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A Bayesian Account of Reconstructive Memory

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Abstract

It is well established that prior knowledge influences reconstruction from memory, but the specific interactions of memory and knowledge are unclear. Extending work by Huttenlocher et al. (*Psychological Review, 98* [1991] 352; *Journal of Experimental Psychology: General, 129* [2000] 220), we propose a Bayesian model of reconstructive memory in which prior knowledge interacts with episodic memory at multiple levels of abstraction. The combination of prior knowledge and noisy memory representations is dependent on familiarity. We present empirical evidence of the influences of prior knowledge at multiple levels of abstraction, showing that the reconstruction of familiar objects is influenced toward the specific prior for that object, while unfamiliar objects are influenced toward the overall category.

Keywords: Long-term memory; Prior knowledge; Bayesian models; Reconstructive memory

Recall of past events can be based on multiple sources of information, such as episodic memories and general knowledge. Information stored in episodic memory provides a direct source of information to guide recall, but this information might be incomplete or noisy. General knowledge about a past event might be helpful for filling in missing details or reducing the effect of noise from episodic memory. For example, when trying to remember the last restaurant we went to and what food we ordered, our recall might be driven not only by vague details of the past restaurant visits but also by general knowledge—perhaps we often go to the same restaurant and we usually order a particular set of dishes. This general knowledge is helpful in guiding recall about past events.

Bartlett (1932) showed that memories are guided by schemas that help to fill in the details of memories. For example, providing additional meaningful information can activate schemas that guide the interpretation of the stimulus and serves as an aid to memory (Bower, Karlin, & Dueck, 1975; Bransford & Johnson, 1972; Carmichael, Hogan, & Walter, 1932).

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Biases need not be from external sources, but they may arise from internal sources as well (Biernat, 1993; Rehnman & Herlitz, 2006). Bartlett showed that the participants themselves bring certain biases to the task. In both temporal and serial reproduction he demonstrated how a person's cultural and social experiences influence reconstruction from memory to conform to their idiosyncratic biases. Kalish, Griffiths, and Lewandowsky (2007) formalized Bartlett's serial reproduction task using iterated learning with Bayesian and human agents. They showed that Bayesian and human learners revert to their prior when inferring the underlying function of a set of coordinates. While serial reproduction is about the evolution from iteration to iteration, the approach presented here will focus on retrieval from memory based on a single specific event.

Previous work by Huttenlocher and colleagues (Crawford, Huttenlocher, & Engebretson, 2000; Huttenlocher, Hedges, & Duncan, 1991; Huttenlocher, Hedges, & Vevea, 2000) has shown that prior knowledge exerts strong influences on reconstruction from memory. Huttenlocher et al. (1991) presented a Bayesian model of category effects positing that reconstruction from memory is a weighted average of specific memory traces and category information. This weighted average ''cleans up'' noisy memory traces and prevents large errors in reconstruction.

In this paper, we first present the basic approach of the model presented by Huttenlocher and colleagues and then introduce a series of extensions to this model. We assume that the observer is presented with an object during study and is instructed to retrieve from memory a feature of that object at a later time. In the experiment reported in this paper, we test memory for one-dimensional stimulus values, such as the size of an object. In this context, the goal for the observer is to reconstruct the original size μ of an object using noisy samples y that are retrieved from memory. Bayes' rule gives us a principled way of combining prior knowledge and evidence from memory:

$$p(\mu|y) \propto p(y|\mu)p(\mu) \tag{1}$$

The posterior probability $p(\mu|y)$ gives the likely stimulus values μ given the noisy memory contents y. This posterior probability is based on a combination of $p(\mu)$, the prior knowledge of the likely sizes of the object and $p(y|\mu)$, the likelihood of obtaining evidence y from memory. This Bayesian approach gives a principled account of how prior knowledge of the world is combined with memory contents to recall information about events.

