Random Tree Model of Meaningful Memory

Weishun Zhong,[1] Tankut Can,[1,2] Antonis Georgiou,[1,3] Ilya Shnayderman,[3] Mikhail Katkov,[1,3] and Misha Tsodyks[1,3,*]

[1] *School of Natural Sciences, Institute for Advanced Study, Princeton, NJ, 08540, USA*
[2] *Department of Physics, Emory University, Atlanta, GA 30322, USA*
[3] *Department of Brain Sciences, Weizmann Institute of Science, Rehovot, 76100, Israel*

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Traditional studies of memory for meaningful narratives focus on specific stories and their semantic structures but do not address common quantitative features of recall across different narratives. We introduce a statistical ensemble of random trees to represent narratives as hierarchies of key points, where each node is a compressed representation of its descendant leaves, which are the original narrative segments. Recall is modeled as constrained by working memory capacity from this hierarchical structure. Our analytical solution aligns with observations from large-scale narrative recall experiments. Specifically, our model explains that (1) average recall length increases sublinearly with narrative length, and (2) individuals summarize increasingly longer narrative segments in each recall sentence. Additionally, the theory predicts that for sufficiently long narratives, a universal, scale-invariant limit emerges, where the fraction of a narrative summarized by a single recall sentence follows a distribution independent of narrative length.

Narratives are a naturalistic form of stimuli for probing the structure and organization of human cognitive functions [1–6]. In the classic work of Bartlett [7], a close link between narrative memory and comprehension was established, and both were shown to vary greatly across individuals. Subsequent studies established that narrative comprehension and recall is strongly linked to a subject's semantic knowledge, such as schemas, that help to interpret new information in the context of prior knowledge (see e.g. [8–11]). It appears therefore that the complexity of memory for meaningful information cannot be captured by simple physics-style models with a few general postulates and mathematical tractability. Indeed, in the psychological literature, most studies aim to relate memory for narratives to their linguistic organization and do not predict generic quantitative features of narrative recall (see e.g. [12, 13]), in contrast to studies of memory for random material where many quantitative experimental and theoretical results are obtained (see e.g. [14]). In particular, some of the authors previously developed a model that predicted the universal relation between the average number of recalled items and the number of items retained in memory after list presentation, and this relation was well supported by experimental results [15]. To enable a similar quantitative description of memory for meaningful material, we recently performed large-scale experiments on recognition and recall of narratives of various lengths [16]. Unsurprisingly, we observed that recall of narratives is better than that of random lists in terms of the fraction of material being recalled. More interesting however are the qualitative differences between these two cases; in particular, people tend to recall information from the narrative in the same order as it is presented [17], as opposed to much more variable recall order of random lists [18–20]; for longer narratives, people compress progressively bigger pieces of information from the narrative into single sentences, resulting in a sublinear growth of recall length with the narrative size [16].

In the current study, we show that despite the more complex nature of meaningful recall, the above statistical regularities can be captured by mathematical modeling. To this end, we propose a simplified model of narrative recall that focuses on describing the statistical aspects of recall across large populations of people rather than addressing individual differences between people and narratives.

Our model is based on two basic principles. The first principle describes the memory encoding of a narrative. Following multiple previous studies, we consider a narrative as a linear sequence of clauses, i.e., the shortest meaningful pieces of text (see e.g. [21]). We assume, however, that after people *comprehend* the narrative, they form a tree-like memory representation of it where, at each level of the tree, information units of a given level of abstraction are encoded [22–24], with each unit representing a summary of a specific segment of the narrative. In particular, the root of the tree represents the whole narrative; the upper-level nodes represent pieces of the narrative that correspond to its main keypoints [25]; and lower levels represent shorter pieces corresponding to progressively finer points [26–29]. Moreover, we assume that a piece corresponding to a particular keypoint is split into pieces corresponding to the finer points that elaborate the original keypoint, resulting in a tree structure of a narrative. We see the evidence for this type of memory representation in the fact that people can easily summarize a familiar narrative at different levels of detail, which we believe is achieved by retrieving the node representations at different tree levels, e.g., retrieving upper nodes evokes the most abstract memory of a narrative in terms of its most general points. An implicit assump-

