

# The Effect for Category Learning on Recognition Memory: A Signal Detection Theory Analysis

## Abstract

Previous studies have shown that category learning affects subsequent recognition memory. However, questions remain as to how category learning affects discriminability during recognition. In this three-stage study, we employed sets of simulated flowers with category- and non-category-inclusion features appearing with equal probabilities. In the learning stage, participants were asked to categorize flowers by identifying the category-inclusion feature. Next, in the studying stage, participants memorized a new set of flowers, half of which belonged to the learned category. Finally, in the testing stage, participants received a recognition test with old and new flowers, some from the learned, some from the not learned, and some from both categories. We applied hierarchical Bayesian signal detection theory models to recognition performance and found that prior category learning affected both discriminability as well as criterion bias. That is, people that learned the category well, exhibited improved discriminability and a shifted bias toward flowers from the learned relative to the not learned category.

**Keywords:** category learning; recognition memory; signal detection theory; Bayesian modeling

## Introduction

Memory research has shown that prior learning experience affects recognition memory. It is often thought that prior learning is encoded into knowledge structures or *schemas* (Bartlett, 1932). In turn, schemas increase recognition of schema-inconsistent information compared to schema-consistent information, while also increasing false alarms to schema-consistent lures compared to schema-inconsistent lures. Because schema acquisition takes time and learning experiences vary among people, most recognition memory tasks have employed either within-subject designs for pre-acquired schemas (Graesser & Nakamura, 1982) or between-subject designs for individuals with different expertise (Castel et al, 2007). As such, traditional experimental designs do not easily allow manipulation of schema acquisition in a way that allows us to assess their effect on recognition memory performance.

A number of recent studies have unveiled strong connections between schematic and categorical knowledge, leading many researchers to postulate profound similarities in the cognitive processes underlying schematic and categorical learning (Sakamoto & Love, 2004). To contribute to the integration of schematic and categorical learning, and to further explore the effects of prior learning on recognition memory, De Brigard et al. (2017) recently employed a set of computer-generated stimuli (flowers) to explore how learning a novel category affects participant's recognition memory for items from the learned category relative to items from a category they did not learn. However, the studies reported by De Brigard et al. (2017) left several unanswered questions. In particular, the findings could not differentiate

between discriminability changes for items from the learned category and a change in response bias because their experiments did not include foils of both learned and not-learned categories, and thus could not provide measures of discriminability and bias for all options. In addition, De Brigard et al.'s (2017) findings did not discriminate between those who learned best and those who learned least during the category learning phase, potentially obscuring effects on discriminability in recognition memory.

In the present study, we used a modified version of De Brigard et al.'s (2017) paradigm in which flowers from learned and non-learned categories appeared in each stage with equal probability. Additionally, the current study included lures from both learned and not-learned categories during the recognition test. As such, we were able to implement full hierarchical Bayesian signal detection theory (SDT) models to data from all participants, as well as separate people by the strength of their learning. This modified experimental paradigm, and the SDT models with which the results are analyzed, enables us to further understand the effect of category learning on recognition memory.

## Category Learning and Recognition Experiment

### Participants

113 individuals participated via Amazon Mechanical Turk (<https://www.mturk.com>) for monetary compensation. All participants were from the United States and had at least 100 approved hits and overall hit rate  $\geq 95\%$ . Three participants were excluded because of failure to follow instructions or terminated the experiment in the middle, so data were analyzed with the remaining 110 individuals. All participants were provided informed consent under a protocol approved by the [hidden for blind review] IRB.

### Materials

Stimulus consisted of MATLAB (2018b)-generated flowers from De Brigard et al. (2017). Flowers varied across five dimensions, with each dimension taking one of three possible values: number of petals (4, 6, or 8), color of petals (blue, green, or yellow), shape of center (circle, triangle, and square), color of center (orange, purple, or turquoise), and number of sepals (1, 2, or 3). Figure 1 illustrates three examples of flowers with different combinations of the features (see further details in De Brigard et al., 2017).

### Procedure

We closely followed the procedure from the fourth experiment in De Brigard et al. (2017), with some modifications (see below). The experiment had three phases:

learning, study, and test. At the beginning of each phase participants read the instructions for 90s.



