **Probability of first recall (PFR).** PFR curves^{30–32} reflect the probability that an item will be
664 recalled first, as a function of its serial position during encoding. To carry out this analysis, we
665 initialized a number-of-participants (17) by number-of-episode-events (30) matrix of zeros. Then,
666 for each participant, we found the index of the episode event that was recalled first (i.e., the episode
667 event whose topic vector was most strongly correlated with that of the first recall event) and filled
668 in that index in the matrix with a 1. Finally, we averaged over the rows of the matrix, resulting in a
669 1 by 30 array representing the proportion of participants that recalled an event first, as a function
670 of the order of the event’s appearance in the episode (Fig. 3A).

671 **Lag conditional probability curve (lag-CRP).** The lag-CRP curve² reflects the probability of
672 recalling a given item after the just-recalled item, as a function of their relative encoding positions
673 (~~or lag~~ lag). In other words, a lag of 1 indicates that a recalled item was presented immediately
674 after the previously recalled item, and a lag of -3 indicates that a recalled item came 3 items before
675 the previously recalled item. For each recall transition (following the first recall), we computed
676 the lag between the current recall event and the next recall event, normalizing by the total number
677 of possible transitions. This yielded a number-of-participants (17) by number-of-lags (-29 to +29;

678 58 lags total excluding lags of 0) matrix. We averaged over the rows of this matrix to obtain a
679 group-averaged lag-CRP curve (Fig. 3B).

680 **Serial position curve (SPC).** SPCs¹ reflect the proportion of participants that remember each
681 item as a function of the item’s serial position during encoding. We initialized a number-of-
682 participants (17) by number-of-episode-events (30) matrix of zeros. Then, for each recalled event,
683 for each participant, we found the index of the episode event that the recalled event most closely
684 matched (via the correlation between the events’ topic vectors) and entered a 1 into that position
685 in the matrix. This resulted in a matrix whose entries indicated whether or not each event was
686 recalled by each participant (depending on whether the corresponding entries were set to one or
687 zero). Finally, we averaged over the rows of the matrix to yield a 1 by 30 array representing the
688 proportion of participants that recalled each event as a function of the events’ order appearance in
689 the episode (Fig. 3C).

690 **Temporal clustering scores.** Temporal clustering describes a participant’s tendency to organize
691 their recall sequences by the learned items’ encoding positions. For instance, if a participant
692 recalled the episode events in the exact order they occurred (or in exact reverse order), this would
693 yield a score of 1. If a participant recalled the events in random order, this would yield an expected
694 score of 0.5. For each recall event transition (and separately for each participant), we sorted all
695 not-yet-recalled events according to their absolute lag (i.e., distance away in the episode). We
696 then computed the percentile rank of the next event the participant recalled. We averaged these
697 percentile ranks across all of the participant’s recalls to obtain a single temporal clustering score
698 for the participant.

699 **Semantic clustering scores.** Semantic clustering describes a participant’s tendency to recall se-
700 mantically similar presented items together in their recall sequences. Here, we used the topic
701 vectors for each event as a proxy for its semantic content. Thus, the similarity between the se-
702 mantic content for two events can be computed by correlating their respective topic vectors. For
703 each recall event transition, we sorted all not-yet-recalled events according to how correlated the

704 topic vector ~~of the closest-matching episode event~~ of the closest-matching episode event was to the
705 topic vector of the closest-matching episode event to the just-recalled event. We then computed
706 the percentile rank of the observed next recall. We averaged these percentile ranks across all of the
707 participant’s recalls to obtain a single semantic clustering score for the participant.

708 **Averaging correlations**

709 In all instances where we performed statistical tests involving precision or distinctiveness scores
710 (Fig. 5), we used the Fisher z-transformation⁶³ to stabilize the variance across the distribution of
711 correlation values prior to performing the test. Similarly, when averaging precision or distinctive-
712 ness scores, we z-transformed the scores prior to computing the mean, and inverse z-transformed
713 the result.

714 **Visualizing the episode and recall topic trajectories**

715 We used the UMAP algorithm³⁶ to project the 100-dimensional topic space onto a two-dimensional
716 space for visualization (Figs. 6, 7). To ensure that all of the trajectories were projected onto the
717 ~~same~~ same lower dimensional space, we computed the low-dimensional embedding on a “stacked”
718 matrix created by vertically concatenating the events-by-topics topic proportions matrices for the
719 episode, the across-participants average ~~recall~~ recalls and all 17 individual participants’ recalls. We
720 then separated the rows of the result (a total-number-of-events by two matrix) back into individual
721 matrices for the episode topic trajectory, the across-participant average recall trajectory, and the
722 trajectories for each individual participant’s recalls (Fig. 6). This general approach for discovering
723 a shared low-dimensional embedding for a collections of high-dimensional observations follows
724 our prior work on manifold learning³⁵.

