

# Semantic influences on episodic memory distortions

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## Abstract

Semantic knowledge can facilitate or distort new memories, depending on their alignment. We aimed to quantify distortions in memory by examining how category membership biases new encoding. Across two experiments, participants encoded and retrieved image-location associations on a 2D grid. The locations of images were manipulated so that most members of a category (e.g. birds) were clustered near each other, but some were in random locations. Memory for an item's location was more precise when it was near members of the same category. Furthermore, typical category members' retrieved locations were more biased towards their semantic neighbors, relative to atypical members. This demonstrates that the organization of semantic knowledge can explain bias in new memories.

**Keywords:** episodic memory; semantic memory; category membership; typicality; 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, it also oversimplifies the complexity in memories that 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 semantic knowledge. We aimed to probe interactions between the two systems by quantifying how semantic knowledge distorts new episodic learning.

Research on schemas, a type of semantic knowledge defined as a structure of associated information (Bartlett, 1932; Ghosh & Gilboa, 2014), sheds some light on how prior knowledge influences new episodic memory formation. The benefit of prior knowledge for episodic memory is widely documented (Bransford & Johnson, 1972; Alba & Hasher, 1983). Similarly, the presence of prior knowledge accelerates the integration of novel words into existing memory networks (Coutanche & Thompson-Schill, 2014). However, new encoding can also be biased by prior knowledge, resulting in false memories or confabulation (Warren, Jones, Duff, & Tranel, 2014; Webb, Turney, & Dennis, 2016). Taken together, these findings suggest that whether prior knowledge helps or hinders encoding depends on the match between the old and new information.

One weakness of this work is that the operationalization of prior knowledge often ignores its rich, hierarchical structure (Collins & Loftus, 1975). 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 (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). As a result, typical items are thought to be more strongly associated with category neighbors, relative to atypical items. The consequences of these strong associations are well documented: typical items are more quickly categorized, more efficiently recognized, and less resistant to disruption by brain damage (Patterson, 2007). Furthermore, the features of typical items are more often attributed to category neighbors (Osherson, Smith, Wilkie, López, & Shafir, 1990; Rips, 1975). As an example, if a typical item, rather than an atypical item, 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 interactions between episodic and semantic memory.

One promising approach to examining such interactions is by considering retrieval as a construction of different sources of information. 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. Yet, it also introduces systematic errors if there are discrepancies between a new memory and prior knowledge. For example, 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 color of shapes is biased towards canonical hues (Persaud & Hemmer, 2014), and estimates of the size of fruits and vegetables are biased by both their superordinate and subordinate mean sizes (Hemmer & Steyvers, 2009). However, it is unknown whether other

properties of semantic knowledge, like category typicality, exert similar distortions on new encoding.

We aimed to quantify distortions in episodic memories due to prior knowledge by examining how differences in category typicality bias new memories for item-location associations. In two experiments conducted on Amazon Mechanical Turk (AMT), participants encoded and retrieved image-location associations on a 2D grid. Critically, the locations associated with each image 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 members were located elsewhere. With this design, participants could learn that items from a certain category tended to be located in a certain area as they encoded item-specific locations.

We used a continuous retrieval measure to disentangle biases driven by semantic knowledge from errors due to forgetting. Critically, these two measures varied independently such that memory for an item could be biased towards or away from category neighbors regardless of its precision. In both experiments, we used these measures to test two predictions. First, we predicted more precise memory for items located near category members, relative to those located farther away, which would replicate past observations that new memories can benefit from prior knowledge if they are aligned. Second, for those typical and atypical items located far from category neighbors, we predicted that their *direction* of error would be different, such that retrieval of typical items would be more biased towards category neighbors relative to atypical items. Such a bias would reflect stronger associations between typical category members and their category neighbors. We did not have strong predictions about precision by typicality, except for the critical notion that any observed differences in bias would be independent of differences in precision.

## Experiment 1: Stimulus Development

In the first experiment, we developed a data-driven approach to create item-location associations for the memory task. Specifically, we used semantic relatedness ratings from a separate set of participants to define the images' locations and sort them according to their typicality.