Figure 1. Examples of MATALB-generated flowers. From left to right: 4 blue petals- orange circle center -1 sepal; 6 green petals- purple triangle center-2 sepals; and 8 yellow petals- blue square center-3 sepals. See more in De Brigard et al., 2017.

In the learning phase, participants were told they would see a flower on the screen and will have to determine whether or not it belonged to the species *avlonia*. Participants were told that *avlonias* differed from other flowers in one simple way (e.g., only *avlonias* have four petals), and their task was to find out what the simple way was. At the beginning of the learning phase, participants were informed of all five possible dimensions—number of petals, color of petals, etc.—across which flowers may vary and saw two example flowers for illustration. They then made binary choices “yes” or “no” on each trial to categorize each flower by pressing “y” or “n”, respectively, and there were 54 trials in total. Immediately after their responses, feedback with the word “Correct” or “Incorrect” was displayed. Participants were ensured that they could guess at the beginning but eventually they would find out the simple way that made a flower an *avlonia*. Each participant was assigned to a category-inclusion feature consisting of one possible value from one of the five dimensions. This assignment was counterbalanced across participants. Flowers that included the learned-feature (i.e., were *avlonias*) appeared on one-third of the trials. The other two-thirds of the trials included flowers displaying the other two values of the same dimension as the category-inclusion value. Since the statistical properties of these two other values were identical to those of the category-inclusion value, we refer to the flowers that included them as belonging to the “Not-learned category” (as opposed to “Learned category”).

In the study phase, participants were asked to memorize 18 flowers. Each flower was shown alone for 5s followed by a 1s blank. One-third of the 18 flowers included the category-inclusion feature (i.e., were *avlonias*) while the other two-thirds included flowers displaying the remaining two values of the same dimension as the category-inclusion feature. To incentivize memorization, participants were told that they would receive an extra bonus for remembering above 85% of the stimuli. None of these 18 flowers were presented during the learning phase (Table 1).

Finally, in the testing phase, participants were told that they would see 54 flowers, one on each trial, and that their task was to remember whether or not stimuli were shown before in the study phase by pressing “yes” or “no”. Of the 54 flowers, 18 were *old*—i.e. were presented in the studying phase—while the remaining 36 were *new*. Of these, 9 were

new flowers from the Learned category, 9 from the Not-learned category, 9 from Both, and 9 from Neither. Of note, these new flowers were not shown during the study phase. All flowers were presented in a random order and each trial was self-paced.

In sum, there were four types of trials in these three phases (Table 1). For each subject, one-third of trials included the learned category inclusion feature, which was chosen randomly from the three possible values from one from of the five dimensions. One-third of the trials included a not-learned category inclusion feature, i.e., the value of a dimension that could define a category of which participants were not aware of. This not-learned category inclusion feature was chosen randomly from the values belonging to the remaining four dimensions different from the dimension with the learned category inclusion feature. All four types of trials appeared equally frequently in the three phases.

Table 1: Probabilities and counts of trials for four types. A, B, C, A', B', and C' represent possible values of one dimension. The number of trials shown in the table is for learning and testing phases only. The number of trials for each feature during the study phase is 2 (not shown).

Learned feature	Not-learned feature	Number of trials	Probabilities
A	A'	6	1/9
A	B'	6	1/9
A	C'	6	1/9
B	A'	6	1/9
B	B'	6	1/9
B	C'	6	1/9
C	A'	6	1/9
C	B'	6	1/9
C	C'	6	1/9

## Results

**Learning.** To test whether participants successfully learned to categorize flowers as *avlonias*, we measured the learning performance by calculating the percentage of correct responses in the learning phase (Figure 2). We found participants were, in general, able to detect the single feature that categorized *avlonias*. The overall accuracy rates for both stimuli during the last twenty trials were 82.3%. Note that because we do not inform participants of the feature in advance, they necessarily begin at 50% accuracy at the beginning of the learning phase.