* Corresponding author: mtsodyks@gmail.com

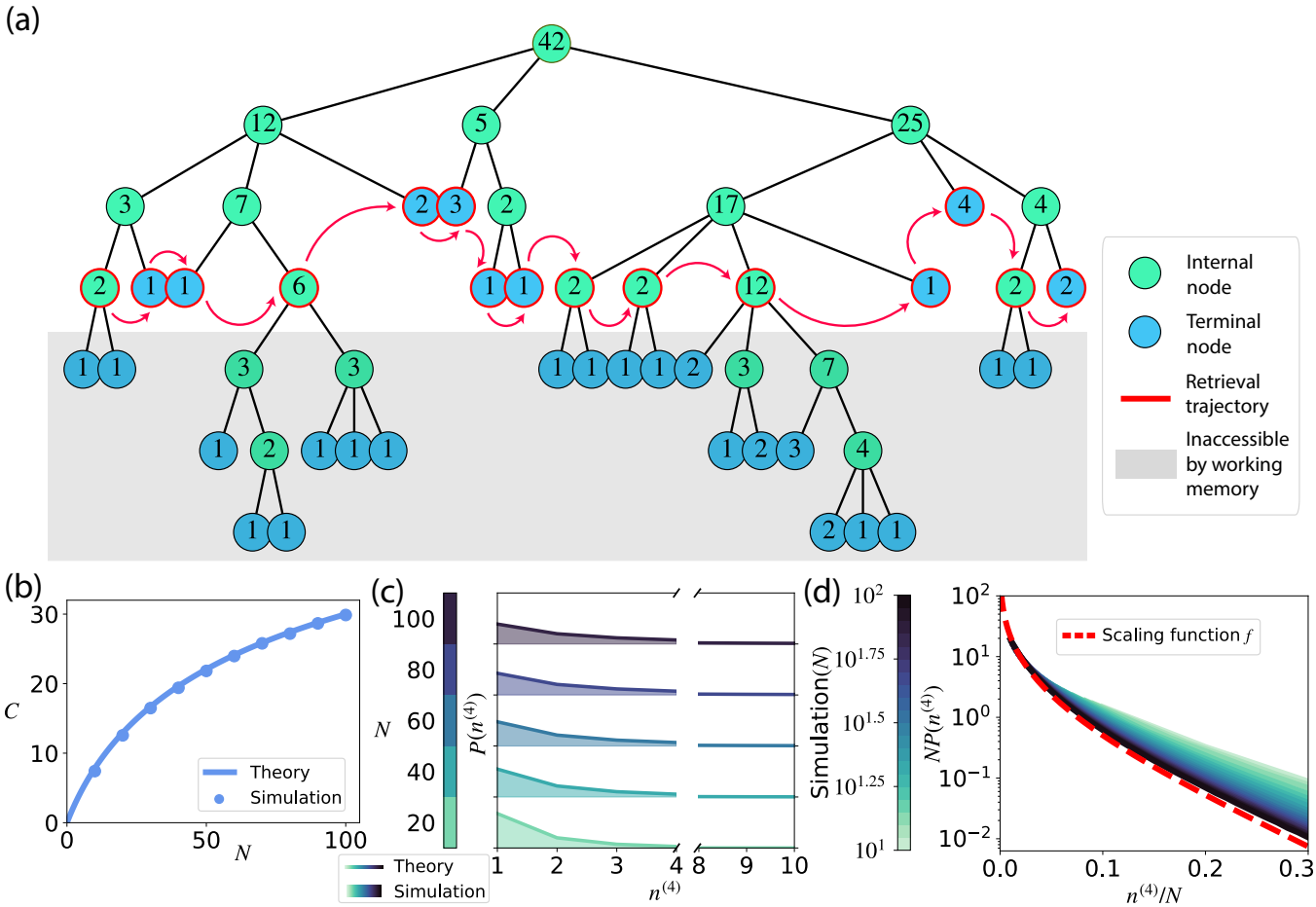

FIG. 1. **Ensemble of random trees.**
(a) Schematics of memory retrieval from a random hierarchical representation. An example of a single realization of the random tree created by the model for $N = 42$ encoded clauses with branching ratio $K = 4$ (empty chunks are omitted). Internal nodes are shown in green, while the terminal nodes (leaves) are shown in blue. The tree generating process starts with the whole narrative contained in the root node (level 1), which is subsequently split into up to 4 chunks at the next level. The splitting continues self-similarly until either a chunk fails to split further (e.g., the blue "4" at level 3) or becomes a single clause (the blue "1"s). The grey shaded area illustrate the limit imposed by working memory capacity as retrieval starts by descending from the root (retrieved nodes are shown in red). (b)-(c) Comparison between analytical solution and numerical simulations. **(b)** Mean recalled length C as a function of encoded length N. Numerical simulations are averaged over 10^4 realizations of random trees (see details in SI). **(c)** Distribution of chunk size at the Dth level $n^{(D)}$ ($D = 4$), given root size $n^{(1)} = N$, range between tick marks in the y-axis corresponds to $[0, 1]$. **(d)** Distribution of compression ratios scaled by N as a function of the compression ratios divided by N. Simulations of different N are shown in different shades of green. The red dashed line is the asymptotic scaling function from Eq. (7).

tion made here is that continuous stimuli, such as a text, is represented by a discrete set of nodes. This is also supported by experiments that show humans naturally segment sequential stimuli (e.g. movies, personal experiences) into discrete units [30–35]. There is also extensive support for the claim that narratives, from folk tales [36] to oral narratives [21, 37], have such a hierarchical, tree-like structure. We argue that this hierarchy is reflected in the mental representation.

The second principle reflects the way people recall a given narrative based on its memory representation described above. We assume that people mentally traverse the tree from upper to lower levels, keeping the intermediate nodes in working memory, in order to constantly maintain the integrity of the narrative in mind. It is in this respect that we believe the recall of meaningful narratives is fundamentally different from the recall of random lists of words. In particular, working memory capacity limits the number of nodes that can simultaneously be kept in mind, thus limiting the number of levels that can be reached during recall. We further assume that when reporting a particular node during recall, people use a single clause to express the content of the corresponding piece.

It seems plausible that a specific instantiation of the memory tree depends both on the narrative structure

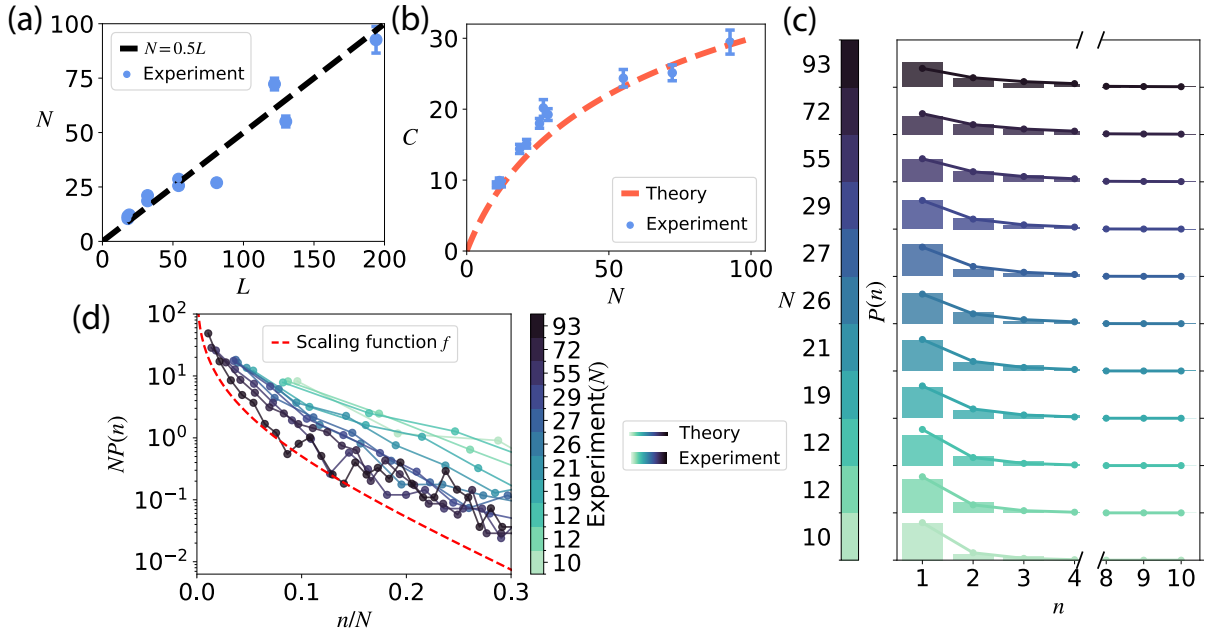

FIG. 2. **Comparison between theory and experiment.** **(a)** Average size of the tree memory representation of each narrative (N), estimated as explained in the text, plotted vs narrative length (L) for 11 narratives in the dataset. Dashed line corresponds to $N = 0.5L$. **(b)** The mean number of recalled clauses C vs average N, for all 11 narratives. Blue filled circles - data. Red dashed line - theoretical prediction obtained from Eqs. (4)-(5) with $K = D = 4$. Error bars in (a,b) are standard error of the mean. **(c)** Normalized empirical histograms of compression ratios for all subjects separately for each narrative, as measured from mapping recalled clauses back to the narrative clauses. Data for different narratives are shown in color corresponding to the colorbar marked with values of N for each narrative. Solid lines - theoretical predictions obtained from Eq. (4) with $K = D = 4$. Range between tick marks in y-axis is $[0, 1]$. **(d)** The distribution of experimentally measured compression ratios relative to N approaches the universal scale-invariant scaling function f in Eq. (7) as N increases.

and on the way a particular person comprehends and subsequently memorizes it. Hence, in order to translate the above two principles into a quantitatively constrained model, we make a highly simplifying assumption about the statistical ensemble of trees encoding different narratives of a particular length in the minds of different people. We build this ensemble by a recursive self-similar process in which a narrative is split into up to K pieces by the random placement of $K-1$ boundaries, and each piece is similarly split into up to K pieces, and so on. We begin this process from the whole narrative and continue it recursively from one layer to the next until splitting stops (see details in SI). K is the parameter of the model, and for the rest of the paper, we choose $K = 4$, i.e., the typical working memory capacity [38], because we believe that it corresponds to the most probable way for people to comprehend the narrative at the most abstract level given limitations of working memory (see [39] for a possible neural mechanism of chunking subject to working memory constraints). In Fig. 1(a), we show an example tree constructed by this process for a narrative consisting of 42 clauses.

