Memorability as An Emergent Property: How Representational Structure Creates Apparent Intrinsic Effects

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Abstract

Some pictures, videos, faces, voices, and words are reliably remembered better than others, a phenomenon known as memorability. This has been widely interpreted as reflecting a stable, intrinsic property of the stimuli themselves. Here we argue that this consistency is better explained by the relational structure of the stimulus sets used to measure memorability, rather than as an intrinsic property of the items. Using simulations with a global matching model of recognition memory, we show that apparent intrinsic memorability emerges naturally from distinctiveness — how dissimilar an item is from others in a given set of encoded images — without any stimulus-intrinsic mechanism. In behavioral experiments, we demonstrate that manipulating the similarity structure of image sets can invert memorability rankings, making previously memorable images forgettable and vice versa. We also show that features previously identified as intrinsically memorable (such as "body-part related") are the most representationally distinctive features in standard databases, explaining their memorability. To address these large variations in distinctiveness we created a new image set that reduced variability in representational distinctiveness, and found it significantly diminishes all feature-memorability relationships. These findings suggest that memorability is not a fixed attribute of items themselves, but an emergent property of which items are distinctive within the context, with implications for how we attribute stable psychological properties to stimuli more broadly.

Introduction

Some pictures (Isola et al., 2014), videos (Cohendet et al., 2018), faces (Bainbridge et al., 2013), voices (Revsine et al., 2025), videogame sprites (Simpson et al., 2025), and words (Xie et al., 2020) are reliably remembered better than others, in a pattern that is strikingly consistent across people. A photograph that one person finds easy to remember tends to be easy for most people to remember; a face that is forgettable for one person tends to be forgettable for many (Isola et al., 2014). This consistency, referred to as *memorability*, has become one of the most actively studied phenomena in memory research over the past decade (Rust & Mehrpour, 2020; Bainbridge et al., 2026). One reason for its growing importance is its clear applied relevance: understanding which stimuli people will remember is important for education (Isola et al., 2014), data visualization (Borkin et al., 2013, 2016), and understanding what aspects of real-life experiences are most likely to be retained (Davis & Bainbridge, 2023).

The prevailing theoretical account of this consistency between people in memory performance is that memorability is an intrinsic property of stimuli: some images simply are more memorable, much like some images are brighter or more colorful (Khosla et al., 2015; Needell & Bainbridge, 2022). The intrinsic interpretation of memorability has drawn support from several converging lines of evidence. Memorability rankings remain stable across different experimental contexts and participant populations (Bylinskii et al., 2015; Kramer et al., 2023; Revsine & Bainbridge, 2025). Memorability can be predicted from patterns of activation in the visual cortex to single images shown in isolation (Bainbridge et al., 2017). And deep learning models like MemNet (Khosla et al., 2015) and ResMem (Needell & Bainbridge, 2022), which take only a single image as input and have no information about the observer or the experimental context, can predict average memory performance with considerable accuracy. The success of these models, which treat memorability as a property that can be read off from an image in isolation, has been particularly influential in solidifying the view that memorability is a stable visual attribute of images themselves (Rust & Mehrpour, 2020; Davis & Bainbridge, 2023). Some have argued that the intrinsicness of memorability arises because it reflects something fundamental about how efficiently individual images are processed visually (e.g., Bainbridge et al., 2026) or the informational utility those particular images hold for the observer. For example, animate stimuli, social stimuli, and emotional stimuli are simultaneously more relevant to ongoing decisions on average and also more memorable (Boger & Firestone, 2026; Bylinskii et al., 2015).

In the current manuscript, we suggest an alternative: we argue that rather than being intrinsic to an image, memorability is an emergent phenomena that arises from interference in memory between stimuli seen in the same context. This alternative starts from a simple observation: nearly every formal model of recognition memory developed over the past fifty years treats memory as fundamentally relational, rather than memory signals being intrinsic to a given stimulus (Gillund & Shiffrin, 1984; Hintzman, 1988; Nosofsky, 1988; Shiffrin & Steyvers, 1997; McClelland & Chappell, 1998). This class of models, termed global matching models, are the dominant theoretical framework for recognition because they account for a wide range of core phenomena within a unified architecture (Osth & Dennis, 2020). In global matching models, whether a person judges an item as "old" or "new" depends not on any fixed property of that item but on how that item relates to everything else in memory. The match signal generated by a test item reflects its overall match to all stored memory traces, not just the single best match (if you have seen many images of mugs, all mugs will feel familiar at test). The criterion for responding "old" is itself calibrated to the expected distribution of match signals (if you studied all items briefly, you will accept even weak signals as evidence of oldness). These two kinds of relational processing create a strong dependence of memory on distinctiveness: items that are unusual relative to other encoded items generate more diagnostic signals and are better remembered (Hunt, 1995; Schmidt, 1991; Nairne, 2006; Konkle et al., 2010). The advantage of distinctive items is one of the oldest and most robust findings in the memory literature (Hunt & Lamb, 2001; Nosofsky, 1984).

In line with these global matching models, we propose that what looks like intrinsic memorability could instead be an emergent property of the structure of the stimulus sets used in memorability experiments, specifically how that structure shapes the surrounding context and thus the distinctiveness of individual items. Memorability researchers acknowledge that local context influences memory measurements, and therefore have frequently attempted to distinguish between extrinsic memorability factors (like attentional states or individual differences) and intrinsic stimulus factors that are claimed to explain unique variance in memory performance (e.g., Bylinskii et al., 2015). In an attempt to isolate the intrinsic factors, experiments aimed at studying memorability have typically made the studied and tested items a particular participant sees be a random sample from large image databases like SUN (Xiao et al., 2016) or THINGS (Hebart et al., 2020). Contextual effects within any given list sampled from the database are acknowledged but treated as noise. It is assumed that randomly sampling images from a large image set should effectively randomize contextual effects, with any effects remaining across these randomized contexts reflecting stimulus-intrinsic properties that will persist regardless of context.

In the current work, we show this does not isolate intrinsic memorability. The large-scale databases from which memorability experiments draw their stimuli are not uniform samples of the space of images, or proportional to how much representational space people have for these images. They contain many more exemplars of some kinds of objects than others. Items that happen to be distinctive within such a database will tend to remain distinctive in any random subsample drawn from it, for the same reason that randomly sampling from a population does not eliminate confounds that are structural properties of that population (e.g., in the social sciences literature: Rothman et al., 2008). So if an image occupies a sparse region of representational space within the database, it will tend to be distinctive in every experiment that draws stimuli from that database, and global matching models predict it will be reliably well-remembered not because it possesses an intrinsic mnemonic property but because of its distinctiveness with respect to that database.

By analogy, consider that red items are generally more visually salient than brown items in most visual environments. Does this make red “intrinsically salient”? Visual saliency models strongly reject this, with evidence repeatedly demonstrating that saliency is entirely relational, determined by how an item stands out relative to its local context (e.g., Itti & Koch, 2001). Red appears salient in many scenes not because that pattern of photoreceptor activation has intrinsic saliency, but because of the distributional regularities of red often being locally distinctive in natural environments. In a scene where the grass and sky were red, a brown object would be more salient than a red one; in a scene where everyone wears red, a brown jacket would stand out. Similarly, we argue that what appears as intrinsic memorability may simply reflect how distinctive items are in a given large-scale database rather than any fundamental property of the stimuli themselves.

In this paper, therefore, we test whether the evidence for intrinsic memorability can be better explained as *emergent* memorability: consistency across people that arises from the average distinctiveness of items in the average tested context. Using simulations with a well-established global matching model of recognition memory (REM; Shiffrin & Steyvers, 1997), we first show that purely relational memory processes reproduce the key empirical signatures of intrinsic memorability — including consistency across different contexts — in a model that has no concept of intrinsic stimulus properties being differentially memorable. We then present behavioral experiments demonstrating that manipulating context can completely invert memorability rankings, making previously memorable images forgettable and vice versa, and that the features identified as "intrinsically memorable" in prior work are precisely those that are most distinctive in the databases used to measure the memorability of the images. Next, we show that changing the structure of the databases used to sample stimuli from in memorability experiments flips which features are most memorable, even with no explicit manipulation of list context. Finally, we show that reducing variability in distinctiveness across a database of images diminishes the extent to which 'intrinsic' features predict memorability. Together, these findings suggest that what has been characterized as a stable property of images is better understood as an emergent property of how images are situated within the broader representational structure of the contexts in which they are encountered and tested. This alternative conceptualization of memorability as emergent has implications for understanding memorability as well as understanding how to think about stimulus-driven effects in memory and cognition more broadly.

Global Matching Models: REM Simulations

To highlight how global matching models can produce memorability effects, we conducted simulations using the REM (Retrieving Effectively from Memory) model framework (Shiffrin & Steyvers, 1997), which represents items as arbitrary vectors of feature values drawn from a geometric distribution, such that some feature values are more common than others. This model has been widely applied and found to explain core phenomena in recognition memory (Malmberg et al., 2019; Mohamed et al., 2026). In the REM framework, like in other global matching models, recognition memory decisions are based on the global similarity between a test item and all stored memory traces. However, while numerous global matching models share the foundational principle that summed similarity (the aggregated similarity between a probe item and all stored memory traces) plays a central role in recognition decisions (e.g., Clark & Gronlund 1996; Osth & Dennis, 2020; Nosofsky, 1988), we focus on REM because it implements this principle through an elegant Bayesian likelihood ratio framework, making it ideal for examining how apparent memorability effects emerge from relational distinctiveness.

In particular, in judging whether an item is “old” or “new”, REM uses what amounts to counterfactual Bayesian reasoning: it computes the likelihood that an observed memory match signal would occur if the item had been studied versus if it had not. The key insight relevant for memorability is that this likelihood ratio is especially diagnostic for items whose features are rare in memory, because a strong match to an unusual item is far more surprising under the "not studied" hypothesis than a strong match to a common one. Consider a person with a distinctive face tattoo. When a tattooed face is studied, the same face on a later recognition test may produce an exceptionally strong memory match signal not because it matches its memory representation better than an average face without a tattoo would, but because the tattoo is rare and therefore greatly reduces the probability of a similar match signal arising from a face that was not studied. In likelihood-ratio terms, the rare feature primarily affects the denominator, since the probability of such a match under the alternative hypothesis that the face was not studied is very small. Therefore, when a match occurs along this rare dimension, it constitutes exceptionally strong evidence that this particular person was studied. In contrast, an average person without distinctive features may actually be more similar to other studied faces (e.g., have a higher summed similarity to the memory set), yet produce a weaker recognition signal because many unstudied faces also share these common features making them not very diagnostic of a true match.

This property makes REM ideal for understanding memorability. Items labeled "highly memorable" often possess features underrepresented in their database, such as animate features in predominantly inanimate object image sets. These rare features, much like the face tattoo, generate strong match signals when an item is studied and later tested. By contrast, false alarms will tend to be common for items that are very similar to many studied items, driving down memorability for such items. Thus, what appears as intrinsic memorability emerges through purely relational mechanisms, arising from how an item's features compare to other items. We therefore used REM to simulate recognition memory experiments and demonstrate how apparent memorability effects arise naturally from these relational principles.