**Memory Accuracy.** We analyzed hit and false alarm (FA) rates separately for flowers of each type (Figure 3). To examine the learning effects for the four conditions (i.e., flowers that belong to the Learned category, Not-learned category, Both categories, Neither category), we implemented a two-way Bayesian repeated measures ANOVA. People exhibited increased hit rates for stimuli containing learned features included in Learned ( $M_{Hit} = 0.65$ ,  $SD_{Hit} = 0.28$ ) and Both ( $M_{Hit} = 0.70$ ,  $SD_{Hit} = 0.35$ ) conditions during the testing phase, but not toward stimuli including not-learned features in Not-learned ( $M_{Hit} = 0.56$ ,  $SD_{Hit} =$

0.28) and Neither ( $M_{\text{Hit}} = 0.58$ ,  $SD_{\text{Hit}} = 0.22$ ) conditions (Figure 2 and Table 2). We followed up with Bayesian paired samples t-tests which showed evidence supporting that hit rates in the Learned condition were higher than those in the Not-learned ( $BF_{10} = 2.15$ ) and Neither conditions ( $BF_{10} = 1.70$ ), but not in the Both condition ( $BF_{10} = 0.25$ ). Similarly, there was evidence indicating that hit rates for the Both condition were higher than those in the Not-learned ( $BF_{10} = 135.38$ ) and Neither condition ( $BF_{10} = 30.56$ ). Hit rates in the not-learned condition were not different from the Neither condition ( $BF_{10} = 0.14$ ). Also, there was weak evidence for FA rates in the Learned condition ( $M_{\text{FA}} = 0.59$ ,  $SD_{\text{FA}} = 0.24$ ) being higher than for the Not-learned ( $M_{\text{FA}} = 0.53$ ,  $SD_{\text{FA}} = 0.23$ ;  $BF_{10} = 0.43$ ) and Neither condition ( $M_{\text{FA}} = 0.53$ ,  $SD_{\text{FA}} = 0.19$ ;  $BF_{10} = 0.61$ ). We found no evidence for differences in other pairs of conditions (Both condition:  $M_{\text{FA}} = 0.57$ ,  $SD_{\text{FA}} = 0.30$ ).

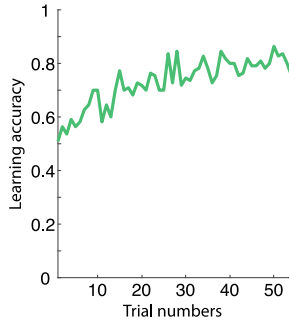


Figure 2. Learning performance during learning phase.

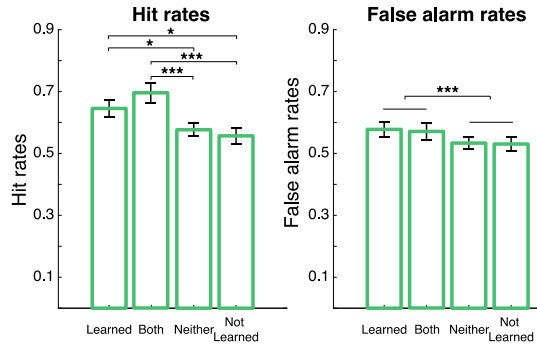


Figure 3. Hit and false alarm rates during testing phase. Left panel: hit rates. Right panel: false alarm rates. Stimulus with the category-inclusion value appeared in the Learned and Both conditions, and not in the Neither and Not-Learned conditions. \*  $BF_{10} > 1$ , \*\*\*  $BF_{10} > 10$ .

Table 2: Bayesian repeated measures ANOVA

Rates	Best models	$BF_{\text{Model}}$	$BF_{10}$
Hit	Learned	11.02	$6.93 \times 10^3$
False Alarm	Learned	13.93	32.35

BF: Bayes Factor.

To explore the effect of category learning separately on response bias and discriminability (e.g.,  $d'$ ), we conducted a hierarchical Bayesian parameter estimation analysis within a SDT framework. To that end, we fit the accuracy data from three groups, i.e., (1) *all* participants ( $n = 110$ ), (2) *experts*, i.e., participants whose accuracy of the last twenty learning trials was greater than or equal to 80% ( $n = 66$ ), and (3) *non-experts*, i.e., participants whose accuracy of the last twenty learning trials was less than 80% ( $n = 44$ ), to a SDT model in which the parameters were estimated using a hierarchical Bayesian approach (Lee, 2008). As such, two parameters of discriminability were estimated: (1) the sensitivity,  $d'$ , that is measured by the distance between the signal and noise distributions indicating the discriminability of the signal trials from the noise trials; and (2) the criterion or bias,  $c$ , that is measured by the distance between the actual criterion used for responding and the unbiased criterion (i.e.,  $d'/2$ ).