We then illustrate the recall process playing out on this tree, assuming that people systematically traverse the memory representation by following each route beginning from the root, until they either reach a leaf or a lowest reachable (D^{th}) level (the levels above the grey shaded area in Fig. 1(a)). We again consider $D = 4$ because it corresponds to working memory capacity. The retrieval trajectory is shown in red on Fig. 1(a). One can see that some of the nodes reached by a retrieval trajectory contain single narrative clauses, while others contain multiple clauses (up to 12 for the illustrated tree). Since we assume that each node, no matter its level, is recalled with a single recall clause, the length of recall is defined by the number of retrieved nodes, while each recall clause summarizes the corresponding number of narrative clauses. It is important to emphasize that while the ensemble of memory representations described above involves a random set of trees, the hypothesized recall process itself is deterministic, i.e. the number of recall clauses and the pieces of the narrative that each one of them corresponds to are fully determined by the memory representation of the narrative.

The model described above can be simulated numerically and allows for an asymptotic mathematical solution as we show below. The length of recall (the number of clauses in recall, C) averaged over the ensemble of trees with N clauses exhibits a characteristic saturating form for increasing N, see Fig. 1(b). We also computed the distribution of the number of narrative clauses summarized by single recall clauses (i.e., compression ratios of different recall clauses), shown in Fig. 1(c) for compression ratios up to 10 and for different N. One can see that,

as expected, for longer narratives compression ratios of recall clauses tend to increase.

To obtain the analytical approximations for these numerical results, we derive a recurrence relation for the distribution of the number of clauses represented by nodes at a given level l, $P(n^{(l)})$, with

$$P(n^{(1)}) = \delta(n^{(1)} - N), \tag{1}$$

since the upper node represents all of the narrative clauses retained in memory after acquisition. When a node at level l with $n^{(l)}$ clauses is split randomly into K nodes of level $l+1$ (some of them empty), the distribution of the size of each of the resulting nodes can be computed by the "stars and bars" method ([40]) by considering all possible configurations of $n^{(l)}$ stars and $K-1$ bars and only counting the number of stars to the left of the left-most bar. This results in the following recursive expression (for $n^{(l+1)} \leq n^{(l)}$, 0 otherwise):

$$P(n^{(l+1)}|n^{(l)}) = \frac{Z_{K-1}(n^{(l)} - n^{(l+1)})}{Z_K(n^{(l)})}, \tag{2}$$

$$Z_K(n) := \binom{n+K-1}{K-1}. \tag{3}$$

Applying this recursive expression and integrating over intermediate levels results in the distribution of the node sizes in level D,

$$P(n^{(D)}) = \sum_{\substack{0 \leq n^{(D-1)} \\ \leq \cdots \leq n^{(1)}}} \prod_{l=1}^{D-1} P(n^{(l+1)}|n^{(l)}) P(n^{(1)}). \tag{4}$$

Note that Eq. (4) defines a Markov chain, see SI for more details. In this version of the stars and bars model, some of the nodes may end up being empty (if two or more bars are adjacent), and the average number of nonempty nodes at level D will define the average length of recall:

$$C = K^{D-1}(1 - P(n^{(D)} = 0)), \tag{5}$$

while the re-normalized distribution of non-zero node sizes corresponds to the distribution of compression ratios introduced above. As N increases, the probability to have an empty node approaches zero, and this equation therefore predicts that C saturates at K^{D-1} (i.e. 64 for our choice of $K = D = 4$) for long narratives. For $K = D = 4$, the analytical results obtained with Eqs. (4)-(5) are very close to numerical simulations, as shown in Fig. 1(b,c). In particular, one can see from Fig. 1(c) that as the narrative gets longer, the distribution of compression ratios shifts to the right, i.e. recall clauses tend to summarize progressively bigger pieces of the narrative.

For long narratives, the distribution of compression ratios, normalized by narrative size ($s = \frac{n}{N}$), asymptotes to a universal scaling function $f(s)$ (see derivations in SI):

$$P(n^{(D)}) = \frac{1}{N} f(n^{(D)}/N), \tag{6}$$

$$f(s_D) = \prod_{l=1}^{D-1} \int_{s_{l+1}}^{1} ds_l \rho(s_{l+1}|s_l) \rho(s_1|1), \tag{7}$$

$$\rho(s_{l+1}|s_l) := \frac{K-1}{s_l} \left(1 - \frac{s_{l+1}}{s_l}\right)^{K-2}. \tag{8}$$

In this limit, $f(s)$ is a scale-invariant probability density function for the normalized compression ratio s, which in particular implies that the average compression ratios grow proportionally to narrative length. The shape of the scaling function computed with Eq. (7) with $K = D = 4$ is shown in Fig. 1(d) in red, together with finite-N simulations from the random tree model.

We now compare our theoretical predictions to experimental data on 11 narratives ranging from 19 to 194 clauses in length, including 8 narratives from our previous study [16] and 3 new narratives selected for this study. All of the narratives, except for two, were chosen from the study by Labov [21] or generated by a Large Language Model (LLM), GPT-4 from OpenAI [41], using Labov's narratives as templates. The original narratives were edited for clarity and spelling. The two remaining narratives were borrowed from [42]. We used the clause segmentation from [21] for narratives sourced from that work, and this clause segmentation was also transferred to GPT4-generated narratives that used the originals as a templates. Each narrative was presented to 100 subjects on their computer screens via the internet platform Prolific (www.prolific.com), who were instructed to recall it as closely as possible to the original. We followed the free recall experimental protocol described in detail in [16]. We used GPT-4 to segment the recalls into single clauses, using the same prompts as in [16] (reproduced in SI). To obtain compression ratios for all recall clauses, we instructed GPT-4 to map each recall clause back to the original narrative and then counted the number of narrative clauses it was mapped to (see SI for details of this analysis). We reason that the narrative clauses to which a given recall clause is mapped correspond precisely to the segment of the narrative encoded by the corresponding node, which was recalled by this clause. The crucial remaining step needed to compare these results to the theoretical predictions above is to estimate the number of clauses in the memory representation of a given narrative for each subject (N). We compute this estimate as the total number of narrative clauses into which at least one recall clause is mapped. We assume that the remaining narrative clauses are either not remembered by the subject, or are not integrated into the tree memory representation of the narrative and hence cannot be recalled. The average values of N obtained for each narrative are plotted against their lengths in Fig. 2(a) and are observed to be close to half the total length of the narrative. With this assumption, experimental results

for the average length of recall and compression ratios up to 10 are quite similar to theoretical predictions, as shown in Fig. 2(b,c), even though no parameters were tuned after the fact to fit the model predictions to the data. Fig. 2(d) shows that for longer narratives, the distribution of compression ratios relative to N indeed approaches the scale-invariant form predicted by Eqs. (6)-(7), with the speed similar to corresponding simulations in the same range of Ns shown in Fig. 1(d).

We emphasize here the crucial role of LLM-assisted techniques in analyzing recall data, particularly the projection from each individual recall into the narrative described above. Since there is no objective ground truth for this procedure, the authors manually performed the mapping for one of the recalls (see SI for details). We observed a substantial variability between individual projections; however, the LLM-computed compression ratios for different recall clauses were closely aligned with the average compression ratios obtained from the authors' projections.

In summary, we showed that despite its highly complex nature, some statistical trends in meaningful narrative recall can be captured by a mathematical model based on two basic principles: random tree-like memory representations and a working memory-limited deterministic recall process. In particular, the model correctly predicts the average length of recall and the distribution of compression ratios over recall clauses as a function of the size of the narrative tree representation. While we do not have a theoretical way to calculate the latter for each narrative/subject, we could estimate the size of the tree using LLM-performed mapping of each recall back into the narrative. We found that the average tree size of a narrative, estimated this way, is very close to one half of the total number of clauses in a narrative for our set of narratives. We currently do not have any theoretical understanding of this observation, and it would be interesting to study whether this simple relation holds for other types of narratives.