### Method

**Participants** 24 participants (23 – 49 years old, 9 female) completed semantic relatedness judgments. The University of Pennsylvania Institutional Review Board (IRB) approved all consent procedures.

**Materials** Stimuli comprised 70 100x100-pixel color images on white backgrounds (35 animals, 35 objects). Based on pilot data, we selected images with equivalently high recognition across these two superordinate categories.

**Odd-Man-Out Procedure** On each trial, participants were presented with three images from a superordinate category and were instructed to click on the image that was least

similar to the other two. Once an image was chosen, the images faded away and three new images were displayed after a 200-ms interval. Participants were encouraged to respond in 2 – 4 seconds. They were instructed to make their decisions based on many factors, like whether animals belonged to the same family or shared similar habitats, and whether objects served a similar purpose or tended to be in similar locations. Based on prior piloting, participants completed a random sample of 2,620 combinations per superordinate category, of the 6,545 possible combinations (choose 3 of 35). The trials were divided into 20 separate batches, expected to take 12 - 15 minutes each, and participants were given 1 week to complete them. Of the 35 invited to participate, 24 completed it and 3 were excluded.

The responses were used to create similarity matrices for each participant and superordinate category. Starting with a 35 x 35 matrix of zeros, for every trial on which an odd image was chosen, the value for the other two increased by 1. The summed values across all trials were then divided by the number of times the two images appeared in the same trial. Cells in the matrix thus ranged from 0 to 1, with higher values corresponding to greater similarity between the items. We computed split-half correlations as a test-retest reliability measure for each participant (group mean  $r = .60$ ,  $SD = .24$ ). The reliability of the 3 excluded participants was  $>3$  SD lower than the group mean (all  $r$ 's  $< .04$ ). Matrices from the 21 remaining participants were averaged into a separate matrix for animals and for objects.

**Image-Location Associations** Each image was paired with a spatial location on a white 600x1200-pixel rectangle with gray gridlines forming a 50x50-pixel grid. The locations were determined by applying multidimensional scaling (MDS) to the similarity matrices from the odd-man-out procedure. Each matrix was projected into two dimensions, where the x and y coordinates of an item determined its location on the grid. Thus the locations of items represented participants' 2D organization of animals and objects.

We then used k-means clustering of these projections to determine the categories within animals and objects that were captured in the 2D locations. The animal and object locations were separately entered into 10 k-means clustering algorithms with 1 to 10 clusters. The optimal number of clusters was chosen by plotting the sum of within-cluster squared error as a function of the number of clusters used in the algorithm. The 'bend' in this elbow plot signifies the fewest number of clusters that minimize the distance between items in the same cluster. This procedure revealed 3 animal categories (birds, mammals, and sea creatures) and 3 object categories (kitchen, tools/personal care, and office). These clusters were used to identify typical and atypical category members. The center of each cluster was defined as the average x and y coordinate of its constituent items. Then the items were sorted by their distance to its center. The closest 20% were labeled 'typical' and the furthest 20% 'atypical'.

## Experiment 1: Memory Task

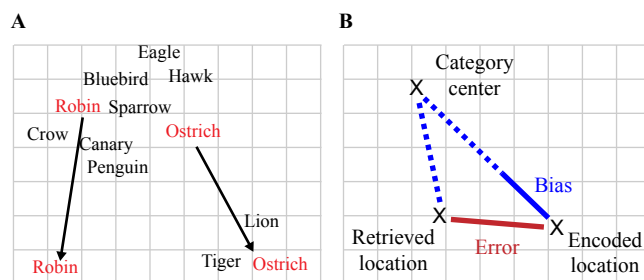
The item-location associations developed in the prior section were used in an episodic memory task. We probed whether the precision of participants' location memory was related to the consistency between an item's spatial location and the locations of its category neighbors, and whether bias was influenced by its category typicality.

### Method

**Participants** There were 25 participants in the experimental group (21 - 65 years old, 9 female) and 35 in the control group (20 - 61 years old, 16 female). The University of Pennsylvania IRB approved all consent procedures.

