Semantic influences on episodic memory distortions

Alexa Tompary^{1*} and Sharon L. Thompson-Schill¹

¹Department of Psychology, University of Pennsylvania, Philadelphia, PA 19104

*Corresponding author:
Alexa Tompary
atompary@sas.upenn.edu

72 pages, 6 figures, 1 table

Word count, abstract: 245

Word count, article body: 15,593

Abstract

Prior knowledge can facilitate or distort new episodic memories, depending on their alignment. However, it remains unclear how the structure of semantic memory explains systematic variation in how new memories are formed and retrieved. We aimed to quantify distortions in memory by examining how category membership and typicality bias new memories. Across four experiments, participants encoded and retrieved image-location associations. Most members of a category (e.g. birds) were located near each other, such that participants could learn locations of categories as they encoded specific image locations. Critically, some typical and atypical category members were in random locations. We decomposed location memory into two measures: error, a measure of episodic specificity, and bias towards other category members, a measure of the influence of prior knowledge. First, we found that location memory was more accurate for images that were spatially consistent with their category membership. Second, when images were spatially inconsistent, retrieval of typical category members was more biased towards other category members relative to atypical ones. These effects replicated across three experiments, disappeared when images were not arranged by category, and were stronger than effects observed with images arranged by visual similarity rather than category membership. Our observations provide compelling evidence that memory is a reconstruction of multiple sources of information, integrating memory for specific events with relevant semantic knowledge. Furthermore, systematic differences in the magnitude of this integration suggest that the organization of semantic memory can govern the extent of distortion in new episodic memories.

Key words: Episodic memory, semantic memory, memory reconstruction, distortion

Introduction

Episodic and semantic memory are commonly studied as distinct cognitive phenomena, the former defined as memory for ‘personal experiences and their temporal relations’ and the latter as memory for the ‘meaning of words, concepts, and classification of concepts’ (Tulving, 1972). While this distinction has led to important characterizations of both memory systems (e.g., A. M. Collins & Loftus, 1975; McClelland, McNaughton, & O’Reilly, 1995) and fruitful investigations of the interactions between them (e.g., McKoon & Ratcliff, 1979; Anderson & Ross, 1980; Simons, Graham, & Hodges, 2002), it also oversimplifies the complexity of memories, which comprise both episodic and semantic elements. In other words, it neglects the critical notion that new experiences are made up of re-combinations of objects, places, and people for which we already have rich semantic knowledge. We aimed to disentangle the separable contributions of semantic and episodic elements to new memory formation and/or retrieval by quantifying how semantic knowledge distorts new episodic learning.

The influence of prior knowledge on new episodic memories is widely documented (Bartlett, 1932; Ghosh & Gilboa, 2014). On the one hand, prior knowledge can enhance new memories (Bransford & Johnson, 1972; Craik & Tulving, 1975). Similarly, the presence of prior knowledge accelerates the integration of novel words into existing memory networks (Coutanche & Thompson-Schill, 2014). At the same time, new encoding can also be biased by prior knowledge, resulting in false memories or confabulation (Koutstaal & Schacter, 1997; Webb, Turney, & Dennis, 2016) or distorted details of true memories (Bartlett, 1920; Loftus & Palmer, 1974). Taken

together, these findings suggest that prior knowledge can help or hinder memory for new events.

What dictates whether prior knowledge is helpful or harmful for new memories? One promising approach to answer this question is to consider retrieval as a construction of different sources of information. Such an account has been useful in explaining errors in a wide variety of cognitive phenomena, including but not limited to object perception, color constancy, and visual short term memory (e.g. Knill & Richards, 1996; Brainard et al., 2006; Heussen, Poirier, Hampton, & Aldrovandi, 2011). According to this view, retrieval is not a veridical recapitulation of past events, but instead an imperfect recombination of event-specific details and other knowledge (Addis, Pan, Vu, Laiser, & Schacter, 2009). Because episodic memories are often noisy and incomplete, successful remembering is thought to combine these partial representations with knowledge from prior experiences (Huttenlocher, Hedges, & Vevea, 2000). Integrating prior knowledge with episodic memories can thus be thought of as a way to improve the ‘signal’ of a memory, resulting in more accurate retrieval. Yet, it also introduces systematic errors if there are discrepancies between a new memory and prior knowledge. In long-term memory, exposure to semantically related words (e.g., sour, candy, sugar) often produces a false memory for a non-studied word (sweet; Roediger & McDermott, 1995). Such errors are also captured with continuous measures of bias; for example, memory for the spatial locations of dots is often biased towards the horizontal and vertical axes of the stimulus display, suggesting that participants group memory for continuous locations into discrete chunks (Huttenlocher, Hedges, & Duncan, 1991), memory for the color of shapes is biased towards canonical hues

(Persaud & Hemmer, 2016), and estimates of the size of fruits and vegetables are biased by both their superordinate and subordinate mean sizes (P. Hemmer & Steyvers, 2009). Taken together, these findings provide compelling evidence that long-term memory is a reconstruction of prior knowledge and new experiences and accounts for variation in how prior knowledge interacts with new memories.

However, one weakness of this work is that the operationalization of prior knowledge often ignores its rich, dimensional structure (A. Collins & Quillian, 1969). In such a structure, concepts vary in the similarity of their features, giving rise to categories. Typical category members are defined as items that share the greatest number of features with other members, and thus are the best examples of that category (E. Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). As a result, typical category members are thought to be more strongly associated with category neighbors, relative to atypical ones. The consequences of these strong associations are well documented: Typical category members are more quickly categorized, more efficiently recognized, and less resistant to disruption by brain damage (Patterson, 2007). Furthermore, the features of typical category members are more often attributed to category neighbors (Rips, 1975; Osherson, Smith, Wilkie, López, & Shafir, 1990). As an example, if a typical category member, rather than an atypical category member, is accompanied by a shock, participants are more likely to anticipate shocks with other category members (Dunsmoor & Murphy, 2014). Examining how new memories are formed in the context of this structure may lead to a better understanding of the reconstruction of episodic and semantic information when retrieving new memories.

We aimed to quantify distortions in episodic memories due to prior knowledge by examining how differences in category typicality bias new episodic memories. In a series of behavioral experiments, participants encoded and retrieved image-location associations on a 2D grid (Figure 1A). The locations associated with the images were determined by semantic relatedness ratings, such that most members of the same category (e.g. birds) were located near each other, but some typical and atypical category members were in random locations (Figure 1B-D). This configuration allows participants to learn that images from a certain category tend to be located in a certain area as they encode the locations of specific images. This general knowledge could only be learned and used if participants integrated learning of new image-specific locations with their prior knowledge of animal and object categories. We used a continuous retrieval measure to disentangle biases driven by semantic knowledge from errors due to forgetting (Figure 1E). Error and bias could vary independently, such that memory for an image could be biased towards or away from category neighbors at the same level of accuracy. We used these measures to quantify the influence of knowledge about a category's general location when retrieving the locations of each image.

Under a reconstruction account, we predicted that the use of this category knowledge would give rise to two distinct effects: (1) retrieval of images located near members of the same category would be more accurate relative to those in random locations, and (2) for images located in random locations, retrieval of typical category members would be more biased in the direction of category neighbors relative to atypical ones. Such a bias would reflect stronger associations between typical category

members and their category neighbors. Finally, although we expected that category typicality would specifically influence bias in memory, we also explored potential differences in their accuracy.

We tested these predictions across four behavioral experiments (summarized in Table 1). In Experiment 1, we developed a novel, data-driven procedure to determine category membership and typicality for a set of animals and objects. In Experiment 2, we designed a conceptual replication using a different procedure for defining category typicality with validated and pre-determined categories. As a preview, both experiments provided evidence in favor of the two predictions outlined above, suggesting that participants relied on a mixture of event-specific details and category knowledge to support retrieval and that the organization of this category knowledge explained differences in distortion of new episodic memories. In Experiments 3 and 4, we examined possible explanations for the observed differences in bias by category typicality. In Experiment 3, we asked whether the utility of category knowledge during encoding differentially influenced how typical and atypical category members processed, by assessing memory for their perceptual details. In Experiment 4, we developed a set of stimuli that could be organized by a non-semantic property (i.e., arbitrary image color) to examine whether the observed biases in memory were driven by the visual similarity of the images rather than their conceptual structure.

Figure 1 General experiment design (A) Experiment procedure. Participants encoded each image-location three times by dragging the image onto a red dot marking its location. After a 5-minute break, participants retrieved the location of each image. (B) Image locations for Experiments 1 and 3 in the experimental groups. (C) Image locations for Experiment 2. (D) Spatial consistency and category typicality for the 'bird' category. Black indicates spatially 'consistent' and green/bold font indicates spatially 'inconsistent' images. All inconsistent images were either typical (italicized) or atypical (not italicized) category members. Gray dot indicates the center of all spatially consistent images in a category. (E) Example of retrieval measures for an image biased towards its category's cluster center. Solid red line indicates error. Solid blue line indicates unadjusted bias. Bias is quantified as an image's unadjusted bias as a proportion of error (solid blue line divided by red line).

General Methods

Methods described in this section pertain to all four experiments, unless specified below or in the specific methods section for each experiment.

Participants

Participants completed all experiments on Amazon Mechanical Turk (AMT; see Supplemental Methods for eligibility requirements). The University of Pennsylvania IRB approved all consent procedures. Participants were assigned either to experimental or control conditions.

Materials

Images: Stimuli consisted of 70 100 x 100-pixel color images of two superordinate semantic categories (animals and objects) on white backgrounds from the Bank of Standardized Stimuli (Brodeur, Dionne-Dostie, Montreuil, & Lepage, 2010). Piloting was conducted to choose the images in each condition to ensure that high levels of image recognition were matched across the two superordinate categories.

Image-location associations: In all experiments, participants learned and retrieved associations between images and locations on a grid. The locations of images were determined by the semantic similarity of the concepts, as assessed by separate cohorts of participants who completed either an odd-man out task (e.g. Connolly, Gleitman, & Thompson-Schill, 2007), a procedure where participants viewed three images and chose the image that was least similar to the other two (Experiments 1, 3 and 4) or a

typicality ranking task (Experiment 2). Both procedures enabled us to produce a 2-dimensional array of image locations that closely resembled the relations among concepts in semantic space, clustering according to their category membership. This 2D mapping was the basis for the image locations in the memory experiments. The center of each category's cluster was derived by computing the mean x and y coordinates over all images belonging to that cluster. See the Supplemental Methods for more details about the odd-man-out procedure (Figure S6) and the ranking procedure (Figure S7).

In all experiments, we manipulated a subset of images such that their spatial locations no longer corresponded to their category membership (Figure 1D). As an example, in Experiments 1 and 3, the 20% most typical and 20% most atypical category members in a category cluster were assigned a new, random location, with the constraint that the location was closer to another cluster center than to its original cluster center. The remaining 60% of images were left in place, so that participants would be able to learn that different categories were generally associated with a particular spatial location. Thus, in total, 42 images were associated with locations that were consistent with their semantic similarity ('spatially consistent'), and 28 were displaced to a random location ('spatially inconsistent'). Of the 28 spatially inconsistent images, 14 were typical category members and 14 were atypical category members. Finally, the displays for animals and objects were arranged on the left and right sides of the screen, randomized for each participant. Thus, locations for most images were spatially consistent with semantic knowledge (e.g. several birds were located in a cluster), but some images were inconsistent (a few birds were located closer to other clusters of animals than to the other birds; Figure 1B-C).

191 In each of the four experiments, the above methods were applied to subjects in
192 the experimental group. In the control group, the images paired with each location were
193 shuffled separately for animals and objects such that both groups viewed the same
194 locations, but the images did not cluster by category. In other words, the locations that
195 had originally been associated with spatially (in)consistent or (a)typical category
196 members were associated with random images, rendering these conditions
197 meaningless. This control group ensures that any effects observed in the experimental
198 group are driven by differences in the spatial consistency and category typicality of
199 images relative to their semantic category, rather than idiosyncrasies in the stimulus
200 display (e.g., spatial clustering).

202 **Procedure**

203 *Overview:* All experiments comprised an encoding phase and a retrieval phase,
204 separated by a 5-minute break when participants were free to complete other tasks or
205 internet browsing (Figure 1A). Before beginning encoding, participants were presented
206 with a white 600 x 1200 pixel rectangle with light gray gridlines spaced to form 50 x 50
207 pixel grids. The size of the grid was derived from browser measurements of past AMT
208 participants collected from pilot data to increase the likelihood that a participant could
209 view the entire screen without zooming out. Participants were instructed to adjust the
210 size of their browser, without zooming, so they could see the entire grid. The experiment
211 would not advance until the entire grid was visible.

Encoding: On each trial, participants viewed an image beneath the grid and a red dot on the grid corresponding to that image's location. They were instructed to drag each image onto the dot, to click the mouse button or press the 'enter' key once the image was positioned over the dot, and to try to remember each image's location for a later memory test. After this movement, the participant immediately advanced to the next trial. Trials were self-paced, and participants were unable to proceed to the next trial if they had not moved the image directly over the red dot. To ensure sufficient memory for the locations, all trials were presented three times, in separate blocks. The order of trials was randomized for each participant, separately for each block. The encoding instructions were followed by two practice trials to familiarize participants with the task before beginning encoding.

Retrieval: The timing and task were identical to those from the encoding phase, but with no red dot marking the location of the image. Participants were instructed to drag the image to its associated location and to make their best guess if they had forgotten it. The trial order was randomized for each participant. In experiments 2 – 4, participants also made confidence ratings and in Experiment 3, they also completed an exemplar memory test. These procedures are described in the Methods sections specific to that experiment.

Statistical analyses

We developed two measures to quantify memory accuracy (error) and the influence of category knowledge (bias) for each image (Figure 1E). Error was defined as the

Euclidian distance between an image's encoded location and its retrieved location, where greater values indicate worse memory, and perfect memory would correspond to an error of 0. Bias was defined as the proportion of total error in the direction of an image's category cluster. To compute this, we first found each image's unadjusted bias by subtracting the Euclidean difference between its encoded location and its cluster center from the Euclidean difference between its retrieved location and cluster center. Then, we divided this unadjusted bias by the amount of error for the image. Thus, a bias score between 0 and 1 indicates that retrieval is biased towards the image's cluster center, and a score between 0 and -1 indicates that retrieval was biased away from the cluster center. These two measures are statistically independent, such that two memories with the same amount of error could differ in whether their retrieval was biased towards or away from their respective cluster centers.

Both measures were averaged across trials, by spatial consistency (consistent vs. inconsistent), and then by category typicality (atypical vs. typical). Effects on average error and bias were assessed with two-tailed paired t-tests and repeated measures ANOVAs. We report effect sizes for all significant effects, including partial η^2 for main effects or interactions of ANOVAs and Cohen's d for effect sizes of within-subject comparisons. The equation used to calculate Cohen's d accounted for the high correlations across these within-subject conditions (Lakens, 2013; Goulet-Pelletier & Cousineau, 2018):

$$d = \frac{M_2 - M_1}{\sqrt{S_1^2 + S_2^2 - 2r S_1 S_2}}$$

M_1 and S_1 are the mean and standard deviation of one condition, M_2 and S_2 are the mean and standard deviation of the other condition, and r is the correlation between the

two. Bootstrapped 95% confidence intervals for these effect sizes were generated as well. Considering the correlation between conditions results in effect sizes that are more representative of the reported within-subject statistical tests and are comparable across the four experiments reported here, but it is important to note that such effect sizes are inflated compared to effect sizes from between-subject designs and thus may be less generalizable to other experiments in the literature (Lakens, 2013).

In Experiments 2 – 4, participants rated their confidence in their memory for the locations, and in Experiments 3, participants also completed an exemplar memory test. Error and bias were analyzed as a function of these behavioral measures. Because the options were not consistently used (e.g. some participants never chose ‘Forgot item’ as a confidence response), resulting in unequal amounts of data in each confidence bin, linear mixed-effects models were used to investigate how confidence or exemplar memory related to error and bias. Participant intercepts and slope terms for each included predictor variable were modeled as random effects. The significance of a given contrast was obtained using Satterthwaite approximate degrees of freedom, resulting in F or t statistics and corresponding p values. Estimated marginal means (EMMs) were computed to test their simple effects. Tests of simple effects were corrected for multiple comparisons with a Bonferroni correction, depending on the number of tests conducted. Where this correction is applied, the raw p -values are reported alongside the corrected α and number of tests conducted. Figures 3B, 3D, and 4C-D, which visualize the results of mixed-effects models, display averages across trials within participants for each condition for easier interpretation. Because there is no clear precedent for generating standardized effect sizes for mixed-effects models, we computed Cohen’s d for all

pairwise contrasts of participants' average error and bias separately at each level of confidence and exemplar memory accuracy (Supplemental Results, Figure S4).