The model has two parameters: the maximal splitting ratio in the random tree ensemble of narrative representations and the maximal depth of the recall process. Importantly, these parameters were not fine-tuned to match the model and the data but rather both were taken to be equal to human working memory capacity. The model hence suggests the critical role of working memory capacity in controlling narrative encoding and recall. This novel suggestion should be further investigated in future studies.

The narrative encoding scheme hypothesized in this study is clearly very simplified, and real schemes must contain multiple deviations from a strict hierarchy, such as, e.g., direct causal links between different keypoints. The effects of these non-hierarchical encoding features could be studied at the level of individual recalls; however, we believe that, as the results presented in the study show, they are relatively minor at the statistical level.

Finally, the self-similarity of tree representations suggested in this study resembles the statistical similarity in autobiographical recall at different time scales observed in [43]. It will be interesting to pursue this analogy and investigate further whether the statistics of recall of long narratives at different levels is also similar. In particular this would imply that as narratives get longer, the average recall length saturates, with each clause becoming more and more abstract, summarizing progressively longer parts of the narrative.

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[1] Perry W Thorndyke. Cognitive structures in comprehension and memory of narrative discourse. *Cognitive psychology*, 9(1):77–110, 1977.

[2] Gordon H Bower. Experiments on story understanding and recall. *The Quarterly Journal of Experimental Psychology*, 28(4):511–534, 1976.

[3] Hongmi Lee, Buddhika Bellana, and Janice Chen. What can narratives tell us about the neural bases of human memory? *Current Opinion in Behavioral Sciences*, 32:111–119, 2020.

[4] Uri Hasson, Janice Chen, and Christopher J Honey. Hierarchical process memory: memory as an integral component of information processing. *Trends in cognitive sciences*, 19(6):304–313, 2015.

[5] Yulia Lerner, Christopher J Honey, Lauren J Silbert, and Uri Hasson. Topographic mapping of a hierarchy of temporal receptive windows using a narrated story. *Journal of neuroscience*, 31(8):2906–2915, 2011.

[6] Lucas M Bietti, Ottilie Tilston, and Adrian Bangerter. Storytelling as adaptive collective sensemaking. *Topics in cognitive science*, 11(4):710–732, 2019.

[7] Frederic Charles Bartlett. *Remembering: A study in experimental and social psychology*. Cambridge university press, 1995.

[8] Joseph W Alba and Lynn Hasher. Is memory schematic? *Psychological Bulletin*, 93(2):203, 1983.

[9] Christopher Baldassano, Uri Hasson, and Kenneth A Norman. Representation of real-world event schemas during narrative perception. *Journal of Neuroscience*, 38(45):9689–9699, 2018.

[10] David E Rumelhart. Notes on a schema for stories. In *Representation and understanding*, pages 211–236. Elsevier, 1975.

[11] Roger C Schank and Robert P Abelson. *Scripts, plans, goals, and understanding: An inquiry into human knowledge structures*. Psychology press, 2013.

[12] Perry W Thorndyke and Frank R Yekovich. A critique of schema-based theories of human story memory. *Poetics*, 9(1-3):23–49, 1980.

[13] Walter Kintsch. *Comprehension: A paradigm for cognition*. Cambridge university press, 1998.

[14] Michael J Kahana. Computational models of memory search. *Annual Review of Psychology*, 71(1):107–138, 2020.

[15] Michelangelo Naim, Mikhail Katkov, Sandro Romani, and Misha Tsodyks. Fundamental law of memory recall. *Physical review letters*, 124(1):018101, 2020.

[16] Antonios Georgiou, Tankut Can, Mikhail Katkov, and Misha Tsodyks. Large-scale study of human memory for meaningful narratives. *arXiv:2311.04742v3*, 2023.

[17] Tom Trabasso and Linda L Sperry. Causal relatedness and importance of story events. *Journal of Memory and language*, 24(5):595–611, 1985.

[18] Michael J Kahana. Associative retrieval processes in free recall. *Memory & cognition*, 24(1):103–109, 1996.

[19] Endel Tulving. Subjective organization in free recall of" unrelated" words. *Psychological review*, 69(4):344, 1962.

[20] Marc W Howard and Michael J Kahana. Contextual variability and serial position effects in free recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 25(4):923, 1999.

[21] William Labov. *The language of life and death: The transformation of experience in oral narrative*. Cambridge University Press, 2013.

[22] W Kintsch. Toward a model of text comprehension and production. *Psychological Review*, 1978.

[23] Jean M Mandler and Nancy S Johnson. Remembrance of things parsed: Story structure and recall. *Cognitive psychology*, 9(1):111–151, 1977.

[24] Morton Ann Gernsbacher. *Language comprehension as structure building*. Psychology Press, 2013.

[25] Roy Bar-Haim, Lilach Eden, Roni Friedman, Yoav Kantor, Dan Lahav, and Noam Slonim. From arguments to key points: Towards automatic argument summarization. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4029–4039, Online, July 2020. Association for Computational Linguistics.

[26] Arthur C Graesser, Keith K Millis, and Rolf A Zwaan. Discourse comprehension. *Annual review of psychology*, 48(1):163–189, 1997.

[27] T.A. van Dijk and W. Kintsch. *Strategies of Discourse Comprehension*. Monograph Series. Academic Press, 1983.

[28] Robert F Lorch and Elizabeth P Lorch. Topic structure representation and text recall. *Journal of educational psychology*, 77(2):137, 1985.

[29] Arie Cattan, Lilach Eden, Yoav Kantor, and Roy Bar-Haim. From key points to key point hierarchy: Structured and expressive opinion summarization. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki, editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 912–928, Toronto, Canada, July 2023. Association for Computational Linguistics.

[30] Gabriel A Radvansky and Jeffrey M Zacks. Event boundaries in memory and cognition. *Current opinion in behavioral sciences*, 17:133–140, 2017.

[31] Jeffrey M Zacks, Todd S Braver, Margaret A Sheridan, David I Donaldson, Abraham Z Snyder, John M Ollinger, Randy L Buckner, and Marcus E Raichle. Human brain activity time-locked to perceptual event boundaries. *Nature neuroscience*, 4(6):651–655, 2001.

[32] Aya Ben-Yakov and Richard N Henson. The hippocampal film editor: sensitivity and specificity to event boundaries in continuous experience. *Journal of Neuroscience*, 38(47):10057–10068, 2018.

[33] Kristjan Kalm, Matthew H Davis, and Dennis Norris. Neural mechanisms underlying the grouping effect in short-term memory. *Human brain mapping*, 33(7):1634–1647, 2012.

[34] Christopher Baldassano, Janice Chen, Asieh Zadbood, Jonathan W Pillow, Uri Hasson, and Kenneth A Norman. Discovering event structure in continuous narrative perception and memory. *Neuron*, 95(3):709–721, 2017.

[35] Jie Zheng, Andrea GP Schjetnan, Mar Yebra, Bernard A Gomes, Clayton P Mosher, Suneil K Kalia, Taufik A Valiante, Adam N Mamelak, Gabriel Kreiman, and Ueli Rutishauser. Neurons detect cognitive boundaries to structure episodic memories in humans. *Nature neuroscience*, 25(3):358–368, 2022.

[36] Benjamin N Colby. A partial grammar of eskimo folktales 1. *American anthropologist*, 75(3):645–662, 1973.