For example, suppose the feature values of objects are Gaussian distributed, $\mu \sim N(\mu_0, \sigma_0^2)$, where μ_0 and σ_0^2 are the prior mean and variance of the feature values. Furthermore, when a specific object value μ_s is studied, suppose this leads to samples y drawn from episodic memory with the samples having a Gaussian noise distribution centered on the original studied value, $y \sim N(\mu_s, \sigma_m^2)$. The variance of the noise process, σ_m^2, controls the degree to which the stored episodic representations resemble the original studied object features. The exact source of the noise is not modeled in this account, but this could be related to decay or interference with other events entering memory. Standard Bayesian techniques can now be used to calculate the posterior distribution in Eq. 1. The conditional probability of recalled stimulus value μ_r given the contents of memory y is given by a Gaussian distribution with mean μ_n,

$$\mu_n = w\mu_0 + (1 - w)\bar{y} \tag{2}$$

where $w = (1/\sigma_0^2)/[(1/\sigma_0^2)+(n/\sigma_m^2)]$ and n is the number of samples taken from episodic memory. Note that the mean of the recalled stimulus values is a weighted linear combination of the prior mean μ_0 and the mean of memory content $\bar{y}$. The prior mean μ_0 is weighted more heavily in recall when the prior has a higher precision $(1/\sigma_0^2)$ and when the memory noise increases. This corresponds to the intuitive notion that if the prior is strong, it will have a strong influence on recall. Similarly, if memory contents are very noisy, the prior will also exert a strong influence on recall.

This model predicts systematic biases toward the category center, or prior category mean, at reconstruction. Fig. 1 illustrates these biases and the effect of the strength of the prior. The small vertical lines represent the small noisy samples (around .2) drawn from episodic memory at the time of test. In panels A1–3, we simulate drawing a single sample (n = 1) from memory. The dashed lines represent prior knowledge, and the solid lines represent the posterior distribution that forms the basis for recall. Using classical statistical inference (panel A1) with an uninformative prior, the posterior is centered on the mean of the memory sample—there is no effect of the prior. Using Bayesian inference (panels A2 and A3), we specified a prior with mean μ_0 = .4. We simulated a relative vague prior with precision

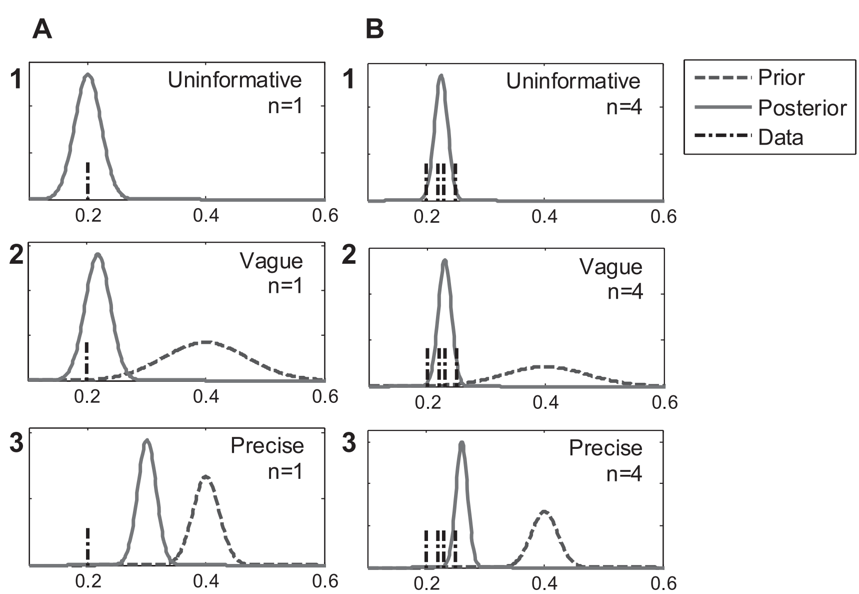

Fig. 1. Illustrations of a Bayesian account for the systematic biases in reconstructive memory due to prior knowledge. Small vertical lines represent samples drawn from episodic memory. Panels 1A–B show classical statistical inference, panels 2A–B show Bayesian inference with a relatively vague prior, panels 3A–B show Bayesian inference with a relatively precise prior.

$1/\sigma_0^2 = 200$. Using the Bayesian inference procedure as described above, the resulting posterior is slightly shifted toward the prior (A2). For a relative precise prior with precision $1/\sigma_0^2 = 2000$, the result is a posterior that is shifted much more away from the data and toward the prior (A3). Panels B1–3 show the results when four samples ($n = 4$) are drawn from memory. In this case, the evidence from memory is stronger, which decreases the influence of the prior. Subsequently, the posterior distribution is less influenced by the prior.