Table 1. Similarities and differences across the four experiments

	Experiment 1	Experiment 2	Experiment 3	Experiment 4
Images	70 animals and objects	160 animals and objects	70 animals and objects with similar lures	70 exemplars of 6 objects
Categories	3 animal and 3 object categories, derived from odd-man-out	4 animal and 4 object categories, pre-determined	Same as Exp 1	3 vehicles and 3 household objects, arbitrary colors
Typicality	Derived from odd-man-out	Derived from list ranking task	Same as Exp 1	Distance between image color and the center color of its object set
Locations	Derived from odd-man-out	Clustered by categories, locations evenly distributed	Same as Exp 1	Same as Exp 1
Retrieval	Drag image to encoded location	Same as Exp 1	Choose encoded image, drag to location	Same as Exp 1
Confidence	None	Rate confidence of location	Rate confidence of image Rate confidence of location	Rate confidence of location

Experiment 1

In Experiment 1, participants encoded image-location associations, where the location of each image was either spatially consistent or spatially inconsistent with its category membership. This experiment was designed to test two predictions: (1) retrieval of an

image's location would be more accurate if its encoded location was spatially consistent with its category membership, by being located near other category members, and (2) for images whose locations were not spatially consistent with their category membership, retrieval of a typical category member would be more biased towards its category's cluster center, relative to an atypical one.

Methods

Participants: 70 participants were equally divided into the experimental group (N = 35; 15 females; mean age = 38.9; SD = 10.9; range 21-71 years) and the control group (N = 35; 16 females; mean age = 37.1; SD = 10.8; range 20-61 years). Participants were paid \$5 upon completion of the experiment.

Results

Spatial consistency: We first tested the prediction that location memory would be more accurate for images that were near its category center relative to images in random locations (Figure 2A). We computed a 2 (group: experimental, control) x 2 (spatial consistency: consistent, inconsistent) ANOVA which revealed a main effect of spatial consistency $F_{(1,68)} = 26.96, p < .001, \eta_p^2 = .28$, no main effect of group, $F_{(1,68)} = 0.75, p = .39, \eta_p^2 = .01$, and a significant interaction between group and spatial consistency, $F_{(1,68)} = 18.10, p < .001, \eta_p^2 = .21$. This interaction reflected more error for spatially inconsistent images relative to consistent images in the experimental group, $t_{(34)} = -7.31, p < .001, d = -1.24$, but not in the control group, $t_{(34)} = -0.61, p = .54, d = -0.10$, where images did not cluster by category (Figure 2B). Location memory was more accurate for

images that were located near their category centers relative to those that were in random locations, suggesting that over the course of the experiment, participants learned that different categories were likely to be located in certain parts of the grid, and the use of this knowledge aided memory for images whose locations matched this spatial organization.

Category typicality: As a reminder, in cases where the location of an image was not aligned with its category membership, we predicted that retrieval of typical category members would be biased towards their category center (Figure 2C). To test this prediction, we conducted a 2 (group: experimental, control) x 2 (category typicality: typical, atypical) ANOVA with bias of spatially inconsistent images as the dependent variable. We found no reliable main effect of typicality, $F_{(1,68)} = 3.57$, $p = .06$, $\eta_p^2 = .05$, or group, $F_{(1,68)} = 2.06$, $p = .16$, $\eta_p^2 = .13$, but a reliable interaction, $F_{(1,68)} = 11.69$, $p = .001$, $\eta_p^2 = .15$, (Figure 2D). This interaction reflected greater bias for typical category members relative to atypical category members in the experimental group, $t_{(34)} = 3.52$, $p = .001$, $d = 0.60$, but not the control group, $t_{(34)} = -1.16$, $p = .25$, $d = -0.20$. As predicted, a larger proportion of the error in the placement of typical category members was in the direction of their category clusters, relative to the error of atypical category members.

We were concerned that these effects might have arisen simply because typical images were placed more centrally in the grid, which happens to be close to most category clusters, while atypical images were placed at edges of the grid far from the clusters. To test this possibility, we computed each image's average bias towards the two other clusters in the category. A similar group x typicality ANOVA found no main

effects or interaction (all $F < 0.07$, all $p > .80$). This suggests that participants' retrieval of typical category members was biased specifically towards the cluster center corresponding to their category.

Figure 2 Experiment 1 **(A)** We predicted that images whose locations were spatially consistent with their category (e.g. located near other category members) would be remembered more accurately than images in random locations. Gray circle indicates the center of a category cluster. Arrows indicate the encoded and retrieved locations of images from that category. Shorter arrows signify more accurate memory. **(B)** Average error as a function of spatial consistency, where greater values indicate larger errors in location memory. Scrambled 'consistent' and 'inconsistent' conditions in the control group indicate error for images that were randomly assigned to the spatially consistent and inconsistent locations in the experimental group. **(C)** Of all spatially inconsistent images, we predicted that typical category members would be retrieved closer to their category center relative to atypical members. **(D)** Average bias by category typicality and group, where > 0 indicates retrieval closer to the category center than originally encoded and < 0 indicates retrieval away. **(B, D)** Scrambled 'typical' and 'atypical' conditions in the control group indicate images randomly assigned to the locations of typical and atypical category members in the experimental group. Gray dots indicate participants. Error bars indicate standard error of the mean (SEM) across participants. $** p < .01$; $*** p < .001$.

After confirming that bias in memory differed according to an image's category typicality, we next explored whether category typicality influenced memory accuracy (Figure S1). To do this, we entered the average error of spatially inconsistent images

into a 2 (group: experimental, control) x 2 (category typicality: typical, atypical) ANOVA. This revealed no main effect of group, $F_{(1,68)} = 0.02$, $p = .88$, $\eta_p^2 = 0.004$, or of typicality, $F_{(1,68)} = 0.79$, $p = .38$, $\eta_p^2 = .01$, but a reliable interaction, $F_{(1,68)} = 4.44$, $p = .04$, $\eta_p^2 = .06$. This interaction reflected greater error for typical images relative to atypical images in the experimental group, $t_{(34)} = 2.34$, $p = .03$, $d = .40$, but not in the control group $t_{(34)} = -0.79$, $p = 0.43$, $d = -.13$, suggesting that location memory for atypical category members was more accurate relative to location memory for typical category members. Taken together, this suggests that the structure of a category influenced both the magnitude and direction of error in location memory for images whose spatial locations did not correspond to their category membership.

Discussion

In Experiment 1, we found that participants' retrieval was more accurate for images that were spatially consistent with their category membership, in line with prior observations that new memories are enhanced if they are consistent with prior knowledge. This demonstrated that participants were able to learn that the locations of many images aligned with their category membership and use this knowledge to aid retrieval of images whose locations were consistent with this organization.

Furthermore, we observed biases in location memory that reflected the use of this same knowledge of category locations. First, regardless of category membership, images that were located randomly were retrieved closer to their category's cluster center relative to their encoded location. Already, this suggests that participants' reliance on semantic knowledge distorted memory for images whose locations did not

map on the spatial organization that mirrored their category membership. Critically, we also found variation in the extent to which these memories were distorted. When sorting the spatially inconsistent images by category membership, typical category members were more biased towards their category neighbors relative to atypical ones. This finding provides novel evidence that variations in the structure of semantic knowledge, like category membership and typicality, can govern the extent of distortion in new episodic memories.

Experiment 2

Category membership and typicality in Experiment 1 were derived using a data-driven procedure, based on semantic judgments provided by a separate cohort of participants. We developed Experiment 2 as a conceptual replication with three goals. First, we aimed to investigate whether we would observe the same effects using conditions that were derived from a more validated procedure for identifying typical and atypical category members. Second, we aimed to rule out the possibility that memory was more accurate for spatially consistent images because their spatial locations were more densely clustered, increasing the likelihood of guessing the correct location. Replicating the effects observed in Experiment 1 with these changes would confirm that these effects generalize across different task parameters and an expanded set of images.

Third, we added a confidence measure to understand how the strength of memory for each image location may modulate its influence by prior knowledge. Past work has shown that weaker memory for specific events are more likely to draw on other sources of memory. One consequence of this reconstruction process is that less

confident memories are prone to more error and are more biased by category information (Persaud & Hemmer, 2016; Brady, Schacter, & Alvarez, 2018). We predicted that, if participants drew on a combination of memory of specific locations and knowledge of category locations, they would rely more on category knowledge when memories for specific locations were weak. This would result in (1) a larger difference in accuracy for spatially inconsistent versus consistent images for low-confident memories, and (2) more biased retrieval, where low-confident images would be retrieved closer to their category center (Brady et al., 2018). As we did not have strong predictions about whether confidence would differentially relate to the observed typicality effects, we conducted an exploratory analysis of their interaction.

Methods

Participants: 70 participants took part in Experiment 2, half in the experimental group (N = 35; 14 females; mean age = 38.8; SD = 10.4; range = 22-70 years) and half in the control group (N = 35; 16 females; mean age = 38.3; SD = 11.8; range = 24-72 years). Participants were paid \$10 upon completion of the experiment.

Materials: Stimuli comprised 160 100x100-pixel color images on white backgrounds (80 animals, 80 objects). These 2 superordinate categories were each divided into 4 categories with 20 images each: birds, insects, sea creatures, mammals, clothes, furniture, kitchen, and office. The categories were selected from prior studies of categorization norms (Deyne et al., 2008; Uyeda & Mandler, 1980). Category typicality was determined with a list ranking procedure completed by a separate group of

participants. See Supplemental Methods and Figure S7 for details of this procedure and the resulting rankings.

To generate images' locations, the memory grid was divided into halves with animals on one side, and objects on the other. On each side, all images were spaced uniformly apart, resulting in an even distribution of images across the grid. Each side's locations were divided into four quadrants, and the four categories were randomly assigned to different quadrants.

Like in Experiment 1, the spatial locations of a subset of images were manipulated such that their locations no longer were consistent with semantic knowledge (Figure 1C). To do this, the 15% most typical and 15% most atypical category members were swapped with the typical and atypical members of other categories such that each quadrant had an equal number of typical and atypical images from the other three categories. The remaining 70% of images were randomly assigned to locations within their category's quadrant. In total, 112 images were in locations that were spatially consistent with their category membership ('consistent'), and 48 were associated with a random location ('inconsistent'). Of the 48 inconsistent images, 24 were typical and 24 were atypical category members. The sides (animals on right or left) and quadrants were randomized for each participant.

Procedure: The timing, task, instructions, and statistical analyses were identical to those of Experiment 1, with the exception of an added confidence measure. After each retrieval trial, participants chose from four options to report the confidence in their

location memory: ‘Very confident’, ‘Somewhat confident’, ‘Guessed’, and ‘Forgot item’.
Clicking on an option automatically advanced the participant to the next trial.

Results

Spatial consistency: Like in Experiment 1, we first computed a 2 (group: experimental, control) x 2 (spatial consistency: consistent, inconsistent) ANOVA to test whether spatial consistency with category knowledge influenced the accuracy of location memory. This revealed a main effect of consistency, $F_{(1,68)} = 38.63$, $p < .001$, $\eta_p^2 = .36$, and no main effect of group, $F_{(1,68)} = 0.01$, $p = .91$, $\eta_p^2 = .008$. There was a significant interaction between group and consistency, $F_{(1,68)} = 35.33$, $p < .001$, $\eta_p^2 = .34$, explained by greater error for spatially inconsistent images relative to spatially consistent images in the experimental group, $t_{(34)} = -7.35$, $p < .001$, $d = -1.24$, but not in the control group, $t_{(34)} = -0.24$, $p = .81$, $d = -0.04$ (Figure 3A). Replicating the observations in Experiment 1, retrieval was more accurate for images located close to their category center.

We next sought to investigate how error was modulated by participants’ reported confidence. Focusing on the experimental group, we entered consistency and confidence of each trial into a mixed-effects model with error as the dependent measure. We found a strong interaction between spatial consistency and confidence, $F_{(3, 1522.36)} = 3.14$, $p = .02$, in addition to significant main effects of consistency, $F_{(1, 49.27)} = 38.77$, $p < .001$, and confidence, $F_{(3, 46.90)} = 83.18$, $p < .001$ (Figure 3B). The main effect of confidence reflected less error for more confident responses relative to less confident responses for all pairwise comparisons of confidence responses (all $t < -3.5$, all $p < .002$, $\alpha = .008$ with Bonferroni correction for 6 tests). Pairwise tests of error by

consistency for each confidence response revealed that the difference in error by consistency is greater only for less confident memories (very confident: $t_{(398.18)} = -0.52$, $p = .60$; somewhat confident: $t_{(100.17)} = -6.13$, $p < .001$; guessed: $t_{(119.95)} = -5.58$, $p < .001$; forgot item: $t_{(663.30)} = -3.70$, $p < .001$; $\alpha = .0125$ with Bonferroni correction for 4 tests), confirming our prediction of a greater use of category knowledge when retrieving weaker memories relative to strong ones.

Category typicality: As in Experiment 1, we examined how category typicality modulated bias in memory, again predicting that retrieval of typical category members would be more biased towards their category center than retrieval of atypical category members. We conducted the same 2 (group: experimental, control) x 2 (category typicality: typical, atypical) ANOVA of bias for spatially inconsistent images. This analysis revealed a significant interaction between group and typicality, $F_{(1,68)} = 4.20$, $p = .04$, $\eta_p^2 = .06$, in addition to a main effect of group, $F_{(1,68)} = 6.61$, $p = .01$, $\eta_p^2 = .28$, and no main effect of typicality, $F_{(1,68)} = 0.78$, $p = .38$, $\eta_p^2 = .01$ (Figure 3C). As in Experiment 1, the interaction reflected more bias for typical category members relative to atypical category members in the experimental group, $t_{(34)} = 2.14$, $p = .04$, $d = .36$, but not the control group, $t_{(34)} = -0.80$, $p = .43$, $d = -0.14$.

We also investigated how confidence modulated bias with a linear mixed effects linear model of confidence and typicality as predictors, focusing only on the experimental group (Figure 3D). This analysis revealed a main effect of confidence, $F_{(3, 48.69)} = 10.04$, $p < .001$. There was no reliable effect of typicality, $F_{(1, 75.45)} = 0.22$, $p = .64$, and no significant interaction between typicality and confidence, $F_{(3, 1033.28)} = 2.09$, $p =$

.10. To understand the main effect of confidence, we computed comparisons across confidence responses, collapsed over typicality ($\alpha = .008$, Bonferroni correction for 6 tests). We found that ‘very confident’ responses were less biased towards their cluster center relative to ‘somewhat confident’: $t_{(23.29)} = -3.87$, $p < .001$, and relative to ‘guessed’: $t_{(28.46)} = -3.0$, $p = .006$. Interestingly, ‘forgot item’ responses were less biased relative to ‘guessed’ responses, $t_{(18.66)} = 2.76$, $p = .01$, and relative to ‘somewhat confident’ responses: $t_{(22.61)} = 2.89$, $p = .009$, but these comparisons do not survive correction for multiple comparisons.

We next aimed to replicate the influence of category knowledge on the accuracy of spatially inconsistent images observed in Experiment 1. We conducted the same 2 (group: experimental, control) x 2 (category typicality: typical, atypical) ANOVA of average error for spatially inconsistent images (Figure S1). This revealed no effect of group, $F_{(1,68)} = 1.24$, $p = .27$, $\eta_p^2 = .19$, and a reliable main effect of typicality, $F_{(1,68)} = 9.65$, $p = .003$, $\eta_p^2 = 0.12$. This was qualified by an interaction between typicality and group, $F_{(1,68)} = 5.77$, $p = .02$, $\eta_p^2 = .08$, such that there was greater error for typical category members relative to atypical ones in the experimental group $t_{(34)} = 3.44$, $p = .002$, $d = .58$, but not in the control group $t_{(34)} = 0.59$, $p = .56$, $d = .10$. As in Experiment 1, memory for the location of typical category members was less accurate than that of atypical category members.

Figure 3 Experiment 2 **(A)** Average error by spatial consistency, where greater values indicate less accurate location memory. **(B)** Average error by spatial consistency and reported confidence in the experimental group. Statistics reflect the simple effects of a mixed-effects model. **(C)** Average bias of spatially inconsistent images by typicality and group, where > 0 indicates that trials were retrieved closer to its category cluster than originally encoded and < 0 indicates retrieval away. **(D)** Average bias by typicality and reported confidence in the experimental group. Statistics reflect results of trial-level mixed-effects models. **(A-D)** Gray dots indicate participants. Error bars indicate standard error of the mean (SEM) across participants. Scrambled conditions in the control group indicate retrieval of the images at locations to which spatially (in)consistent and (a)typical images had been assigned in the experimental group; these locations were randomly assigned images in the control group. * $p < .05$; *** $p < .001$.

Discussion

In Experiment 2, we replicated and extended the findings of Experiment 1. Across both experiments, participants were able to learn that images of a certain category were likely to appear in the same area of the grid, and this knowledge affected their retrieval of specific image locations. First, memory was more accurate if the images spatially clustered near others from the same category. For images that were randomly located

531 far from their category cluster, participants made systematic errors: memory for typical
532 category members was less accurate than for atypical ones, and a larger proportion of
533 their error was in the direction of their category's cluster center. These results were
534 observed in both experiments despite differences in the numbers and types of
535 categories, method of determining typicality, and mapping between category
536 membership and spatial location. These observations provide strong evidence for the
537 theory that episodic retrieval is supported by integrating over multiple sources of
538 information: memory for specific image-location associations, and knowledge of
539 categories and their mapping to a general location. This integration can either benefit or
540 harm memory for individual images, depending on whether these sources are in conflict.