725 We optimized the manifold space for visualization based on two criteria: First, that the 2D em-
726 bedding of the episode trajectory should reflect its original 100-dimensional structure as faithfully
727 as possible. Second, that the path traversed by the embedded episode trajectory should intersect
728 itself a minimal number of times. The first criteria helps bolster the validity of visual intuitions
729 about relationships between sections of episode content, based on their locations in the embed-

ding space. The second criteria was motivated by the observed low off-diagonal values in the episode trajectory’s temporal correlation matrix (suggesting that the same topic-space coordinates should not be revisited; see Fig. 2A). For further details on how we created this low-dimensional embedding space, see [Supporting Supplementary Information](#).

Estimating the consistency of flow through topic space across participants

In Figure 6B, we present an analysis aimed at characterizing locations in topic space that different participants move through in a consistent way (via their recall topic trajectories; [also see Supp. Fig. 4](#)). The two-dimensional topic space used in our visualizations (Fig. 6) comprised a 60×60 (arbitrary units) square. We tiled this space with a 50×50 grid of evenly spaced vertices, and defined a circular area centered on each vertex whose radius was two times the distance between adjacent vertices (i.e., 2.4 units). For each vertex, we examined the set of line segments formed by connecting each pair successively recalled events, across all participants, that passed through this circle. We computed the distribution of angles formed by those segments and the x -axis, and used a Rayleigh test to determine whether the distribution of angles was reliably “peaked” (i.e., consistent across all transitions that passed through that local portion of topic space). To create Figure 6B, we drew an arrow originating from each grid vertex, pointing in the direction of the average angle formed by the line segments that passed within 2.4 units. We set the arrow lengths to be inversely proportional to the p -values of the Rayleigh tests at each vertex. Specifically, for each vertex we converted all of the angles of segments that passed within 2.4 units to unit vectors, and we set the arrow lengths at each vertex proportional to the length of the (circular) mean vector. We also indicated any significant results ($p < 0.05$, corrected using the Benjamani-Hochberg procedure) by coloring the arrows in blue (darker blue denotes a lower p -value, i.e., a longer mean vector); all tests with $p \geq 0.05$ are displayed in gray and given a lower opacity value.

Searchlight fMRI analyses

In Figure 8, we present two analyses aimed at identifying brain regions whose responses (as participants viewed the episode) exhibited a particular temporal structure. We developed a searchlight

analysis wherein we constructed a $5 \times 5 \times 5$ cube of voxels ~~following~~²³ centered on each voxel in the brain²³, and for each of these cubes, computed the temporal correlation matrix of the voxel responses during episode viewing. Specifically, for each of the 1976 volumes collected during episode viewing, we correlated the activity patterns in the given cube with the activity patterns (in the same cube) collected during every other timepoint. This yielded a 1976×1976 correlation matrix for each cube. Note: participant 5’s scan ended 75s early, and in [Chen et al. \(2017\)](#)²³’s publicly released dataset, their scan data was zero-padded to match the length of the other participants’. For our searchlight analyses, we removed this padded data (i.e., the last 50 TRs), resulting in a 1925×1925 correlation matrix for each cube in participant 5’s brain.

Next, we constructed a series of “template” matrices. The first template reflected the time-course of the episode’s topic proportions matrix, and the others reflected the timecourse of each participant’s recall topic proportions matrix. To construct the episode template, we computed the correlations between the topic proportions estimated for every pair of TRs (prior to segmenting the topic proportions matrices into discrete events; i.e., the correlation matrix shown in Figs. 2B and 8A). We constructed similar temporal correlation matrices for each participant’s recall topic proportions matrix ([Figs Fig. 2D](#), [Supp. Fig. 5](#)). However, to correct for length differences and potential non-linear transformations between viewing time and recall time, we first used dynamic time warping⁶⁴ to temporally align participants’ recall topic proportions matrices with the episode topic proportions matrix. An example correlation matrix before and after warping is shown in Fig. 8B. This yielded a 1976×1976 correlation matrix for the episode template and for each participant’s recall template.