1. Extending the basic approach

The approach sketched above formed the basis for the theory by Huttenlocher and colleagues. We propose an extension to this theory where prior knowledge can come from multiple sources. We will conduct a behavioral experiment using natural objects such as fruits and vegetables for which participants have preexperimental knowledge. We expect that such naturalistic stimuli are associated with more structured knowledge representations where knowledge can be described at several levels of abstraction. For example, we expect that participants not only have prior knowledge at the category level (e.g., ''I expect fruits to be roughly of this size'') but also at the object level (e.g., ''I expect an apple to be of this size''). We predict that the influence of the object and category prior knowledge depends on an individual's familiarity with the object and category. If a participant studies an object with which they are familiar, for example, a chayote (a type of gourd), then they can use their knowledge about the common size of this object to aid their reconstruction and correct an otherwise noisy memory trace at test. Another participant that studies the same chayote, who does not know this object, might be able to recognize it as a vegetable and can use his general knowledge at the category level to guide reconstruction. In the experiment, we will test some of the predictions from this extended theory and focus on the role of multiple sources of prior knowledge in reconstructive memory.

2. Experiment

In the following experiment we first measured the perceived size of common natural objects such as fruits and vegetables as an estimate of participants' prior knowledge for these objects (norming phase). In the second phase of the experiment we assessed recall memory for size. We used the observed size ranges from the norming phase as the foundation for the study sizes in order to encourage the use of prior knowledge.

We predict that the effect of prior knowledge at the category and object level will be observed by systematic deviations toward the mean of the object and category prior at reconstruction. At the category level, this means that small objects (e.g., raspberries) will be overestimated while large objects (e.g., pineapple) will be underestimated. At the object level, this means that objects presented at relatively small sizes (e.g., a small apple relative to all apples) will be overestimated while large objects (e.g., a large apple) will be underestimated.

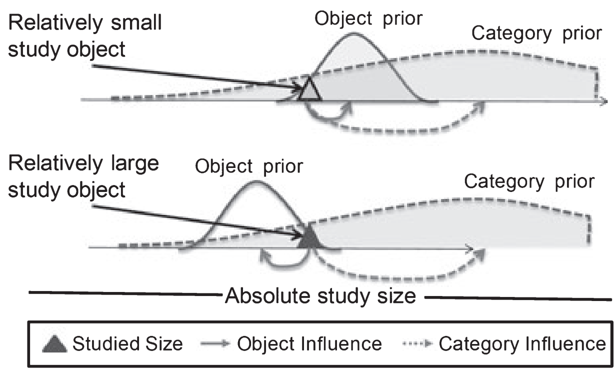

Fig. 2. Predicted influences of category and object level priors for two objects studied at the same size.

Separating out the contributions from category and object level is difficult because in many cases, the effects might operate in the same direction. This is illustrated in Fig. 2, top panel. If an object is studied at a size that is small relative to both the category and object prior (e.g., a small apple), both of these priors will result in a positive bias. They are both operating in the same direction, toward the category center. The clearest demonstration of independent contributions of object and category level prior knowledge is provided when the effects go in opposite directions. For example, in Fig. 2, bottom panel, the object (e.g., a large strawberry) is studied at a size that is large relative to the object prior but small relative to the category prior. In this case, the category effect leads to an overestimation while the object effect will lead to an underestimation of the object at reconstruction. The crucial comparison is between the top and bottom panel. In both cases, the objects are shown at exactly the same size during study. Because both the category and object level effects might operate simultaneously, it is unclear what the combined result is. However, we predict that objects that are studied at the same absolute study size can be differentially biased when the objects are associated with different object-level prior knowledge.

3. Methods

3.1. Participants

Participants were undergraduate students at the University of California, Irvine. There were 18 participants in the norming phase and 25 participants in the test phase.

3.2. Materials and procedure

For the norming phase there were 37 images in two categories: fruits and vegetables. For the test phase, 24 of the objects from each of the norming categories were

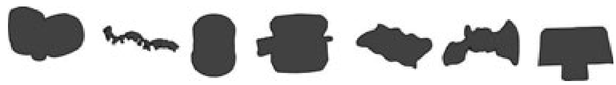

Fig. 3. Examples from the shapes category created by drawing outlines of objects filled in blue.

used. See Fig. 4 for examples. Another class of stimuli was also developed: abstract shapes created by drawing outlines of objects and filling with blue. See Fig. 3 for examples.

3.3. Norming phase

All materials were presented on two computer screens. A reference object was presented on the left screen and the object of interest was presented on the right screen. Participants were asked to make three size judgments for each object: ''What is the smallest (or average or largest) size of an object like this?'' Participants manipulated the size of the object using a slider. Responses were measured on a scale from 0 to 1 (where 1 corresponds to the maximum size of the computer screen). Images were blocked by category (fruits and vegetables) and presented in random order within each block. Images were initialized at 1 of 4 sizes relative to the overall screen size: .2, .4, .6, or .8.