[37] William Labov and Joshua Waletzky. Narrative Analysis: Oral Versions of Personal Experience. In June Helm, editor, *Essays on the Verbal and Visual Arts: Proceedings of the 1966 annual spring meeting of the American ethnological society*, pages 12–44, 1966.

[38] Nelson Cowan. The magical mystery four: How is working memory capacity limited, and why? *Current directions in psychological science*, 19(1):51–57, 2010.

[39] Weishun Zhong, Mikhail Katkov, and Misha Tsodyks. Hierarchical working memory and a new magic number. *bioRxiv*, pages 2024–08, 2024.

[40] P Flajolet. *Analytic Combinatorics*. Cambridge University Press, 2009.

[41] Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

[42] B. Johnstone. *Stories, Community, and Place: Narratives from Middle America*. Indiana University Press, 1990.

[43] Elizabeth A Maylor, Nick Chater, and Gordon DA Brown. Scale invariance in the retrieval of retrospective and prospective memories. *Psychonomic Bulletin & Review*, 8(1):162–167, 2001.

Supplementary Information for "Random Tree Model of Meaningful Memory"

Weishun Zhong[1], Tankut Can,[1,2] Antonis Georgiou,[1,3] Ilya Shnayderman[3], Mikhail Katkov,[1,3] and Misha Tsodyks[1,3]
[1] *School of Natural Sciences, Institute for Advanced Study, Princeton, NJ, 08540, USA*
[2] *Department of Physics, Emory University, Atlanta, GA 30322, USA*
[3] *Department of Brain Sciences, Weizmann Institute of Science, Rehovot, 76100, Israel*

A. Random tree ensemble and numerical simulations

The ensemble of random trees is built by a self-similar splitting process: it begins with the root node that contains all N clauses and progressively splits it into smaller and smaller nodes at lower levels. At each level l, a node of size $n^{(l)}$ randomly splits into K nodes at level $l+1$, of sizes $n_i^{(l+1)} \geq 0$, $i = 1, \ldots, K$, such that

$$\text{(split)} \qquad n^{(l)} = \sum_{i=1}^{K} n_i^{(l+1)}. \tag{S.1}$$

This is achieved by randomly inserting $K-1$ dividing bars among $n^{(l)}$ clauses. More precisely, $n^{(l)}$ clauses and $K-1$ divisions are randomly placed in $n^{(l)} + K - 1$ positions, and $n_i^{(l+1)}$ is defined as the number of clauses to the left of the first bar for $i = 1$, between $(i-1)^{th}$ and i^{th} bars for $i = 2, ..., K-1$ and to the right of the last bar for $i = K$. A child node with $n_i^{(l+1)}$ clauses stops splitting further, and becomes a leaf, if

$$\text{(stop)} \qquad \begin{aligned} & n_i^{(l+1)} = n^{(l)} \ \text{ or} \\ & n_i^{(l+1)} \leq 1. \end{aligned} \tag{S.2}$$

The entire splitting process ends once all the children nodes have met the stopping condition.

To simulate recall, as described in the main text, we cut all the nodes below the Dth level and retrieve all the leaves of the remaining tree. The size of a retrieved node is then considered to be the compression ratio for the corresponding recall clause, as explained in the paper. To obtain the numerical results presented in Fig. 1(b)-(c), for each value of N, 10,000 random tree realizations were constructed with the splitting parameter $K = 4$, and for each tree, recall was simulated with $D = 4$. For the results shown in Fig. 1(d), 20 different values of N were sampled uniformly on a log scale from $N = 10$ to $N = 100$, and $10,000N$ random realizations were simulated for each N in order to obtain good statistics for the tail of the compression ratios distribution.

B. Analytical solution of the model

Mathematically, the splitting process described above is akin to the problem of the weak composition of an integer n into K-tuples of nonnegative integers, a process called "Stars and Bars" [40] (S&B), which counts all possible configurations of splitting n "stars" into K bins by placing $K-1$ "bars" among them. However, the S&B process is only an approximation of the tree generation process described in Eq. (S.1)-(S.2) because of the first stopping condition in Eq. (S.2). In S&B, a node stops splitting only when it becomes non-splittable, i.e., when the second condition in Eq. (S.2) is met. However, as $n^{(l)}$ becomes large, the probability of having $n_i^{(l+1)} = n^{(l)}$ becomes increasingly small, and the approximation using S&B converges to the exact distribution. In fact, for the range of N considered in this paper (main text Fig. 1-2), there is little difference between the theory and the simulation, and the approximation is nearly exact. It is in this sense that we refer to the solution obtained below using S&B as an analytical solution to Eq. (S.1)-(S.2).

The total number of weak compositions is given by the S&B Theorem 2 [40],

$$Z_K(n) = \binom{n+K-1}{K-1}, \tag{S.3}$$

which states that there are $Z_K(n)$ ways to partition n indistinguishable objects (stars) into K distinguishable adjacent bins (whose boundaries correspond to bars), by placing $K-1$ bars randomly among the $n+K-1$ total positions, where each position can either be occupied by a star or a bar.

Now consider splitting $n^{(l)}$ stars into K bins. Due to the symmetry among the bins, without loss of generality, we can focus on the first bin. The total number of configurations with the first bin having $n^{(l+1)}$ stars is $Z_{K-1}(n^{(l)} - n^{(l+1)})$,

since there are $n^{(l)} - n^{(l+1)}$ remaining stars that have to be divided into $K-1$ remaining bins. Therefore, the probability of observing $n^{(l+1)}$ stars in the first bin of the $(l+1)^{th}$ level is given by

$$P(n^{(l+1)}|n^{(l)}) = \frac{Z_{K-1}(n^{(l)} - n^{(l+1)})}{Z_K(n^{(l)})}. \tag{S.4}$$

We are interested in computing the distribution of node sizes (or compression ratios) at level D, $p(n^{(D)})$, which can be obtained by repeatedly applying Eq. (S.4) starting from level 1:

$$P(n^{(D)}) = \sum_{\substack{0 \le n^{(D-1)} \\ \le \cdots \le n^{(1)}}} \prod_{l=1}^{D-1} P(n^{(l+1)}|n^{(l)}) P(n^{(1)}) \tag{S.5}$$

$$= \sum_{n^{(D-1)}} P(n^{(D)}|n^{(D-1)}) P(n^{(D-1)}), \tag{S.6}$$

$$P(n^{(1)}) = \delta(n^{(1)} - N). \tag{S.7}$$

Eq. (S.6) defines a Markov chain $\{n^{(1)}, n^{(2)}, \ldots, n^{(D)}\}$ with transition probabilities given by $P(n^{(l+1)}|n^{(l)})$. We can define the state vector as the probability distribution of compression ratios at the lth level,

$$\mathbf{P}^{(l)} := \left(P(n^{(l)} = 0), P(n^{(l)} = 1), \ldots, P(n^{(l)} = n^{(1)})\right)^{\mathbf{T}} \tag{S.8}$$

and the transition matrix as the conditional probabilities in Eq. (S.4),

$$(\boldsymbol{\mathcal{T}})_{ij} := P(n^{(l+1)} = i | n^{(l)} = j). \tag{S.9}$$

In particular, the transition matrix satisfies $(\boldsymbol{\mathcal{T}})_{i>j} = 0$, and has nonzero eigenvalues $\lambda_i = 1/Z_K(i)$, i.e., Eq. (S.9) is an upper triangular invertible matrix. With the definitions in Eq. (S.8) and Eq. (S.9) we can rewrite the marginals as

$$\mathbf{P}^{(D)} = \boldsymbol{\mathcal{T}}^{D-1} \mathbf{P}^{(1)}. \tag{S.10}$$