541 The introduction of a confidence measure provided further support for this theory.
542 First, we found that for low-confident responses, error was more likely to be modulated
543 by spatial consistency such that images located far from their cluster center were
544 remembered less accurately than those located near their cluster center. However, as
545 confidence in location memory increased, there was a less of a difference in error by
546 consistency. This suggests that to retrieve stronger episodic memories, there is less of
547 a need to rely on other information, like knowledge of the clustering of the images by
548 category. When focusing on spatially inconsistent images, we found that low-confident
549 memories were more biased towards category neighbors relative to high-confident
550 memories, again consistent with the notion that less strong episodic memories will be
551 more distorted by other sources of knowledge (Brady et al., 2018). The finding that
552 memory was less biased for images which were forgotten entirely is puzzling; this effect

should be interpreted with caution as this option was used the least frequently and consequently is the most under-powered and most variable condition in this analysis.

Experiment 3

Experiments 1 and 2 suggest that the way that prior knowledge is organized can shape how new episodic memories are formed and retrieved. In particular, we find that prior knowledge biases new memories differently based on their category typicality. How does the presence of category information as an organizing structure during learning give rise to this bias? One possibility is that because typical category members are more strongly associated with other category members relative to atypical ones, interacting with a typical category member automatically brings to mind richer category information, resulting in less of a need to deeply encode or attend to its idiosyncratic features. This difference in processing may make encoding of typical category members more efficient, but at a cost to memory for other features that are unique to the encoded event.

This line of reasoning was inspired by observations that stimuli are often better remembered when they violate or are irrelevant to a salient task structure (Goodman, 1980; Love, Medin, & Gureckis, 2004; Sakamoto & Love, 2004; Bejjani & Egner, 2019). Moreover, distinct features of a stimulus can be processed differently according to whether the features align with the task structure. Evidence for this idea can be found in experiments where participants learned that certain facial attributes dictated a face's spatial location. Location memory was better for faces with these attributes, but memory for other facial attributes was impaired, suggesting that the presence of a guiding

organization during encoding aided memory for features that adhered to the organization at the cost of memory for idiosyncratic features (Sweegers & Talamini, 2014; Sweegers, Coleman, van Poppel, Cox, & Talamini, 2015). If typical images in the present experiments are thought of as more adherent to the organizational properties that determine category membership, and thus are less deeply processed, we would predict that memory for their idiosyncratic features may be impaired relative to that of atypical category members.

We tested this prediction by assessing whether memory for a different feature of the stimuli is modulated by category typicality. To do this, we adapted the procedure in Experiment 1 by adding an exemplar memory test. During retrieval, participants were tested for their exemplar memory by choosing between the encoded image and a highly similar perceptual lure. They then dragged the chosen image to its encoded location. We predicted that exemplar memory for typical category members would be worse than for atypical members in the experimental group, where category membership was related to most images' locations and thus was a salient feature for participants to learn during encoding. In the control group, where participants encoded the same images but in random locations, we expected no difference in exemplar memory by typicality.

We also conducted exploratory analyses to understand how exemplar memory interacted with location memory. Like exemplar memory, the location associated with each image can be thought of as an idiosyncratic feature of memory for the animals and objects, because the locations are newly learned and specific to the context of the experiment. Importantly, for spatially inconsistent images, this feature is in direct conflict with the organizational scheme guiding image locations. Already, our findings in

Experiments 1 and 2 are consistent with this notion when considering the location of the spatially inconsistent images as an idiosyncratic detail. Memory for the locations of typical category members was less accurate and more biased than memory for locations of atypical category members, perhaps because their locations were less deeply encoded. Thus, we predicted that poor exemplar memory would be related to even stronger bias for typical category members, as memory for both features may be correlated within each image-location association.

Methods

Participants: 230 participants took part in Experiment 3, divided into the experimental group (N = 115; 44 females; mean age = 35.3; SD = 8.4; range = 22-63 years) and the control group (N = 115; 55 females; mean age = 36.7; SD = 10.0; range = 19-67 years). See Supplemental Methods for the procedure used to determine the number of participants recruited. Participants were paid \$5 upon completion of the experiment.

Materials: Experiment 3 was designed to be as similar as possible to Experiment 1, while adding exemplar memory and confidence measures during retrieval. Thus, encoded stimuli consisted of 70 color images on white backgrounds (35 animals, 35 common objects) and these stimuli were shown during retrieval along with 35 animal lures and 35 object lures. The images were taken from a variety of public datasets (Brodeur et al., 2010; Konkle & Caramazza, 2013; Russo et al., 2018; Stark, Yassa, Lacy, & Stark, 2013). The 70 animals and objects presented during encoding corresponded to those in Experiment 1, but the images representing each animal and

object were replaced by images drawn from the datasets published by Stark and colleagues, which feature perceptually matched pairs of images commonly used in behavioral studies examining pattern separation (Kirwan, Jones, Miller, & Stark, 2007). If an image from Experiment 1 did not have a corresponding pair of images in this database, a second image was found from a different database or from the internet and matched with the one used in Experiment 1. Piloting conducted with 35 pilot participants demonstrated that there was no difference in exemplar memory between typical and atypical images and that accuracy for a given image was not at ceiling or at floor.

Procedure: The timing, task, and instructions were identical to that of Experiment 1, except for the retrieval task. On each retrieval trial, a similar lure appeared next to the encoded image (right/left presentation randomized). Participants were instructed to choose the image they had encoded, drag it to its location, and confirm their answer by clicking continue or pressing the space bar (Figure 4A). Then, participants completed two confidence measures. First, they assessed confidence for the image they chose ('Very confident', 'Somewhat confident', 'Completely guessed'). Next, they assessed confidence of their retrieved location ('Very confident', 'Somewhat confident', 'Completely guessed'). See the Supplemental Results for analyses of exemplar memory, error (Figure S2B), and bias (Figure S3B) by confidence.

Results

Exemplar memory: We first tested the prediction that the image details of atypical category members would be more deeply encoded than those of typical category

members. To do this, we compared exemplar memory as a function of category typicality. As a reminder, we predicted that a difference in exemplar memory by typicality would only be present in the experimental group, where category membership was related to most images' locations and thus was a salient feature for participants to learn and use. We quantified exemplar memory as the proportion of trials in which participants chose the correct image. Note that in this analysis, in contrast to all other analyses conducted up to this point, typicality in the control group refers to the true typicality of the category members, not of the images that were located in the positions assigned to typical category members in the experimental group.

As we predicted, we found that atypical category members were more accurately recognized than typical ones in the experimental group, $t_{(114)} = 2.96$, $p = .004$, $d = .28$, but not in the control group, $t_{(114)} = 0.94$, $p = .35$, $d = 0.09$ (Figure 4B). When comparing across groups, the experimental group exhibited better exemplar memory for atypical category members, $t_{(228)} = -3.10$, $p = .002$, $d = -0.41$, and to a lesser extent for typical ones $t_{(228)} = -1.95$, $p = .05$, $d = -0.26$. However, a 2 (group: experimental, control) x 2 (typicality: typical, atypical) ANOVA did not reveal a significant interaction between group and typicality, $F_{(1,228)} = 1.95$, $p = .16$, $\eta_p^2 = .008$, so differences in exemplar memory by typicality across the groups should be interpreted with caution. This ANOVA also revealed a significant main effect of group, $F_{(1,228)} = 8.07$, $p = .005$, $\eta_p^2 = .12$, and of typicality, $F_{(1,228)} = 7.48$, $p = .007$, $\eta_p^2 = .03$. In summary, when images were presented in a context where category membership was relevant to the location memory task, participants exhibited better memory for the image details of atypical category members relative to typical ones.

668

669 *Spatial consistency:* Before considering how exemplar memory influenced location
670 memory accuracy, we first confirmed that retrieval of spatially consistent images was
671 more accurate than retrieval of images in random locations, replicating our observations
672 in Experiments 1 and 2 (see Supplemental Results). We next explored whether
673 exemplar memory and consistency interacted to influence accuracy, focusing on the
674 experimental group. To do this, we computed a mixed-effects linear model with error as
675 the dependent variable and spatial consistency, exemplar memory accuracy, and their
676 interaction as independent variables (Figure 4C). Exemplar memory reliably related to
677 error, $F_{(1, 123.6)} = 20.57, p < .001$. There was no reliable interaction between exemplar
678 memory and consistency, $F_{(1, 6178.8)} = 3.55, p = .06$. In post-hoc comparisons ($\alpha = .0125$
679 when Bonferroni-corrected for 4 tests), we found that for spatially inconsistent images,
680 error was reliably greater when exemplar memory was incorrect relative to when
681 exemplar memory was intact, $t_{(430.92)} = -4.32, p < .001$, while for spatially consistent
682 images, this difference did not survive correction for multiple comparisons $t_{(234.77)} = -$
683 $2.35, p = .02$. At the same time, there was greater error for spatially inconsistent relative
684 to consistent images regardless of exemplar memory accuracy (exemplar memory
685 correct: $t_{(187.92)} = -8.14, p < .001$, exemplar memory incorrect: $t_{(955.07)} = -7.10, p < .001$).
686 In some, exemplar memory accuracy was related to location memory only for spatially
687 inconsistent images, with worse performance on the exemplar test relating to less
688 accuracy in location memory.

689

Category typicality: After replicating the observation from Experiments 1 and 2 that typical category members were retrieved closer to their category center than atypical category members (see Supplemental Results), we next tested whether exemplar memory and typicality interacted to influence bias in location memory (Figure 4D). We predicted that typical category members with poor exemplar memory would be more biased than ones with intact exemplar memory. We also conducted exploratory comparisons of bias by typicality separately for correct and incorrect exemplar memory ($\alpha = .0125$, 4 tests). Contrary to our prediction, we found no reliable difference in bias by exemplar memory accuracy, neither for typical category members, $t_{(306.43)} = 0.38$, $p = .70$, nor atypical category members $t_{(316.27)} = -0.86$, $p = .39$. When considering images that were correctly remembered, retrieval was more biased for typical relative to atypical category members, $t_{(192.84)} = 4.52$, $p < .001$. In contrast, there was no reliable difference of typicality for images with incorrect exemplar memory, $t_{(830.02)} = 1.64$, $p = .10$. However, we found no interaction between exemplar memory and typicality, $F_{(1, 3069.36)} = 0.87$, $p = .35$, so differences in bias by category typicality should be interpreted with caution. Finally, there was no reliable main effect of exemplar memory, $F_{(1, 101.27)} = 0.12$, $p = .73$. In sum, when participants remembered the details of the images, typical images were retrieved closer to their category center relative to atypical images, but when participants forgot the exemplar, this difference in bias by category typicality was attenuated.

Figure 4 Experiment 3. **(A)** Retrieval instructions and display. **(B)** Performance on the exemplar memory test by group and category typicality. **(C)** Average error in the experimental group, by spatial consistency and by performance on the exemplar memory test (correct versus incorrect). Statistics reflect results of trial-level mixed-effects models. **(D)** Average bias by typicality and performance on the exemplar memory test in the experimental group, where values > 0 indicate that trials were retrieved closer to neighbors than originally encoded and values < 0 indicate retrieval away from neighbors. **(B-D)** Statistics reflect simple effects that survive a Bonferroni correction for 4 comparisons ($\alpha = 0.0125$). Gray dots indicate participants. Error bars indicate SEM. ** $p < 0.01$; *** $p < 0.001$.

Discussion

In Experiment 3, we sought to understand whether differences in depth of processing led to differences in how participants remembered typical and atypical category members. We found that, when category information was salient and useful during

encoding, there was better memory for the image details of atypical category members over typical ones. This suggests that the idiosyncrasies of typical category members are more poorly remembered than those of atypical category members, consistent with the notion that typical category members may be processed less deeply and more efficiently than atypical ones. Critically, this difference in processing occurred only in an encoding context where category information was made more salient by the associated spatial configuration. In the control group, where category information did not dictate the locations of images, there was no difference in exemplar memory for typical and atypical category members. Note that while these results are consistent with our predictions, the lack of a reliable interaction prevents us from strongly interpreting these differences in exemplar memory across the two groups, and more work is needed to provide evidence for this interpretation.

We also replicated the observation in Experiments 1 and 2 that images located in random locations were less accurately remembered relative to images located close to their category center. Furthermore, this difference in memory accuracy was magnified for images with incorrect exemplar memory, although the interaction between spatial consistency and exemplar memory was not statistically reliable. This gives rise to an intriguing possibility that for spatially inconsistent images, exemplar accuracy is a marker for the fidelity of each image-location association in that incorrect exemplars accompanied less accurate location memory. Alternatively, exemplar memory did not strongly modulate location memory for spatially consistent images, perhaps because participants could rely on prior knowledge to guide retrieval regardless of the fidelity of their memory of the specific image and its location.

747 Interestingly, exemplar memory also influenced how category typicality
748 influenced bias, with stronger bias towards category neighbors for typical category
749 members relative to atypical ones, but only for images with intact exemplar memory.
750 Bias was not reliably affected by typicality for images with incorrect exemplar memory.
751 Notably, we chose our sample size based on a power analysis that included estimates
752 of exemplar memory accuracy, expecting that there would be fewer trials with incorrect
753 exemplar memory and any comparisons of typicality by accuracy would be less
754 powered when limited to trials with incorrect exemplar memory. Thus, we are confident
755 that this analysis was sufficiently powered to identify differences by typicality for trials
756 with incorrect exemplar memory. However, counter to our prediction, this difference in
757 bias was not driven by changes in memory for the typical category members, as there
758 was no indication of increased bias for typical category members with incorrect
759 exemplar memory over ones with intact exemplar memory. We speculate that typical
760 and atypical images with incorrect exemplar memory were similarly poorly encoded,
761 with less processing of their category typicality, and thus retrieval of their locations was
762 equally prone to influence by category neighbors. For stronger memories, as indicated
763 by correct exemplar memory, retrieval of typical images was more biased than that of
764 atypical images, suggesting a difference in processing that protects atypical category
765 members from the influence of category neighbors. Indeed, while not significant, the
766 retrieval of atypical category members was numerically less biased when their exemplar
767 was correctly remembered relative to when it was forgotten.

768 Interestingly, how memory for details of the exemplars affects bias seems
769 different from how reported confidence relates to bias, although both measures can be

thought of as markers of memory strength. In this experiment as well as in Experiment 2, confidence in location memory did not interact with category typicality to influence bias (see Supplemental Results, Figure S3A-B). In contrast, images with intact exemplar memory exhibited a robust difference in bias by typicality, while images whose specific exemplar was forgotten did not. We discuss this potential discrepancy in more depth in the General Discussion.

In summary, we find that encoding in the context of a particular organizational structure alters memory for individual exemplars, in particular for details that are orthogonal or in opposition to the salient structure: memory for specific images and for random locations. Together, these results provide a possible explanation for why we observe differences in bias for location memory for typical and atypical category members, and opens up new testable questions about the relationship between the use of prior knowledge and the depth or efficiency of new encoding.

Experiment 4

In the prior three experiments, we found that location memory was more biased by category knowledge for typical category members relative to atypical ones. What can such biases tell us about category typicality? One possibility is that images of typical category members are more strongly influenced by other category members because they are more strongly associated; for example, retrieval of typical words is more clustered than retrieval of atypical words in a free recall task (Bousfield, Cohen, & Whitmarsh, 1958). Alternatively, typical category members may look more similar to other category members, and this increased visual similarity may make it easier to

confuse the locations of typical category members with other images that happen to be near its cluster center. This explanation would not require prior semantic knowledge, but rather would apply to any stimuli that vary in visual similarity.

Experiment 4 aimed to adjudicate between these two possibilities. We developed a set of stimuli whose organization mimicked that of the categories employed in Experiments 1 - 3, but category typicality was determined by arbitrary assignment of colors to different manmade objects (Figure 5A). As an example, instead of using a superordinate category (e.g., birds) that comprised different basic level concepts (e.g., robins and eagles), in Experiment 4 a basic level category (e.g., lamps) comprised multiple exemplars of the concept (e.g. different styles of lamps), with an arbitrarily assigned color for the category (e.g. all lamps had a greenish hue). The color of each exemplar image was sampled from a distribution (e.g., each lamp could be more or less green). The exemplars assigned colors from the ends of this distribution were labeled 'atypical' and the exemplars assigned colors from the center of this distribution were labeled 'typical'. Thus 'typical' exemplars looked more similar to other category members relative to 'atypical' exemplars because they were closer in color. Note that this was the only sense in which the images were typical or atypical; the assignment of a particular exemplar to a specific color was randomly determined.