The temporal structure of the episode’s content (as described by our model) is captured in the block-diagonal structure of the episode’s temporal correlation matrix (e.g., Figs. 2B, 8A), with time periods of thematic stability represented as dark blocks of varying sizes. Inspecting the episode correlation matrix suggests that the episode’s semantic content is highly temporally specific (i.e., the correlations between topic vectors from distant timepoints are almost all near zero). By contrast, the activity patterns of individual (cubes of) voxels can encode relatively limited information on their own, and their activity frequently contributes to multiple separate functions^{65–68}. By nature, these

784 two attributes give rise to similarities in activity across large timescales that may not necessarily
785 reflect a single task. To ~~enable a more sensitive analysis of~~ identify brain regions whose shifts in
786 activity patterns mirrored shifts in the semantic content of the episode or recalls, we restricted
787 the temporal correlations we considered to the timescale of semantic information captured by our
788 model. Specifically, we isolated the upper triangle of the episode correlation matrix and created a
789 “proximal correlation mask” that included only diagonals from the upper triangle of the episode
790 correlation matrix up to the first diagonal that contained no positive correlations. Applying this
791 mask to the full episode correlation matrix was equivalent to excluding diagonals beyond the
792 corner of the largest diagonal block. In other words, the timescale of temporal correlations we
793 considered corresponded to the longest period of thematic stability in the episode, and by extension
794 the longest period of thematic stability in participants’ recalls and the longest period of stability we
795 might expect to see in voxel activity arising from processing or encoding episode content. Figure 8
796 shows this proximal correlation mask applied to the temporal correlation matrices for the episode,
797 an example participant’s (warped) recall, and an example cube of voxels from our searchlight
798 analyses.

799 To determine which (cubes of) voxel responses matched the episode template, we correlated the
800 proximal diagonals from the upper triangle of the voxel correlation matrix for each cube with the
801 proximal diagonals from episode template matrix⁶⁹. This yielded, for each participant, a voxelwise
802 map of correlation values. We then performed a one-sample *t*-test on the distribution of (Fisher
803 *z*-transformed) correlations at each voxel, across participants. This resulted in a value for each
804 voxel (cube), describing how reliably its timecourse followed that of the episode.

805 We further sought to ensure that our analysis identified regions where the activations’ temporal
806 structure specifically reflected that of the episode, rather than regions whose activity was simply
807 autocorrelated at a timescale similar to the episode template’s diagonal. To achieve this, we used
808 a phase shift-based permutation procedure, whereby we circularly shifted the episode’s topic
809 proportions matrix by a random number of timepoints (rows), computed the resulting “null”
810 episode template, and re-ran the searchlight analysis, in full. (For each of the 100 permutations, the
811 same random shift was used for all participants). We *z*-scored the observed (unshifted) result at

each voxel against the distribution of permutation-derived “null” results, and estimated a p -value by computing the proportion of shifted results that yielded larger values. To create the map in Figure 8C, we thresholded out any voxels whose similarity to the unshifted episode’s structure fell below the 95th percentile of the permutation-derived similarity results.

We used an analogous procedure to identify which voxels’ responses reflected the recall templates. For each participant, we correlated the proximal diagonals from the upper triangle of the correlation matrix for each cube of voxels with the proximal diagonals from the upper triangle of their (time-warped) recall correlation matrix. As in the episode template analysis, this yielded a voxelwise map of correlation coefficients for each participant. However, whereas the episode analysis compared every participant’s responses to the same template, here the recall templates were unique for each participant. As in the analysis described above, we t -scored the (Fisher z -transformed) voxelwise correlations, and used the same permutation procedure we developed for the episode responses to ensure specificity to the recall timeseries and assign significance values. To create the map in Figure 8D we again thresholded out any voxels whose scores were below the 95th percentile of the permutation-derived null distribution.

Neurosynth decoding analyses

Neurosynth³⁹ parses a massive online database of over ~~14,000~~ 14000 neuroimaging studies and constructs meta-analysis images for over ~~13,000~~ 13000 psychology- and neuroscience-related terms, based on NIfTI images accompanying studies where those terms appear at a high frequency. Given a novel image (tagged with its value type; e.g., z -, t -, F - or p -statistics), Neurosynth returns a list of terms whose meta-analysis images are most similar. Our permutation procedure yielded, for each of the two searchlight analyses, a voxelwise map of z -values. These maps describe the extent to which each voxel ~~specifically~~ specifically reflected the temporal structure of the episode or individuals’ recalls (i.e., relative to the null distributions of phase-shifted values). We inputted the two statistical maps described above to Neurosynth to create a list of the 10 most representative terms for each map.