Since we start with a root node with N encoded clauses,

$$P_i^{(1)} = \delta_{iN}. \tag{S.11}$$

$\mathbf{P}^{(D)}$ can be obtained by using Eq. (S.10) and C can be computed as

$$C = K^{D-1}\left(1 - (\mathbf{P}^{(D)})_0\right). \tag{S.12}$$

Asymptotic scale-invariant compression ratios distribtuion

In the limit of large n, and assuming $n \gg K$, we can use Stirling's approximation to write

$$\log Z_K(n) = \log \frac{n^{K-1}}{(K-1)!} + O(\log n). \tag{S.13}$$

Then we can rewrite the conditional probability given by Eq. (S.4) in terms of the normalized compression ratios $s_l = n^{(l)}/N$:

$$\rho(s_{l+1}|s_l) \equiv NP(Ns^{(l+1)}|Ns^{(l)}) = N\frac{Z_{K-1}(N(s_l - s_{l+1}))}{Z_K(Ns_l)} \approx (K-1)\frac{1}{s_l}\left(1 - \frac{s_{l+1}}{s_l}\right)^{K-2}. \tag{S.14}$$

C. Experimental data collection

In our experiments, we used a set of 11 narratives. The narratives are based on the oral retelling of personal experiences told by real people, as presented in [21, 42], and variants of those generated by GPT-4. Original narratives were corrected for spelling and clarity. 8 of the narratives and the corresponding recall data were taken from our previous publication [16]. We performed additional recall experiments on 3 new narratives of similar style with $L = 81, 122, 194$, two taken from [42] and the longest one from [21] (reproduced in the section below). We followed the experimental protocol in [16]: for each narrative, 100 subjects were recruited from the online crowd-sourcing platform called Prolific (www.prolific.com), and presented with the narratives on a computer screen with rolling text. After the presentation of the narrative, the subjects were asked to perform a free recall experiment and write down their recall of the narrative, including as many details as possible.

After collecting the recalls, each recall is segmented into clauses by GPT-4 using the following prompt:

Prompt 1 Recall Segmentation

```
Provide a word-for-word segmentation of the following narrative into linguistic clauses,
numbered in order of appearance in the narrative: {recall of a narrative}
```

where the {`recall of a narrative`} box is a placeholder for the recall from the subjects. An example output of a segmented recall is provided in Section E 2.

D. Recall mapping and compression ratios

We utilized zero-shot prompting with OpenAI's model `gpt-4-turbo-2024-04-09` to project each individual recall back into the corresponding narrative, as shown schematically in Fig. S1. For a given recall clause, the compression ratio n is defined as the number of narrative clauses it is projected into. Recall clauses that do not get any projections are considered to be mistaken intrusions, with their overall fraction being 2.7%. They are not included in the calculation of recall length presented in Fig. 2(b). Self-referencing mistakes, where a recall clause is mistakenly mapped to the segment with the same serial position (segment number), can also occur in the LLM-generated mappings. As in Section E 3 for clause number 20 that is mistakenly mapped to segment number 20. However, our analysis found that this happens rarely, accounting for only 1% of all mapped clauses for the longest narrative ($L = 194$) and 0.3% for the second longest ($L = 130$).

The recall mapping prompt, Prompt 2, is a text block that takes the recall clauses and narrative segments as arguments. After specifying the recall clauses and narrative segments (e.g., Sections E 1- E 2), Prompt 2 is given to GPT-4, which outputs the mapping (e.g., Section E 3).

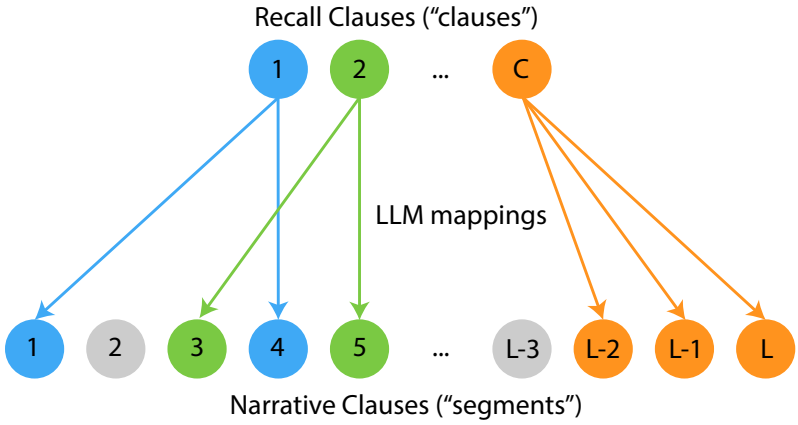

FIG. S1. **Schematics for recall mappings.** Top: C recall clauses ("clauses" in the prompts). Bottom: L narrative clauses ("segments" in the prompts). Arrows: mappings generated by LLMs.

Prompt 2 Recall Mapping

System Prompt

```
You are an AI designed to map a human recall split into clauses and an original narrative
split into segments, both provided in JSON format.  Your task is to generate a JSON
output that maps the clauses to the relevant segments.  Clauses can be mapped to multiple
segments, and the same segment can be mapped multiple times.  If a recall clause cannot be
mapped to any narrative segment, return an empty list.  Here is an example of the desired
output format:
```

```
{"mappings":
   [{"clause": 1, "segments": [1]},
    {"clause": 2, "segments": [3, 7]},
    {"clause": 3, "segments": []},
    {"clause": 4, "segments": [2, 4, 5, 7]}]
}
```