Simulations of Memorability as an Emergent Property

We generated simulated data that had the same approximate structure as the most well understood memorability database (Kramer et al., 2023), which provides memorability ratings for the images and features of the THINGS database (Hebart et al., 2020). We used the same number of images and with the same number of features. Hebart et al. (2020) showed that human similarity for this database were well-captured by a sparse set of 49 distinct visual and semantic features; thus, we first generated a large set of 26,107 simulated items (the number of images in THINGS), each represented by a vector of 49 feature values. The 49 feature values for each item were generated randomly and independently from a geometric distribution (see Shiffrin & Steyvers, 1997), and thus have no particular meaning and no intrinsic relationship to memorability. Items were then “shown” to the model, and episodic memory encoding followed standard REM parameters (see detailed implementation in the method section). To mimic the structure of typical memorability experiments as well as our subsequent behavioral experiments, we designed the study and test items to be random subsets from this large THINGS-like database. In particular, we randomly selected a subset of 1,600 items from the larger set of

26,107 items. From this subset, we then conducted 10,000 independent recognition memory experiment simulations, each involving a simulated participant studying a random draw of 40 items and then being tested on 40 items: 20 of the studied items (old) intermixed with 20 additional items drawn from the 1,600-item subset that were not studied in that simulation (new foils). This method replicates the conditions used in our behavioral experiments and is similar to the methods widely used in the literature.

For each simulated recognition test, we compute the hit rate (calling an item old when it was old) for each item and the false alarm rate (calling an item old when it was new) for that same item across the 10,000 simulation runs. By evaluating variability and consistency in item memorability across these simulated runs, we directly assess how differences in memorability naturally emerged from the global matching process without any assumptions of inherently memorable features or items.

Accurate measures of memorability would require ROC analysis, with confidence reports or bias manipulations, because typically the way participants trade-off hits and false-alarms in long-term memory is asymmetric and non-linear (e.g., Brady et al., 2023). However, for the purposes of comparison to the existing memorability literature, we focus here on hit rate and/or corrected recognition rate (hits minus false alarms). All of our analyses both in the simulation and the subsequent behavioral experiments are robust to using more accurate measures like d’ or d_a, however, because we set neutral and fixed criterion in these simulations (see Methods).

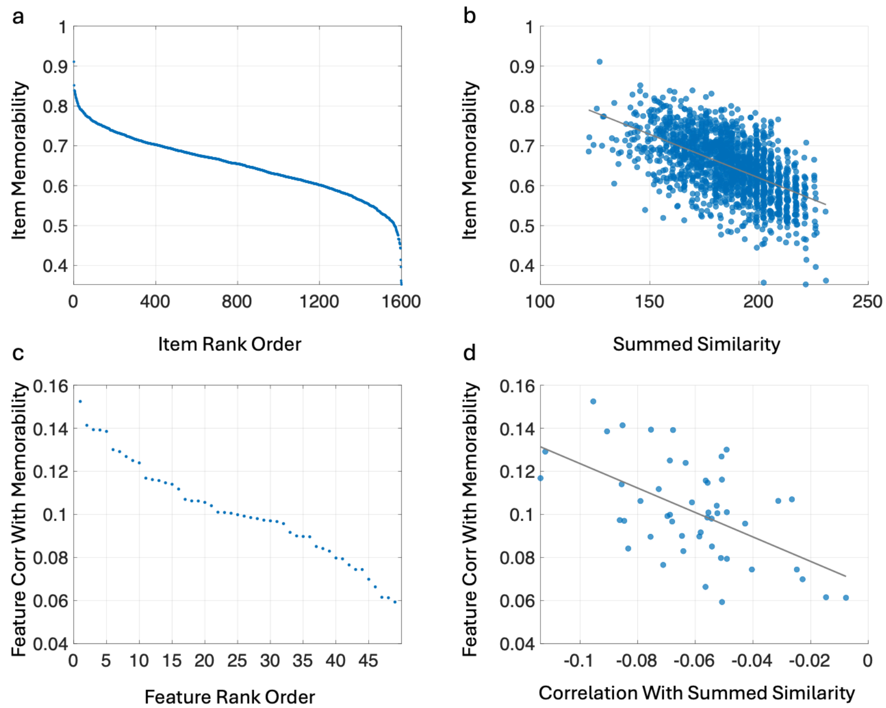

Fig. 1 | Global matching models produce apparent intrinsic memorability through purely relational mechanisms. We simulated recognition memory using the REM model across 1,600 items, each represented by 49 features, conducting 10,000 independent recognition experiments with random draws of 40 items each. **(a)** Items showed consistent differences in memorability (hit rate minus false alarm rate) when rank-ordered across simulations, mimicking "intrinsic memorability" effects observed empirically. **(b)** However, these memorability differences were strongly predicted by how similar each item was to all other items in the image set ($r = -0.56$, $p < 0.01$), where more distinctive items were more memorable. **(c)** Individual “features” (of the 49 randomly generated values for each item) also showed reliable correlations with memorability when rank-ordered by correlation strength. **(d)** Each feature's correlation with memorability was predicted by how much that feature correlated with overall item similarity ($r = -0.44$, $p < 0.01$), demonstrating that while there are reliable item-wise and feature-wise memorability differences in the simulation, these memorability effects emerge from relational distinctiveness rather than intrinsic feature or item properties.

We find that some items consistently showed higher hit rates than others across “participants” (Fig. 1a), mimicking apparent intrinsic memorability. However, in this simulation all features are randomly generated and contain no actual semantic or visual information that could make them intrinsically memorable. Thus, this memorability could not be predicted by anything intrinsic about the features themselves, but instead was strongly predicted by each item's distinctiveness in the overall image set; e.g., how dissimilar it was to other items in the image set. As noted above, many specific aspects of the distinctiveness of an item and its features play a role in REM's decision. But, in line with the general structure of global matching models, we found items that are more similar to other items in aggregate (summed similarity of raw feature representations, not differentiating by rare vs. common features as REM does) have greater interference in matching and thus worse memory performance (memorability vs. summed similarity to all other items across all of the features: $r = -0.56$, $p < 0.01$; Fig. 1b). Thus, even in this simplified analysis that does not capture the full extent of REM's variance between items, items that appeared intrinsically memorable were simply those that happened to be more distinct from other items that appeared in the same memory lists, which were, on average, items that were distinct from other items in the image set.

One of the core take-aways of the memorability literature has been that not only do images vary in memorability, but this image-level variance is predictable based on the features of the images (Kramer et al., 2023). For example, of the 49 visual and semantic features, some predict better memorability (e.g., body part-relatedness) and some worse memorability (e.g., electronics). Does the same occur here, where features are arbitrary and such relationships could not be intrinsic? In our simulations, individual features also show reliable correlations with memorability (Figure 1). Crucially, however, each feature's correlation with memorability was predicted by how much that feature correlated with overall item similarity, not by anything intrinsic to the features ($r = -0.44$, $p < 0.01$; Fig. 1d).

Overall, this simulation demonstrates that apparent memorability effects much like those that are typically observed can emerge from relational distinctiveness rather than intrinsic feature properties. With no intrinsic features that are in any way tied to memorability, REM reproduces the key aspects of the data that are generally argued to provide evidence for intrinsic memorability. This is evidence that such a pattern is not diagnostic of intrinsic memorability.

REM Simulations of Context-Independent Memorability

Our initial REM simulations demonstrate that distinctiveness can create reliable empirical patterns of memorability as an emergent property of stimulus structure, without any of the stimuli or features being intrinsically memorable. The claim that similarity of items to other items studied in the same context, as in this simulation, can explain memorability effects might seem contradicted by previous work in the memorability literature showing robustness of rank-ordered memorability to large context changes (e.g., Bylinskii et al., 2015). For example, memorability for the same target images in two dramatically different context conditions tends to be similar (Spearman $\rho = 0.60$ for hit rates): within-category (e.g., amusement park images studied alongside other amusement parks) and across-category (amusement park images studied alongside houses, pastures, and mountains). This large change in context should be the strongest possible test of whether context and distinctiveness matter, since adding similar category members should maximally alter which items stand out. Yet memorability remained stable, providing the strongest evidence to date that memorability reflects intrinsic properties independent of context. Is this compatible with our emergent memorability account?

To test this, we simulated both experimental contexts in REM to test whether this consistency requires intrinsic memorability. We generated 21 categories with 300 items each (75 targets, 225 fillers), matching the structure of Bylinskii et al. (2015). Items were represented as 49-feature vectors, with the first 10 features defining category membership (e.g., being identical for all category members). We maintained the same model parameters with one exception. Consistent with empirical data, we varied the recognition criterion between experiments: within-category simulations used a criterion of 20, while across-category simulations used a criterion of 5 to reflect participants' actual tendencies to adopt a more conservative criterion as items become more similar (e.g., Nosofsky & Kantner, 2006).

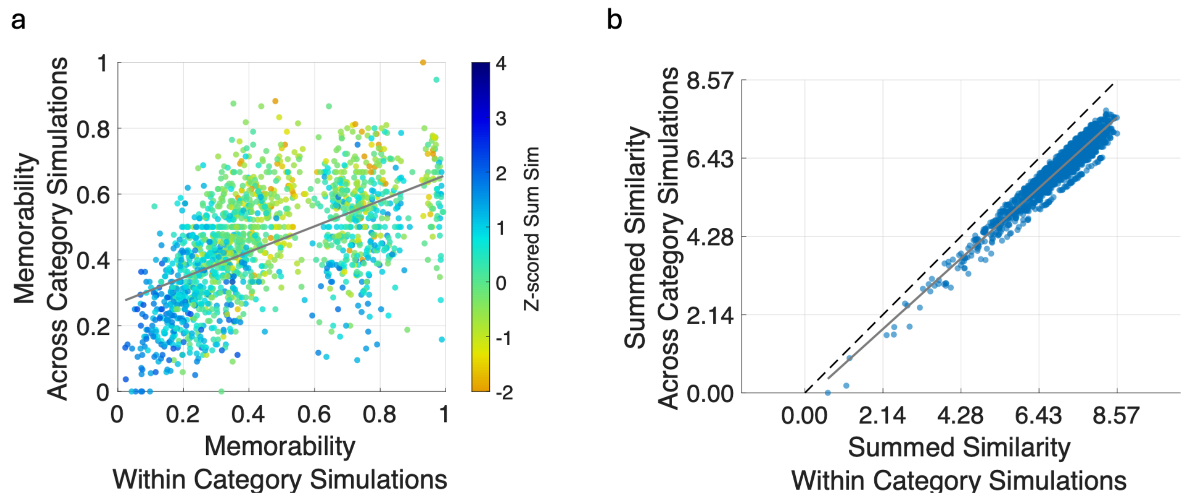

Fig 2 | Context-independent memorability emerges from preserved distinctiveness. (a) Memorability consistency across within-category (Simulation 1, x-axis) and across-category (Simulation 2, y-axis) contexts in REM simulations. Each point represents one of 1,575 target items, color-coded by average z-scored summed similarity (blue = less distinctive, yellow-green = more distinctive). Items maintain rank-order memorability across contexts (Spearman $\rho = 0.60$, $p < 0.01$), with more distinctive items showing higher memorability in both contexts (within-category $\rho = -0.25$, $p < 0.01$; across-category $\rho = -0.54$, $p < 0.01$). Gray line: regression fit. **(b)** Summed similarity correlation across contexts. Each point shows one item's summed similarity in within-category (Exp1, x-axis) versus across-category (Exp2, y-axis) contexts. The high correlation ($r = 0.93$, $p < 0.01$) reveals that items distinctive in the full database remain distinctive within their category. Black dashed line: identity ($y = x$); gray line: regression fit. Points lie below identity indicating that adding category members uniformly increases similarity.