3.4. Memory phase

The study sizes of the images were sampled from the size ranges collected in the norming phase. For sampling, we used a truncated Gaussian distribution between the minimum and the maximum of the individual object range. The objects were never shown outside of the minimum–maximum range. The shapes category was yoked to the vegetable category for size and orientation on the screen. The specific study size for each shape was the same as that of its yoked vegetable. Participants were shown a continuous random sequence of study and test images. The images were blocked by category (fruits, vegetables, and shapes). Each study image within each category was presented a total of three times during the experiment, and there was always a related intervening test trial between presentations. The study size for a given image remained constant across the three repetitions. Each participant completed three blocks of 72 study and test images, and trials and blocks were randomized across subjects. Study images were presented for 2 s. At test participants were asked to make two memory judgments. They were first asked to make a recognition decision about whether they remembered seeing the object at study. Second, they were asked to make a recall judgment about the size of the object at study using the slider on the screen to manipulate the size of the object. The object remained on the screen until the participant was satisfied with the current size judgment and clicked a button to continue. Responses were measured on a scale from 0 to 1. On test trials, the images were shown randomly at 1 of 4 sizes: .2, .4, .6, and .8. The slider was initiated at the corresponding location.

4. Results

4.1. Norming phase

Fig. 4 depicts the 24 objects from the vegetable category. The top panel indicates the range of the size judgments for individual objects averaged over participants. The results follow a natural order: the mean ''average'' size judgment for mushrooms is smaller than for bell peppers, which are all smaller than celery, and so on. Participants expressed a large degree of agreement, although variability does increase with the magnitude of the objects.

4.2. Memory phase

Reconstruction error (reconstructed size—studied size) was used to measure performance in each category. Reconstruction error as a function of category and object class is plotted in Fig. 5. Positive reconstruction error indicates overestimation while negative reconstruction error indicates underestimation. The observed pattern of correction toward the category center as indicated by negative slopes for all categories supports the prediction of category effects.

To assess the influence of object priors, we divided the study objects into four classes based on the study sizes relative to the minimum and maximum acceptable sizes as assessed in the norming experiment. We divided the range between the minimum and maximum in four equal ranges and named those ranges ''very small,'' ''small,'' ''large,'' and ''very large.'' Fig. 6 illustrates this discretization process. These classes therefore give the sizes of objects relative to the mean of the object—for example, a ''very large'' object might be an apple that is studied at close to the maximum size (relative to all apples). For each of the four relative object classes we divide the absolute study sizes into the top, middle, and bottom 33% percentile. Mean reconstruction error was calculated separately for the trials that fell into these top, middle, and bottom bins. Because we applied this procedure separately for each relative object size, the absolute study sizes do not line up between relative object sizes (see Fig. 5).

The results show a regular pattern for different object classes (very small < small < large < very large). This difference in intercepts by relative study size supports the prediction of object prior effects. To measure the effects of prior knowledge on reconstruction memory at both the category and object level, a regression model was fitted to each subject assuming a fixed slope and separate intercepts for each relative object size. Average slopes and intercepts are reported in Table 1.

The slope for each category was significantly different from zero (fruits: $t[24] = -4.714$, $p = .000$, vegetables: $t[24] = -5.657$, $p = .000$, shapes: $t[24] = -10.754$, $p = .000$). This is consistent with a category-level influence of prior knowledge. A repeated measures ANOVA for the fruit and vegetable categories showed a significant main effect of intercept ($F[3.72] = 14.359$, $p = .000$). A significant trend was observed such that intercepts for very small objects were larger than that of relatively small objects ($F[1,24] = 4.403$, $p = .037$), as was that of relatively small to relatively large objects ($F[1,24] = 7.902$, $p = .010$), and relatively large to relatively very large objects ($F[1,24] = 6.022$, $p = .022$). These differences