If typical images are retrieved closer to their similarly-colored category neighbors relative to atypical images, that would provide support for the notion that biases due to category typicality observed in Experiments 1 - 3 are driven in part by the visual similarity of features across different category members. It would also provide support for the notion that biases in memory can be driven by newly-learned, arbitrary

mappings, like colors assigned to manmade objects, rather than stable semantic information, like knowledge of animal taxonomy and object function.

Methods

Participants: 70 participants took part in Experiment 4, either in the experimental group (N = 35; 17 females; mean age = 34.6; SD = 8.1; range = 22-61 years) or the control group (N = 35; 12 females; mean age = 34.2; SD = 9.6; range = 25-64 years). Participants were paid \$5 upon completion of the experiment.

Materials: Stimuli consisted of 70 100x100-pixel images on white backgrounds (35 vehicles, 35 household objects; Brady et al., 2018). To mimic the six categories in Experiments 1 – 3, the images comprised exemplars of three vehicles (planes, trains and cars) and three household objects (chairs, lamps, and clocks).

To mimic variance in category typicality, we created variance in how similar object exemplars were within each category by changing their colors (Figure 5A). First, we assigned each category a central color by choosing six equidistant points around a 360-degree color space (i.e. each value separated by 60°). We then generated six normal distributions ($\sigma = 20^\circ$) around these points. The width of these normal distributions ensured that the range of colors assigned to each category covered a largely unique color range. Next, we pseudo-randomly sampled from each of these distributions to assign each image to a unique color that fell within its category's color range. Images with color values farthest from their category's central color were 'atypical' category members, and images with colors closest to their category's central

color were ‘typical’ category members. To ensure that the range of colors assigned to spatially (in)consistent and (a)typical conditions was consistent across categories, the normal distribution for each category was divided into 5 bins, where the breaks between bins captured cumulative probabilities bounded by the following z-statistics: [inf -1.405 -0.202 0.202 1.405 inf]. Colors for atypical images were sampled from the two bins that comprised the tails of the distribution, colors for typical images were sampled from the bin comprising the center of the distribution, and colors for all spatially consistent images were evenly sampled from the two remaining bins.

To ensure that any differences in category typicality were driven by color and not by other perceptual features of the images, the assignment of the six color ranges to the six categories and the assignment of colors to images within each category were randomized separately for 6 counterbalancing groups (See Supplemental Methods). In other words, the 6 groups viewed different combinations of image-color associations and different image exemplars associated with typical and atypical colors, minimizing the possibility that any observed influences of color typicality would be driven by idiosyncrasies of the other features of the images.

The number and locations of images in each category were exactly matched to the memory displays derived for Experiment 1. Specifically, locations that belonged to the bird category in Experiment 1 were assigned a color category with the same number of category members, and the locations of the (a)typical birds were now assigned (a)typically-colored images. Thus, in addition to learning the locations of individual exemplars of an object, participants could learn that the object corresponded to a range of colors and a general location on the grid. Spatially ‘consistent’ images were located

near images of the same object in the same color range, and ‘inconsistent’ images were in random locations. Critically, analogously to Experiments 1 and 2, the colors of half of the spatially inconsistent images were ‘typical’ or sampled from the center of that category’s color distribution, and the colors of the other half of the images were ‘atypical’, or sampled from the tails of the category’s color distribution.

Procedure: The timing, task, and instructions were identical to that of Experiment 1, with the identical confidence measure from Experiment 2. See the Supplemental Results for analyses of error (Figure S2C) and bias (Figure S3C) by confidence.

Results

Spatial consistency: We first examined whether the same differences in accuracy by spatial consistency observed in Experiments 1 - 3 would extend to stimuli organized by object type and color (Figure 5B). In line with those experiments, we predicted that memory would be more accurate for spatially consistent images relative to inconsistent ones (e.g. green lamps that were located near each other versus ones that were in random locations). A 2 (group: experimental, control) x 2 (spatial consistency: consistent, inconsistent) ANOVA revealed a significant main effect of consistency, $F_{(1,68)} = 76.87$, $p < .001$, $\eta_p^2 = .53$, and no reliable main effect of group, $F_{(1,68)} = 3.68$, $p = .06$, $\eta_p^2 = .40$. Critically, the ANOVA also revealed an interaction between group and consistency, $F_{(1,68)} = 16.52$, $p < .001$, $\eta_p^2 = 0.20$. Like in Experiment 3, both the experimental group, $t_{(34)} = -7.78$, $p < .001$, $d = -1.32$, and control group, $t_{(34)} = -4.16$, $p < .001$, $d = -0.70$, exhibited greater error for spatially inconsistent images relative to

consistent images, suggesting that the dense clustering of images in spatially consistent locations may have aided retrieval in both groups, but this difference in error by spatial consistency was greater for the experimental group relative to the control group. This suggests that the organization of images by object and color further aided memory for images whose locations were consistent with that spatial organization.

Color ('category') typicality: As a reminder, our critical prediction was that retrieval of typically colored images would be more biased towards the similarly colored exemplars of the same object relative to atypically colored images. This finding would be analogous to the biases due to category membership seen in the first three experiments. However, there was no reliable difference in bias for typical images relative to atypical images in the experimental group, $t_{(34)} = 1.46$, $p = .15$, $d = 0.25$, or in control group, $t_{(34)} = 0.76$, $p = .45$, $d = .13$ (Figure 5C). Furthermore, a 2 (group: experimental, control) x 2 (typicality: typical color, atypical color) ANOVA did not reveal a main effect of typicality, $F_{(1,68)} = 2.38$, $p = .13$, $\eta_p^2 = .03$, or a significant typicality by group interaction, $F_{(1, 68)} = 0.17$, $p = 0.68$, $\eta_p^2 = .002$. Interestingly, this analysis revealed a main effect of group, $F_{(1, 68)} = 18.75$, $p < .001$, $\eta_p^2 = 0.51$, with more bias regardless of category typicality in the experimental group relative to the control group, $t_{(68)} = 4.33$, $p < .001$, $d = 1.04$. Taken together with the error analyses, this suggests that when images were organized by color and object type, the retrieval of spatially inconsistent images was biased towards the center of their object clusters, even though their accuracy did not differ from subjects whose images were not organized by object type and color.

As typically-colored and atypically-colored images did not differ in the proportion of error that was biased towards their category cluster, it may seem like the color manipulation simply was not effective, and that participants did not meaningfully encode the colors of each image or use color information during retrieval. However, we uncovered one piece of evidence that this manipulation may have had a limited effect. When considering an image's *unadjusted* bias, we found that typically-colored images were retrieved closer to their category center relative to atypically-colored images in the experimental group, $t_{(34)} = 2.05$, $p = .048$, $d = .35$, and not in the control group, $t_{(34)} = -0.30$, $p = .76$, $d = -.05$. However, there was no reliable interaction between group and typicality, $F_{(1, 68)} = 1.91$, $p = .17$, $\eta_p^2 = 0.03$. While not robust, this provides some evidence that participants attended to the colors of each image during encoding and used this information to a limited degree during retrieval.

Finally, for comparison to Experiments 1 - 3, we also examined location memory accuracy among the spatially inconsistent images to understand how the typicality of an image's color, relative to the mean color of its object category, influenced bias in location memory (Figure S1). As a reminder, retrieval of typical category members was less accurate than retrieval of atypical category members in the prior experiments. We asked whether there were analogous differences in error by the 'typicality' of the colors assigned to each image. A 2 (group: experimental, control) by 2 (typicality: typical color, atypical color) ANOVA revealed no reliable main effects or interaction between typicality and group, all $F < 0.49$, all $p > 0.48$. The lack of an effect suggests that memory accuracy was not influenced by the typicality of an image's color.

Figure 5 Experiment 4. **(A)** Typicality determined by color. The six vertical lines on the color bar indicate the center color of six categories. The distribution indicates the range of colors sampled for all exemplars of 'lamp'. Typical and atypical lamps reflect the distance between their color and the color at the center of the lamp distribution. **(B)** Average error by spatial consistency and group. **(C)** Average bias by color typicality and group. Gray dots indicate participants. Error bars indicate SEM. *** $p < .001$.

Discussion

The aim of Experiment 4 was to understand whether the biases in memory by category typicality observed in Experiments 1 – 3 could be driven by visual similarity of the images. Over the course of encoding specific image-location associations, participants also learned that exemplars of a certain type of object, like lamps, tended to be located in certain areas of the screen and associated with a certain color. This organization influenced the retrieval of specific images, such that images in random locations were retrieved less accurately. Note that differences in accuracy here could be driven either by images clustering by object type, by color, or by a combination of the two.

The critical comparison was of bias in retrieval based on whether the arbitrary colors of encoded objects were more or less similar to the mean color of each object set. This continuous variation in color within an object set mirrors the graded manner in which category members vary in their similarity to a central tendency or prototype of each category. Analogously to the typical and atypical category members in spatially inconsistent locations in Experiments 1 – 3, images whose colors were closest or farthest from the mean color of that object were randomly located. We found weak evidence that typically colored images were retrieved closer to their category clusters, but only when employing a different bias measure that did not account for error. Moreover, in contrast to Experiments 1 – 3, color typicality did not influence accuracy or bias by their category clusters. This suggests that visual similarity alone cannot explain the bias effects observed in Experiments 1 – 3. Rather, bias in retrieval in Experiments 1 – 3 may be driven primarily by the strength of associations between category members, but also in small part by their visual similarity.

One reason why visual similarity did not robustly influence memory may be that the task was more difficult than in Experiments 1 - 3, since participants needed to encode the locations of many exemplars of the same object sets, rather locations of unique animals and objects. Differences in difficulty could also explain the strong main effect of group on bias in this experiment, where the experimental group exhibited more bias relative to the control group regardless of category typicality. However, accuracy in Experiment 4 was not reliably worse than in Experiment 1 when averaging across all conditions (see Comparisons Across Experiments), which suggests that Experiment 4 was not meaningfully more difficult. Another possibility is that the feature that gave structure to each category was based purely on color, which was newly learned and arbitrarily assigned. In contrast, images in Experiments 1 – 3 were organized by multiple features of animals and objects that likely were learned long before participants began the experiment. Moreover, features that give rise to visual similarity may also be correlated with other dimensions of similarity. For example, a cardinal and a bluejay look similar because they both have wings, a perceptual feature that also serves the same function. Thus, differences in images' typicality by color may have been less well encoded and thus did not bias retrieval as strongly as in the prior experiments.

Comparisons Across Experiments

The four experiments varied in the number of images and categories and the manner in which their locations were organized. In the following section, we provide a direct comparison of effects across the four experiments.

Average error: First, to understand whether the details of each experiment induced differences in their difficulty, we investigated whether average error across all images differed across the four experiments. We computed a 2 (group: experimental, control) x 4 (experiment: 1 – 4) ANOVA with average error as the dependent variable. This analysis revealed no main effect of experiment, $F_{(3, 432)} = 1.01$, $p = .39$, $\eta_p^2 = 0.007$, no main effect of group, $F_{(1, 432)} = 1.99$, $p = .16$, $\eta_p^2 = 0.005$, and no group by experiment interaction, $F_{(3, 432)} = 0.70$, $p = .55$, $\eta_p^2 = 0.005$. This suggests that the average memory accuracy across all images was not reliably different across the four experiments or across the experimental and control groups, despite many differences across the experiments.

Error by spatial consistency: We next investigated whether the relationship between accuracy and spatial consistency with category knowledge differed across the four experiments. To do this, we first created a difference score for each participant to capture the extent to which their accuracy was influenced by spatial consistency. To do this, we subtracted their average error for spatially consistent images from their average error for spatially inconsistent images, where greater values indicate a larger difference in error by spatial consistency. We then computed a 2 (group: experimental, control) x 4 (experiment: 1 – 4) ANOVA with this difference score as the dependent variable. This analysis revealed a strong main effect of group, $F_{(1, 432)} = 86.04$, $p < .001$, $\eta_p^2 = 0.17$, reflecting the greater difference in error by spatial consistency for the experimental group relative to the control group that was observed in all four experiments. There was also a main effect of experiment, $F_{(3, 432)} = 6.27$, $p < .001$, $\eta_p^2 = 0.04$, and no group by

experiment interaction, $F_{(3, 432)} = 1.12$, $p = 0.34$, $\eta_p^2 = 0.008$. The main effect of experiment reflected a larger difference in error by consistency in Experiment 4 relative to Experiments 1 – 3, all $t > 3.01$, all $p < .003$, and no difference amongst Experiments 1 – 3, all $t < 0.61$, all $p > .54$, when collapsing across the experimental and control groups. As a reminder, in Experiments 1 – 3, participants learned that most members of a category tended to be clustered in the same general location, while in Experiment 4, most exemplars of the same object within the same color range were clustered. As participants in Experiment 4 needed to discriminate and encode many exemplars of an object, it may be that participants' overall memory in this experiment was driven less by object and color information and more by the uneven density of spatial locations present in both the experimental and control groups. However, the lack of a reliable interaction suggests that the extent to which memory accuracy was governed by an image's spatial consistency was not meaningfully different across the four experiments. See Figure 6A for a comparison of standardized effect sizes for each group and experiment.

Bias by typicality: We next asked whether there were differences in bias by category typicality across the four experiments. To do this, we computed a difference score to capture the extent to which each participant differed in their bias by category (or color) typicality. To do this, we subtracted their average bias for atypical category members from their average bias for typical ones, such that positive values indicate more bias for typical relative to atypical category members. We then entered these difference scores into a 2 (group: experimental, control) x 4 (experiment: 1 – 4) ANOVA. This analysis revealed the expected main effect of group, $F_{(1, 432)} = 21.37$, $p < .001$, $\eta_p^2 = 0.05$, and no

reliable main effect of experiment, $F_{(3, 432)} = 0.63$, $p = 0.60$, $\eta_p^2 = 0.004$, or group by experiment interaction, $F_{(3, 432)} = 1.36$, $p = 0.26$, $\eta_p^2 = 0.009$. This suggests that despite the numerous differences across the four experiments, the extent to which the organizational structure of the images biased memory for specific images did not meaningfully differ. See Figure 6B for a comparison of effect sizes of bias by typicality for both the experimental and control groups in each experiment.

Figure 6 Effect sizes across experiments. **(A)** Standardized difference in mean error for spatially consistent images versus spatially inconsistent images. **(B)** Standardized difference in mean bias for typical versus atypical images. Points represent mean effect size and lines represent bootstrapped 95% confidence intervals. 0 on the x-axis reflects no difference in error by consistency or bias by typicality.

General Discussion

Across four experiments, we aimed to understand how variations in the organization of semantic knowledge governs distortions in new episodic memories. To do this, we developed a novel location memory task, where participants encoded associations between images and locations. Critically, most images were spatially clustered by their category membership, such that participants could learn associations between an

image's category and its spatial location, but a minority of images were located in random locations. Using a reconstruction framework, we predicted that retrieval of episodic memories may be supported by a mixture of recalled details of the original event as well as more general knowledge. Here we operationalized 'general knowledge' as the learned locations for each category of images, which could only be used if participants recruited their semantic knowledge of animal and object categories as they encoded specific image-location associations. Indeed, we found that manipulating the alignment between new memories and general knowledge influenced both the accuracy and distortion of new memories. First, memory was more accurate for images located near others from the same category, confirming learning of the category-location associations. Second, for images that were in random locations, participants made systematic errors: More typical category members were retrieved as closer to neighbors of the same category than atypical category members. These results replicated across multiple experiments despite differences in the number and type of categories presented, method of determining typicality, specific images used, and mapping between category membership and spatial location. Below, we discuss these findings through the lens of memory reconstruction, position our observations of category typicality in the context of research on the structure of semantic memory, and consider some limitations of the current design and opportunities for future work.

Memory as reconstruction

Our main findings provide strong evidence for the theory that episodic retrieval is a reconstructive process, rather than a reproductive process. In other words, the retrieval

of episodic memories is not veridical, but instead is supported by the integration of different sources of information, including (but not limited to) memory for the details of the event, prior knowledge relevant to the event, and one's expectations about what may or may not have happened (Bartlett, 1932; Schacter & Addis, 2007). In this section, we discuss several of our observations in terms of this framework: why some memories are more easily remembered than others, why some memories are systematically distorted, and how prior knowledge interacts with memory strength, operationalized here as reported confidence.

First, if a newly experienced event is consistent with prior knowledge, combining the details of that event with prior knowledge is thought to enhance its retrieval by reducing noise. In our experiments, an image located near category neighbors could be retrieved by combining memory for its location with knowledge about the general location of images from the same category, resulting in more accurate retrieval of these images' associated locations. In contrast, for images in random locations, this same integration would result in greater errors because the image's location conflicts with the locations of much of its category. Such findings are consistent with a large and diverse body of work showing that prior knowledge facilitates new memory formation and retrieval (Posner & Keele, 1968; Bransford & Johnson, 1972; Craik & Lockhart, 1972; Schulman, 1974). Our findings extend these results by showing that prior knowledge can improve encoding of new, unrelated features of a concept. In our experiments, participants mapped images onto spatial locations on a grid. These locations were not intrinsically related to the images (e.g., nothing about the concept of a 'spatula' implies that it should be located on the top right corner of a grid). However, by associating these

locations with the semantic organization of the images, participants learned to treat location as a new ‘feature’ of the image associated with its category membership. Thus, prior knowledge can help to organize the encoding of unrelated contextual details.