Our REM simulations closely replicated the human findings. Items in Figure 2a showed consistent memorability across contexts (Spearman $\rho = 0.60$, $p < 0.01$), despite REM having no concept of intrinsic memorability. Just as in our prior REM simulations, memorability in both experiments was predicted by summed similarity without assuming anything intrinsic about the items. The color gradient in Figure 2a shows that items with lower summed similarity (more distinctive, shown in yellow-green) tended to be more memorable in both contexts, with within-category memorability correlating with summed similarity in the within-category context (ρ

$= -0.25$, $p < 0.01$) and across-category memorability also showing this relationship with its own context ($\rho = -0.54$, $p < 0.01$).

The mechanism becomes clear when examining summed similarity across contexts. Figure 2b shows that items that were distinct in the across-category context remained distinct within-category (Pearson $r = 0.93$, $p < 0.01$). Adding category members had a main effect of increasing all items' summed similarity, but preserved the rank order of distinctiveness. This explains how in previous work, highly memorable items like Thomas the Tank Engine maintained their rank order both within the amusement park category and across all other categories (e.g., Bylinskii et al., 2015). It remained an outlier because its distinctive features (a rare combination of animate face features with mechanical features) are uncommon both among other amusement parks and across mixed categories. Adding exemplars from the same amusement park category like ferris wheels and roller coasters shifts Thomas's summed similarity higher but doesn't eliminate its outlier status or affect its rank order with respect to distinctiveness. Since both contexts sample from the same database, items that are distinct in the full image set tend to remain distinct within their category.

Implications of REM Simulations.

Our simulations demonstrate that apparent intrinsic memorability can emerge naturally from global matching processes without assuming intrinsic item properties. In a global matching model, some items consistently show better memory performance than others (Fig. 1a), mirroring what has been called *intrinsic memorability* in the literature. However, our analyses reveal that this apparent item-specific property can also easily be explained by the relational property of distinctiveness: how different an item is from other items seen in the same list.

While REM successfully produces these memorability-like effects through distinctiveness mechanisms, we should be clear that no model captures all processes that give rise to memory. For example, REM lacks explicit representations of semantic knowledge structures, attentional weighting during encoding, and strategic control processes. Yet its ability to generate apparent memorability without these complexities suggests that phenomena attributed to *intrinsic memorability* may emerge naturally from basic relational structure rather than requiring elaborate cognitive mechanisms.

As noted, the connection between REM's decision process and our summed similarity measure is indirect. REM computes likelihood ratios from feature matches and mismatches through a complex, nonlinear computation considering both presence and absence of features. Our summed similarity metric therefore provides only an approximation of the causes of variation in memorability between the items in the model. Alternative global matching models like the Hybrid-Similarity Exemplar Model use summed similarity, per se, as the relevant memory signal (e.g., Nosofsky, Ehinger, & Osth, 2025), making the summed similarity metric more directly interpretable. However, without the Bayesian likelihood computation these models require additional mechanisms to capture memorability phenomena (e.g., assumptions about variation in self-similarity). That our simple measure in REM predicts memorability suggests the core principle of relational distinctiveness captures these complexities at a coarse level without any requirement for variation between items in intrinsic memorability or self-similarity.

Understanding Memorability in Real-World Images

Our REM simulations demonstrate that global matching models naturally reproduce the primary evidence cited for intrinsic memorability (consistent memorability patterns across contexts) without invoking any concept of intrinsic item properties. We suggest that this finding flips the burden of proof: if the signature phenomena of "intrinsic memorability" emerge from purely relational mechanisms in the most common, long-standing models of recognition memory, what positive evidence supports the intrinsic account?

While we cannot prove intrinsic memorability does not exist, we can test a specific prediction that is unique to global matching models and inconsistent with intrinsic accounts: that memorability in existing image sets should be well explained by the similarity structure between the items studied in a given list, and that explicitly manipulating this structure should change what appears memorable. If memorability emerges from relational distinctiveness patterns rather than intrinsic characteristics, the same items should show different memorability when similarity context changes, or even just when the database items are sampled from changes.

A critical gap between our REM simulations and real-world memorability concerns the representational space itself. While REM demonstrates how distinctiveness mechanisms can produce apparent intrinsic memorability in abstract feature spaces, where the features have no meaning, to understand real-world memorability we must specify the representational space within which distinctiveness operates in human memory. Before any particular memory episode occurs, perception and cognition have already structured the world into a particular representational format. This perceptual and semantic representational structure generates psychological similarity: how likely different stimuli are to be confused, how readily people generalize across them, and which dimensions are most salient for categorization and reasoning (Shepard, 1987; Nosofsky, 1986; Gärdenfors, 2000; Kemp & Tenenbaum, 2008). This structure likely reflects the interaction between sensory input and the organism's learning history, evolutionary pressures, and behavioral goals (Kriegeskorte & Kievit, 2013). Episodic memory operates on top of this pre-existing structure: when we encode a particular image or event, the memory representation inherits the structure and biases of the underlying perceptual and semantic space (e.g., Nagy et al., 2025).

This raises a key question for understanding human memorability in real image sets: what are the "features" that determine distinctiveness in human cognition? Clearly people represent some aspects of the environment more than others, and this will shape their representations and thus memory confusions. Consider that humans devote vastly more representational capacity to faces than to blades of grass, despite encountering far more individual blades of grass in our lives. This demonstrates that representational structure does not map one-to-one with frequency in the world or statistical regularities in our environment. Instead, this experience-dependent representational space is also driven by the utility and biological importance of different features. This shaping is evident in the representational space of the THINGS database (the dominant database of images used to study memorability). The similarity structure of this database, as captured by the 49-dimensional feature embedding that explains human similarity judgments (Hebart et al., 2020), devotes substantial representational capacity to features related to animacy (body parts, animals, insects) because human cognition allocates disproportionate neural and attentional resources to animate things, given their ecological and social importance (Nairne et al., 2017).

This rich representational structure humans have has critical implications for understanding memorability. But the key implication is not that some features are intrinsically memorable because human memory devotes more representational capacity to them. Instead, emergent memorability accounts argue that memory fundamentally depends on how a particular image database samples from that underlying representational space. It is not intrinsic to the representational space itself.

Consider the 49-dimensional THINGS representational space. On its own, the unequal allocation of representational resources towards animate features does not make animate items more or less memorable. Rather, memorability emerges from the interaction between that representational structure and the distribution of items in a particular studied list. If a database contains many animate items, such that animate items are common on individual study lists, they will occupy densely-packed regions of representational space, making individual animate items less distinctive and therefore less memorable. Conversely, if animate items are rare in an image set and therefore rare on individual study lists, they become highly distinctive within that context. Thus, the apparent "intrinsic memorability" of animate items in standard databases might reflect not animacy itself, nor even the extra representational capacity devoted to those features, but the fact that animate items are relatively sparse in the database despite falling in a region of representational space to which humans devote substantial resources. According to this emergent memorability account, the memorability phenomenon previously observed is the product of distinctiveness in the tested context, not the representational structure itself

To test the emergent memorability account, we used the THINGS database to construct three complementary representational dissimilarity matrices (RDMs), operationalizing how similar vs. dissimilar items were in this representational space: one was derived from the 49-dimensional feature embeddings known to capture human similarity judgments (Hebart et al., 2020), and a second was based on macaque IT cortex neural activity patterns (Papale et al., 2025), serving as a biological model of object representation. These 49 dimensional features and IT patterns are at the concept/category level, not the image level. Thus, where required to get individual image predictions, we also use a third RDM based on pooled computer vision models (ResNet18, VGG16, AlexNet, and CLIP), but we use human and monkey data where possible. These measures are inherently noisy: Human ratings reflect entire categories (what Hebart et al call ‘concepts’) rather than specific images, meaning in those rankings we lack good estimates of within-concept variability; monkeys are not humans and monkey visual processing regions capture only one component of the full representational space underlying memory. Yet these representational spaces can nonetheless provide complementary tools for examining how distinctiveness within representational space shapes what we remember.

Using these representational spaces and human memorability data, we test three predictions of the emergent memorability account. First, we demonstrate that explicitly manipulating the similarity context of individual study lists can completely invert memorability rankings, making previously "memorable" items forgettable and vice versa. Second, we show that in the original THINGS image set, item distinctiveness predicts which features appear memorable, and critically, when we systematically change the image set's similarity structure, these same features lose their apparent intrinsic memorability while new features emerge as memorable. This pattern is consistent with distinctiveness but inconsistent with intrinsic properties. Finally, we demonstrate that reducing variability in item distinctiveness across an image set does not merely change which items appear memorable, but reduces the overall strength of feature-memorability relationships, suggesting that as image sets better approximate uniform sampling of representational space, apparent "intrinsic memorability" collapses toward zero.

Inverting Memorability Through Direct Manipulation of Distinctiveness.

Our first behavioral experiment directly tests whether these distinctiveness accounts generalize from computational models to human memory by attempting to invert memorability rankings through systematic manipulation of context. If memorability truly stems from intrinsic item properties, items should maintain their rankings regardless of context, as previously claimed (e.g., by Bylinskii et al., 2015). However, if memorability emerges from relational distinctiveness, then altering which items are most distinct within study lists should flip these rankings entirely. Notably, we manipulate context in a way that does not just shift all items upward and downward in terms of their overall similarity to other items studied (which is not diagnostic of emergent vs intrinsic memorability, as shown by the simulation), but instead differentially shift distinctiveness across items.

In each study/test block, we selected five critical items from the THINGS database spanning the full memorability range based on (Kramer et al., 2023) scores: one item each from the lowest 20%, 20-40%, 40-60%, 60-80%, and highest 20% memorability bins. The key manipulation strategically constructed the similarity context around each critical item. Originally highly memorable items were surrounded in the study list with many similar items from the database (8 similar items), reducing their distinctiveness in the list context. Conversely, originally poorly memorable items were placed in lists with few or no similar items (0 similar items), making them the most distinctive items in their list context. This approach directly manipulates the relational property of distinctiveness while keeping the intrinsic properties of the items themselves unchanged.