User Prompt

Input JSON for Recall Clauses:

```
{clauses}
```

Input JSON for Original Narrative Segments:

```
{segments}
```

E. Example narrative ($L = 194$)

1. *Segmented clauses from the narrative*

Originally from Mary Costa: "The death of her youngest daughter" [21]

```
{"segments": {
    "1": "My daughter died.",
    "2": "It'll be twenty-eight years this month.",
    "3": "The thirtieth of this month, yeah.",
    "4": "She died at Methodist Hospital.",
    "5": "She had an operation for appendicitis.",
    "6": "It was late Saturday afternoon when they operated, very late.",
    "7": "Sunday morning, my oldest daughter, Victoria, went to the hospital to
       see how she was.",
    "8": "She was still under ether.",
    "9": "Back then, they used a lot of ether.",
    "10": "There was a chair there.",
    "11": "They were just starting to get people out of bed, you know.",
    "12": "So, Victoria saw the chair,",
    "13": "and she said to the nurse, 'What's this chair doing here?'",
    "14": "The nurse said, 'Well, we've got to get her out of bed.'",
    "15": "She said, 'What are you talking about? She's still under ether.'",
    "16": "'She's too sick.'",
    "17": "But the nurse said, 'Well, that's the doctor's orders.'",
    "18": "So, they went to get her out of bed,",
    "19": "and she passed out,",
```

```
    "20": "and they had to put her back in bed."
    "21": "See, here, she never - I don't know if they knew or what,",
    "22": "but I blame them for the blood clot she got, taking her out of bed.",
    "23": "So, when she was walking around to come home after ten days,",
    "24": "I was waiting for the call from the hospital.",
    "25": "I didn't have a phone then.",
    "26": "The lady from the store who had a phone called me, 'Mrs. Costa,' at a quarter to five at night.",
    "27": "'Mrs. Costa, they just called you from the hospital.",
    "28": "Go pick Marie up.",
    "29": "She's discharged.'",
    "30": "I had all the clothes laid out on the table.",
    "31": "And Rita was - I was cooking,",
    "32": "I said, 'Rita, finish the cooking.'",
    "33": "'Daddy will be home soon.'",
    "34": "He was working down in the yard.",
    "35": "I said, 'And put a big pot of coffee on,' because she had been wishing for coffee.",
    "36": "And you know, every morning, that first cup of coffee, I offered it to her.",
    "37": "When I get up in the morning, the first cup is hers.",
    "38": "Since she's gone, I never forget that.",
    "39": "So I said, 'Put a pot of coffee on,",
    "40": "and send for some cake from the bakery.'"
    "41": "I'm going to get Marie; they called me.""
    "42": ""All right, mother, go ahead," she said, "I'll finish up.""
    "43": "And I went myself. You know, I had the coat on my arm.",
    "44": "She was operated on in March -",
    "45": "No, April! So that was the thirtieth.",
    "46": "She was operated - ten days before, so that would be the twentieth.",
    "47": "The twentieth of April, right? It was kind of chilly.",
    "48": "Oh, and I had everything in a bag,",
    "49": "and I had the coat on my arm and her dress hanging on my arm.",
    "50": "She saw me from the windows, from Wolf Street.",
    "51": "She said, "My mother's just coming.""
    "52": "She was with the girls, saying goodbye to everyone - you know how it is.",
    "53": "They told me on the phone, it would be ten dollars more for her board.",
    "54": "And to make sure I brought her girdle to put on.",
    "55": "I said, "All right, I'll be right over.""
    "56": "And I went.",
    "57": "But when I got there, the nurse said to me, "Sit down, Mrs. Costa, sit here for a while.""
    "58": "So I sat down, and I was praying for another lady in the hospital that had an operation for her gall bladder.",
    "59": "She lived near my sister, and she had ten children.",
    "60": "They had said she was in very bad shape."
    "61": "I prayed, "Oh dear God, don't take that mother away from her children.""
    "62": "I was praying for her, you know.",
    "63": "Then a little nurse's aide went to the closet and got some blankets.",
    "64": "I started getting the chills,"
    "65": "and I was thinking about it,"
    "66": "when the aide said to the nurse, "Oh, she's going into a cold sweat now.""
```

```
    "67": "The nurse hung up the phone and came to me. She said, "Mrs. Costa, has your daughter ever had a fainting spell?"",
    "68": ""Oh my God!" I said, "Don't tell me you're running for my daughter!"",
    "69": ""Yes," she said, "come on in."",
    "70": "So, I went into the room.",
    "71": "And my daughter was on the bed with her bedroom slippers and her housecoat on.",
    "72": "And the beads of sweat - honest to God, not to exaggerate, they were that big.",
    "73": "It came - just poured from her -",
    "74": "I said, "What did you do, kill my daughter?",
    "75": "You killed her! You killed her!"",
    "76": "That's what I kept yelling.",
    "77": "And the doctor rushed in,",
    "78": "see, they were trying to get the doctor, you know.",
    "79": "She was a lady doctor.",
    "80": "Dr. Schwartz actually did the operation, but she was his assistant, Dr. Montique."
    "81": "She was a lady doctor.",
    "82": "So, she came in and she said -",
    "83": "I said, "You killed my daughter - what did you do to her?"",
    "84": "She said, "We don't know what happened, Mrs. Costa."",
    "85": "She took me away from the bed.",
    "86": "The nurse said to me, "Talk to her."",
    "87": "I said, "Talk to her? My daughter's dying, what am I supposed to tell her?"",
    "88": "And I was screaming.",
    "89": "My hair was all pulled out.",
    "90": "I went hysterical, you know what I mean? She was only eighteen years old.",
    "91": "Beautiful girl, you can see from her picture.",
    "92": "And just as I turned my back, my daughter passed away.",
    "93": "She was getting ready to go home.",
    "94": "I had the clothes and everything ready.",
    "95": "My husband was waiting for her.",
    "96": "He came home, went upstairs to shave and wash, then sat on the step, waiting.",
    "97": ""When is the mother coming?"",
    "98": "The hospital kept calling.",
    "99": "The people in the office didn't know what had happened yet.",
    "100": "They kept calling the store, trying to reach us."
    "101": "They asked, "When is the mother coming to pick up Marie?",
    "102": "She's discharged."",
    "103": "And Rita said "That's strange, the mother went to the hospital. She should be there."",
    "104": "So they came back to the hospital to look for us.",
    "105": "Rita said, "Gee, that's strange,"",
    "106": "she said, "Mother must've gotten really worked up about Marie."",
    "107": "You know, I've always had a bad heart.",
    "108": ""Mother must've gotten so upset about Marie, she probably made herself sick," Rita thought.",
    "109": "So she came over with my son-in-law, in the car.",
    "110": "And I was in the main hallway, at the office.",
    "111": "I was all pulled apart.",
    "112": "One doctor wanted to give me a shot.",
    "113": "I said, "Get out of here,",
    "114": "I'll kick you," I said.",
```

```
    "115": ""You killed my daughter, now you want to kill me?"",
    "116": "Another nurse came over.",
    "117": "See, they all knew me.",
    "118": "I had three operations in no time, not even a year.",
    "119": "And I knew all the nurses.",
    "120": ""Mrs. Costa, please, take -""
    "121": ""Get out!" I said, "Don't you dare come near me."",
    "122": "I was so hysterical.",
    "123": "I was banging my head against the wall and everything.",
    "124": "They had to grab me.",
    "125": "Then they brought me to the office, see.",
    "126": "When Rita came in and saw me like that, she asked, "Mother, what
       happened?"",
    "127": "I said, "We lost Marie.",
    "128": "Marie died."",
    "129": "Well, that's this one. This is a picture of Rita.",
    "130": "She went down like lightning.",
    "131": "Dropped to the floor, and that's a marble floor.",
    "132": "She went down like lightning.",
    "133": "And the back of her leg, it felt just like a pole.",
    "134": "Hard like a pole, the back of her leg.",
    "135": "And that girl is suffering.",
    "136": "Thirty - no, twenty-eight years since her sister died?",
    "137": "When she gets that pain, it's like she has phlebitis from it.",
    "138": "She suffers - seven, eight, nine weeks at a time.",
    "139": "She can't walk, she goes through such pain since then.",
    "140": "And how did they figure how Marie died?"
    "141": "The girl who was walking with Marie,",
    "142": "told the doctor that Marie was saying goodbye to Arlene.",
    "143": "And all Marie said to that girl was, "Oh, I've got a pain in my leg
       and I can't see."",
    "144": "And then Marie collapsed.",
    "145": "Later, they said it was a blood clot.",
    "146": "I said, "Don't you dare touch my daughter.",
    "147": "I'll burn this hospital down!",
    "148": "I don't care who's in it."",
    "149": "I said, "Don't you dare touch my daughter.",
    "150": "You want to find out what she died from.",
    "151": "But if you touch my daughter, I'll kill you."",
    "152": "I wouldn't let them touch her.",
    "153": "So when I got home - they took me home.",
    "154": "I was screaming in the car.",
    "155": "I couldn't get out, you know, I couldn't -",
    "156": "I was screaming!",
    "157": "Everybody came out, coming out of their doors because they could
       hear the screams.",
    "158": "My husband was sitting on the step.",
    "159": "He asked, "What's the matter? What happened to you?"",
    "160": "Well, my hair was all pulled, and my face - I was a mess."
    "161": "I didn't know what I had done to myself.",
    "162": "I said, "Mike, we lost Marie. Marie died." It was just a shock.",
    "163": "My husband had a heart attack.",
    "164": "Yes, he had a heart attack.",
    "165": "Then my son, Michael, yeah. That night.",
    "166": "Right there, my Michael came, and my Michael collapsed.",
    "167": "He had a heart attack too, no kidding.",
    "168": "It was all - my two sisters were here, waiting until about half-past
       four.",
```

```
    "169": "They waited because they knew she was coming home that day, waiting for the call.",
    "170": "My younger sister had brought an orange for Marie, and I had never seen an orange like it. It was a big orange, like that.",
    "171": "She said, "Mary, look, when they call you, when you pick Marie up, let us know, and we'll come over."",
    "172": "I said, "All right."",
    "173": "So, I got home and called everybody, told them what happened.",
    "174": "I called my brother-in-law.",
    "175": "He was an undertaker.",
    "176": "My sister's husband - he's passed away now too. God rest his soul.",
    "177": "Maybe you know him...",
    "178": "So they were waiting for my call, you know,",
    "179": "but instead, I sent my son James, he was little then.",
    "180": "I said, "Go tell Aunt Millie and Aunt Jenny.""
    "181": "They had cleaned the pavement,",
    "182": "and done the cement work, and they were cleaning the pavement.",
    "183": "They said, "Here comes little Jamie," and now they said,",
    "184": ""Maybe he's come to tell us Marie's home."",
    "185": "But when he got there, the poor kid's eyes were all red.",
    "186": "They said, "James, what's the matter, honey?",
    "187": "Why are you crying?"",
    "188": ""Aunt Jenny, Aunt Millie, Marie died," he said.",
    "189": "Well, my sisters and my mother, you know, they were all alive.",
    "190": "It was a shock to everybody. That was a shock that -",
    "191": "The neighborhood - Annie at the store always says, "Mrs. Costa," every time I go in there, she reminds me, "I just picture Marie standing at that step, looking over here." She used to stand at that step.",
    "192": "She was a real quiet girl, pleasant, didn't talk much,",
    "193": "but she was so good, I can't even tell you.",
    "194": "That's all. So that's what happened."
    }
}
```