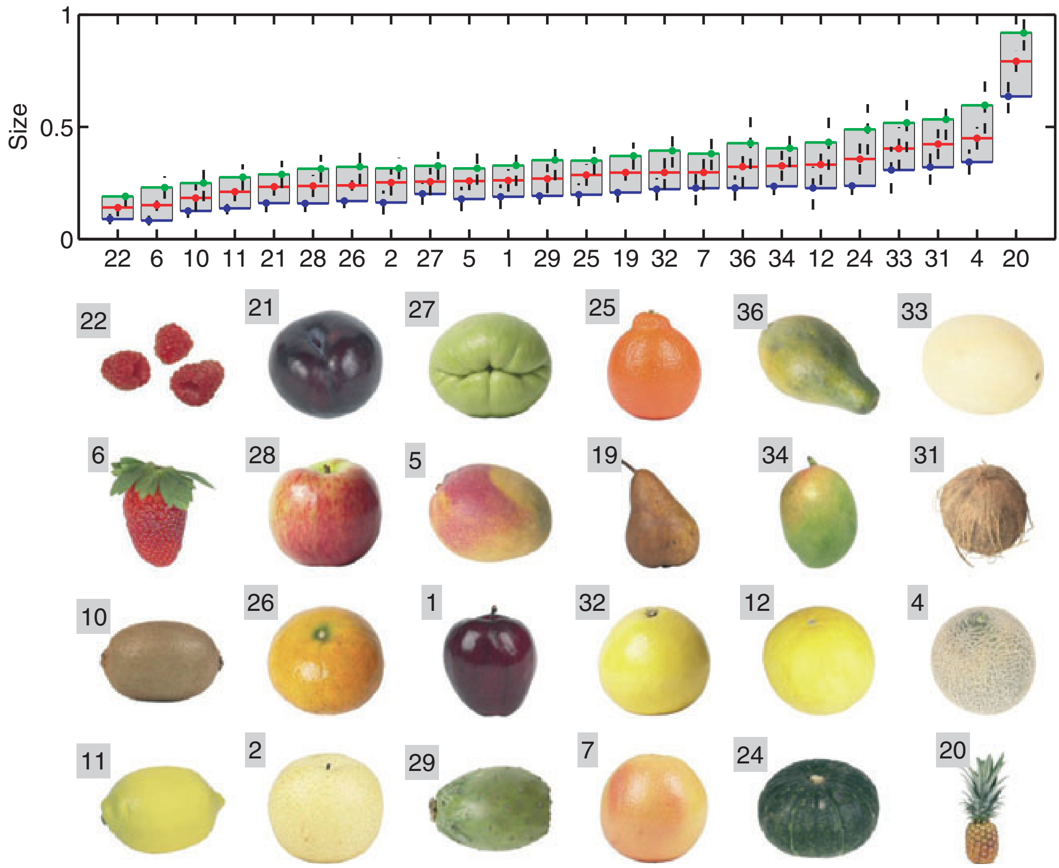

Fig. 4. Norming results for the fruit category. The objects are in reading order by the mean of the ''average'' rating. The bar graph shows the range of size judgments for individual objects. The scale on the vertical axis ranges from 0 to 1, where 1 corresponds to the maximum size of the computer screen. For each bar, the mean of the ''small,'' ''average,'' and ''large'' sizes are indicated by the bottom line, middle line, and top line, respectively. The vertical lines correspond to the 25–75% confidence interval across participants.

are consistent with an object-level influence of prior knowledge. A repeated measures ANOVA for the shape category found no effect of intercept ($F[3,72] = .453$, $p = .716$). This lack of difference between the intercepts in the shape category indicates that there is no object-level effect for the objects for which the participants have no preexperimental knowledge.

5. Model

The results showed that natural stimuli such as fruits and vegetables are associated with multiple levels of preexperimental prior knowledge, each exerting an influence on reconstructive memory such that objects studied at the same absolute size can be differentially biased depending on the prior knowledge at the object level. In our first extension of the

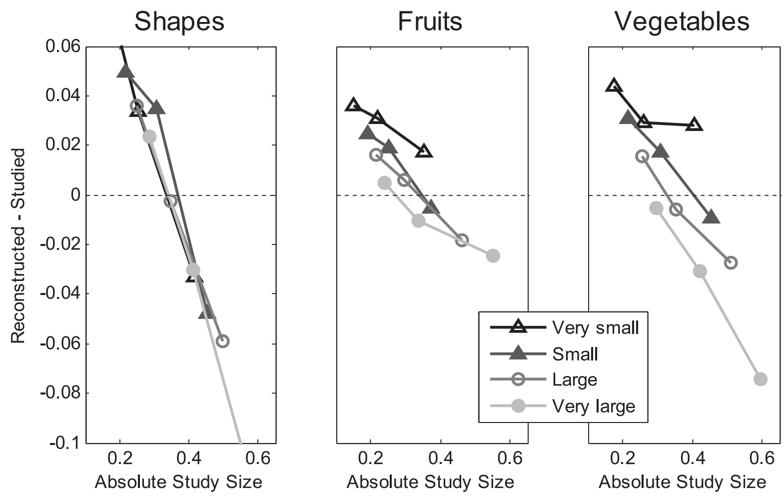

Fig. 5. Reconstruction error as a function of category and object class. Study objects are divided into four classes relative to the mean of the object: ''very small,'' ''small,'' ''large,'' and ''very large.'' Negative slopes show correction toward the category center and are indicative of category-level knowledge effects. Intercept differences by relative study size are indicative of object-level knowledge effects.