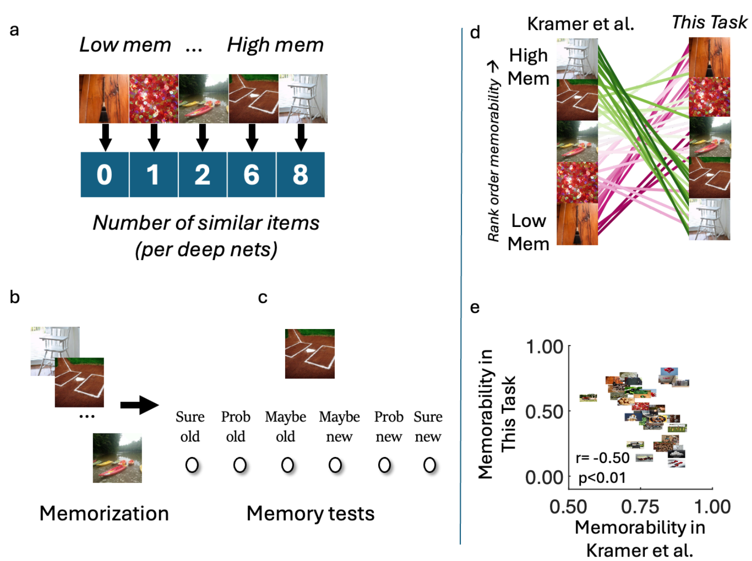

Fig. 3 | Memorability rankings can be inverted by manipulating similarity context. (a) Experimental design: Five critical items were selected from different memorability bins (lowest 20% to highest 20% based on Kramer et al., 2023) in each block. We systematically manipulated similarity context by including 8 similar items for the most memorable critical item, decreasing to 0 similar items for the least memorable critical item. **(b)** Participants studied a stream of 40 images. **(c)** Memory was tested with 10 consecutive recognition trials (the 5 critical items and 5 maximally dissimilar items) using a 6-point confidence scale. **(d)** Memorability inversion: Critical items' memorability in this task compared to their original Kramer et al. rankings of those same images, plotted in ascending order of original claimed intrinsic memorability. Each line represents one critical item, with colors ranging from green (originally highly memorable) to purple (originally poorly memorable). The crossing lines demonstrate successful memorability inversion through similarity context manipulation. The 5 items shown on each side are simply examples; each line is a separate item from the experiment. **(e)** Intrinsic memorability accounts predict a positive relationship between previously measured memorability and the current experiments' memorability measure, such that the same items are memorable in both experiments; emergent accounts predict a flip because we flipped distinctiveness. By plotting the original memorability scores against the memorability in this task we see a significant inversion ($r = -0.50$; $p<0.01$) demonstrating that the distinctiveness was a better predictor of item memorability than any intrinsic property. Note that the paradigms were not equated in overall list length or difficulty, so overall performance cannot be easily compared; we are simply interested in rank order across items.

Intrinsic memorability accounts that treat memorability as an item-specific fixed property like brightness predict a positive relationship, such that the same items should be memorable in this experiment as were memorable in the original experiment, since the item's features stay the same; emergent accounts predict a flip because we flipped distinctiveness. We found that memorability in this new experiment was in fact flipped from the original memorability of the items: comparing the original memorability scores of the items from Kramer et al. (2023) against the memorability in this task we see a significant inversion ($r = -0.50$; $p<0.01$; see Figure 3). This suggests that the distinctiveness was a better predictor of item memorability than intrinsic properties of the images.

These results demonstrate that the distinctiveness-based account from our computational simulations can be extended to human memory behavior; at least with strong, explicit context manipulations. Items previously classified as highly memorable, likely due to their distinctiveness in prior episodic list contexts, lost that advantage when placed in contexts containing many similar items. In contrast, items initially considered poorly memorable became significantly more memorable when presented in list contexts where they stood out. This inversion in memorability rankings provides evidence that memory performance is predicted by an item's relational distinctiveness without any consideration of its intrinsic memorability properties.

Despite successfully inverting memorability rankings, this experiment differs from conventional memorability paradigms in a crucial way: we deliberately constructed similarity contexts rather than randomly sampling from a large database. One might object that such explicit manipulation of similarity structure represents an artificial scenario that does not reflect how memorability studies are typically conducted. The field's reliance on random sampling from large databases is specifically intended to eliminate contextual biases by averaging across many different similarity contexts. If our distinctiveness account is correct, however, then random sampling cannot eliminate these effects. Instead, the similarity structure of the database itself should determine which items appear memorable, even when items are randomly sampled for individual experiments.

By measuring distinctiveness using both human-derived and neural similarity spaces, we can next assess whether putatively intrinsically memorable items stand out from their context along dimensions that are psychologically and biologically meaningful in previous memorability data, as emergent accounts would predict. To test this, we reanalyzed the Kramer et al. (2023) memorability findings, asking how database structure predicts which ‘features’ predict item memorability. We focus on Kramer et al. (2023) because their work provides in many ways the strongest and most interpretable evidence for the intrinsic memorability account. They show how the 49-features derived from human similarity data in the THINGS database (Hebart et al., 2020) relate to memorability. They find, for example, that images high on the body-part related feature are among the best remembered by participants, whereas items that score high on the electronics/technology feature tend to be poorly remembered by participants. This feature-level analysis offers both greater statistical power and greater interpretability than item-level memorability scores alone: rather than asking whether a particular image happens to be well-remembered with no clear explanation for why, they ask which psychological dimensions systematically predict memorability. We can therefore straightforwardly ask whether those dimensions are also ones that track distinctiveness within the structure of the database.

The feature-based analysis also has the benefit that understanding representational distinctiveness at the concept level is likely to be more straightforward than at the image-level. Any noise in the representations we assume for items, or systematic deviations in these representations from actual human representations, will necessarily reduce the ability of a distinctiveness-based account to explain real memorability data (Simpson et al., 2026). Such remaining variance cannot be assumed to be intrinsic simply because it is not explained well by a particular noisy, uncertain representational space, especially given that the burden of proof based on the model-based simulations should be to provide positive evidence for intrinsicness rather than assume uncaptured variance is intrinsic. However, the greater reliability of measures at the feature level provide a stronger test of how much can be explained by distinctiveness, alleviating this concern to a significant extent.

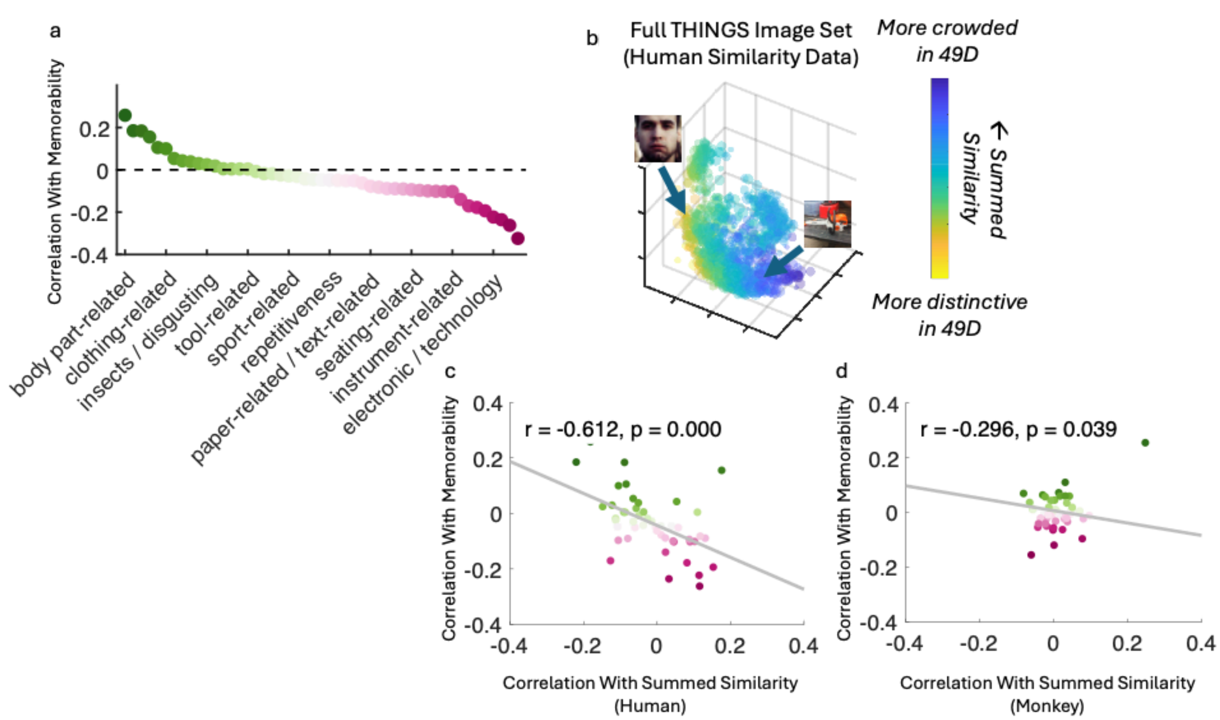

Fig. 4 | The most memorable features in THINGS are the most representationally distinct in the image set. We reanalyzed the original Kramer et al. (2023) memorability data using, as did Kramer et al., the 49 features derived from human summed similarity measures in Hebart et al. (2020). **(a)** Individual features showed reliable correlations with memorability when rank-ordered by correlation strength, displayed along a color gradient from green (high memorability) to purple (low memorability), replicating Kramer et al's analysis. **(b)** Distinctiveness measured via summed similarity: All concepts in THINGS projected onto the first three principal components of the 49-dimensional feature space. Point size corresponds to concept frequency, and color indicates summed similarity. Highly memorable images like faces that are high on memorable features like body parts also seem to appear greenish-yellow (indicating high distinctiveness), while poorly memorable images like chainsaws that are high on non memorable features like electronics also appear to be dark blue (indicating low distinctiveness). **(c)** Each feature's correlation with memorability plotted against its correlation with summed similarity in the Hebart et al. space, and **(d)** plotted against summed similarity computed in monkey neural space, showing that features that predict high summed similarity (low distinctiveness) are the same ones that are least memorable in both human ($r = -0.612$, $p < 0.001$) and the less robustly measured monkey ($r = -0.296$, $p = 0.039$) similarity spaces.

The Similarity Structure of an Image Set Determines What Will Be Memorable.

We find that individual features out of the 49 visual and semantic features isolated by Hebart et al. (2020) show reliable correlations with memorability (Figure 4a, reproducing Kramer et al.'s analysis). However, we also find that, in line with emergent memorability predictions, the features most predictive of memorability are those that, in the THINGS image set, are most related to distinctiveness: a strong prediction of the emergent memorability account and one that has no reason to be true according to the intrinsic memorability account. In particular, the extent to which features predict memorability is strongly related to the extent to which those features predict overcrowding in the image set (summed similarity vs. memorability: $r = -0.612$, $p < 0.001$; Figure 4). Similarly, using activity along multi-unit array as our features (see methods for further details), we find that features that predict human memorability also predict summed similarity in the monkey neural representations ($r = -0.296$, $p = 0.039$), although naturally these measures are less reliable and less aligned with human representations. In other words, "body-part related" predicts memorability, as shown by Kramer et al.; but we show that it is also one of the single best predictors of low summed similarity to other items in the THINGS image set, which is a unique and highly diagnostic prediction of emergent memorability theories.

This reanalysis of the original Kramer et al. (2023) data indicates that what has been interpreted as "intrinsic memorability" of visual features can, in line with our model-based simulations, more accurately be explained by each feature's distinctiveness within the image set. How distinctive a feature is in the feature space humans use to represent the THINGS database (using as our proxy the human similarity space and the monkey neural space) predicts how that feature will relate to memorability measured in the THINGS database. The fact that summed similarity at the database level reliably predicts which features are judged as memorable demonstrates that randomly sampling from large image databases does not eliminate systematic biases in representational space. Instead, such sampling preserves inhomogeneities that continue to produce consistent memorability effects. This finding challenges a core assumption underlying the intrinsic memorability framework, that random sampling sufficiently controls for context and distinctiveness. In reality, we suggest these sampling procedures inadvertently preserve the very structural regularities that give rise to memorability.