The hierarchical model of SDT is able to partially pool individual parameters by taking into account group-level distributions, thus yielding more reliable estimates than non-hierarchical, full individual difference models. In this model, individual parameters are drawn from group-level (normal) distributions with estimated means and standard deviations. The model assumes that the estimated means quantify discriminability and criterion-bias for each of the four conditions, and precision quantifies the similarity among individual behavior.

In this implementation, our SDT model has four parameters per condition, reflecting properties of the average subject and how the subjects vary: mean discriminability  $\mu_d$ , precision of discriminability  $\tau_d$ , mean criterion  $\mu_c$ , and precision of criterion  $\tau_c$ . The prior on the mean discriminability was set to be very wide so as to be uninformative over the range of reasonable  $d'$  values (i.e., 0-4), with only a slight pull toward 0, consistent with previous research. Specifically, individual  $d_i$  was drawn from a normal distribution with mean and precision  $\mu^d \sim N(0, 0.001)$  and  $\tau^d \sim \text{Gamma}(0.001, 0.001)$ , respectively. Individual  $c_i$  was then drawn from the normal distribution with two group-level parameters  $\mu^c \sim N(0, 0.001)$  and  $\tau^c \sim \text{Gamma}(0.001, 0.001)$ . We implemented the hierarchical SDT model in JAGS, a sampler that utilizes a version of the BUGS programming language (Version 3.3.0) called from MATLAB (The MathWorks, Inc., Natick, Massachusetts, United States). Posterior distributions were approximated by 3 Monte Carlo Markov Chain methods with 5000 samples from each chain, after a burn-in of 1000 samples. Convergence of chains was evaluated with the  $\hat{R}$  statistic.

We first estimated the mean sensitivity and mean criterion-bias for each condition by calculating the posterior distributions of hit and FA rates for all participants--group (1). We found that in the Learned condition, this was skewed toward 1 for both hit and false alarm rates, significantly above the other three conditions (Figure 4A), indicating the people had both more hits and more false alarms in this condition. Furthermore, for participants from group (2, expert-learners),

hit and FA rates in both Learned and Both conditions were skewed toward 1, significantly above than those under Not-learned and Neither conditions (Figure 4B), whereas for participants from group (3, non-expert-learners) there were no differences (Figure 4C), suggesting the main effect was driven by the expert-learners.

To further investigate differences in discriminability/bias we performed a two-way Bayesian repeated measures ANOVA on estimated individual sensitivity and criterion-bias measures from each group. For individual sensitivity/ $d'$  of all subjects (1), we found main effects for Learned and Not-learned conditions as well as their interaction, while for criterion-biases, we only found a main effect for the Learned condition. For group (2, expert-learners), we found a significant main effect for the Learned condition and a significant interaction between the Learned and Not-learned conditions as well as their interaction, while for criterion-biases we did not observe main effects of conditions or their interaction (Table 3). These results indicate that participants who clearly excelled at learning the category during the learning stage—which we here operationalize as those participants whose accuracy for the last twenty trials was above 80%—were more sensitive to (i.e., increased discriminability/ $d'$ ) flowers with learned condition and also and tended to say 'old' more often for these in general (i.e., Learned and Both conditions) compared to flowers with features that were not-learned (i.e., Not-learned and Neither conditions).

Follow-up Bayesian paired sample t-tests on sensitivity and criterion-bias for participants from group (1)—i.e. all participants—showed decisive evidence supporting that the sensitivity  $d_i$  for the Learned condition ( $d_{\text{Learned}} = 0.18 \pm 0.05$ ) was higher than for the other three conditions ( $d_{\text{Not-learned}} = 0.07 \pm 0.11$ ,  $d_{\text{Neither}} = 0.12 \pm 0.03$ ,  $d_{\text{Both}} = 0.38 \pm 0.18$ ), while the sensitivity  $d_i$  for Both was higher than the Not-learned and Neither conditions. As for the criterion-bias  $c_i$ , the evidence was also decisive supporting that the bias  $c_i$  for the Learned condition ( $c_{\text{Learned}} = -0.32 \pm 0.38$ ) was lower than for the other three conditions ( $c_{\text{Not-learned}} = -0.12 \pm 0.23$ ,  $c_{\text{Neither}} = -0.15 \pm 0.34$ ,  $c_{\text{Both}} = -0.39 \pm 0.28$ ), while the criterion-bias  $c_i$  for Both was lower than the Not-learned and Neither conditions. No strong evidence supported any differences between Not-learned and Neither conditions for both sensitivity  $d_i$  and bias  $c_i$ . (Table 4A).