Supporting information Data availability

~~Supporting information is available in the online version of the paper~~ The fMRI data we analyzed
are available online here. The behavioral data is available here.

Code availability

All of our analysis code may be downloaded here.

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1001 **~~Author information~~**Competing interests

1002 The authors declare no competing ~~financial interests. Correspondence and requests for materials~~
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1004 **Figures**

Figure 1: Topic weights in episode and recall content. We used detailed, hand-generated annotations describing each manually identified time segment from the episode to fit a topic model. Three example frames from the episode (first row) are displayed, along with their descriptions from the corresponding episode annotation (second row) and an example participant’s recall transcript (third row). We used the topic model (fit to the episode annotations) to estimate topic vectors for each moment of the episode and each sentence of participants’ recalls. Example topic vectors are displayed in the bottom row (blue: episode annotations; green: example participant’s recalls). Three topic dimensions are shown (the highest-weighted topics for each of the three example scenes, respectively), along with the 10 highest-weighted words for each topic. [Supplementary](#) Figure 2 provides a full list of the top 10 words from each of the discovered topics.

Figure 2: Modeling naturalistic stimuli and recalls. All panels: darker colors indicate greater values; range: [0, 1]. **A.** Topic vectors ($K = 100$) for each of the 1976 episode timepoints. **B.** Timepoint-by-timepoint correlation matrix of the topic vectors displayed in Panel A. Event boundaries discovered by the HMM are denoted in yellow (30 events detected). **C.** Average topic vectors for each of the 30 episode events. **D.** Topic vectors for each of 265 sliding windows of sentences spoken by an example participant while recalling the episode. **E.** Timepoint-by-timepoint correlation matrix of the topic vectors displayed in Panel D. Event boundaries detected by the HMM are denoted in yellow (22 events detected). For similar plots for all participants, see [Supplementary](#) Figure 5. **F.** Average topic vectors for each of the 22 recall events from the example participant. **G.** Correlations between the topic vectors for every pair of episode events (Panel C) and recall events (from the example participant; Panel F). For similar plots for all participants, see [Supplementary](#) Figure 6. **H.** Average correlations between each pair of episode events and recall events (across all 17 participants). To create the figure, each recalled event was assigned to the episode event with the most correlated topic vector (yellow boxes in panels G and H).

Figure 3: Naturalistic extensions of classic list-learning memory analyses. **A.** The probability of first recall as a function of the serial position of the event in the episode. **B.** The probability of recalling each event, conditioned on having most recently recalled the event *lag* events away in the episode. **C.** The proportion of participants who recalled each event, as a function of the serial position of the events in the episode. All panels: error ribbons denote the bootstrap-estimated 95% confidence interval.

Naturalistic extensions of classic list-learning memory analyses. **A.** The probability of first recall as a function of the serial position of the event in the episode. **B.** The probability of recalling each event, conditioned on having most recently recalled the event *lag* events away in the episode. **C.** The proportion of participants who recalled each event, as a function of the serial position of the events in the episode. All panels: error ribbons denote bootstrap-estimated standard error of the mean.

Figure 4: Novel content-based metrics of naturalistic memory: precision and distinctiveness. **A.** The episode-recall correlation matrix for a representative participant (P17), chosen for their large number of recall events (for analogous figures for other participants, see Supp. Fig. 5). The yellow boxes highlight the maximum correlation in each column. The example participant's overall precision score was computed as the average across the (Fisher z-transformed) correlation values in the yellow boxes. Their distinctiveness score was computed as the average (over recall events) of the z-scored (within column) event precisions. **B.** The across-participants (Pearson's) correlation between precision and hand-counted number of recalled scenes. **C.** The correlation between distinctiveness and hand-counted number of recalled scenes. **D.** The correlation between precision and the number of recalled episode events, as determined by our model. **E.** The correlation between distinctiveness and the number of recalled episode events, as determined by our model.