In particular, all image sets possess a similarity structure, and our simulations suggest that this structure directly determines which features will predict memorability within that context even when items for each participant are randomly sampled and thus participant-specific context varies. Consistent with this, our analysis shows that the representational distinctiveness of features in the THINGS database explains which features predict memorability in that image set. Items with animate features are extremely distinctive on average in the THINGS database, as relatively few animate items are present in this database despite their rich representational basis in the human similarity data and monkey neural data; whereas electronics objects cluster densely together in the features that explain representation of items in the database, which creates systematic biases that persist even with random sampling. This representational mismatch gives rise to features like body parts appearing intrinsically memorable when they may owe their memorability to being underrepresented in the image set relative to the richness with which humans process and represent them. The same mechanism explains why artificial objects like tools and electronics appear poorly memorable: not because they lack inherent memorability, but because they are overrepresented in the image set relative to their distinctiveness in human representational space, leading to interference in memory.

This finding is crucial because it reveals that prior research attributing memorability to intrinsic features and other non-distinctiveness factors can be explained by a distinctiveness-based argument. Features like body parts appear memorable not because they possess intrinsically memorable properties, but because they occupy a sparse region of the representational space; one that, relative to people’s visual and semantic representational space, is underrepresented by the image set.

We next consider a key causal prediction of the emergent memorability account with respect to this image set argument: if we systematically change the similarity structure of an image set, features that were originally "intrinsically memorable" should lose their memorability advantage, while a new set of features should emerge as apparently memorable. This prediction directly contradicts intrinsic memorability accounts, which would expect features to maintain their memorability regardless of the makeup of the database that is used to test memorability.

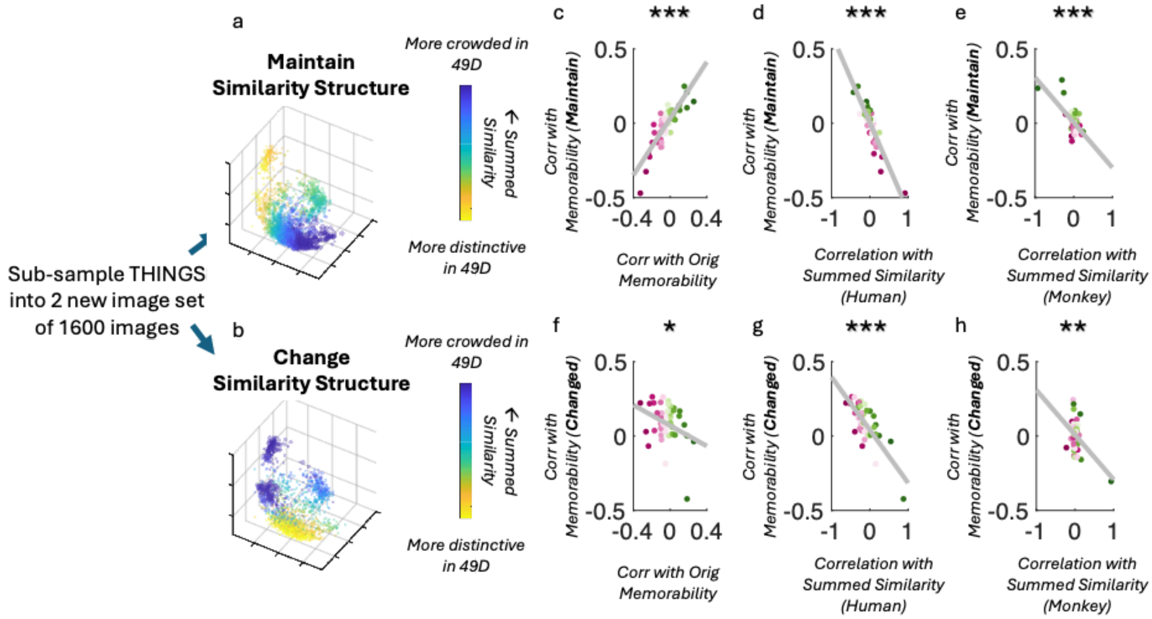

Fig. 5 | Changing the similarity structure of an image set changes what's memorable. We sub-sampled the THINGS database into two image sets of 1600 images each with contrasting similarity structures. **(a)** The "maintained similarity structure" image set preserves the original representational distribution, here visualized with concepts projected onto the first three principal components of 49-dimensional feature space. Point size corresponds to concept frequency and color indicates summed similarity. **(b)** The "changed similarity structure" image set partially inverts the representational distribution. Concepts that were associated with poor memorability occupied overrepresented and crowded (dark blue) regions of space in the maintained image set became distinct now (yellow) in the changed image set. **(c)** The full THINGS and maintained image sets show a strong positive correlation in feature-memorability relationships ($r = 0.84$, $p < 0.001$) as expected. Furthermore, features' memorability in the maintained image set is predicted by distinctiveness in both **(d)** human ($r = -0.89$, $p < 0.001$) and **(e)** monkey ($r = -0.63$, $p < 0.001$) similarity spaces, in line with the results with the full THINGS image set. **(f)** However, when the similarity structure was changed to change the distinctiveness of features, the same features inverted their memorability ($r = -0.33$, $p = 0.02$). A new set of features became memorable, and the old memorable ones become forgettable. Which features are newly memorable is again predicted by distinctiveness in both **(g)** human ($r = -0.75$, $p < 0.001$) and **(h)** monkey ($r = -0.45$, $p < 0.01$) similarity spaces, even though it is a different set of features than was previously memorable.

To directly test whether memorability is a consequence of similarity structure rather than an intrinsic property of images, we sub-sampled the THINGS database into two 1600-image image sets with contrasting representational distributions (Figure 5). The first (the *maintained* image set) preserved the original similarity structure of the full database. The second (the *changed* image set) changed it and partially inverted it (to the degree possible), so that concepts previously occupying crowded and overrepresented regions of feature space now became relatively distinct. It was not possible to fully invert the similarity structure because of the discrete nature of the database: Only so many animate items were available when subsampling the THINGS database, for example. Nonetheless, the changed image set switched the relative prevalence of different features in the image set, and thus significantly changed the similarity structure with respect to the Hebart et al. (2020) features.

If memorability were intrinsic to images, the same features should predict memory performance regardless of which image set a given image appears in. Instead, in a recognition memory experiment with these stimuli (see Methods), we found the opposite. The feature-memorability relationships in the *maintained* image set closely replicated those of the full THINGS database ($r = 0.84$, $p < .001$; Figure 5), and distinctiveness in this dataset predicted memorability, using both human and monkey similarity spaces to measure distinctiveness ($r = -0.89$ and $r = -0.63$ respectively, both $p < 0.001$). When similarity structure was *changed*, however, the same features that had previously predicted good memory now predicted poor memory ($r = -0.33$, $p = .02$), with a new set of features becoming memorable. The particular features that were now memorable was again predicted by their distinctiveness in both human ($r = -0.75$, $p < 0.001$) and monkey ($r = -0.45$, $p < .01$) similarity spaces, even though they were new features compared to the *maintained* image set. These results show that which features are memorable is not fixed but depends on the context in which images are encountered, which is determined by the image set that lists are sampled from.

The consistent negative correlations between feature summed similarity and memorability across both image sets support our proposed underlying mechanism: features that create the greatest distinctiveness within their representational context (which is reflected in the to-be-remembered items presented on a study list) enhance memory performance, regardless of the specific semantic content of those features. That is, animate features predict memorability in the original image set and maintained image set not because these features are animate semantically, but because animate images are underrepresented in the original THINGS image set relative to their importance in human representational structure. Representing animate items more, in proportion to their importance in representational space, makes animate semantic features predict *poor* memorability instead. This relationship holds across different similarity measures, as demonstrated by correlations with both human-derived and monkey IT neural similarity measures.

These findings expose a fundamental limitation in current memorability research: simply randomizing stimulus selection without controlling for underlying similarity structure cannot isolate "intrinsic" properties. The critical factor in determining memorability is not the categorical balance of stimuli, but their distribution in, and distinctiveness from, other list items, in people's internal representational space. Our results demonstrate that memorability can emerge naturally from relative distinctiveness within that space.

Notably, in this data, we find correlations between summed similarity (as a measure of distinctiveness) and memory that are comparable to those predicted in our global matching model simulations where there is no intrinsic memorability at all. Thus, in addition to the simulations flipping the burden of proof by showing emergent memorability in completely standard recognition memory models can explain supposedly intrinsic memorability effects, they also point to the idea that this may be all there is: the analogous size of the memorability results here to the simulation with no intrinsic memorability at all provide additional evidence against intrinsic memorability and suggest that memory effects emerge from the relationship between stimulus properties and the overall similarity structure of the encoding context, not from inherent properties of the stimuli themselves.

Reducing Variability In Distinctiveness Reduces Variability in Memorability.

Some intrinsic memorability claims acknowledge that extrinsic effects (like overloading with similar items, as in the *changed* image set) may impact memorability in addition to intrinsic effects (e.g., Bylinskii et al., 2015). In theory, then, intrinsic memorability could still exist, with all of our reported effects being extrinsic memorability effects that ride-on-top of these intrinsic effects. Notably, there is no positive evidence for this: we have shown so far that the full set of results typically taken to reflect intrinsic memorability can easily arise in simpler models that have no such concept, and tested direct causal predictions of our emergent account. In both image set manipulations, the majority of the variance in image memorability was captured by our summed similarity metric, even when the relationship between features and memorability flipped. This not only directly contradicts prior claims that the stimulus intrinsic properties account for the majority of the variance in image memorability (Bainbridge et al., 2013; Davis & Bainbridge, 2023), but also provides strong positive evidence that distinctiveness accounts for memorability.

However, to further extend this emergent framework, we next sought an even stronger test case: If memorability variation arises largely from distinctiveness variation, then to the extent that it is possible to uniformly sample from representational space, we should reduce variability in distinctiveness and diminish the variability that is typically observed in how different features relate to memorability, without any overloading of similar items at all. This experiment thus tests whether we can "erase" a significant fraction of the variation in memorability by constructing an image set where all items are as close as possible to equally distinct within the similarity structure, which we term the *reduced* image set, as it aimed to reduce distinctiveness variation.

The intrinsic account predicts the same correlation between visual features and memorability in such an image set as the original and the *maintained* image set above. However, the emergent account predicts that feature-memorability correlations will be substantially reduced in the reduced image set compared to the maintained image set; that is, that variation in these visual and semantic features will not produce nearly as much variation in memory performance if the features do not covary with overall distinctiveness. Quantitatively, therefore, the emergent account predicted that across all 49 features, the summed squared correlation with corrected recognition should drop significantly, demonstrating that previously identified "memorable" image features predict memory because they increase an image's distinctiveness within a specific image set (and vice versa for non-memorable features). In the absence of features' ability to predict variability in the summed similarity, these same features should reduce their predictive power about memory.

In building this new image set, we were able to reduce summed similarity variation: whereas the *maintained* image set showed broad variability in summed similarity across concepts (Mean = 0.18, SD = 0.00322), reflecting the uneven crowding of representational space that characterizes the THINGS image database, the *reduced* variability image set showed a sharply peaked distribution around the same mean (SD = 0.00156), confirming that differences in distinctiveness had been successfully reduced (Figure 6). Note that any reduction in variability in summed similarity in this *reduced* image set almost certainly overestimates the true amount of equalization of distinctiveness we achieved, as our manipulation is necessarily imperfect: we designed an image set to reduce variability in similarity at the level of concepts rather than individual images, whereas memory must be measured with actual images; the 49-dimensional feature space captures only some aspects of the perceptual and semantic dimensions along which humans actually confuse items in memory; and both the feature measurements and memorability scores are estimated with noise. Each of these factors would be expected to attenuate the observed reduction in feature-memorability correlations relative to what would be expected under a perfect equalization of true distinctiveness. Nonetheless, we make a strong directional prediction that reducing variation in summed similarity should reduce variation in memorability.