**Materials** See Stimulus Development section.

**Image-Location Associations** The locations paired from each image were derived from semantic relatedness judgments such that category neighbors were clustered together (see Stimulus Development). The locations of the typical and atypical items were manipulated to be inconsistent with the semantic relatedness ratings. Specifically, they were randomly assigned locations closer to one of the other two cluster centers from the same superordinate category (Figure 1A). In total, 42 images were associated with locations consistent with the ratings ('consistent'), and 28 were associated with a random location ('inconsistent'). Of the inconsistent items, 14 were typical and 14 were atypical category members. The projections for animals and objects were arranged side-by-side, randomized for each participant (Figure 3A).



**Figure 1** (A) Consistency and typicality for 'birds'. Black indicates 'consistent' and red indicates 'inconsistent' items. Inconsistent items were either typical or atypical category members. (B) Retrieval measures for an item biased towards its category neighbors. Solid red line indicates error. Solid blue line indicates bias.

In the control group, all image-location pairings were randomly shuffled within superordinate category. This group viewed the same locations as the experimental group, but the images assigned to the locations did not cluster by category. In other words, the locations that had originally been associated with (in)consistent or (a)typical images could be associated with any image in that superordinate category, rendering these conditions meaningless.

**Memory Procedure** The memory experiment comprised an encoding phase and a retrieval phase, separated by a 5-minute break. On each encoding trial, participants viewed an image beneath the grid and a red dot corresponding to that image's location. They were instructed to drag the image onto the dot, click the mouse button once it was positioned over the dot, and memorize its location for a later memory test. Images were presented three times, in three rounds of encoding separated by 1-min breaks. The retrieval task was identical to encoding, but with no dot. Participants were instructed to drag the image to its associated location. The trial order was randomized<sup>1</sup>.

**Statistical Analyses** Two dependent measures were established to quantify error and bias for each image (Figure 1B). Error was defined as the distance between an image's encoded and retrieved location, where greater values indicate less precision. Bias was defined as the relative difference in distance between an item's cluster center and its encoded versus retrieved location: (encoded - center) - (retrieved - center). Thus, values > 0 indicate that retrieval was biased *towards* the cluster center, and < 0 indicate bias *away* from the cluster center. Both measures were averaged across trials by consistency with the relatedness ratings (consistent vs. inconsistent) and by typicality (atypical vs. typical) and entered into two-tailed paired t-tests and repeated measures ANOVAs.

### Results

**Error** We computed a group (experimental, control) x consistency (consistent, inconsistent) ANOVA to examine if memory precision was modulated by the consistency of item locations with those of other category members. This revealed a main effect of group,  $F_{(1,58)} = 7.04, p = .01$ , and consistency,  $F_{(1,58)} = 8.46, p = .005$ . These effects were qualified by an interaction,  $F_{(1,58)} = 5.82, p = .02$  (Figure 2A), driven by less error for consistent items relative to inconsistent items in the experimental group,  $t_{(24)} = 4.11, p < .001$ , but not the control group,  $t_{(34)} = 0.63, p = .54$ .

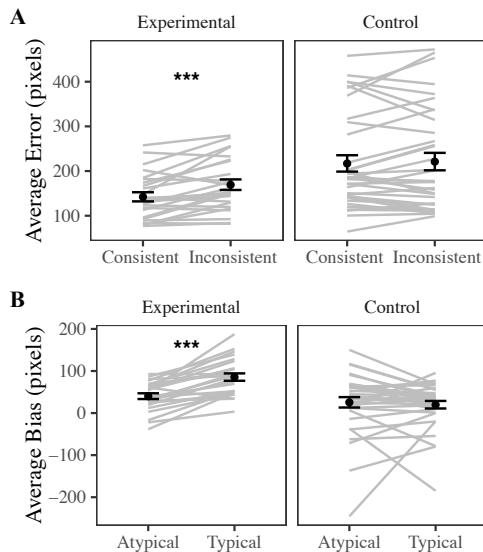
We next asked whether, among the inconsistent items, there were differences in precision by typicality. A group x typicality (typical, atypical) ANOVA revealed a main effect of group,  $F_{(1,58)} = 4.16, p = .046$ , but no reliable effect of, or interaction with, typicality (both  $F$ 's < 2.03,  $p$ 's > 0.16).