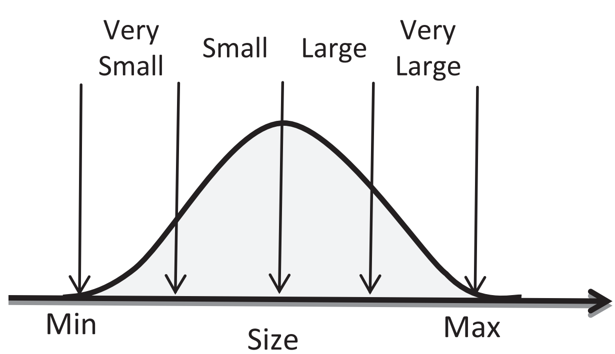

Fig. 6. Example of the Gaussian distribution for a simulated object prior. The four regions label the study sizes relative to the object prior.

basic model by Huttenlocher and colleagues, we propose that prior knowledge can be represented at multiple levels of abstraction which can independently influence reconstruction from memory. We propose a simple mixture model where the prior mean and variance (μ_0, σ_0^2) is a combination of category and object level priors,

$$\mu_0 = z\mu_i + (1 - z)\mu_c \tag{3}$$

$$\sigma_0^2 = z\sigma_i^2 + (1 - z)\sigma_c^2 \tag{4}$$

where (μ_i, σ_i^2) represents the object prior associated with object *i* and (μ_c, σ_c^2) represents the category prior. The variable z weights the contribution of the object prior relative to the category prior. We assume that this weighting is determined by

Table 1
Mean slopes and intercepts by category and relative object size

	Fruits		Vegetables		Shapes	
	M	*SD*	*M*	*SD*	*M*	*SD*
Slope	−.120	.127	−.191	.169	−.415	.201
Intercepts						
Relative object size						
Very small	.057	.049	.089	.062	.144	.075
Small	.048	.045	.075	.058	.148	.072
Large	.040	.044	.065	.059	.142	.072
Very large	.035	.054	.047	.065	.143	.016

Note: n = 25.

$$z \sim \text{Bernouli}(\theta_i) \tag{5}$$

where θ_i is a constant that represents the familiarity of an object. In this model, familiar objects lead to a prior that is more dependent on the object rather than the category. Similarly, this implements the intuitive notion that for unfamiliar objects, it is unlikely that the object prior is reliable and inference instead reverts to a higher-level prior based on categorical knowledge.

As before, we assume that the computational goal for the participant is to invert the forward memory model and reconstruct the original event given the noisy memory contents and prior knowledge about the study event. The solution to this computational problem was described in Eq. 2.

We applied the model in Eqs. 2–5 to our experimental setup and aimed for qualitative fits to the data as opposed to detailed quantitative fits. We used three values of θ corresponding to no object familiarity ($\theta = 0$), medium familiarity ($\theta = .4$), and high familiarity ($\theta = .7$). In this model, the category prior can represent a combination of a priori knowledge about the category as well as knowledge accumulated during the experiment (such as the distribution learned for the shapes category). Here, we will not distinguish between these two sources for the category prior and use a single prior with $\mu_c = .5$ and $1/\sigma_c^2 = 20$. This is a relatively vague prior that is centered near the mean of study sizes we used in the experiment. For the object priors, we simulated Gaussians with means centered across the range [0,1] and precision $1/\sigma_i^2 = 200$. This implements a relatively precise object prior compared to the category prior. For the study sizes, we drew samples from the object priors and rejected samples outside the [0,1] range. For the purpose of data analysis, we categorized the study sizes into four classes: ''very small,'' ''small,'' ''large,'' and ''very large'' (as illustrated in Fig. 6). These size indications are relative to the object prior. Just as in the experiment, the label ''very small'' refers to an object that was presented at study at a value close to the minimum size for that particular object. This size is *not* related to the absolute study size. For example, we can simulate a very small pineapple that is still larger than most other fruits. Finally, we ran the simulation with a memory precision of $1/\sigma_m^2 = 50$.