Another prediction from this memory reconstruction framework is that systematic errors can occur when there is conflict between prior knowledge and the formation of new memories. In these cases, integration of these two sources of information would result in a distorted memory that is somewhere between the veridical event and what would have been expected from prior knowledge. Indeed, it is well known that episodic memories can be easily distorted by many sources of information, including retroactive interference, gist-based false memory driven by interference with the surrounding context, and more (Loftus & Palmer, 1974; Roediger & McDermott, 1995). Additional evidence for distortion in memory comes from the use of continuous reports, which allows retrieval to be broken down into item-specific error and systematic influences of a particular category or structure (Huttenlocher et al., 1991; P. Hemmer & Steyvers, 2009; Persaud & Hemmer, 2016). This work demonstrates that new memories can be biased towards similar stimuli, for example, that memory for the color of an object is biased towards a canonical color. We extended this work by showing that, in contexts where semantic knowledge can aid the formation of new memories for spatial locations, memory for these locations was biased towards category members. Moreover, while we had strong predictions that category typicality would influence the direction of error, we also explored whether such influences would also result in differences in accuracy, or absolute error independent of its direction. Interestingly, by assessing error in memory as a function of typicality, we also found that typical category members were less

1114 accurately remembered in Experiments 1, 2, and 3 (Figure S1). The fact that typical
1115 images were both less accurate and more biased by category neighbors opens up
1116 interesting new questions for future research about the relationship between different
1117 sources of error in memory. At the same time, both findings provide evidence for the
1118 notion that semantic knowledge can exert an influence on new memory formation.

1119 A memory reconstruction framework also considers the relative strengths of prior
1120 knowledge and memory for specific events, such that retrieval of an event will rely more
1121 on prior knowledge if the strength of the event memory is weak relative to when it is
1122 strong (Brady et al., 2018). This may explain observations that prior knowledge only
1123 begins to influence new memory after a delay (Lewis & Durrant, 2011; Payne et al.,
1124 2012; van Kesteren, Rijpkema, Ruiter, & Fernández, 2013). One possibility for the
1125 increasing influence of prior knowledge on new memory over time is that as the details
1126 of the specific events decay, general knowledge is more strongly weighted in the
1127 reconstruction of the memory. In Experiments 2 and 3, we found an interaction between
1128 confidence and the spatial consistency of image locations with their category
1129 membership, such that the benefit of semantic knowledge (i.e. increased accuracy for
1130 spatially consistent images versus inconsistent images) was weaker for images whose
1131 locations were confidently remembered. In the same experiments, we found that more
1132 confident memories were less biased towards category members. Both observations
1133 would be predicted by the integration of specific memories and semantic knowledge in
1134 situations where specific memories are weak and prior knowledge is strong, providing
1135 additional support for the memory reconstruction framework.

Although a reconstruction framework can be used to formalize how we can integrate over any number and type of information sources to support memory, it is particularly valuable for understanding interactions between episodic and semantic memory. Although the distinction between semantic and episodic memory proposed by Tulving (1972) has long shaped their separate examination, there is ample evidence of interactions between the two systems, including demonstrations that newly learned associations can prime lexical judgments (McKoon & Ratcliff, 1979) and that the order in which a list of studied words is recalled is affected by their semantic similarity (Howard & Kahana, 2002). These and many other findings call into question whether the two systems are separate (Anderson & Ross, 1980; Greenberg & Verfaellie, 2010; McKoon, Ratcliff, & Dell, 1986) and highlight the importance focusing on the similarities and differences in the processes that underlie both systems (e.g. Cox, Hemmer, Aue, & Criss, 2018). By demonstrating that the use of semantic knowledge can systematically aid or distort memories for new events, our results add support to the notion that the two systems are constantly interacting. We take this one step farther by demonstrating that separate semantic and episodic elements of the *same event* can interact to inform memory retrieval. In our experiments, each trial was composed of multiple ‘episodic’ elements, including the visual features of an image and its spatial location, and ‘semantic’ elements, including the image’s category membership and typicality. Separately manipulating and tracking variations in these elements afforded us a unique opportunity to expand our understanding of memory reconstruction by investigating how complex semantic structures like category membership may influence new episode

formation, and by assessing episodes composed of multiple features that could differently vary in memory strength, both of which are discussed in more detail below.

One important avenue for future work is to understand *when* this reconstruction process supports memory. For instance, prior knowledge may shape how a new experience is encoded by combining event-specific and general knowledge at the time the specific event is experienced. Alternatively, event-specific and general knowledge may be separately encoded and then integrated during retrieval. Interestingly, past work has provided evidence for both mechanisms. The reconstruction theory posits that bias emerges during retrieval, when integrating the noisy, but unbiased, details of the experience with other prior knowledge (Pernille Hemmer & Persaud, 2014). Alternatively, prior knowledge may not distort memory for the event itself but instead constrains its search space during retrieval, such that retrieval is biased towards other category members because the locations near other category members are the most likely options to choose from. At the same time, however, there is also evidence that prior knowledge shapes encoding, as it can enhance reading comprehension and various perceptual tasks (Posner, Goldsmith, & Welton Jr, 1967; Bransford & Johnson, 1972; Ratcliff & McKoon, 1995), which likely do not rely on retrieval computations. Similarly, neuroscientific evidence suggests prior knowledge influences both encoding and retrieval of new memories. Recent work in humans and rodents has revealed a role for the hippocampus and prefrontal cortex when encoding experiences that are related to prior knowledge (Tse et al., 2011; van Kesteren, Fernández, Norris, & Hermans, 2010; Bein, Reggev, & Maril, 2014), but also when retrieving them (van Kesteren, Rijpkema, Ruiter, & Fernández, 2010). Taken together, this suggests that prior

knowledge likely plays an important role at both encoding and retrieval. Pinpointing when biases in new memories emerge may benefit from causal manipulations that can isolate encoding and retrieval computations.

An important feature of our design is that retrieval could be quantified as a continuous variable, allowing us to quantify both the direction and magnitude of error for each trial. However, this measurement is unable to disentangle the types of error in memory that underpin the observed differences in bias by category typicality; for instance, bias in memory may be characterized as either a relatively small distortion, where error is minimal but systematically influenced by category knowledge, or as a swap error, where bias towards an image's category center is due to conflating memory for its location with the location of another image near the cluster center. It seems likely that location memory for typical category members would be more likely to be swapped in such a manner, thus explaining the increased bias towards the category center.

Although we did not originally design the reported experiments to adjudicate between these possibilities, we attempted to characterize participants' retrieval in a manner that captured both types of error by binning each retrieved location as a function of the relative distance between its encoded location and cluster center (Figure S5). We found that across all experiments in which stimuli were organized by category, retrieval was closer to their encoded locations than to their respective cluster centers. Although typical category members were overall more likely to be retrieved closer to their category center relative to atypical ones, they were still most likely to be retrieved closer to their actual encoded locations. While this exploratory analysis should be interpreted with caution, it hints at the possibility that the difference in bias by category typicality

was driven by small differences in the magnitude of error, rather than qualitative differences in how these category members were retrieved.

Possible explanations for differential bias by category typicality

We chose to employ category typicality as a means to quantify how semantic knowledge influences new memories, as typicality underscores many neural and behavioral phenomenon (Patterson, 2007), including decision response times and recognition (E. H. Rosch, 1973; E. Rosch et al., 1976) as well as variation in deficits in semantic dementia (Bozeat et al., 2003; Rogers, Patterson, Jefferies, & Lambon Ralph, 2015). More importantly, category typicality directly influences new memory formation. When encoding lists of exemplars from a certain category, typical category members are more likely to be recalled (Schmidt, 1996) and more likely to be falsely inserted when they are not included in the list (Roediger & McDermott, 1995; Smith, Ward, Tindell, Sifonis, & Wilkenfeld, 2000). Of particular relevance are observations of asymmetries in linking new information to typical and atypical category members. For instance, fast mapping, a phenomenon by which learning the name of a novel object is facilitated by the presence of a known foil (Carey & Bartlett, 1978; Coutanche & Thompson-Schill, 2014) is more likely to occur when the foil is a typical image relative to an atypical image (Coutanche & Koch, 2017). Similarly, asymmetries by typicality are seen when generalizing new knowledge about a category. In these category-based induction experiments, participants are more likely to attribute new properties of an exemplar to members of the same category if the exemplar is a typical category member (Rips, 1975; Osherson et al., 1990; Dunsmoor & Murphy, 2014). Our

1227 experimental manipulation demonstrates a complementary effect – having acquired new
1228 knowledge about a category (e.g. most birds are located in a certain part of the grid)
1229 participants were more likely to distort their memory of typical images such that their
1230 locations complied more with this general knowledge.

1231 Upon observing that category typicality explained variance in distortions in new
1232 memories, we developed Experiments 3 and 4 in order to understand what properties of
1233 semantic memory drive such distortions. One possibility is that relative to atypical
1234 category members, typical category members are more strongly influenced by the
1235 location of members of the same category because they are more densely connected,
1236 and activating a typical category member is more likely to activate information about the
1237 rest of the category (Anderson, 1983). A spreading activation account would mirror
1238 observations that participants are more likely to cluster the recall of typical category
1239 members relative to atypical ones (Bousfield et al., 1958). In our experiment, greater
1240 spread of activation for typical category members would mean that learning about a
1241 typical category member's location would activate more representations of category
1242 members with conflicting locations. As a result, their retrieval be more prone to
1243 interference from these conflicting locations. Alternatively, because typical category
1244 members by definition share more features with others (E. Rosch & Mervis, 1975), they
1245 may be more confusable, such that locations of typical category members may have
1246 been more likely to be swapped for the location of a category neighbor that happened to
1247 be near its cluster center. This explanation could be applied to any set of stimuli that
1248 vary in visual similarity. Indeed, in an experiment where many exemplars of a category
1249 (e.g. different backpacks) were assigned colors sampled from a distribution around a

central color, memory for the color of each exemplar was biased towards the central color (Brady et al., 2018). In Experiment 4, we assigned exemplars of different manmade objects with colors that determined their typicality. We found that, relative to atypically colored images, typically colored images were retrieved closer to their respective cluster, but only when using a measure of unadjusted bias, unlike what was used in Experiments 1 - 3. It is worth noting that effects observed in Experiment 4 may be weaker because the object-color associations were new and arbitrary, and thus may be more difficult to retain relative to the well-known features that determined typicality in Experiments 1 - 3. Regardless, this result suggests that the observed differences in bias by category typicality is driven in some small part by differences in visual similarity, but visual similarity is likely one of many features that differentiates typical and atypical category members and gives rise to differences in their bias.

Another possibility is that because typical category members are the closest match to their category, they are already closely associated with a rich trove of semantic knowledge, so there is less of a need to encode other, idiosyncratic details. This may result in more efficient encoding in circumstances where the information is consistent with prior knowledge, but may impair in-depth processing of any other details (Sweegers & Talamini, 2014; Sweegers et al., 2015). In Experiment 3, we added an exemplar memory test as a way to understand the depth of encoding, or memory strength, of typical and atypical category members. Performance on this test depended on the encoding context: When category information predicted the locations of most images, memory for atypical category members was greater than memory for typical ones, but when category information was not relevant during encoding (in the control

group), there was no difference in exemplar memory by typicality. This suggests that typical category members may be processed in a way that discounts their idiosyncratic features when category membership is salient during learning. Alternatively, atypical images may be more memorable because their distinctiveness from other category neighbors draws attention to their specific details and preserves their memory as a result. Consistent with this interpretation, schema-inconsistent memories are sometimes better remembered than schema-consistent ones (e.g., Bower, Black, & Turner, 1979; Sakamoto & Love, 2004). This suggests that the details of memoranda are better remembered if they are sufficiently differentiated from the salient organizational structure guiding learning. This account may also explain the observed differences in bias when considering exemplar memory accuracy: when exemplar memory was preserved, typical images were retrieved closer to their category neighbors relative to atypical images, but when exemplars were forgotten, this difference was no longer reliable. It may be that for atypical category members, worse exemplar memory is associated with a larger influence of semantic knowledge, and this larger influence negates the difference in bias between typical and atypical category members. A caveat of this interpretation, however, is that there was no reliable difference in bias for atypical category members as a function of exemplar memory, as would be predicted by this account, although the direction of the effect is numerically consistent. Future work that systematically varies the degree of similarity between memoranda and their overarching organization could help to better adjudicate between these two accounts.

Interestingly, such a difference in processing the details of the exemplars seems to be unrelated to processing details of the location. We reported that, in Experiments 2

and 3, less confident responses were more biased towards category centers, with typical category members showing greater bias than atypical ones, but confidence in location memory did not interact with category typicality to influence bias (Figure S3A-B). In contrast, images with intact exemplar memory exhibited a robust difference in bias by typicality, while images whose specific exemplar was forgotten did not. At first glance, these results seem discrepant, as exemplar memory and location confidence both seem to index the strength of memory for the specific image-location association, suggesting both that low-confident responses or incorrect exemplar memory should give rise more bias due to a stronger influence of semantic knowledge. However, our results suggest that memory for different *elements* of an event may differ in their susceptibility to bias from prior knowledge. Memory for the specific exemplar may be a better index of the ‘semantic’ element of each memory, where weaker memory disrupts the biasing effect of other category members, while location confidence corresponds to an ‘episodic’ element, which is more prone to distortion by category members if it is weak. Analogously to prior work showing that episodic memory can be affected by multiple sources of prior knowledge, like the average size of an object and the average size of its category members (P. Hemmer & Steyvers, 2009), it may be that memory of an event is composed of multiple, separable sources of event-specific information that differently interact with general or semantic information.

Our priority was to establish whether any aspect of semantic memory could influence distortions in episodic memory. To achieve this aim, we prioritized developing a distinction between category members that was robust across participants, choosing to leverage typicality within categories for the reasons described above. However,

typicality is one of many ways that category membership is organized and measured. The graded structure of categories is also well characterized by the frequency that its members are encountered in the environment; their central tendency, or similarity to other category members (or, inversely, their distinctiveness from all other category members); their accessibility, or output dominance, characterized as the frequency with which an item is produced as an example of a category. These characteristics are often highly correlated, such that typical category members are more easily accessible (Schmidt, 1996). Indeed, past observations of clustering in free recall are well explained by category typicality, but more variance is explained by accessibility (Smith et al., 2000). Because we did not control for familiarity or accessibility when choosing our stimuli, it is possible that these dimensions of semantic knowledge could be used to obtain similar biases in episodic memory. Either way, our results demonstrate that the internal structure of a category can explain the extent of distortions in new episodic memories. One promising future avenue of research may to understand potential commonalities and distinctions in how semantic knowledge distorts new memories along these multiple dimensions.

Conclusions

We have presented an investigation of the costs and beneficial influences that semantic knowledge exerts on new episodic memories. This work demonstrates that semantic knowledge and episodic memory are closely intertwined and offers an opportunity to better understand how information supported by these two systems is integrated in the context of new memory formation.

1342 **Data and Code Availability**

1343 Stimuli, raw data, and analysis code that support the findings of the four memory
1344 experiments will be made publicly accessible upon acceptance of the manuscript. Raw
1345 data and analysis code dedicated to stimulus development will be made available upon
1346 request.

1347

1348 **Acknowledgements**

1349 This research was funded by NIH F32 NS108511 to A.T. and NIH R01 DC009209 to
1350 S.T.S.

References

- Addis, D. R., Pan, L., Vu, M.-A., Laiser, N., & Schacter, D. L. (2009). Constructive episodic simulation of the future and the past: Distinct subsystems of a core brain network mediate imagining and remembering. *Neuropsychologia*, 47(11), 2222–2238.
- Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior*, 22(3), 261–295.
- Anderson, J. R., & Ross, B. H. (1980). Evidence against a semantic-episodic distinction. *Journal of Experimental Psychology: Human Learning and Memory*, 6(5), 441–466.
- Bartlett, F. C. (1920). Some experiments on the reproduction of folk-stories. *Folklore*, 31(1), 30–47.
- Bartlett, F. C. (1932). A theory of remembering. In *Remembering: A study in experimental and social psychology*. New York: Cambridge University Press.
- Bein, O., Reggev, N., & Maril, A. (2014). Prior knowledge influences on hippocampus and medial prefrontal cortex interactions in subsequent memory. *Neuropsychologia*, 64, 320–330.
- Bejjani, C., & Egner, T. (2019). Spontaneous task structure formation results in a cost to incidental memory of task stimuli. *Frontiers in Psychology*, 10.
- Bousfield, W. A., Cohen, B. H., & Whitmarsh, G. A. (1958). Associative clustering in the recall of words of different taxonomic frequencies of occurrence. *Psychological Reports*, 4, 39–44.
- Bower, G. H., Black, J. B., & Turner, T. J. (1979). Scripts in memory for text. *Cognitive Psychology*, 11(2), 177–220.
- Bozeat, S., Ralph, M. A. L., Graham, K. S., Patterson, K., Wilkin, H., Rowland, J., ... Hodges, J. R. (2003). A duck with four legs: Investigating the structure of

1377 conceptual knowledge using picture drawing in semantic dementia. *Cognitive*
1378 *Neuropsychology*, 20(1), 27–47.