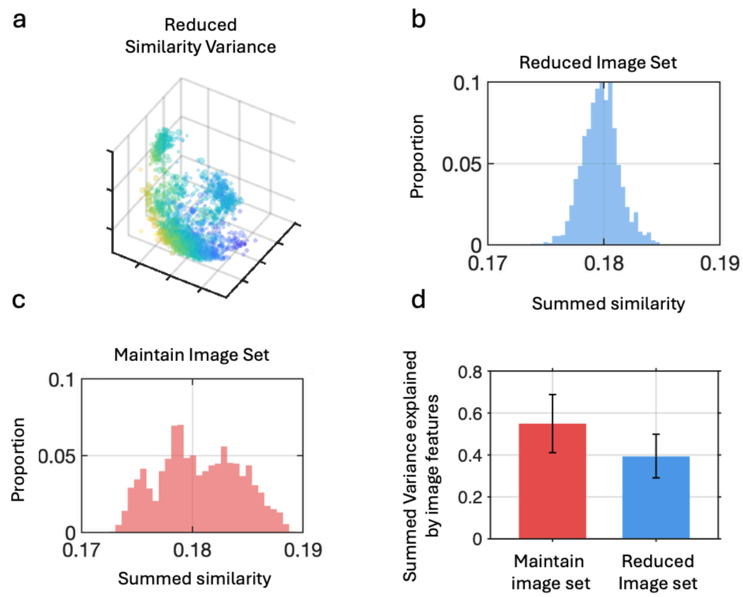

Fig. 6 | Reducing variability in summed similarity reduces memorability. We compared two image sets to test whether equalizing distinctiveness reduces memorability: the previously mentioned maintained image set preserving natural similarity structure, and a reduced variability image set where items were selected to minimize differences in summed similarity. **(a)** All concepts in the reduced variability image set projected onto the first three principal components of 49-dimensional feature space. The roughly uniform green color reflects the reduced variability in each concept's similarity to other concepts in this database. **(b,c)** Histograms comparing the distribution of weighted summed similarity across concepts. The maintained image set **(c)** exhibits broad variability in summed similarity, reflecting uneven crowding in representational space (Mean = 0.18; SD = 0.00322). The reduced variability image set **(b)** shows a sharply peaked, narrow distribution (Mean = 0.18; SD = 0.00156), indicating successful partial reduction of similarity variability. **(d)** Variance explained by image features: Feature-memorability correlations were substantially reduced in the reduced variability image set compared to the maintained image set. Across 49 features, the average squared correlation with corrected recognition dropped by 27%, with bootstrap confidence intervals confirming this reduction was statistically reliable ($p = 0.036$).

Nonetheless, consistent with our emergent memorability account, this attempted equalization of distinctiveness substantially reduced the ability of image features to predict memorability: across all 49 features, the average squared correlation with corrected recognition dropped by 27% relative to the *maintained* image set, with bootstrap confidence intervals confirming this reduction was statistically reliable ($p = 0.036$). When items are roughly equally distinct from one another, the features that normally track distinctiveness — and therefore memorability — significantly reduce their predictive power.

Note that the *reduced* image set has no more than about 10% of each high level category in it (animals and food are highest at about 10%). In other words, it isn't overloading any one thing in particular, it's making each thing be present in a proportion closer to that implied by people's internal visual and semantic representation. This pattern reveals that the closer an image set gets to being equally spaced in human representational space, the less image features predict memorability.

Overall, the convergence across our analyses — in REM simulations, in reanalyses of the Kramer et al. data, and in direct manipulations of database structure — points toward a coherent account in which memorability is better understood as emerging from the emergent effects of distinctiveness than as residing in individual images or features.

General Discussion

Memory for images has long been treated as a stable property of those images: some pictures are simply more memorable than others, and this memorability reflects something fundamental about their content; in the same way some images have more colors or are brighter, some images are more intrinsically memorable. The present work challenges this view.

Drawing on global matching models of recognition memory, we proposed that what looks like intrinsic memorability is better understood as an emergent consequence of relational structure: how similar or distinct an item is relative to everything else a person is tasked with remembering on a study list. We formalized this account using the REM model, showing that distinctiveness within a stimulus set — not any fixed property of individual images — is sufficient to produce the memorability effects documented in the literature. Reanalyses of the THINGS database confirmed that the features that predict human memorability are precisely those that track distinctiveness within the image sets used to study memorability, and direct manipulations of image set structure showed that the same features can flip from memorable to forgettable depending on the image set images are sampled from. Finally, reducing variation in how well features predict distinctiveness also reduces apparent variation in memorability. In other words, manipulating the image set to better match our internal representation of objects alters what is memorable. Taken together, these findings suggest that memorability is not a property to be explained at the level of individual images but a relational phenomenon that emerges from how distinct items are in visual and conceptual similarity. This has significant implications for how we design memorability experiments, interpret their results, and apply their findings to real-world scenarios.

Memorability as Emergent From Relational Processes

Our findings join a growing body of work arguing for the importance to memory performance of the relational context in which items are studied. For example in REM (Shiffrin & Steyvers, 1997), a boost for distinctive features emerges automatically from the Bayesian likelihood ratio: a test item with a rare feature generates an extremely small denominator probability under the hypothesis that it was not studied, producing a large likelihood ratio without any need to posit item-level variation in the importance of features to memory. The item appears memorable not because of anything fixed about it, but because its rare features make it maximally diagnostic against the background of everything else in memory.

Naturally, even with a distinctiveness framing, many open questions remain about the precise mechanisms involved: how encoding depth, individual differences, and the specific representational geometry of different domains interact to shape what gets remembered. Our own simulations, while capturing the core logic of how distinctiveness drives memorability, do not speak to all of these factors. But we believe the accumulation of evidence across approaches makes clear that the methods that have been used to establish intrinsic memorability (e.g., the consistency of memorability scores across participants within stimuli sampled randomly from the same image set or related image sets with the same biases) do not rule out a relational account, because any study that samples from the same image distribution will inherit the same similarity structure. The challenge we lay down for intrinsic memorability is therefore a relatively simple one: to establish that memorability is intrinsic rather than relational, one would need to show that images identified as memorable in one context retain that memorability advantage when placed in a context constructed to neutralize their distinctiveness. Our experiments suggest they will not.

Our work aligns with related conclusions reached from fundamentally different directions. For example, Nosofsky, Ehinger, and Osth (2025) show that a model based on relational similarity structure accounts for a wide range of context-dependent memorability effects in real-world image domains. Their approach relies on fitting a cognitive model directly to individual-item recognition data rather than working at the level of image set structure. At the same time, their model retains an item-level component (a self-similarity boost for items with salient distinctive features) that functions somewhat like a local intrinsic memorability term, so the strength of their conclusions about memorability being solely emergent are less clear than the ones we reach in the current work. To the extent that the self-similarity boost in the hybrid model captures the same phenomenon as REM's distinctive-feature advantage, our account suggests it may also be reducible to relational distinctiveness, falling out of the likelihood ratio rather than requiring a separate item-level parameter.

Computational Memorability Models Inadvertently Measure Distinctiveness.

The same logic we apply to behavioral memorability applies to the enthusiasm surrounding deep learning models of memorability, such as ResMem (Needell & Bainbridge, 2022) and its predecessor MemNet (Khosla et al., 2015). It also applies to neural signatures of memorability identified in the brain, such as memorability-sensitive responses in the medial temporal lobe (Bainbridge et al., 2017) and the magnitude of the IT population response (Jaegle et al., 2019).

The deep learning models achieve impressive prediction accuracy on their training distributions, and this success has been taken as evidence that memorability is a decodable intrinsic visual property. Indeed, recent work has argued that because ResMem makes predictions from a single image with no access to the experimental context, its success demonstrates that it has identified properties intrinsic to the image (Davis & Bainbridge, 2023). But a model that learns to predict memorability scores from a fixed image distribution will necessarily internalize that distribution's similarity structure, and it has no way to distinguish between an image that is memorable because of something fixed about it and an image that is memorable because it happens to be distinctive within the particular image set it was trained on. The lack of access to the experimental context at test time is therefore not the relevant kind of context-independence needed to validate intrinsicness claims; the training distribution has already supplied the context. Indeed, consistent with this view of internalized distinctiveness, Jaegle et al. (2019) found that the same correlation between response magnitude and memorability emerges in convolutional neural networks trained only to categorize objects, with no memory objective at all, suggesting that any system that learns the statistics of a visual and semantic distribution will produce a magnitude signal that can be found to track memorability, because the features that drive distinctiveness are also the features that are represented internally in humans and deep neural networks. The same logic applies to the brain. The brain internalizes the representational structure that best captures a lifetime of experience, and so correlations between activity and average-distinctiveness in memorability experiments are to be expected, and need not reflect any fixed property of the image itself. For a simplified example, consider animacy: memorability scores reliably come from databases that underrepresent animate images (like THINGS), and thus animate images frequently appear memorable. Animate images also selectively activate certain areas of cortex and certain deep net features (e.g., Jozwik et al., 2022). The fact that finding these regions of cortex or deep net features can be used to predict memorability from a single image provides no evidence for the intrinsicness of animate features' memorability; they simply show that the behavioral measure used led to animacy being confounded with distinctiveness, and that animacy can be ascertained from cortex or deep nets. Thus, in an emergent memorability account, the success of both artificial models and biological signatures stems not from uncovering fundamental intrinsic properties of memorability that can be decoded from images independent of context, but instead from internalizing the similarity structure of training data and the distinctiveness of images within that similarity structure.

In line with this prediction, the limitations of these models become apparent when tested on novel image sets. Independent benchmarks by Hagen and Espeseth (2023) revealed dramatic performance degradation when ResMem was evaluated across multiple image sets. Variance explained dropped precipitously from approximately 45% on in-distribution data to only 13% on PASCAL-S natural images, 5% on the THINGS object image set, and 2% on object crops, overall representing over 90% reductions in variance explained in out of distribution data. Even the newer ViTMem model, despite outperforming ResMem, still showed substantial drops (20%, 9%, and 4% respectively), indicating that current memorability prediction models rely heavily on image set-specific statistical regularities rather than universal principles.

Thus, we believe that consistent with our overarching point, these models' partial success within their training distributions can be better understood through the lens of distinctiveness measurement rather than intrinsic property detection. By training on vast collections of images, these models become sophisticated at extracting statistical regularities about which types of images are typically distinctive within standard experimental contexts. When ResMem predicts that a person-containing image is more memorable than a building, it leverages learned knowledge that such images are typically more distinctive in memorability research image sets, the same representational biases that create apparent "intrinsic memorability" in human experiments.

As noted above, the failure of computational models to generalize outside their training image set parallels the evidence about human memorability in our behavioral experiments. Just as ResMem's correlation dropped from 0.67 to 0.36 when tested on new image sets, our rank inversion experiment showed that the same Kramer et al. (2023) items exhibited a significant negative correlation ($r = -0.50$) between their original memorability scores and memorability in our manipulated contexts.

This convergence across methodological approaches strengthens the distinctiveness account. Computational models fail when tested on image sets with different distributional properties, while behavioral memorability estimates invert when identical items are placed in different similarity contexts. In both cases, what appeared to be stable intrinsic properties proved to be artifacts of specific representational structures.