For participants from group 2, this analysis revealed strong evidence that support differences in sensitivity  $d_i$  ( $d_{\text{Learned}} = 0.290 \pm 0.048$ ,  $d_{\text{Not-learned}} = 0.119 \pm 0.107$ ,  $d_{\text{Neither}} = 0.126 \pm 0.084$ ,  $d_{\text{Both}} = 0.339 \pm 0.083$ ) in almost all pairwise contrast except Not-learned versus Neither. The same trend was also found in bias  $c_i$  ( $c_{\text{Learned}} = -0.360 \pm 0.359$ ,  $c_{\text{Not-learned}} = -0.073 \pm 0.262$ ,  $c_{\text{Neither}} = -0.161 \pm 0.365$ , and  $c_{\text{Both}} = -0.543 \pm 0.191$ ). These results suggest that participants who mastered

the learned features well in the learning stage were overall more sensitive to flowers with that features.

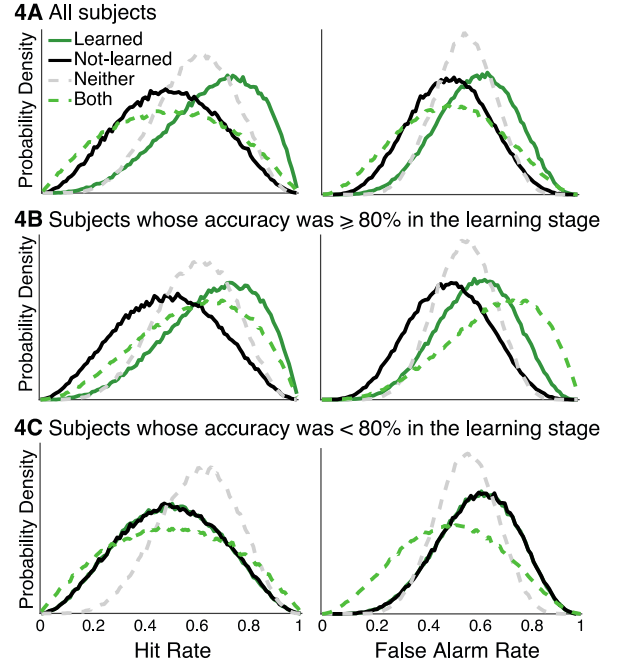


Figure 4. Posterior distribution of hit and FA rates for each of the four conditions.

For participants from group 3, the sensitivity  $d_i$  of Learned condition ( $d_{\text{Learned}} = 0.069 \pm 0.077$ ) was higher than those of Not-learned condition ( $d_{\text{Unlearned}} = 0.003 \pm 0.080$ ) and lower than those of Both condition ( $d_{\text{Both}} = 0.391 \pm 0.413$ ), but indifferent from those of Neither condition ( $d_{\text{Neither}} = 0.096 \pm 0.019$ ). The sensitivity  $d_i$  of Both condition were higher than those of the other conditions, and the  $d_i$  of Not-learned condition were lower than those of Neither condition. As for biases  $c_i$ , the Bayesian paired t test did not show strong evidence supporting any differences between pairs of conditions ( $c_{\text{Learned}} = -0.264 \pm 0.415$ ,  $c_{\text{Unlearned}} = -0.183 \pm 0.155$ ,  $c_{\text{Neither}} = -0.135 \pm 0.294$ , and  $c_{\text{Both}} = -0.132 \pm 0.176$ ), except moderate evidence suggesting differences in  $c_i$  between Learned and Neither conditions as well as Learned and Both conditions.