Fig. 7A shows the model predictions. Overall, the results show effects of both the category and object prior. Objects that were studied at small sizes with respect to the category and the object prior are overestimated while large study sizes relative to the object and category prior are underestimated. Also, as expected, variations in familiarity can modulate the influence of the object prior. For $\theta = 0$, there is no influence of the prior. This situation is comparable to the experimental results for the shapes category for which participants did not have any preexperimental knowledge specific to the object.

When comparing the slopes in this simulation and the experimental results in Fig. 5, an important discrepancy arises. In the experimental data, the effect of the category prior is stronger for the shapes compared to the fruits and vegetables (see Table 1 for the difference in estimated slopes across categories). In the simulation in Fig. 7A, the effect of the category prior is more or less constant across the levels of familiarity. The difference in category prior cannot be explained due to differences in the study size distributions because the shapes category was yoked to the vegetables category and exactly the same sizes were presented across the two categories.

These experimental results raise an interesting issue about the relative effects of the priors. For objects that have presumably very little prior knowledge, we see relative strong effects of the priors, exactly opposite to what the basic Bayesian approach would predict.

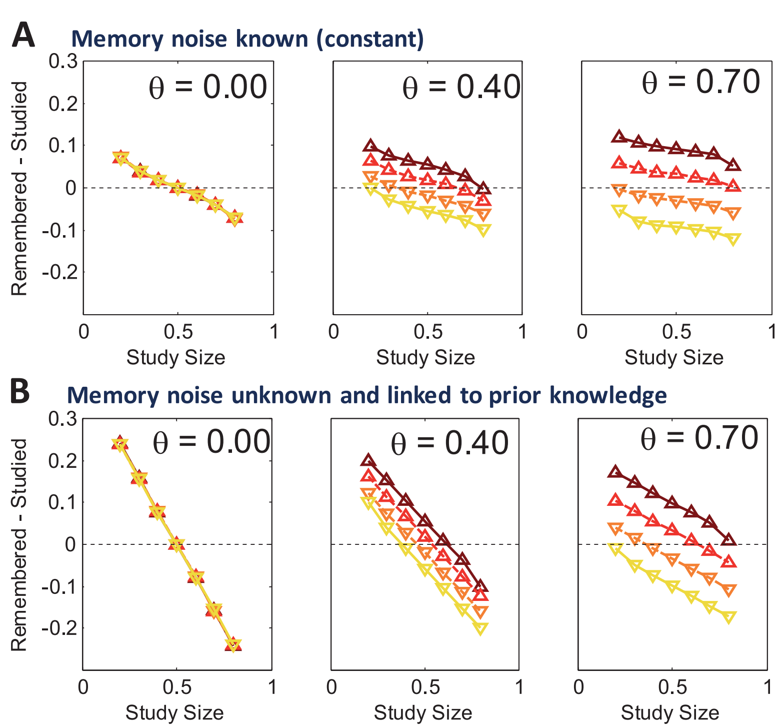

Fig. 7. (A) Model predictions when memory noise is a constant parameter. (B) Model predictions when memory noise is an unknown variable.

This suggests that an additional change to the theory is needed to fully explain the data. We will now describe a change to the noise process that governs the sampling of memory representations. This additional extension will lead to a model that is able to qualitatively describe our findings.

In the basic approach, the memory noise ${\sigma_m}^2$ is treated as a constant parameter and the theory does not explain how this parameter is set or varies across experimental conditions. Moreover, this approach assumes that the observer knows the memory noise parameter during the inference process. However, it seems unlikely that the observer has access to such knowledge. We propose that the memory noise is itself an unobserved variable which needs to be estimated from the data (i.e., the memory samples) and prior knowledge. From a statistical point of view, we propose a system where the goal is to make inferences about data with an unknown mean and unknown variance. In the statistics literature, several solutions exist for this problem, and we follow a standard approach (e.g., Gelman, Carlin, Stern, & Rubin, 2003) that allows an analytic solution.