1379 Brady, T. F., Schacter, D. L., & Alvarez, G. A. (2018). The adaptive nature of false
1380 memories is revealed by gist- based distortion of true memories. *PsyArXiv*.

1381 Brainard, D. H., Longère, P., Delahunt, P. B., Freeman, W. T., Kraft, J. M., & Xiao, B.
1382 (2006). Bayesian model of human color constancy. *Journal of Vision*, 6(11), 10–
1383 10.

1384 Bransford, J. D., & Johnson, M. K. (1972). Contextual prerequisites for understanding:
1385 Some investigations of comprehension and recall. *Journal of Verbal Learning*
1386 *and Verbal Behavior*, 11(6), 717–726.

1387 Brodeur, M. B., Dionne-Dostie, E., Montreuil, T., & Lepage, M. (2010). The Bank of
1388 Standardized Stimuli (BOSS), a new set of 480 normative photos of objects to be
1389 used as visual stimuli in cognitive research. *PLOS ONE*, 5(5), e10773.

1390 Carey, S., & Bartlett, E. (1978). Acquiring a single new word. *Papers and Reports on*
1391 *Child Language Development*, 15, 17–29.

1392 Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic
1393 processing. *Psychological Review*, 82(6), 407–428.

1394 Collins, A., & Quillian, R. (1969). Retrieval time from semantic memory. *Journal of*
1395 *Verbal Learning and Verbal Behavior*, 8, 240–247.

1396 Connolly, A. C., Gleitman, L. R., & Thompson-Schill, S. L. (2007). Effect of congenital
1397 blindness on the semantic representation of some everyday concepts.
1398 *Proceedings of the National Academy of Sciences*, 104(20), 8241–8246.

1399 Coutanche, M. N., & Koch, G. E. (2017). Variation across individuals and items
1400 determine learning outcomes from fast mapping. *Neuropsychologia*,
1401 106(Supplement C), 187–193.

- 1402 Coutanche, M. N., & Thompson-Schill, S. L. (2014). Fast mapping rapidly integrates
1403 information into existing memory networks. *Journal of Experimental Psychology:*
1404 *General*, 143(6), 2296–2303.
- 1405 Cox, G. E., Hemmer, P., Aue, W. R., & Criss, A. H. (2018). Information and processes
1406 underlying semantic and episodic memory across tasks, items, and individuals.
1407 *Journal of Experimental Psychology: General*, 147(4), 545–590.
- 1408 Craik, F. I. M., & Lockhart, R. S. (1972). Levels of processing: A framework for memory
1409 research. *Journal of Verbal Learning and Verbal Behavior*, 11(6), 671–684.
- 1410 Craik, F. I. M., & Tulving, E. (1975). Depth of processing and the retention of words in
1411 episodic memory. *Journal of Experimental Psychology: General*, 104(3), 268–
1412 294.
- 1413 Deyne, S. D., Verheyen, S., Ameel, E., Vanpaemel, W., Dry, M. J., Voorspoels, W., &
1414 Storms, G. (2008). Exemplar by feature applicability matrices and other Dutch
1415 normative data for semantic concepts. *Behavior Research Methods*, 40(4),
1416 1030–1048.
- 1417 Dunsmoor, J. E., & Murphy, G. L. (2014). Stimulus typicality determines how broadly
1418 fear is generalized. *Psychological Science*, 25(9), 1816–1821.
- 1419 Ghosh, V. E., & Gilboa, A. (2014). What is a memory schema? A historical perspective
1420 on current neuroscience literature. *Neuropsychologia*, 53, 104–114.
- 1421 Goodman, G. S. (1980). Picture memory: How the action schema affects retention.
1422 *Cognitive Psychology*, 12(4), 473–495.
- 1423 Goulet-Pelletier, J.-C., & Cousineau, D. (2018). A review of effect sizes and their
1424 confidence intervals, Part I: The Cohen's d family. *The Quantitative Methods for*
1425 *Psychology*, 14(4), 242–265.

- 1426 Greenberg, D. L., & Verfaellie, M. (2010). Interdependence of episodic and semantic
1427 memory: Evidence from neuropsychology. *Journal of the International*
1428 *Neuropsychological Society*, 16(5), 748–753.
- 1429 Hemmer, P., & Steyvers, M. (2009). Integrating episodic memories and prior knowledge
1430 at multiple levels of abstraction. *Psychonomic Bulletin & Review*, 16(1), 80–87.
- 1431 Hemmer, Pernille, & Persaud, K. (2014). Interaction between categorical knowledge
1432 and episodic memory across domains. *Frontiers in Psychology*, 5.
- 1433 Heussen, D., Poirier, M., Hampton, J. A., & Aldrovandi, S. (2011). An effect of semantic
1434 memory on immediate memory in the visual domain. In B. Kokinov, A. Karmiloff-
1435 Smith, & N. J. Nersessian (Eds.), *European Perspectives on Cognitive Science*
1436 (p. 6). New Bulgarian University Press.
- 1437 Howard, M. W., & Kahana, M. J. (2002). When Does Semantic Similarity Help Episodic
1438 Retrieval? *Journal of Memory and Language*, 46(1), 85–98.
- 1439 Huttenlocher, J., Hedges, L. V., & Duncan, S. (1991). Categories and particulars:
1440 Prototype effects in estimating spatial location. *Psychological Review*, 98(3), 352.
- 1441 Huttenlocher, J., Hedges, L. V., & Vevea, J. L. (2000). Why do categories affect
1442 stimulus judgment? *Journal of Experimental Psychology: General*, 129(2), 220–
1443 241.
- 1444 Kirwan, C. B., Jones, C. K., Miller, M. I., & Stark, C. E. L. (2007). High-resolution fMRI
1445 investigation of the medial temporal lobe. *Human Brain Mapping*, 28(10), 959–
1446 966.
- 1447 Knill, D. C., & Richards, W. (Eds.). (1996). *Perception as Bayesian inference*.
1448 Cambridge University Press.
- 1449 Konkle, T., & Caramazza, A. (2013). Tripartite organization of the ventral stream by
1450 animacy and object size. *Journal of Neuroscience*, 33(25), 10235–10242.

- 1451 Koutstaal, W., & Schacter, D. L. (1997). Gist-based false recognition of pictures in older
1452 and younger adults. *Journal of Memory and Language*, 37(4), 555–583.
- 1453 Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science:
1454 a practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, 4.
- 1455 Lewis, P. A., & Durrant, S. J. (2011). Overlapping memory replay during sleep builds
1456 cognitive schemata. *Trends in Cognitive Sciences*, 15(8), 343–351.
- 1457 Loftus, E. F., & Palmer, J. C. (1974). Reconstruction of automobile destruction: An
1458 example of the interaction between language and memory. *Journal of Verbal*
1459 *Learning and Verbal Behavior*, 13(5), 585–589.
- 1460 Love, B. C., Medin, D. L., & Gureckis, T. M. (2004). SUSTAIN: A network model of
1461 category learning. *Psychological Review*, 111(2), 309–332.
- 1462 McClelland, J. L., McNaughton, B. L., & O'Reilly, R. C. (1995). Why there are
1463 complementary learning systems in the hippocampus and neocortex: Insights
1464 from the successes and failures of connectionist models of learning and memory.
1465 *Psychological Review*, 102(3), 419–457.
- 1466 McKoon, G., & Ratcliff, R. (1979). Priming in episodic and semantic memory. *Journal of*
1467 *Verbal Learning and Verbal Behavior*, 18, 463–480.
- 1468 McKoon, G., Ratcliff, R., & Dell, G. S. (1986). A critical evaluation of the semantic-
1469 episodic distinction, 12(2), 295–306.
- 1470 Osherson, D. N., Smith, E. E., Wilkie, O., López, A., & Shafir, E. (1990). Category-
1471 based induction. *Psychological Review*, 97(2), 185–200.
- 1472 Patterson, K. (2007). The reign of typicality in semantic memory. *Philosophical*
1473 *Transactions of the Royal Society B: Biological Sciences*, 362(1481), 813–821.
- 1474 Payne, J. D., Tucker, M. A., Ellenbogen, J. M., Wamsley, E. J., Walker, M. P., Schacter,
1475 D. L., & Stickgold, R. (2012). Memory for semantically related and unrelated

1476 declarative information: The benefit of sleep, the cost of wake. *PLoS ONE*, 7(3),
1477 e33079.

1478 Persaud, K., & Hemmer, P. (2016). The dynamics of fidelity over the time course of
1479 long-term memory. *Cognitive Psychology*, 88, 1–21.

1480 Posner, M. I., Goldsmith, R., & Welton Jr, K. E. (1967). Perceived distance and the
1481 classification of distorted patterns. *Journal of Experimental Psychology*, 73(1),
1482 28.

1483 Posner, M. I., & Keele, S. W. (1968). On the genesis of abstract ideas. *Journal of*
1484 *Experimental Psychology*, 77(3p1), 353.

1485 Ratcliff, R., & McKoon, G. (1995). Bias in the priming of object decisions. *Journal of*
1486 *Experimental Psychology: Learning, Memory, and Cognition*, 21(3), 754–767.

1487 Rips, L. J. (1975). Inductive judgments about natural categories. *Journal of Verbal*
1488 *Learning and Verbal Behavior*, 14(6), 665–681.

1489 Roediger, H. L., & McDermott, K. B. (1995). Creating false memories: Remembering
1490 words not presented in lists. *Journal of Experimental Psychology: Learning,*
1491 *Memory, and Cognition*, 21(4), 803.

1492 Rogers, T. T., Patterson, K., Jefferies, E., & Lambon Ralph, M. A. (2015). Disorders of
1493 representation and control in semantic cognition: Effects of familiarity, typicality,
1494 and specificity. *Neuropsychologia*, 76, 220–239.

1495 Rosch, E. H. (1973). On the internal structure of perceptual and semantic categories. In
1496 T. E. Moore (Ed.), *Cognitive development and acquisition of language* (pp. 111–
1497 144). San Diego: Academic Press.

1498 Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal
1499 structure of categories. *Cognitive Psychology*, 7(4), 573–605.

- 1500 Rosch, E., Mervis, C. B., Gray, W. D., Johnson, D. M., & Boyes-Braem, P. (1976). Basic
1501 objects in natural categories. *Cognitive Psychology*, 8(3), 382–439.
- 1502 Russo, N., Hagmann, C. E., Andrews, R., Black, C., Silberman, M., & Shea, N. (2018).
1503 Validation of the C.A.R.E. stimulus set of 640 animal pictures: Name agreement
1504 and quality ratings. *PLOS ONE*, 13(2), e0192906.
- 1505 Sakamoto, Y., & Love, B. C. (2004). Schematic influences on category learning and
1506 recognition memory. *Journal of Experimental Psychology: General*, 133(4), 534–
1507 553.
- 1508 Schacter, D. L., & Addis, D. R. (2007). The cognitive neuroscience of constructive
1509 memory: remembering the past and imagining the future. *Philosophical*
1510 *Transactions of the Royal Society of London B: Biological Sciences*, 362(1481),
1511 773–786.
- 1512 Schmidt, S. R. (1996). Category typicality effects in episodic memory: Testing models of
1513 distinctiveness. *Memory & Cognition*, 24(5), 595–607.
- 1514 Schulman, A. I. (1974). Memory for words recently classified. *Memory & Cognition*, 2(1),
1515 47–52.
- 1516 Simons, J. S., Graham, K. S., & Hodges, J. R. (2002). Perceptual and semantic
1517 contributions to episodic memory: evidence from semantic dementia and
1518 Alzheimer's disease. *Journal of Memory and Language*, 47(2), 197–213.
- 1519 Smith, S. M., Ward, T. B., Tindell, D. R., Sifonis, C. M., & Wilkenfeld, M. J. (2000).
1520 Category structure and created memories. *Memory & Cognition*, 28(3), 386–395.
- 1521 Stark, S. M., Yassa, M. A., Lacy, J. W., & Stark, C. E. L. (2013). A task to assess
1522 behavioral pattern separation (BPS) in humans: Data from healthy aging and
1523 mild cognitive impairment. *Neuropsychologia*, 51(12), 2442–2449.

- 1524 Sweegers, C. C. G., Coleman, G. A., van Poppel, E. a. M., Cox, R., & Talamini, L. M.
 1525 (2015). Mental schemas hamper memory storage of goal-irrelevant information.
 1526 *Frontiers in Human Neuroscience*, 9, Article 629.
- 1527 Sweegers, C. C. G., & Talamini, L. M. (2014). Generalization from episodic memories
 1528 across time: A route for semantic knowledge acquisition. *Cortex*, 59, 49–61.
- 1529 Tse, D., Takeuchi, T., Kakeyama, M., Kajii, Y., Okuno, H., Tohyama, C., ... Morris, R.
 1530 G. M. (2011). Schema-dependent gene activation and memory encoding in
 1531 neocortex. *Science*, 333(6044), 891–895.
- 1532 Tulving, E. (1972). Episodic and semantic memory. In E. Tulving & W. Donaldson
 1533 (Eds.), *Organization of Memory*. New York: Academic Press.
- 1534 Uyeda, K. M., & Mandler, G. (1980). Prototypicality norms for 28 semantic categories.
 1535 *Behavior Research Methods & Instrumentation*, 12(6), 587–595.
- 1536 van Kesteren, M. T. R., Rijpkema, M., Ruiter, D. J., & Fernández, G. (2013).
 1537 Consolidation differentially modulates schema effects on memory for items and
 1538 associations. *PLoS ONE*, 8(2), e56155.
- 1539 van Kesteren, M. T. R. van, Fernández, G., Norris, D. G., & Hermans, E. J. (2010).
 1540 Persistent schema-dependent hippocampal-neocortical connectivity during
 1541 memory encoding and postencoding rest in humans. *Proceedings of the National*
 1542 *Academy of Sciences*, 107(16), 7550–7555.
- 1543 van Kesteren, M. T. R. van, Rijpkema, M., Ruiter, D. J., & Fernández, G. (2010).
 1544 Retrieval of associative information congruent with prior knowledge is related to
 1545 increased medial prefrontal activity and connectivity. *The Journal of*
 1546 *Neuroscience*, 30(47), 15888–15894.
- 1547 Webb, C. E., Turney, I. C., & Dennis, N. A. (2016). What's the gist? The influence of
 1548 schemas on the neural correlates underlying true and false memories.
 1549 *Neuropsychologia*, 93, Part A, 61–75.

Supplemental Results

All Experiments

Error by typicality: While we had strong predictions that category typicality would influence images' *direction* of error, it was less clear if category typicality would similarly affect their *magnitude* of error. For example, the use of category knowledge may have created small, systematic distortions for typical category members, but atypical category members may have exhibited the same extent of error in all directions. Here, we plot average error by typicality in the four experiments (Figure S1). We found that in Experiments 1 – 3, error was greater for typical category members relative to atypical category members in the experimental group, suggesting that the influence of category knowledge resulted in greater error in addition to systematic bias. Statistics are reported in the main text for Experiments 1, 2 and 4, and in the supplement for Experiment 3.

Figure S1. Average memory accuracy by category typicality in each experiment. Gray dots signify participants. Error bars indicate SEM. * $p < .05$; ** $p < .01$; *** $p < .001$

Error by spatial consistency and confidence: In the main text, we reported how confidence and spatial consistency with category membership interacted to influence error in Experiment 2, finding that the difference in error by spatial consistency was greatest when reported confidence was weakest. We aimed to replicate this effect in Experiments 3 and 4. See Figure S4 for a comparison of the effect sizes across the three experiments.

In Experiment 3, focusing on the experimental group, we entered spatial consistency, confidence, and their interaction into a mixed-effect model with error as the dependent measure (Figure S2B). This revealed main effects of consistency, $F_{(1, 149.87)} = 81.47, p < .001$, and confidence, $F_{(2, 129.49)} = 99.17, p < .001$, qualified by an interaction, $F_{(2, 1625.85)} = 3.32, p = .04$. This interaction was driven by the same pattern of effects as Experiment 1, with less of a difference in error between spatially consistent and inconsistent images for increasingly confident responses (very confident: $t_{(708.66)} = -2.63, p = .009$; somewhat confident: $t_{(325.63)} = -7.14, p < .001$; guessed: $t_{(303.20)} = -7.77, p < .001$; Bonferroni-corrected $\alpha = .017$ for 3 tests). This replicates the effects observed in Experiment 2 and suggests that when memory for specific image locations was weaker, participants relied more on their knowledge of a category's likely location on the grid.