**Bias** We next asked whether the direction of error differed for typical versus atypical category members. We computed a group x typicality ANOVA amongst the inconsistent items, with bias as the dependent variable (Figure 2B). We found a main effect of group,  $F_{(1,58)} = 9.89, p = .003$  and typicality,  $F_{(1,58)} = 5.46, p = .02$ , and a group x typicality

<sup>1</sup>Due to a bug, the trial order and locations of the inconsistent items were randomized identically in all participants. Findings from this cohort are reported in this proceeding. After finding the error, we ran a replication experiment (N = 35) where both were randomized individually. All findings were successfully replicated.

interaction,  $F_{(1,58)} = 14.12$ ,  $p < .001$ . This interaction was driven by greater bias towards category neighbors for typical items relative to atypical items in the experimental group,  $t_{(24)} = 6.76$ ,  $p < .001$ , but not the control group,  $t_{(34)} = 0.55$ ,  $p = .59$ .

As predicted, typical items were retrieved as closer to their category neighbors relative to atypical items. It could be the case, however, that this bias was driven by an unrelated difference in how typical and atypical items' locations were retrieved – one possibility is that typical items were retrieved more centrally in the display. To test this possibility, we computed each item's average bias towards the two other clusters in the superordinate category and entered it into a group x typicality ANOVA. There was no main effect of or interaction with typicality (both  $F$ 's  $< .34$ , both  $p$ 's  $> .56$ ). This suggests that retrieval of typical items was specifically biased towards category neighbors.



**Figure 2** Experiment 1 results. (A) Average error by consistency. (B) Average bias by category typicality. Condition labels in the control group indicate the locations to which (in)consistent and (a)typical items had been assigned in the experimental group; these locations were randomly assigned images in the control group. Lines indicate participants. Error bars signify standard error of the mean (SEM). \*\*\*  $p < .001$ .

## Discussion

We found that participants' retrieval was more precise for items located near category neighbors, replicating prior observations of enhancements in memories that are consistent with prior knowledge. Furthermore, of the items that were located far from category neighbors, typical items were more biased towards their category neighbors relative to atypical items, despite no reliable differences in precision. Together, these results suggest that differences in typicality govern the extent of distortion in new memories.

## Experiment 2: Stimulus Development

In Experiment 1, we developed data-driven methods to sort items by category typicality and assign them to spatial locations based on their semantic relatedness. We next developed a conceptual replication, using different stimuli, to investigate whether we would observe the same effects with more standard procedures to define category membership and typicality.

## Method

**Participants** 216 participants (27 per category) completed an item ranking procedure. 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 (80 animals, 80 objects). These superordinate categories were 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 investigating categorization norms (Deyne et al., 2008; Uyeda & Mandler, 1980).

**Ranking Procedure** We modified a validated item ranking task (Djalal, Ameer, & Storms, 2016) to sort category members by their typicality. Extensive instructions with examples were given to ensure participants understood the sorting procedure. 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 three boxes in any order. This resulted in a row of 10 images per box. Then, within each box, participants sorted the 10 images on a scale ranging from most (a)typical to less (a)typical. Arrows and labels in the two boxes indicated the direction that images were to be sorted. The resulting spatial positions in the two boxes were concatenated into a ranked list of category typicality and averaged across participants.

## Experiment 2: Memory Task

Results from the ranking task were used in Experiment 2 to define category membership and typicality for a memory task identical to that of Experiment 1. We also aimed to rule out the possibility that memory was more precise for consistent items because they were more densely clustered, increasing the likelihood of guessing the correct location.