As before, we assume that noisy memory samples y are drawn from episodic memory with a Gaussian noise distribution $y \sim N(\mu_s, {\sigma_m}^2)$ that is centered around the original studied value μ_s. Instead of assuming a constant noise variance ${\sigma_m}^2$, the noise variance is sampled from an inverse-χ^2 distribution:

$$\sigma_m^2 \sim Inv - \chi^2(v_0, \sigma_0^2) \tag{6}$$

and the mean of the stimulus values is assumed to be conditionally dependent on the noise variance:

$$\mu_s | \sigma_m^2 \sim N(\mu_0, \sigma_m^2 / \kappa_0) \tag{7}$$

The constants υ_0 and κ_0 represent the prior degrees of freedom and the prior sample size, respectively. The goal for the observer is to calculate the conditional probability of recalling size μ_s given the contents y in memory. For notational purposes we will refer to this conditional probability as μ_r, where $\mu_r \sim \mu_s \mid y$. This leads to the following solution:

$$\mu_r \sim t_{v_0+n}(\mu_n, \sigma_n^2) \tag{8}$$

$$\mu_n = \frac{k_0}{k_0 + n}\mu_0 + \frac{n}{k_0 + n}\bar{y} \tag{9}$$

$$\sigma_n^2 = \frac{v_0\sigma_0^2 + (n-1)s^2 + (k_0 n / k_0 + n)(\bar{y} - \mu_0)^2}{(v_0 + n)(k_0 + n)} \tag{10}$$

Note the similarity of Eq. 9 to Eq. 2. In both cases, the mean of the recall distribution is a linear combination of the prior mean and the mean of the observed memory samples. Fig. 8 shows a graphical representation of the complete model. Shaded nodes represent observed

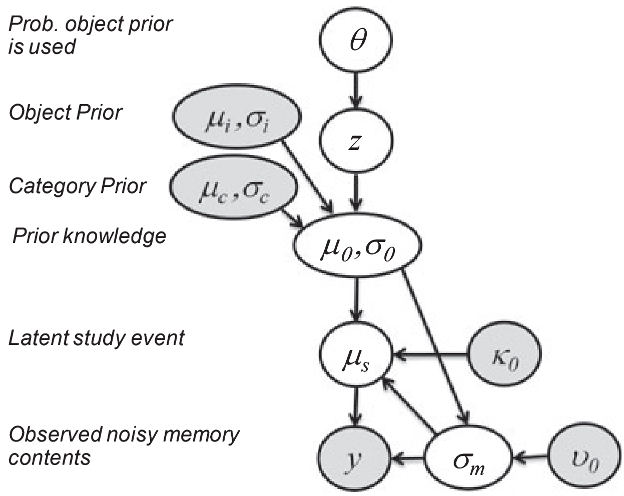

Fig. 8. The graphical model representation for the Bayesian model for reconstructive memory.

variables while nodes without shading represent unobserved variables. The arrows indicate the conditional dependencies between the variables.

Note also that memory noise is modeled as an unobserved variable and that there is a coupling between the memory noise variance and the prior variance of the study event. This corresponds to intuitive notions about memory; if we encode objects with which we are not very familiar and have little associated prior knowledge, it is more difficult to store accurate representations in memory for that object. In contrast to the previous model where memory noise was left as an unexplained parameter, this model explains memory noise as a variable dependent on prior knowledge. We simulated this model in the same manner as the previous model. We used the same category and object priors and set $\upsilon_0 = 5$ and $\kappa_0 = 5$. The results are shown in Fig. 7B. Note that the model predicts that the category prior is relatively strong for the low familiarity conditions. This somewhat paradoxical effect falls out of the model because of the coupling between memory and noise and prior knowledge. Objects with weak priors (e.g., shapes) are associated with relatively noisy samples from memory. The result is that the prior exerts a stronger influence to reduce the effects of the memory noise. On the other hand, objects with strong priors (e.g., fruits and vegetables) are associated with relative precise samples from memory, leading to a reduced influence of the prior overall.

6. Conclusion

We have given a Bayesian account of reconstructive memory, where reconstruction of the size of the original study event is influenced by prior knowledge at multiple levels. This follows from our empirical evidence that reconstruction from memory is influenced by prior knowledge at multiple levels of abstraction. Unfamiliar objects lead to inferences that are more influenced by the category center, whereas familiar objects lead to inferences that are more influenced by the object prior. A novel assumption of the model is that memory noise is unknown to the observer and becomes part of the inference process. This assumption is different from the basic approach as described by Huttenlocher et al. (1991, 2000) but is consistent with empirical data showing that category effects exert a greater influence when the observer has no preexperimental knowledge for the object, that is, the object is unfamiliar. While it seems counterintuitive that a vague prior exerts a stronger influence in reconstructive memory, this is to be expected if we couple the memory noise process to the prior.

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