Overrepresentation of Some Aspects of the World Compared to Experience

We do not deny that humans, on average, represent more useful features about some items (e.g., faces) than others (e.g., individual blades of grass), and thus are typically better at discriminating faces from novel foils than blades of grass; that is, people's representational space is not equally split between all items. What is important for the present argument is that while memory operates on top of whatever representational structure exists, memory itself is relational, not intrinsic (just as red is relationally salient, not intrinsically salient).

Under a relational account, the fact that humans allocate disproportionate representational resources to animate, social stimuli (up to 50% of representational space: Jozwik et al., 2022) does not by itself predict that those stimuli will be more or less memorable. What matters is whether such stimuli are over- or underrepresented in a given image set relative to their footprint in human representational space. When a database samples the world in a way that leaves regions of high representational importance sparsely populated, items in those regions become distinctive by default. This appears to be the case for animate and social categories in standard databases like THINGS (Hebart et al., 2019). In daily life, we see many more human-centered events than the THINGS database contains, and we care deeply about encoding their details. We encounter far fewer empty fields, gothic cathedrals, bundles of straw, and unidentifiable electronics than the THINGS database contains. This mismatch, rather than anything intrinsic to animate or social items, is what makes them appear memorable in standard experiments. They occupy regions of representational space that the database underrepresents relative to how richly humans represent them.

On this view, the question of why humans have expanded representational capacity for certain categories is worth pursuing, but it is a different question from why those categories tend to appear memorable in standard experiments — and conflating the two may have contributed to the appeal of intrinsic memorability accounts. Expertise, evolutionary pressures, and ecological importance have all been proposed as contributors to the unequal allocation of cognitive and neural resources across different categories (Nairne et al., 2017; New, Cosmides, & Tooby, 2007; Caramazza & Shelton, 1998). In general, representational structure does not simply reflect statistical regularities in the environment, it also reflects the utility and biological relevance of different kinds of information, though the precise mechanisms remain actively debated (Nairne et al., 2017).

In short, representational structure shapes the conditions under which distinctiveness arises, but distinctiveness, not representational structure per se is what drives memory. Apparent category-level, feature-level and item-level differences in memorability likely reflect the former masquerading as the latter.

The Importance of Image Sets

Our findings raise important questions about what constitutes appropriate image sets for measuring memory. A practical implication of our emergent memorability account is that there is no such thing as a neutral image set. Every collection of stimuli carries a similarity structure that directly shapes which features will appear memorable and which will not, and randomly sampling from an image set does not eliminate this, it simply inherits it. Our simulations show that even small random samples drawn from THINGS (Hebart et al., 2019) recapitulate the original database's similarity structure, producing memorability patterns that look consistent and stable across participants but are in fact a direct result of how the database is organized rather than properties of the images themselves.

This has concrete consequences for how the field uses large image databases. THINGS was constructed by systematically sampling concrete, picturable nouns from American English.

This is a principled procedure, but one that produces a distribution of object concepts that mismatches human representational space in important ways (Hebart et al., 2019; Contier et al., 2024). The database contains many more exemplars of categories like tools than of categories like faces, despite the vastly greater importance of social and animate stimuli in human experience and neural representation (Hebart et al., 2020). This mismatch means that animate, social stimuli end up relatively distinctive within the database. This is not because faces are intrinsically distinctive (and thus memorable), but because the database underrepresents them relative to how humans actually carve up the visual world in the visual and semantic representations that support memory formation.

By manipulating similarity structures across image sets, we altered which items were remembered or forgotten, showing that memorability rankings can be completely inverted when context changes. This challenges the foundational assumption that consistency across contexts implies intrinsic properties. Our work demonstrates that this assumption is unfounded. Consistency can emerge naturally from relational processes when image sets share similar representational asymmetries like underrepresenting animate objects despite humans large representational space for such features.

The emergent memorability account makes a strong prediction that as databases are constructed to more closely approximate the actual distribution of equal sampling across human representational space, distinctiveness will become more equalized across items, and the apparent variability in memorability will shrink accordingly. We show a version of this in our final experiment, but the broad implication for researchers is that stimulus selection is not a neutral act: the choice of database, and of how to sample from it, actively determines what will look memorable in the resulting experiment. So what is a perfect database to measure memorability? We argue there is no such database: Consider three candidates. A memory list that perfectly equates spacing in human representational space would have no variation in memorability at all. One that matches the frequency of items in the world would vastly oversample unimportant stimuli like ants and leaves, which matter little to humans and would therefore be confusable and poorly memorable. And a database that matches the statistics of human experience would still mismatch representation in key ways, devoting far more space to blades of grass and less to large mammals like elephants and zebras than people actually store, leading to unequal memorability for that reason. A key aspect of the emergent memorability account is in fact that no ground truth memorability can exist outside of the context of a particular database or list.

Measurement and Model Predictions

A final consideration concerns how memory performance should be measured to assess memorability, regardless of whether it is intrinsic or emergent. The most common paradigm in the memorability literature is continuous recognition, in which participants view a long stream of images and respond to each one, typically pressing a key when they detect a repeat (e.g., Isola et al., 2014; Bainbridge et al., 2013). This method produces hit rates and false alarm rates that are heavily skewed, with very few false alarms. What false alarms are present vary as a function of sequence position and other factors that have nothing to do with memory per se. Limited false alarms, with no confidence data for responses, severely limits the ability to accurately measure memory (Brady et al., 2023; Wickelgren, 1968; Wixted, 2007). Corrected recognition (i.e., hits minus false alarms) is also widely known to conflate sensitivity and bias (see Brady et al., 2023 for a review), so a reasonable number of false alarms combined with a bias manipulation or confidence estimate is required to derive the full receiver operating characteristic and compute a bias-free sensitivity measure like d_a that is appropriate for recognition memory (Macmillan & Creelman, 2004; Wixted & Mickes, 2010). In the present work, rather than continuous recognition – which gives rise to heavily biased criterion – we used a more standard study-test procedure with confidence ratings, which allows proper ROC analysis. Because we did not have any extreme response biases, we did not find major differences between d_a and corrected recognition in our data (see Methods for validation), and thus focused on corrected recognition to make our work comparable to previous work in this field. However, this may not hold in paradigms with the more extreme response biases typical of continuous recognition tasks, where bias-free measurement is likely to matter considerably more.

One implication of our proposed REM framework with respect to measurement is that hits and false alarm rates may be important to analyze separately rather than collapsed into a single sensitivity measure when considering memorability. The model makes distinct predictions for the two: items that are typical of a well-represented category — say, a common household object in a database full of common household objects — will generate not only relatively high hit rates, but also high false alarm rates because novel exemplars of that category will match many stored traces. By contrast, items with rare or unusual features — our face-tattoo example — are predicted to generate high hit rates through a strong self-match likelihood ratio, while their rarity should simultaneously suppress false alarms to similar-looking lures, since those features are unlikely to appear in other stored traces. This dissociation between hit and false alarm rates is not captured by any single-number memorability score, but it is a natural prediction of global matching models and deserves more systematic attention in future work on item-level and feature-level memorability.

Conclusion

The memorability literature has built up an impressive body of findings over the past two decades, and we do not dispute that consistency in what people remember is a real and robust phenomenon. Although intrinsic memorability is, in principle, unfalsifiable, our findings suggest that the methods typically used to support its existence fall short. What we have argued is that this consistency has been systematically misattributed. Consistency does not require items to have fixed, intrinsic memory properties. It requires only that the distributional structure shaping what is distinctive remains stable across studies, which it does whenever studies draw from the same image databases. Once this is recognized, the apparent paradox between consistency and context-dependence dissolves: memorability can be both highly consistent within a given experimental tradition and highly mutable when the similarity structure of the stimulus set changes, exactly as our experiments show.

The relational, emergent account we have advanced is grounded in well-established principles of global matching models that have successfully explained a wide range of memory phenomena for decades. What we have done is apply these principles to the question of memorability, showing that they are sufficient to explain the patterns that have been taken as evidence for something more intrinsic. This does not close the book on memorability research; it reframes what the most important questions are. Rather than asking which images are memorable and why, the more productive questions may be: what is the representational structure of the stimulus sets we use, how does that structure shape distinctiveness, and how can we design experiments that disentangle distributional effects from genuine item-level variation (if such variation exists)? How can we scale up memorability to the real world once we acknowledge the emergent nature of memorability? Answering these questions will require new image sets, new experimental designs, and a closer dialogue between the memorability literature and the broader cognitive science of recognition memory.

Methods

Computational Modeling: REM

Basic REM Simulation of Memorability

We implemented the REM (Retrieving Effectively from Memory) model with standard parameters from Shiffrin & Steyvers (1997) to test whether apparent memorability effects could emerge from purely relational processes, as implemented in this model. Items were represented as vectors of 49 features, with each feature value drawn from a geometric distribution (with parameter g = 0.65), resulting in integer values starting from 1. During encoding, each feature was stored with a probability of 0.3, and if stored, was encoded correctly with a probability of 0.6 (otherwise encoded as a random value drawn from the same geometric distribution).

We generated a set of 26,107 simulated items to serve as our simulated item database — the same size as the THINGS database we used in our behavioral experiments. To mimic typical memorability experimental conditions, including those in our behavioral experiments, we next randomly selected a subset of 1,600 items from the larger database, then conducted 10,000 independently simulated recognition memory experiments. Each simulation studied 40 items; recognition was then tested on 20 randomly-chosen studied items plus 20 additional foils drawn from the 1,600-item subset. Across the 10,000 simulations, each item served as both a studied probe and a foil probe in different runs, allowing per-item hit and false-alarm rates to be estimated.

Recognition decisions followed standard REM likelihood ratio procedures. For each test item, familiarity was calculated by comparing the test item against all stored memory traces (global matching) vs. the likelihood of these same features being stored if the item was not seen (defined as the generative distribution of items, the geometric distribution). The overall familiarity signal was then computed as the mean likelihood ratio across all stored traces. Recognition responses were determined by comparing this familiarity signal to a fixed criterion of 1.0. For each item across all simulation runs, we calculated hit rate (proportion of correct "old" responses when studied) and false alarm rate (proportion of incorrect "old" responses when unstudied), with memorability operationalized as corrected recognition (hit rate minus false alarm rate).

For each item, we also approximated its distinctiveness in the feature space by computing the summed similarity of it to all other items. We did this by calculating the average Euclidean distance to all other items in the image set in the 49-d feature space. Euclidean distance between two items was computed as the L2 norm of the difference between their feature vectors. This measure quantified each item's average distance from other items, with larger values indicating greater distinctiveness. Note that unlike the model itself, this distance metric does not take into account that some features are more rare and thus more informative, nor does it take into account that only items with many overlapping features (not just a few) will give rise to confusable memory signals. It therefore provides only an approximation of the decision rule of the model, but one that can be easily applied to other realistic items in realistic feature spaces.

Bylinskii et al. (2015) Context Manipulation Simulation

We generated 21 scene categories, each containing 300 items (75 targets and 225 fillers), matching the structure of Bylinskii et al. (2015). Items were represented as 49-feature vectors with all parameters identical to our initial REM implementation: features drawn from a geometric distribution ($g = 0.65$), encoding probability = 0.3, and correct encoding probability = 0.6. To create categorical structure, we designated the first 10 features as category-defining features. For each category, we generated a category prototype by drawing 10 feature values from the geometric distribution. All items within that category shared these 10 category-defining feature values, while the remaining 39 features varied independently across items.