2. Segmented clauses from an individual recall


```
{"clauses": {
    "1": "It had been 28 years since the narrator's daughter, Marie, passed away.",
    "2": "Marie had been operated on for appendicitis at Methodist Hospital.",
    "3": "After the surgery, they used a lot of ether.",
    "4": "When the nurse tried to get Marie out of bed, she passed out.",
    "5": "She had to be put back in bed.",
    "6": "The narrator blamed the hospital staff for a blood clot Marie developed from being moved too soon.",
    "7": "After 10 days, the hospital called to say Marie was discharged.",
    "8": "The narrator went to pick her up.",
    "9": "She brought clothes and coffee for Marie.",
    "10": "Marie had been wishing for it.",
    "11": "However, when the narrator arrived, a nurse told her to sit down and wait.",
    "12": "The narrator prayed for another patient.",
    "13": "Then a nurse informed her that Marie was sweating heavily and appeared to be in distress.",
    "14": "The narrator rushed into the room.",
    "15": "She saw Marie sweating profusely.",
```

```
    "16": "In a panic, she accused the doctors and nurses of killing her daughter.",
    "17": "Soon after, Marie passed away while preparing to come home.",
    "18": "The hospital staff had tried to contact the family.",
    "19": "When the narrator's other daughter, Rita, and son-in-law arrived, they found the narrator in a state of hysterics.",
    "20": "The news was devastating.",
    "21": "It led to more health complications for family members."
}
```

3. LLM output

```
{"mappings":
   [{"clause": 1, "segments": [1, 2],
    {"clause": 2, "segments": [4, 5]},
    {"clause": 3, "segments": [8, 9]},
    {"clause": 4, "segments": [11, 14, 18, 19]},
    {"clause": 5, "segments": [20]},
    {"clause": 6, "segments": [21, 22]},
    {"clause": 7, "segments": [23, 24, 26, 27, 28]},
    {"clause": 8, "segments": [43, 56]},
    {"clause": 9,  "segments": [30, 31, 35, 39, 40, 41]},
    {"clause": 10, "segments": [35]}
    {"clause": 11, "segments": [57]},
    {"clause": 12, "segments": [58, 59, 60, 61]},
    {"clause": 13, "segments": [66, 67]},
    {"clause": 14, "segments": [70]},
    {"clause": 15, "segments": [71, 72, 73]},
    {"clause": 16, "segments": [74, 75, 76, 83, 146, 147, 148, 149, 150, 151]},
    {"clause": 17, "segments": [93]},
    {"clause": 18, "segments": [98, 99, 100]},
    {"clause": 19,  "segments": [104, 105, 106, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126]},
    {"clause": 20, "segments": [20]}
    {"clause": 21, "segments": [107, 108, 133, 134, 135, 136, 137, 138, 139, 163, 164, 165, 166]}
}
```

F. Comparison between LLM- and Human-generated Mappings

To compare the mappings performed by GPT-4 with those by humans, seven human evaluators (all the authors and one colleague) performed the projections described above for the example recall in Section E 2 of the "The death of her youngest daughter" narrative presented in Section E 1, and compression ratios for all recall clauses were obtained as described in Section D. The results are shown in Fig. S2. The scatter plots display the compression ratios for consecutive recall clauses based on the individual human mappings, overlaid on the corresponding compression ratios obtained with the GPT-generated map.

In general, mappings can be highly subjective, resulting in significant variance among human participants. Despite this substantial variability, the compression ratios produced by the LLM closely align with the corresponding averages over human evaluators, as shown in Fig. S2.

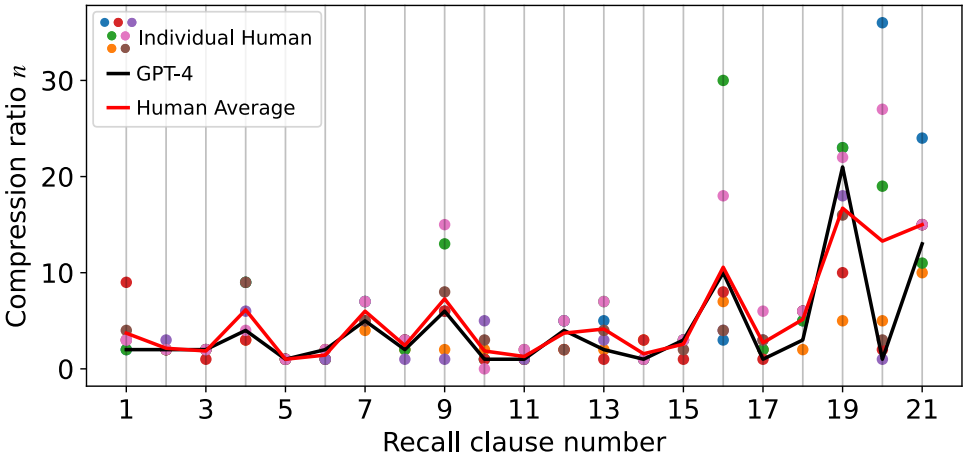

FIG. S2. **Comparison Between Human and LLM Recall Mappings.** Compression ratios for consecutive recall clauses ($C = 21$). Colored filled circles represent the mappings performed by seven human evaluators. The red line indicates the average compression ratio across the human mappings, while the black line represents the mapping generated by GPT-4.