Figure 5 illustrates the joint posterior distributions of discriminability and bias for each condition. The main panel shows 15000 samples from the joint posterior of the mean  $\mu^d$  and  $\mu^c$ . The side panels show the marginal distribution for each of the group-level means. For all subjects, the group-level sensitivity  $d_i$  differed the most between Both and Not-learned conditions, and the group-level biases  $c_i$  were negative in Both and Learned conditions. That is, participants exhibited better sensitivity toward flowers with learned features and a tendency to overrespond "yes" in the recognition memory tasks (Figure 5A). For subjects whose accuracy in the last twenty learning trials was greater than or equal to 80%, the difference in the group-level sensitivity  $d_i$  between Learned and Both conditions was less but the

difference between Learned and Not-learned or Neither were greater. The group-level biases  $c_i$  in Learned and Both conditions were more negative than those in Not-learned and Neither conditions (Figure 5B). The results suggested that participants who learned category-relevant features well had better discriminability and stronger biases toward flowers with learned features. For subjects whose accuracy in the last twenty learning trials was less than 80%, the group-level

sensitivity  $d_i$  differed the most between Both and Not-learned conditions, whereas the group-level biases  $c_i$  became closer to each other across conditions (Figure 5C). The results indicated that participants who did not learn the category-relevant features well had worse discriminability and little biases toward flowers with learned features.

Table 3: Bayesian repeated measures ANOVA

Datasets	SDT parameters	Best models	BF <sub>Model</sub>	BF <sub>10</sub>
All subjects	$d_i$	Learned+Not-learned+Learned×Not-learned	$5.39 \times 10^{26}$	$1.43 \times 10^{73}$
	$c_i$	Learned	12.04	$4.17 \times 10^{13}$
Experts	$d_i$	Learned+Not-learned+Learned×Not-learned	25.97	$1.27 \times 10^{51}$
	$c_i$	Learned+Not-learned+Learned×Not-learned	884.46	$1.27 \times 10^{19}$
Non-Experts	$d_i$	Learned+Not-learned+Learned×Not-learned	$1.40 \times 10^8$	$1.19 \times 10^{13}$
	$c_i$	Null model	4.26	1.00

$d_i$  and  $c_i$  are individual sensitivity and biases estimated by the hierarchical Bayesian parameter estimation.

Table 4A: Bayesian paired sample t test for sensitivity and bias with all subjects.

Category comparison	Sensitivity $d_i$	Bias $c_i$
Learned vs. Not-learned	$4.19 \times 10^{12}$	$6.04 \times 10^4$
Learned vs. Neither	$1.73 \times 10^{23}$	$9.03 \times 10^2$
Learned vs. Both	$8.77 \times 10^{16}$	0.773
Not-learned vs. Neither	$3.24 \times 10^2$	0.183
Not-learned vs. Both	$1.53 \times 10^{27}$	$3.87 \times 10^{10}$
Neither vs. Both	$8.72 \times 10^{25}$	$2.03 \times 10^6$

Table 4B: Bayesian paired sample t test for sensitivity and bias with only subjects whose accuracy of the last twenty learning trials was above or equal to 80% (i.e., experts)

Category comparison	Sensitivity $d_i$	Bias $c_i$
Learned vs. Not-learned	$2.37 \times 10^{14}$	$1.75 \times 10^5$
Learned vs. Neither	$7.29 \times 10^{22}$	$1.48 \times 10^2$
Learned vs. Both	$3.06 \times 10^2$	$1.04 \times 10^3$
Not-learned vs. Neither	0.154	0.810
Not-learned vs. Both	$8.56 \times 10^{19}$	$3.25 \times 10^{18}$
Neither vs. Both	$3.48 \times 10^{19}$	$3.85 \times 10^8$

Table 4C: Bayesian paired sample t test for sensitivity and bias with only subjects whose accuracy of the last twenty learning trials was less than 80% (i.e., non-experts).

Category comparison	Sensitivity $d_i$	Bias $c_i$
Learned vs. Not-learned	$1.15 \times 10^2$	0.411
Learned vs. Neither	1.35	1.63
Learned vs. Both	$2.64 \times 10^3$	1.24
Not-learned vs. Neither	$4.26 \times 10^6$	0.30
Not-learned vs. Both	$4.92 \times 10^4$	0.41
Neither vs. Both	$9.94 \times 10^2$	0.16