We then simulated two experimental contexts corresponding to Bylinskii et al.'s design. In the within-category simulation, we conducted separate recognition memory experiments for each of the 21 categories. For each simulation run, we randomly sampled 30 targets and 90 fillers from within a single category, encoded them following standard REM procedures, and tested recognition memory against a decision criterion of 20. In the across-category simulation, we tested the same target items in mixed-category contexts. For each simulation run, we randomly sampled 30 targets and 90 fillers across all 21 categories and tested recognition memory against a criterion of 5. The different criteria reflected participants' strategic adaptation to different list similarity structures: within-category lists produce higher baseline familiarity due to shared category features, necessitating a more conservative criterion. For the across-category context, we conducted 1,000 simulation runs; for the within-category context, we conducted 1,000 simulation runs per category (21,000 total), so that each target accumulated comparable data in both contexts. This yielded stable memorability estimates (hit rate minus false alarm rate) for each target item. False alarm rates were computed by testing each target's familiarity signal against separately generated novel lures.

Finally, we again computed summed similarity using the same L2 norm approach described above. Mirroring the structure of the simulated memory experiments, in the within-category simulation each item's summed similarity was computed as the average Euclidean distance to all other items within its category. In the across-category simulation, each item's summed similarity was computed as the average Euclidean distance to all items across all categories.

Behavioral Validation Experiments

Inversion Experiment. To test whether our computational modeling findings generalized to human memory, we designed an experiment to directly invert memorability rankings by manipulating the similarity of the other items studied (the context) to each item. For each of the 8 study/test blocks, five critical items were selected from the THINGS database spanning different memorability levels based on Kramer et al. (2023) scores: one item each from the lowest 20%, 20-40%, 40-60%, 60-80%, and highest 20% memorability bins, giving 40 total items stratified across these memorability bins.

We systematically manipulated each critical item's distinctiveness by varying the number of similar context items in study lists, with the number assigned based on each critical item's original memorability bin: 8 similar items for the top 20% (most memorable), 6 for the 60–80% bin, 2 for the 40–60% bin, 1 for the 20–40% bin, and 0 for the bottom 20% (least memorable). Because we needed item-wise similarity metrics to select these (which are not available for THINGS from any human-derived source), item similarity was computed using representational dissimilarity matrices derived from an average across the 4 RDMs derived from ResNet18,VGG16, AlexNet and CLIP; in each case focusing on the highest non-output layer. Each study list contained 40 images: 35 controlled context items (17 similar items distributed across the 5 critical items as described above, plus 18 additional non-similar exemplars), and 5 additional items selected from the critical items and maximally dissimilar fillers to maintain consistent list length.

Participants performed 8 blocks of study and tests. In each block participants studied a sequential stream of 40 images, then completed 10 consecutive recognition trials (testing all 5 critical items and all 5 maximally dissimilar items, with old/new status determined by whether each item had appeared in the study stream) judging whether each image was 'old' or 'new' using a 6-point confidence scale. Memorability for each critical item was calculated as corrected recognition, then compared to original Kramer et al. (2023) rankings to assess ranking inversion.

Representational Similarity Analysis

To provide a common representational framework for our analyses, we constructed representational dissimilarity matrices (RDMs) for both humans and monkeys. These RDMs summarize the pairwise dissimilarities between all object concepts in the THINGS image set and form the basis for all our similarity memorability analyses. Note that these are at the concept level (effectively categories; e.g., all “keys” or “straws”), not per image.

We derived a behavioral similarity RDM from the large-scale THINGS similarity image set (Hebart et al., 2020). This image set provides human behavioral judgments summarized as 49-dimensional SPOSE embeddings for each of the 1,854 object concepts. We treated each embedding as a feature vector and computed pairwise dissimilarities using 1 − Pearson correlation, yielding a symmetric 1,854 × 1,854 RDM. Concept-level memorability values were then attached by aligning each concept to Kramer et al. 's memorability scores. In parallel, we constructed an RDM from the THINGS Ventral Stream Spiking image set (Papale et al., 2025). For each concept, multi-unit spiking responses from macaque V1, V4, and IT were reduced to a 49-dimensional feature space using principal component analysis to make them comparable to the SPOSE embeddings; this captured nearly all of the variance in these responses. As in the human case, we then computed pairwise dissimilarities as 1 − Pearson correlation, yielding a concept-level RDM structurally matched to the human space.

Concept-Weighted Similarity. For both human and monkey spaces, we derived a category-weighted dissimilarity measure for each concept. To do this, we took the dissimilarity of each concept to all others in the RDM. These dissimilarities were then weighted by the relative prevalence of each comparison concept's category (i.e., concepts that contained more exemplars contributed proportionally more, to match the memory experiments where generally items are chosen randomly without respect to the concept they belong to). Because we would not expect items that overlap very little to have much impact on the memory of an item, and would expect a disproportionate amount of interference to arise from very similar items (in line with nearly all global matching models of memory: Nosofsky 1991; Shiffrin & Steyvers 1997 and other work on how representational distance relates to memory confusability: e.g., Nosofsky, 1992; Shepard, 1987; Schurgin et al., 2020), we used a previously used Gaussian transformation of distance to similarity (Nosofsky, 1992). In particular, the weighted dissimilarities were transformed using a Gaussian kernel centered at minimum dissimilarity (mean = 0, SD = 2) to ensure that very similar concepts contributed most to the measure. This produced a single weighted similarity score for each concept, which we use throughout the paper to relate representational structure to memorability. The resulting human and monkey RDMs, with their associated concept-level memorability scores and category-weighted similarity measures, serve as the foundation for all RSA results.

Image Set Structure Manipulations

Maintained Image Set. The maintained image set was designed to preserve the original THINGS database structure by maintaining natural feature-similarity relationships. For each concept, we calculated a representativeness score based on how well it matched the original correlation pattern between features and similarity. The representative score for each concept was the sum across all of the feature values multiplied by the sign of that feature's correlation with similarity, weighted by the squared magnitude of the correlation. These scores were normalized to create a probability distribution, and 1,600 concepts were sampled with replacement based on these probabilities, ensuring the image set preserved the original representational structure. If a concept was sampled more than once, a distinct image from that concept was added to the database.

Changed Image Set. The changed image set systematically inverted the original representational structure through a two-stage process. First, we identified features positively and negatively correlated with memorability in the original image set. We then computed concept scores by subtracting weighted positive feature values and adding weighted negative feature values (weighted by squared correlation coefficients). From the top 500 scoring concepts (those high on "non-memorable" features), we selected 160 concepts using a greedy algorithm that maximized dissimilarity by starting with the highest scoring concept and iteratively adding concepts with minimum average similarity to already selected items. This created a sparse sampling of typically non-memorable concepts. Second, we selected 1,440 additional concepts from those scoring high on positive memorability features, sampled with probability proportional to their squared positive scores. This oversampling of typically memorable concepts combined with sparse sampling of typically non-memorable concepts changed the representational structure of the database in the direction of inverting the feature relationships to memorability.

Reduced Image Set Construction. The reduced image set was constructed to reduce correlations between image features and weighted similarity across concepts using an optimization procedure. We tested 500 different exponential transformations of memorability-predicting feature scores with exponents ranging from 0.01 to 0.5 (in 0.01 increments, replicated 10 times each). For each transformation, concept scores were normalized from 0 to 1, raised to the test exponent, and used as sampling probabilities for selecting 1,600 concepts with replacement. For each candidate image set, we computed Spearman correlations between all 49 feature dimensions and weighted similarity values (computed as above). The composite score was calculated as the sum of the mean of the absolute correlations and the maximum absolute correlation. The final image set was selected based on the lowest composite score. This procedure resulted in an image set with the same average summed similarity but reduced variability across items in this summed similarity (Mean = 0.18; SD = 0.00156) compared to the maintained image set (Mean = 0.18; SD = 0.00322).

Experimental Procedures and Analysis

Statistical Analysis and Exclusion Criteria:

All experiments used within-subjects designs with no randomization of participants to groups required. Consistent with our typical lab practice, data exclusion criteria were (1) Subjects who responded with the same key for more than 80% of trials (response bias), (2) Subjects with more than 20% of trials with reaction times <200ms (fast responses) or >7500ms (slow responses), (3) Subjects with poor overall performance (difference between hits and false alarms < 0.05). After subject exclusion, individual trials with reaction times <200ms or $>10{,}000$ms were additionally removed from analysis.

Participants:

Inversion Experiment. The final sample consisted of 50 participants recruited from UC San Diego and took part in this study in exchange for course credit. 4 additional participants were run and excluded based on the above criteria.

Image Set Structure Experiments. The final sample consisted of 450 participants across the three image sets: 150 participants in the maintained image set, 150 participants in the changed image set, and 150 participants in the reduced image set, all recruited from UC San Diego and took part in this study in exchange for course credit. Across all 3 stimulus set experiments 152 additional participants were excluded based on the above criteria. All procedures were approved by the UC San Diego Institutional Review Board, and participants provided informed consent. Experiments were run online and completed on participants' personal devices.

Recognition Memory Task. All 3 image set experiments used identical recognition memory procedures. Each participant completed 16 study/test blocks. In each block, they viewed a study list of 40 images, then completed 40 recognition test trials (20 old, 20 new) judging each as 'old' or 'new' on a 6-point confidence scale. Corrected recognition (CR), calculated as hit rate minus false alarm rate, served as the primary memory measure across all experiments.

Notably, corrected recognition (CR) is not an appropriate measure of memory performance in the general case (see Brady et al., 2023). However, it is what has been used in the memorability literature historically and thus makes our results more comparable to the results presented by Kramer et al. (2023). In this particular case, because we had a separate study and test period in all of our experiments and 50% of items were old vs. new at test, people's criteria were relatively neutral (criterion $c = 0.29$), thus making this measure relatively unbiased. Notably, this is unlike the continuous recognition paradigm common in this literature (Berch, 1976; Donaldson & Murdock Jr., 1968; Fox & Osth, 2023; Han & Dobbins, 2008; Rhodes & Jacoby, 2007) where the criterion can exceed 0.8. In the continuous recognition paradigm there are generally few false alarms because the default response if you do not hit a key is "new" — you only hit keys for old items — and very few items are actually old, leading to near floor false alarm rates that make accurate measurement of memory performance difficult or impossible. This also leads to the data being at a point in the ROC where accurate measures like d_a and d' differ most from corrected recognition. By contrast, at the more neutral response criterion people use in our experiment, hits minus false alarms is highly correlated with more accurate measures like d_a ($r = 0.98$, $p < 0.01$), though because we could not measure the slope of the z-ROC per category, we computed d_a with a fixed slope of 0.80 (Didi-Barnea et al., 2016) in this case which is approximately what is generally found in recognition memory experiments.

Feature Analysis. For each image set, we extracted the 49 visual and semantic features per concept following Hebart et al. (2020). We computed Spearman correlations between feature values and CR scores across concepts. Bootstrap analysis with 1,000 iterations was conducted, resampling participants to estimate confidence intervals for each feature's squared correlation with memory. Additionally, we implemented participant-level logistic regression analysis to assess individual consistency with group patterns, using leave-one-out cross-validation following Kramer et al. (2023).

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