In Experiment 4, using the same model (Figure S2C), we found main effects of spatial consistency, $F_{(1, 50.52)} = 49.08, p < .001$, and confidence, $F_{(3, 39.35)} = 8.63, p < .001$, but no consistency by confidence interaction, $F_{(3, 1129.60)} = 1.77, p = .15$. For consistency with Experiments 2 and 3, we computed pairwise tests of error by consistency for each level of reported confidence. This revealed less error for spatially consistent images relative to inconsistent images at all levels of confidence (all $t < -2.84$, all $p < .005$; Bonferroni-corrected $\alpha = .0125$ for 4 tests). The absence of an interaction in Experiment 4 may be driven by the change in stimuli for this experiment, which may have changed the way participants used the confidence responses. For example, visual inspection suggests that the main effect of confidence is much stronger in Experiment 2 and 3 relative to Experiment 4, as the spread of error across levels of confidence is much more narrow in Experiment 4, possibly signifying that confidence is a less informative marker of memory strength in this experiment.

Figure S2. Error by consistency and confidence. Average error by confidence and consistency in Experiment 2 (A), Experiment 3 (B), and Experiment 4 (C). The data from Experiment 2 (replotted from Figure 3D) is included above for comparison with the other experiments. Gray dots signify participants. Error bars indicate SEM. Statistics reflect simple effects that survive Bonferroni correction for the number of tests conducted within each experiment (Experiments 2 & 4: $\alpha = .0125$, Experiment 3: $\alpha = .0167$). ** $p < .01$; *** $p < .001$

Bias by typicality and confidence: We also sought to replicate the influence of confidence on bias observed in Experiment 2, which revealed a main effect of confidence such that there was less bias for the most confident responses. See Figure S4 for a comparison of the effect sizes across the three experiments.

In Experiments 3 and 4, we computed separate mixed effects models with confidence and typicality with bias as the dependent variable, again focusing only on the experimental group. In Experiment 3 (Figure S3B), this model revealed a main effect of confidence, $F_{(2, 98.64)} = 3.80$, $p = .03$, and a main effect of category typicality, $F_{(1, 1921.76)} = 21.85$, $p < .001$. There was no reliable interaction, $F_{(2, 2908.71)} = 2.21$, $p = .11$. As in Experiment 2, the main effect of confidence was driven by less bias for ‘very confident’ responses relative to ‘somewhat confident’ responses, $t_{(78.79)} = -2.47$, $p = .016$, and relative to ‘guessed’ responses, $t_{(101.64)} = -2.52$, $p = .013$, both of which survive correction for multiple corrections (3 tests, $\alpha = .0167$). There was no difference in bias between ‘somewhat confident’ and ‘guessed’ responses, $t_{(91.66)} = -0.67$, $p = 0.50$. The main effect of typicality was driven by greater bias for typical category members relative to atypical category members for ‘very confident’ responses, $t_{(622.79)} = 3.27$, $p = .001$, and for ‘somewhat confident’ responses, $t_{(329.80)} = 3.56$, $p < .001$, but not for ‘guessed’ responses, $t_{(279.10)} = 1.18$, $p = .24$ (3 tests, $\alpha = 0.167$). In Experiment 4 (Figure S3C), the same group $\times$ typicality ANOVA revealed no main effects or interaction, all $F < 1.85$, all $p > .15$.

Retrieval in Experiments 2 and 3 was modulated by reported confidence such that stronger memories, as indexed by high confidence, were less biased towards their category centers. This suggests that retrieval of weaker memories relied more on knowledge of each category’s general location and thus memory for their locations was more distorted. Furthermore, the main effect of category typicality in Experiment 3 suggests that confidence and category typicality may separately and independently bias retrieval, although this was not observed in Experiment 2. Interestingly, in Experiment 4, bias was not affected by confidence at all, despite other observations that more confidence was related to memory accuracy. This null result may be explained by the possibility that confidence was not as strong as an index of memory as it was in Experiments 1 – 3.

Figure S3. Bias by typicality and confidence. Average bias (as a proportion of error) by confidence and typicality in Experiment 2 (**A**), Experiment 3 (**B**), and Experiment 4 (**C**). Results from Experiment 2 (replotted from Figure 3B) are included here for comparison with other experiments. Gray dots signify participants. Error bars indicate SEM. Statistics reflect simple effects that survive Bonferroni correction for the number of tests conducted within each experiment (Experiments 2 & 4: $\alpha = .0125$, Experiment 3: $\alpha = .0167$). ** $p < .01$; *** $p < .001$

Figure S4. Effect sizes of error and bias across experiments, by confidence and exemplar memory. **(A)** Standardized difference in mean error for spatially consistent versus inconsistent images. 0 on the x-axis reflects no difference in error by consistency. **(B)** Standardized difference in the mean bias relative to 0, averaged across typical and atypical images. 0 on the x-axis reflects no reliable bias towards category clusters. Points represent mean effect size. Lines represent bootstrapped 95% confidence intervals.

Swap errors: One open question is whether the observed distortions in memory are due to small but systematic changes in retrieval, or large errors where participants mistook an image for a different one – a swap error. Although there is no clear way to identify swaps in these experiments, one way to adjudicate between these possibilities is by approximating the profile of a swap error by identifying retrieved locations that were closer to their category cluster. Since most members of a category were clustered in the same area, a swap error would look like a very large bias towards its category cluster. While this profile cannot directly pinpoint swap errors, decomposing retrieval in this way may provide a course hint at possible differences in biases.

To quantify this, we drew a line between each image's encoded location and cluster center, and we projected its retrieved location onto the line. We then sorted the projected distances of all images into four bins, separated by three landmarks along the line: the image's encoded location, its category's cluster center, and the halfway point between the two (Figure S5). The resulting four bins were: (1) 'Biased away', or images whose projected retrieval was farther from their cluster center relative to their encoded locations, (2) 'Closer to Encoded', or images whose retrieval was biased towards their cluster center, but was retrieved closer to its encoded location than its cluster center, (3) 'Closer to Cluster', or images whose retrieval was closer to their cluster center than their encoded location, and (4) 'Beyond Cluster', for images retrieved in locations extending beyond their cluster center. The proportions of trials in these bins were entered into ANOVAs separately for each experiment. Planned paired t-tests of the difference by typicality were performed separately for each bin. Significance for these tests was Bonferroni-corrected for four comparisons ($\alpha = .0125$).

In Experiment 1, a 4 (bin) x 2 (typicality: typical, atypical) ANOVA revealed a main effect of bin, $F_{(3,102)} = 15.93$, $p < .001$, $\eta_p^2 = 0.50$, a main effect of typicality, $F_{(1, 34)} = 4.23$, $p = .047$, $\eta_p^2 = 0.00$, and a reliable interaction, $F_{(3, 102)} = 2.93$, $p = .04$, $\eta_p^2 = 0.08$. This interaction was driven by more atypical category members biased away from their cluster center relative to typical ones p , $t_{(34)} = -3.04$, $p = .004$, $d = -0.51$. No other comparisons reached significance, $p > 0.09$.

In Experiment 2, the same ANOVA revealed similar effects: a main effect of bin, $F_{(3,102)} = 37.12$, $p < .001$, $\eta_p^2 = 0.77$, no reliable main effect of typicality, $F_{(1, 34)} = 1.03$, p

= .32, $\eta_p^2 = 0.00$, and a reliable interaction, $F_{(3, 102)} = 10.54$, $p < .001$, $\eta_p^2 = 0.24$. Here, there were more atypical trials than typical trials that were biased away from their cluster center, $t_{(34)} = -3.65$, $p < .001$, $d = -0.62$, and biased towards the cluster center but still retrieved closer to their encoded location, $t_{(34)} = -3.05$, $p = .004$, $d = -0.52$. However, more typical trials were retrieved closer to their cluster center, $t_{(34)} = 3.27$, $p = .002$, $d = 0.55$, and beyond their cluster center, $t_{(34)} = 3.40$, $p = .002$, $d = 0.58$.

In Experiment 3, we again found a main effect of bin, $F_{(3, 342)} = 35.62$, $p < .001$, $\eta_p^2 = 0.43$, no reliable main effect of typicality, $F_{(1, 114)} = 0.27$, $p = .61$, $\eta_p^2 = 0.00$, and a reliable interaction, $F_{(3, 342)} = 5.21$, $p = .002$, $\eta_p^2 = 0.04$. Here, more atypical trials were biased away from their cluster center, $t_{(114)} = -3.82$, $p < .001$, $d = -0.36$, and more typical trials were retrieved beyond their cluster center $t_{(114)} = 3.11$, $p = .002$, $d = 0.29$. No other comparisons reached significance, all $p > 0.28$.

We found a different pattern in Experiment 4. The same ANOVA revealed a main effect of bin, $F_{(3, 102)} = 15.59$, $p < .001$, $\eta_p^2 = 0.54$, no main effect of typicality, $F_{(1, 34)} = 0.07$, $p = .80$, $\eta_p^2 = 0.00$, and no interaction, $F_{(3, 102)} = 0.22$, $p = .88$, $\eta_p^2 = 0.006$. Unlike in Experiments 1 – 3, more trials were retrieved closer to their cluster center than to their encoded locations.

Taken together, these results suggest that a mixture of different errors drives the observed biases in retrieval. It seems likely that many of participants' memories for both typical and atypical category members can be characterized as smaller distortions rather than larger swap errors, as the plurality of trials were biased towards their cluster center but still remained closer to their encoded locations. However, the large proportion of trials retrieved closer to or beyond their category cluster also highlights the possibility that swap errors were also common. When considering typicality, we find that typical category members are more likely to be retrieved closer to or beyond their cluster center relative to atypical ones in Experiments 2 and 3 (and in the same direction in Experiment 1), suggesting that swap errors may contribute more to retrieval of typical category members relative to atypical category members. Finally, memory in Experiment 4 may have been more prone to swap errors, likely due to visually similar exemplars of the six objects that were encoded, rather than visually distinct members of six categories.

Figure S5. Swap error analyses. Proportion of images retrieved, relative to encoded locations and cluster centers. 'Biased Away' indicates the proportion of trials retrieved farther from the cluster center than what was encoded. 'Closer to Encoded' indicates the proportion of retrieved closer to their encoded location than to their cluster center. 'Closer to Cluster' indicates the proportion retrieved closer to their cluster center than their encoded locations. 'Beyond Cluster' indicates the proportion retrieved beyond their category cluster relative to their encoded location. Gray dots signify participants. Error bars indicate SEM. Statistics reflect two-tailed paired-sample t-tests ($\alpha = .0125$, Bonferroni-corrected for 4 comparisons per experiment). ** $p < .01$ *** $p < .001$

Experiment 3

Exemplar memory by typicality and confidence: We used participants' reports of confidence about their chosen images in the exemplar memory test to gain confidence in this measure as an indication of memory strength. To do so, we computed a mixed-effects logistic regression with exemplar memory as a binary dependent variable and confidence, typicality, and their interaction as independent variables. These analyses revealed a main effect of confidence, $\chi^2(2) = 97.73$, $p < .001$, with a greater likelihood of correct exemplar memory for images with higher confidence ratings. There was also a main effect of typicality, $\chi^2(1) = 4.75$, $p = .03$, with a greater likelihood of correct exemplar memory for atypical images relative to typical images, as was reported in the main text. There was no reliable interaction between confidence and typicality, $\chi^2(2) = 1.95$, $p = .38$. Overall, participants' confidence ratings reflected the likelihood that they chose the image that they had encoded, providing justification for our decision to use exemplar memory as an index of memory for the perceptual details of the images.

Error by spatial consistency with semantic knowledge: Before considering location memory as a function of exemplar memory, we first sought to replicate the observations from Experiments 1 and 2 that memory was more accurate for images that were spatially consistent with their category membership. We computed a 2 (group: experimental, control) x 2 (spatial consistency: consistent, inconsistent) ANOVA. This revealed a main effect of spatial consistency, $F_{(1,228)} = 96.14$, $p < .001$, $\eta_p^2 = 0.30$, and no main effect of group, $F_{(1,228)} = 0.007$, $p = .93$, $\eta_p^2 = 0.001$, qualified by an interaction, $F_{(1,228)} = 28.48$, $p < .001$, $\eta_p^2 = 0.11$. Both groups exhibited greater error for spatially inconsistent images relative to consistent images (experimental: $t_{(114)} = -10.47$, $p < .001$, $d = -0.98$; control: $t_{(114)} = -3.23$, $p = .002$, $d = -0.30$), although the interaction indicated that the effect was reliably stronger in the experimental group. As in Experiment 4, the dense clustering of images in spatially consistent locations may have aided retrieval in both groups. However, the reliably stronger effect in the experimental group demonstrates that retrieval was more accurate for images that were spatially consistent with their category membership, replicating Experiments 1 and 2.

Bias by category typicality: Before considering how exemplar memory related to bias in location memory, we first aimed to replicate the finding that typical category members were retrieved closer to their category's cluster relative to atypical members, as was observed in Experiments 1 and 2. We computed a 2 (group: experimental, control) x 2 (typicality: typical, atypical) ANOVA amongst spatially inconsistent images, with the average proportion of bias as the dependent variable. This revealed no main effect of group, $F_{(1,228)} = 0.002$, $p = .96$, $\eta_p^2 = 0.00$, but a main effect of typicality, $F_{(1,228)} = 13.76$, $p < .001$, $\eta_p^2 = 0.06$, qualified by a reliable interaction, $F_{(1,228)} = 10.53$, $p = .001$, $\eta_p^2 = 0.04$. As in Experiments 1 and 2, retrieval was more biased towards the category cluster center for typical images relative to atypical images in the experimental group, $t_{(114)} = 4.96$, $p < .001$, $d = .46$, but not the control group, $t_{(114)} = 0.33$, $p = .74$, $d = .03$.

Error by category typicality: We also aimed to replicate the observed effects from Experiments 1 and 2 showing more error for typical category members relative to atypical category members (Figure S1). An analogous 2 (group: experimental, control) x 2 (typicality: typical, atypical) ANOVA revealed a main effect of typicality, $F_{(1,228)} = 4.09$, $p = .04$, $\eta_p^2 = 0.02$, no main effect of group, $F_{(1,228)} = 0.85$, $p = .36$, $\eta_p^2 = 0.04$, and no reliable interaction, $F_{(1,228)} = 2.84$, $p = .09$, $\eta_p^2 = 0.01$. For comparison with Experiments 1 and 2, we ran post-hoc t-tests to compare error by category typicality and group. As observed in Experiments 1 and 2, we found greater error for typical images relative to atypical images in the experimental group, $t_{(114)} = 2.31$, $p = .02$, $d = 0.22$, but not in the control group, $t_{(114)} = 0.28$, $p = 0.78$, $d = 0.03$.

Supplemental Methods

All Experiments

Amazon Mechanical Turk: All data was collected on Amazon Mechanical Turk (AMT). AMT participants more closely match the demographics of adults in the United States relative to traditional lab experiments (Buhrmester, Kwang, & Gosling, 2011) and the quality of data is equivalent to that collected from lab participants across a number of learning and memory experiments (Brady & Alvarez, 2011; Crump, McDonnell, & Gureckis, 2013). All experiments were restricted to participants who were located in the United States, had completed > 100 HITs with at least a 95% acceptance rate, and had not participated in any prior pilots or other lab experiments that used the same stimuli. These restrictions were chosen to increase the likelihood that participants were native or fluent English speakers who could understand all provided instructions and were naïve to the aim of the experiments. Depending on the length of the task, participants were given a >5-hour time window to complete each experiment so they could choose a suitable time to complete the tasks without interruption.

Software: Stimuli were presented using customized scripts written in HTML and JavaScript. MturkR was used to interface with AMT to post experiments, retrieve data, and pay participants (Leeper, 2017). All statistical analyses were conducted in base R (R Core Team, 2015), with the exception of mixed-effects models, which were computed using *lme4* (Bates, Mächler, Bolker, & Walker, 2015). *lmerTest* was used to provide statistics of main effects and interactions for mixed-effects models (Kuznetsova, Brockhoff, & Christensen, 2017), *emmeans* was used to compute estimated marginal means to provide contrasts of simple their effects (Lenth, 2018), and *bootES* was used to generate bootstrapped confidence intervals around their estimated effect sizes (Kirby & Gerlanc, 2013). All figures were generated with *ggplot2* (Wickham, 2009).

Experiment 1: Stimulus Development

To create the image-location associations used in Experiment 1, we developed a data-driven approach to estimate how images would be spatially organized if their locations adhered to their category membership. To do this, we used relatedness ratings from a

separate set of participants. These ratings were used both to define images' locations and identify their category membership and typicality.

Participants

24 participants (23 – 49 years old, 9 female) completed the experiment. The University of Pennsylvania Institutional Review Board (IRB) approved all consent procedures.

Materials

Images: Stimuli consisted of 70 150 x 150 pixel color images on white backgrounds (35 animals, 35 common objects) from the Bank of Standardized Stimuli (Brodeur, Dionne-Dostie, Montreuil, & Lepage, 2010; <https://sites.google.com/site/bosstimuli/home>). These images were re-sized to 100 x 100 pixels for the memory experiments.