## Discussion

In this study we measured the extent to which learning novel categories influences recognition memory, and we focused on sensitivity and biases estimated in Bayesian SDT modeling. First, we corroborated previous findings that people exhibited biases toward stimuli with learned features compared to stimuli with not-learned features, even when such features are equally sampled during learning and study (De Brigard et al., 2017). That is, hit rates of stimuli with learned features (i.e., learned and both trials) were higher than stimuli with not-learned or random features (i.e., not-learned and neither trials) (Figure 2). False alarm rates showed the same pattern. Going beyond this, we first fit full Bayesian SDT models and compared two measures of discriminability—sensitivity and criterion-bias—in four conditions. We observed that experts exhibited greater sensitivity and more negative criterion-bias than non-experts. We found greater discriminability for Learned and Both conditions than Not-learned and Neither conditions, which suggested people formed better memories of studied flowers with learned features. It is also clear that there was a response bias for Learned and Both conditions (Figure 4), indicating a tendency to overrespond "yes" (i.e., the flower was shown in the study stage) for these, in addition to the actual improved memory sensitivity. These results suggests that category learning affected recognition memory, improving discriminability as well as affecting response bias.

In the current study we employed a yes/no learning strategy for category learning. Future studies may investigate whether different learning strategies may elicit the same biases. For example, supervised (i.e., with explicit guidance on category-inclusion criteria) and unsupervised (i.e., without explicit guidance), or active (i.e., trying to learn category-inclusion criteria with instant feedback) and passive (i.e., merely observing stimuli and their corresponding categories)



learning processes may largely change biases toward stimuli with learned features.

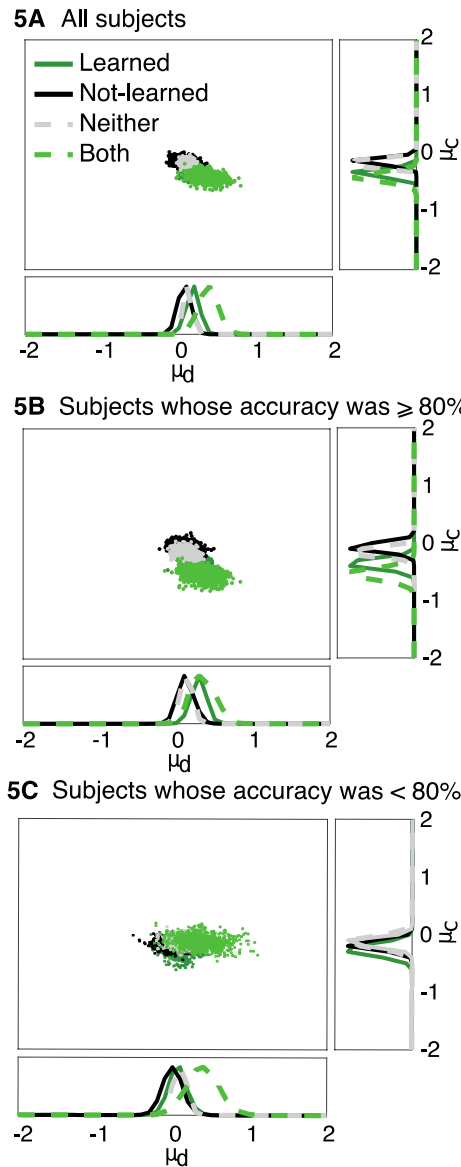


Figure 5: the joint distribution of mean discriminability  $d$  and mean bias  $c$ . The side panels show the corresponding marginal distribution.  $\mu_d$  and  $\mu_c$  are the group-level means of discriminability and criterion.

Here we applied SDT models to measure the effect of category learning on recognition memory. The effect of category learning on recognition memory may also be related to different learning procedures: for example, explicit reasoning and the nature and timing of feedback, which may or may not directly associated with the learned feature only (Ashby & Maddox, 2005). Other categorization models such as the generalized context model (GCM, Nosofsky, 1986), the general recognition theory (GRT, Ashby & Townsend, 1986), or the deterministic exemplar model (DEM, Ashby &

Maddox, 1993) might be worth exploring for refined quantitative accounts of the influence of category learning.

In the current study, participants were given binary choices in the testing stage (old/new). While it allowed us to apply systematic SDT models to probe the effect of category learning on recognition memory, we assumed an equal variance signal detection model. Adopting a confidence scale would provide a refined gauge of discriminability in the recognition memory task and allow us to address the nature of the memory signal more clearly (e.g., address whether unequal variance signal detection model, or a hybrid threshold and signal detection model is more applicable; Wixted, 2007). Broadly, however, our results show that participants discriminate more toward stimuli with learned features than those with not-learned features. These results contribute to our understanding of how prior category learning influences recognition memory.

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