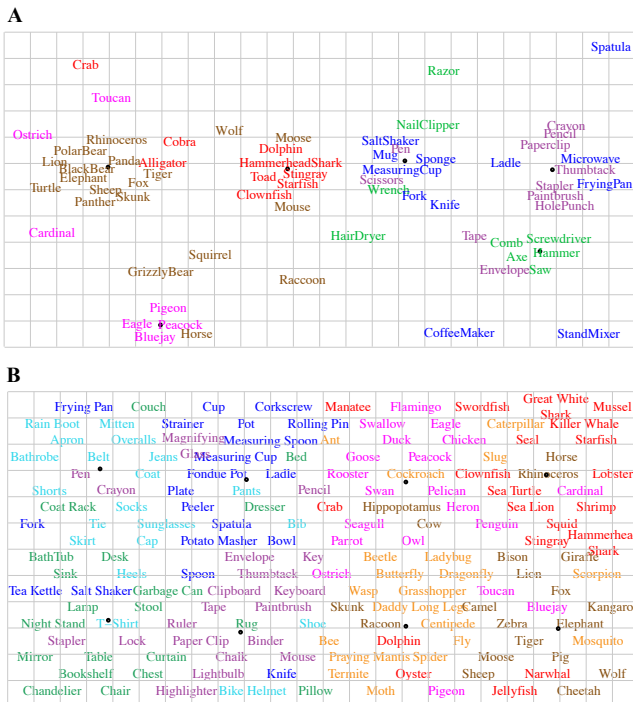
## Method

**Participants** 35 participants were in the experimental group (22 - 70 years old, 14 female) and 35 in the control group (24 - 72 years old, 16 female). The University of Pennsylvania IRB approved all consent procedures.

**Materials** See Stimulus Development section.

**Image-Location Associations** To generate items' locations, the memory grid was divided into halves with animals on one side and objects on the other, randomized across participants. Each side was divided into four quadrants. Within each quadrant, items from one of the four categories were spaced roughly uniformly apart, resulting in an even distribution of items across the grid (Figure 3B).

As in Experiment 1, some items were assigned locations away from category neighbors. The 15% most typical and 15% most atypical items were swapped across categories, where each quadrant had an equal number of typical and atypical items from the other three quadrants from the same superordinate category. In total, 112 images were located in the quadrant consistent with their category ('consistent'), and 48 in a different quadrant ('inconsistent'). Of the 48 inconsistent items, 24 were typical and 24 were atypical category members. In the control group, images were randomly assigned to locations within each superordinate category, identically to the procedure in Experiment 1.



**Figure 3** Example memory displays for Experiment 1 (A) and Experiment 2 (B). Each word represents the location of its corresponding image. Colors indicate categories. Black dots indicate a category's cluster center. Each image-location association was presented and tested one at a time.

**Memory Procedure** The timing and instructions were identical to those of Experiment 1, with an additional confidence measure that will not be discussed.

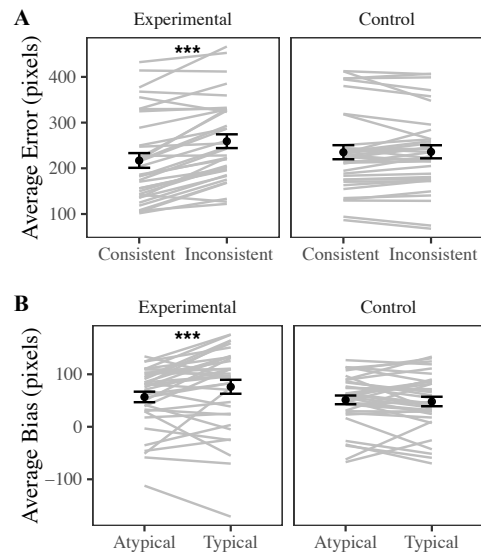
**Statistical Analyses** The analyses were identical to those in Experiment 1.

**Results**

**Error** We computed a group (experimental, control) x consistency (consistent, inconsistent) ANOVA and found a main effect of consistency,  $F_{(1,68)} = 38.63, p < .001$ , but not of group,  $F_{(1,68)} = 0.01, p = .91$ . Critically, there was also a group x consistency interaction,  $F_{(1,68)} = 35.33, p < .001$  (Figure 4A). This interaction was driven by less error for consistent items relative to inconsistent items in the experimental group,  $t_{(34)} = 7.35, p < .001$ , but not the control group,  $t_{(34)} = 0.24, p = .81$ . As in Experiment 1, memory precision was modulated by the consistency of an item's location with those of its category neighbors.

We next asked whether, among the inconsistent items, there were differences in error by typicality. A group x typicality (typical, atypical) ANOVA revealed no main effect of group,  $F_{(1,68)} = 1.24, p = .27$ . Interestingly, in contrast to Experiment 1, we found a main effect of typicality,  $F_{(1,68)} = 9.65, p = .003$ , qualified by a group x typicality interaction,  $F_{(1,68)} = 5.77, p = 0.02$ . This interaction was driven by increased error for typical items relative to atypical items in the experimental group,  $t_{(34)} = 3.43, p = .002$ , but not the control group,  $t_{(34)} = 0.59, p = .56$ .