Procedure

Picture naming: This task was developed to (1) ensure that participants could correctly identify the animals and objects, (2) familiarize the participants to the range of stimuli over which they would be making similarity judgments, and (3) create a pool of qualified participants that would be invited to complete the similarity ratings task. In this task, participants were instructed to name each image as specifically as possible. For example, if they viewed a picture of a bird, they were instructed to name the species of bird if possible. On each trial, participants viewed an image and chose from three options presented below the image: "I know this", "I know this but can't think of its name", or "I don't know what this is". If they chose "I know this", they also typed the name of the animal or object next to their choice. Either pressing the 'enter' key after filling in the name, or clicking on the button corresponding to the other two choices, automatically advanced the participant to the next trial with a 200ms inter-trial-interval (ITI). Otherwise, the trial advanced automatically after 15 seconds of inactivity. Trials were divided into separate animal and object blocks that were randomized across participants. The order of images in each block was randomized for each participant. On average, the task was completed in 2 - 4 minutes.

40 participants were recruited to participate in the picture-naming task. They were compensated with \$1.50. One participant was excluded for entering nonsense words for the majority of animal trials, and an extra participant was recruited as a replacement. As the aim of this task was to ensure that participants had sufficient knowledge of the animals and objects represented in each image, which participants may have even if they do not know the specific name of an image, we developed a lenient criterion for analyzing this task. Close neighbors of an image, such as crocodile for alligator, lizard for gecko, utility knife or razor for box cutter, were accepted as correct. Misspelled names were included if they matched the correct image name with a maximum generalized Levenstein edit distance of 0.3. Using these criteria, 94.93% of images (SD: 8.94%) were named correctly. When including “I know this but can’t think of its name” as accurate responses, accuracy rose to 97.71% (SD: 5.47%), signifying near-perfect knowledge of the images. 35 participants who accurately named at least 65 out of 70 images were invited to participate in the next phase of the experiment; the excluded 5 participants named 39 - 62 images correctly.

Odd-man-out: Eligible participants were invited to participate in the odd-man-out (OMO) task. In this task, participants were presented with three animals or three objects and were instructed to click on the picture that ‘did not belong’, or in other words, the animal or object that was least similar to the other two. Once an image was chosen, the three images were replaced by three new images after a 200ms ITI. Trials were untimed, but participants were instructed to respond in 2 – 4 seconds and make their decision as quickly as possible while still being accurate. They were told that there were no right answers, but that some trials would seem easier than others. They were instructed to make their decisions based on many factors, instead of focusing on one. For animal trials, this included factors like whether they were in the same family, shared similar habitats, and are predators or prey. For object trials, this included factors like whether they served a similar purpose, where they were commonly located, and their size.

For each category, a complete testing of all triplets of images would require 6,545 trials (choose 3 given 35). Piloting of this task with a prior cohort (N = 6) revealed that for each participant, similarity matrices derived from a randomly sub-sampled set of

two-fifths of these combinations were highly correlated with similarity matrices derived from the participant's full set of trials (for all 6 pilot participants, animals: all $r > 0.90$; objects: all $r > 0.81$). Thus, we presented participants with a random sample of 2,620 combinations per category (two-fifths of all possible triplets). This task was divided into 20 separate batches (10 per category) expected to take 12 - 15 minutes each. Each batch comprised 262 trials of a given category and 5 attention checks. In an animal batch, an attention check comprised two animals and one object. Participants were instructed to choose the object. In an object batch, participants were instructed to choose the animal presented with two objects.

Although it is impossible to control the order of HITs that AMT workers choose to work on, we attempted to randomize the order of batches that workers had access to by creating six different sequences of batches, and assigning a worker to one of the sequences based on the last letter or number in their account ID. AMT IDs are randomly generated string of letters and digits, so assigning groups by the last letter or number of a worker's ID is akin to sampling from a uniform distribution of 1 to 36 (26 letters, 10 digits). Within each batch, the trial order was randomized for each participant.

Participants were given 7 days to complete all 20 batches. Upon the invitation to complete the batches, participants were told that they would be compensated \$2.50 per batch, and if they completed all 20 within 7 days, they would receive a bonus of \$5, for a total of \$55. Two reminders were sent over the course of the week, and a third reminder was sent the day before the deadline, only to participants who had already completed >15 batches. If a participant missed 2 or more attention checks in a batch, it was rejected and a message was sent to the participant offering them an opportunity to re-do the batch. Out of the participants whose data were used in the memory task, only one participant needed to re-do a rejected batch. At the end of the week, 24 out of 35 participants had completed all 20 batches. The remaining 11 participants had completed 1 to 13 batches (mean = 4, SD = 4.44).

The OMO judgments were then used to create pairwise similarity matrices for each subject and super-ordinate category (Figures S6A, S6D). Starting with a 35 x 35 matrix of zeros, for each trial in which an image was chosen, the similarity value for the other two presented images increased by one. These similarity values were summed

across all trials and then divided by the number of times the two images appeared in the same trial. Similarity matrices thus ranged from 0 to 1, with higher values corresponding to greater similarity between images. To quantify the test-retest reliability of the ratings for each participant, split-half correlations were derived by re-computing pairwise similarity using the first and last half of the batches that were completed for each subject, and then correlating the lower triangle of the two matrices together. Correlations between the first and last half of batches were high (animals: mean $r = 0.66$, SD = 0.05; objects: mean $r = 0.54$, SD = 0.06) and greater than correlations between each participant's ratings and similarity matrices derived from Latent Semantic Analysis (LSA) and Word2Vec (Figures S6C, S6F). Three subjects, whose split-half correlations for both categories were > 2 SD lower than the group mean, were excluded (all r 's < 0.08), leaving 21 subjects with data to be used to derive the locations for the memory test.

Category membership and typicality: The odd-man-out results were used to derive a 2-dimensional representation of participants' semantic knowledge (Figures S6B, S6E). To do this, the similarity matrices from the 21 participants who completed the odd-man-out task were averaged into two group-level similarity matrices for each super-ordinate category. Classical multi-dimensional scaling was used to project the matrices into 2D spaces. To evaluate how well this projection reflected participants' decisions in the OMO task, we computed the goodness of fit of the projected data to the full similarity space using subsets of the dimensions produced by the scaling procedure. This measure was operationalized as the R^2 between the full similarity matrix and a reconstructed matrix using 1 to 10 coordinate dimensions weighted by their eigenvalues (Figure S6G). While there were no obvious bends in this elbow plot, moving from one to two dimensions resulted in the steepest change in fit, and two dimensions captured 85.5% of the variance in ratings for animals and 70.0% of the variance for objects.

K-means clustering was applied to the 2D coordinates to derive data-driven clusters of images. The optimal number of clusters was determined by computing the within-cluster sum of squared error for solutions with 1 to 10 clusters and using an elbow plot to identify the smallest number of clusters that explained the largest portion

of the error (Figure S6H). For both categories, the data was best explained with 3 clusters. This data-driven procedure resulted in animal clusters corresponding to birds, land mammals, and sea creatures, and object clusters corresponding to kitchen utensils and appliances, tools and personal care items, and office supplies.

The cluster solutions were also used to identify images that were typical and atypical category members. First, a category was operationalized as images belonging to the same cluster (e.g. birds). The center of each cluster was derived by computing the mean x and y coordinate over all cluster images. Then, all images were sorted by their distance to their cluster center. For each cluster, the closest 20% of images were labeled as ‘typical’ category members (e.g. cardinal), and the furthest 20% of images were labeled as ‘atypical’ members (e.g. toucan and ostrich). Note that this data-driven procedure resulted in differing numbers of category members in each group, and thus differing numbers of typical and atypical category members. Table 1 lists the number of images per category and condition.

Counterbalancing: For some categories, the number of category members did not evenly divide into 40%, such that there were an odd number of images assigned as spatially inconsistent that could not be evenly assigned to typical and atypical category members. To account for this and for other variations in the stimulus display, we created 6 counterbalancing groups. In each group, we (1) randomized the assignment of the odd image to a typical or atypical category member, (2) generated a new, random set of spatially inconsistent locations, and (3) counterbalanced whether animals appeared on the left side of the screen and objects on the right, or vice versa. AMT workers were assigned to one of the six groups based on the last letter or number in their Worker ID. Worker IDs are randomly generated string of letters and digits, so using the last letter or number of a worker’s ID is akin to sampling from a uniform distribution of 1 to 36 (26 letters, 10 digits).

Figure S6. Odd-man-out procedure. (A, D) Similarity matrix of all animals and all objects derived from odd-man-out judgments. (B, E) 2D projection of animal and object similarity matrices using classical multi-dimensional scaling. Colors indicates 3 clusters derived with k-means clustering. (C, F) Split-half correlations of the similarity matrices within each participant plotted alongside each participant's correlations with similarity matrices derived from LSA and Word2Vec. Gray dots signify participants. Error bars indicate SEM. (G) Goodness of fit of projected similarity ratings derived from the group-averaged correlation matrix, as a function of the number of reconstructed dimensions. (H) Elbow plot of within-cluster sum of squared error for the k-means clustering algorithm as a function of number of clusters chosen.

Experiments 1 & 3				
Category	Total	Spatially Consistent	Typical	Atypical
Birds	7	4	1 or 2	1 or 2
Mammals	18	11	3 or 4	3 or 4
Sea Creatures	10	6	2	2
Tools/personal care	11	7	2	2
Kitchen	13	7	3	3
Office	11	7	2	2
Experiment 2				
Category	Total	Spatially Consistent	Typical	Atypical
Birds	20	14	3	3
Mammals	20	14	3	3
Sea Creatures	20	14	3	3
Insects	20	14	3	3
Clothes	20	14	3	3
Furniture	20	14	3	3
Kitchen	20	14	3	3
Office	20	14	3	3

Table S1. Number of images in each category in each experiment. **Top.** Experiments 1, 3 & 4. 40% of items in a category (the top and bottom 20%) were assigned as spatially inconsistent. When this proportion gave rise to an odd number of items (e.g. in the bird and mammals category), the odd one was randomly assigned as typical or atypical for each counterbalancing group. In other words, a given counterbalancing group encoded one typical bird and two atypical birds, and another group encoded two typical birds and one atypical bird. Experiment 3 used the same categories, locations, and counterbalancing groups developed for Experiment 1. In Experiment 4, the number of items in each color category was randomly matched to a semantic category such that the number of items in each category varied in the same way as in Experiments 1 and 3. **Bottom.** Experiment 2. As categories were predetermined in Experiment 2, all categories comprised 20 items. 30% of items in a category (the top and bottom 15%) were assigned as spatially inconsistent.

Experiment 2: Stimulus Development

We aimed to replicate Experiment 1 with validated approaches for defining category membership and typicality. To this end, a separate cohort of participants completed a list ranking task to identify typical and atypical members in a fixed set of categories.

Methods

Participants

216 participants (27 per category) completed this task. The University of Pennsylvania IRB approved all consent procedures. Demographics were not collected due to experimenter error.

Materials

Stimuli comprised 160 100x100-pixel color images on white backgrounds. These comprised 8 categories of 20 images: birds, insects, sea creatures, mammals, clothes, furniture, kitchen utensils, and office supplies. The categories were selected from prior studies of categorization norms (Uyeda & Mandler, 1980; Deyne et al., 2008).

Procedure

We employed a validated list ranking task (Figure S7A; Djalal, Ameel, & Storms, 2016). Extensive instructions with examples were given to ensure participants understood the concept of category typicality. For each category, participants viewed 20 images in a box labeled 'Sort these'. Underneath, there were two empty boxes labeled 'Typical' and 'Atypical'. Participants were instructed to drag 10 images into each box. They were allowed to drag images freely across the boxes in any order. Then, within each box, participants sorted the 10 images as most (a)typical to less (a)typical. Arrows and labels indicated the direction that images were to be sorted. The average completion time was 2.6 minutes (SD = 1.9). The resulting positions of the images were concatenated into a ranked list of category typicality and averaged across participants. The top three and bottom three images in each list were assigned as 'typical' and 'atypical' category members that would be 'spatially inconsistent' in the memory experiment, and the images in the middle of the list were assigned as 'spatially consistent' (Figure S7B).

A

B

Figure S7. Ranking procedure (A) Ranking task and instructions for the bird category. **(B)** Average typicality rankings for each category, which could range from 1 (all participants ranked image as most typical) to 20 (all participants ranked image as most atypical). Error bars indicate SEM. Color indicates condition in the memory experiment: green = spatially inconsistent/typical; black = spatially consistent; orange = spatially inconsistent/atypical.

Experiment 3

Power analysis: We chose a new sample size for this experiment to account for the fact that the planned analyses were less powered relative to the analyses in the first two experiments. Specifically, because we planned to analyze error and bias as a function of exemplar memory accuracy, requiring the division of each condition by whether the encoded exemplars were correctly or incorrectly chosen, there would be fewer trials in each condition. To address this, we first piloted a subset of the shuffled control group ($N = 35$) to procure an estimate of exemplar memory accuracy in the absence of informative category knowledge during encoding. We found that accuracy was on average 67.6% (SD 16.6%). We then re-analyzed the influence of category typicality on bias from the experimental group in Experiment 1 ($N = 35$) with a subset of their trials that matched the number of exemplar incorrect trials from the pilot group. We chose to conduct this re-analysis using incorrect trial counts because exemplar accuracy in the initial subset was above 50%, meaning there were fewer incorrect trials than correct trials and any analyses including only incorrect trials would be the least powered.

The subsampling procedure was as follows. First, we matched each participant in Experiment 1 to a participant in the pilot cohort. We randomly subsampled the number of typical and atypical images in the Experiment 1 participant to match accuracy from the pilot participant and derived their average bias separately for typical and atypical category members. We repeated this subsampling procedure 5,000 times per participant. We then computed the effect size of the difference in bias for typical versus atypical category members for each permutation and averaged them. This resulted in an estimated effect size of the difference in bias by typicality that would have been observed in Experiment 1 when limiting the analysis to trials with incorrect exemplar memory, assuming both groups of participants exhibited equivalent memory for the specific images.

As expected, this procedure resulted in a smaller effect size (Cohen's $d = 0.263$) than what was observed in Experiment 1 when including all trials (Cohen's $d = 0.548$). Using a power analysis ($\alpha = 0.05$, power = 0.80), we established that a sample size of 115 participants per group was needed to recover this smaller effect.

Experiment 4

Counterbalancing: In Experiment 4, we aimed match as many features of the experimental design to Experiment 1 as possible in order to understand whether biases in memory are driven by category knowledge or by newly-learned visual similarities of encoded images. Because a data-driven clustering algorithm determined category membership of the stimuli in Experiment 1, the number of category members varied across categories (Table S1). Thus, to match this in Experiment 4, we created 6 counterbalancing groups, where in each one, the categories in Experiment 1 were randomly matched to Experiment 4. For example, because in Experiment 1 there were 7 birds, 18 mammals, and 10 sea creatures, in one counter-balancing group there were 7 lamps, 18 clocks, and 10 chairs, and in another counter-balancing group there were 7 trains, 18 cars, and 10 planes.

As described in the main text, both the assignment of the six color ranges to the six categories and the assignment of colors to images within each category were also randomized separately for the 6 groups. Thus, each group encoded a unique set of stimuli with (1) different numbers of category members per category, (2) categories with different ranges of colors, and (3) different images assigned typical and atypical colors.

References

- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48.
- Brady, T. F., & Alvarez, G. A. (2011). Hierarchical encoding in visual working memory: ensemble statistics bias memory for individual items. *Psychological Science*, 22(3), 384–392.
- Brodeur, M. B., Dionne-Dostie, E., Montreuil, T., & Lepage, M. (2010). The Bank of Standardized Stimuli (BOSS), a new set of 480 normative photos of objects to be used as visual stimuli in cognitive research. *PLOS ONE*, 5(5), e10773.
- Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science*, 6(1), 3–5.
- Crump, M. J. C., McDonnell, J. V., & Gureckis, T. M. (2013). Evaluating Amazon's Mechanical Turk as a tool for experimental behavioral research. *PLOS ONE*, 8(3), e57410.
- Deyne, S. D., Verheyen, S., Ameel, E., Vanpaemel, W., Dry, M. J., Voorspoels, W., & Storms, G. (2008). Exemplar by feature applicability matrices and other Dutch normative data for semantic concepts. *Behavior Research Methods*, 40(4), 1030–1048.
- Djalal, F. M., Ameel, E., & Storms, G. (2016). The typicality ranking task: A new method to derive typicality judgments from children. *PLOS ONE*, 11(6), e0157936.
- Kirby, K. N., & Gerlanc, D. (2013). BootES: An R package for bootstrap confidence intervals on effect sizes. *Behavior Research Methods*, 45(4), 905–927.
- Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, 82(1), 1–26.
- Leeper, T. J. (2017). MTurkR: Access to Amazon Mechanical Turk Requester API via R.
- Lenth, R. (2018). *emmeans: Estimated Marginal Means, aka Least-Squares Means*.
- R Core Team. (2015). *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.
- Uyeda, K. M., & Mandler, G. (1980). Prototypicality norms for 28 semantic categories. *Behavior Research Methods & Instrumentation*, 12(6), 587–595.
- Wickham, H. (2009). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag: New York.