Figure 5: Precision reflects the completeness of recall, whereas distinctiveness reflects recall specificity. A. Recall precision by episode event. Grey violin plots display kernel density estimates for the distribution of recall precision scores for a single episode event. Colored dots within each violin plot represent individual participants' recall ~~precision~~ precisions for the given event. **B.** Recall distinctiveness by episode event, analogous to Panel A. **C.** The set of "Narrative Details" episode annotations(~~generated by~~ ²³) 23 comprising an example episode event (22) identified by the HMM. Each action or feature is highlighted in a different color. **D.** Sentences comprising the most precise (P17) and least precise (P6) participants' recalls of episode event 21. Descriptions of specific actions or features reflecting those highlighted in Panel B are highlighted in the corresponding color. The text highlighted in gray denotes a (rare) false recall. The unhighlighted text denotes correctly recalled information about other episode events. **E.** The sets of "Narrative Details" episode annotations(~~generated by~~ ²³) 23 for scenes comprising episode events described by the example participants in Panel F. Each event's text is highlighted in a different color. **F.** The sentences comprising the most distinctive (P9) and least distinctive (P6) participants' recalls of episode event 21. Sections of recall describing each episode event in Panel E are highlighted with the corresponding color.

Figure 6: Trajectories through topic space capture the dynamic content of the episode and recalls. All panels: the topic proportion matrices have been projected onto a shared two-dimensional space using UMAP. **A.** The two-dimensional topic trajectory taken by the episode of *Sherlock*. Each dot indicates an event identified using the HMM (see *Methods*); the dot colors denote the order of the events (early events are in red; later events are in blue), and the connecting lines indicate the transitions between successive events. **B.** The average two-dimensional trajectory captured by participants’ recall sequences, with the same format and coloring as the trajectory in Panel A. To compute the event positions, we matched each recalled event with an event from the original episode (see *Results*), and then we averaged the positions of all events with the same label. The arrows reflect the average transition direction through topic space taken by any participants whose trajectories crossed that part of topic space; blue denotes reliable agreement across participants via a Rayleigh test ($p < 0.05$, corrected). [For additional detail see *Methods* and Supplementary Figure 4.](#) **C.** The recall topic trajectories (gray) taken by each individual participant (P1–P17). The episode’s trajectory is shown in black for reference. Here, events (dots) are colored by their matched episode event (Panel A).

Figure 7: Language used in the most and least precisely remembered events. **A.** Average precision (episode event-recall event topic vector correlation) across participants for each episode event. Here we defined each episode event's precision for each participant as the correlation between its topic vector and the most-correlated recall event's topic vector from that participant. Error bars denote bootstrap-derived across-participant 95% confidence intervals. The stars denote the three most precisely remembered events (green) and least precisely remembered events (red). **B.** Wordles comprising the top 200 highest-weighted words reflected in the weighted-average topic vector across episode events. Green: episode events were weighted by their precision (Panel A). Red: episode events were weighted by the inverse of their precision. **C.** The set of all episode and recall events is projected onto the two-dimensional space derived in Figure 6. The dots outlined in black denote episode events (dot size is proportional to each event's average precision). The dots without black outlines denote individual recall events from each participant. All dots are colored using the same scheme as Figure 6A. Wordles for several example events are displayed (green: three most precisely remembered events; red: three least precisely remembered events). Within each circular wordle, the left side displays words associated with the topic vector for the episode event, and the right side displays words associated with the (average) recall event topic vector, across all recall events matched to the given episode event.

Figure 8: Brain structures that underlie the transformation of experience into memory. **A.** We isolated the proximal diagonals from the upper triangle of the episode correlation matrix, and applied this same diagonal mask to the voxel response correlation matrix for each cube of voxels in the brain. We then searched for brain regions whose activation timeseries consistently exhibited a similar proximal correlational structure to the episode model, across participants. **B.** We used dynamic time warping⁶⁴ to align each participant's recall timeseries to the TR timeseries of the episode. We then computed the temporal correlation matrix of each participant's warped recalls. Next, we applied the same diagonal mask used in Panel A to isolate the proximal temporal correlations and searched for brain regions whose activation timeseries for ~~an individual~~ each participant consistently exhibited a similar proximal correlational structure to ~~each individual~~ that participant's recall recalls. **C.** We identified a network of regions sensitive to the narrative structure of participants' ongoing experience. The map shown is thresholded at $p < 0.05$, corrected. The top ten Neurosynth terms displayed in the panel were computed using the unthresholded map. **D.** We also identified a network of regions sensitive to how individuals would later structure the episode's content in their recalls. The map shown is thresholded at $p < 0.05$, corrected. The top ten Neurosynth terms displayed in the panel were computed using the unthresholded map.