**Bias** We next focused on differences in bias by typicality and computed a group x typicality ANOVA amongst inconsistent items. We found no reliable main effect of group,  $F_{(1,68)} = 1.47, p = .23$  and a trending effect of typicality,  $F_{(1,68)} = 3.10, p = .08$ . There was a reliable group x typicality interaction,  $F_{(1,68)} = 5.91, p = .02$  (Figure 4B). This interaction was driven by greater bias for typical items relative to atypical items in the experimental group,  $t_{(34)} = 2.56, p = .01$ , but not the control group,  $t_{(34)} = 0.58, p = .56$ , replicating the observed difference in bias by typicality in Experiment 1.



**Figure 4** Experiment 2 results. (A) Average error by consistency. (B) Average bias by category typicality. Lines indicate participants. Error bars signify SEM. \*\*\*  $p < .001$ .

## General Discussion

Across two experiments, we found that manipulating the match with prior semantic knowledge – by leveraging differences in category typicality – can influence the precision and distortion of new memories. Participants were able to learn associations between an image's category membership and its location on a grid, and this knowledge enhanced their memory of the locations of specific items. Precision of this memory was greater if the items clustered near others from the same category. For items that were located away from category neighbors, participants made systematic errors: typical category members were retrieved closer to category neighbors than atypical category members. These results were observed in two experiments despite differences in the number and type of categories, method of determining typicality, and mapping between category membership and spatial location.

Our findings that consistent items were more precise than inconsistent items (in both experiments), and that precision was greater in the experimental group (in Experiment 1 only), are consistent with a large and diverse body of work showing that prior knowledge facilitates memory for related stimuli (Alba & Hasher, 1983). Our findings extend these results by showing that prior knowledge can improve encoding of new, unrelated features of an item. In our experiment, participants mapped items onto spatial locations on a grid. These locations were not intrinsically related to the items (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 items, participants treated location as a new 'feature' of items that was explained well by their category membership. Thus, prior knowledge can help to organize the encoding of unrelated contextual details.

When locations did not match expectations, participants' memory was prone to systematic biases. In both experiments, retrieval of typical category members was more biased towards category neighbors relative to retrieval of the atypical category members. While it is well known that memory can be easily distorted (Loftus & Palmer, 1974; Roediger & McDermott, 1995), much of this past work is focused on discrete differences in memory retrieval (e.g. was a word recalled or not). Using continuous reports allows retrieval to be broken down into item-specific error and systematic influences of a particular category or structure (Huttenlocher, Hedges, & Duncan, 1991; Hemmer & Steyvers, 2009; Persaud & Hemmer, 2014). This prior work also demonstrates that new encoding 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 semantic knowledge can exert a stronger or weaker influence on new encoding depending on semantic properties like the typicality of category members, and that such bias can operate independently of memory precision.

What can these biases tell us about how category

members are organized; specifically, why is memory for typical members more biased towards neighbors? One possibility is that typical items are more strongly 'pulled' by neighboring items on account of their stronger associations. This interpretation would mirror observations that participants are more likely to cluster the recall of typical items relative to atypical items (Bousfield, Cohen, & Whitmarsh, 1958). Alternatively, because typical items are more similar to other category members, it may be easier to confuse their locations with other item locations that happen to be near the cluster center. This explanation is not specific to category membership but could be applied to any set of memoranda that vary in similarity. Yet another possibility is that because typical items are the closest match to their category, they are more efficiently encoded, but at a cost to in-depth processing of their novel details (Sweegers, Coleman, van Poppel, Cox, & Talamini, 2015) – like their associated location. As we cannot adjudicate between these interpretations with the present design, we have developed follow-up experiments to examine these alternatives.

In summary, we have presented an investigation of the biases that semantic knowledge exerts on episodic encoding. This work demonstrates that semantic knowledge and episodic memory are closely intertwined and offers an opportunity to better understand the interactions between the two systems.

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