Supplementary information:

Comparing human statistical learning performance in active and passive conditions

Task	Test type	Mean	SD	N	z-value	p
Passive	Conditional test	0.56	0.19	37	2.04	0.04*
	Joint test	0.71	0.20	35	5.59	0.001*
	Single test	0.80	0.22	35	5.48	0.001*
	Equal Single test	0.50	0.17	35	0.0	1
Active	Conditional test	0.60	0.20	35	3.06	0.002*
	Joint test	0.61	0.22	35	2.8	0.005*
	Single test	0.74	0.14	35	7.55	0.001*
	Equal Single test	0.51	0.20	35	0.37	0.71

Table S1. Tests results and GLM significance levels of the human control experiments shown in Figure 1C. See Methods for details of computing significance.

Within the Active condition, human participants acquired the statistical structure of the shape occurrences according to the same pattern on the TARGET and DISTRACTOR stimuli sets leading to very similar albeit slightly reduced performance with the DISTRACTOR stimuli during the test session (Figure S1; Table S1). This result supports the idea that favoring only one subset of the stimuli by feedback/reward does not significantly influence the distribution of implicit learning across the entire set. Interestingly, while participants' performance was very similar in the Passive and Active conditions, there was nevertheless one exception: the average familiarity judgment in the Passive condition was significantly higher than in the Active condition in the Joint Test, where always co-occurring base pairs had to be compared with random pairing of two shapes (Joint Test; GLM: N = 70, z = 2.27, p = 0.023, Figure 1C; Table S2). This finding suggests that while compared to an undirected passive exploration of the input, an explicit categorization task with feedback does not have a general negative effect on human unsupervised learning across *all* categories (joint, conditional, single) in terms of coding statistical structure of the stimuli, it does have some noticeable negative influence *selectively* affecting the learning of joint statistics. Such a negative effect of a specific task on noticing correlation among elements is in agreement with earlier reports finding that sensitivity to co-

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occurrence probabilities is reduced in age groups where top-down effects are more widespread due to increased prefrontal influence (1).

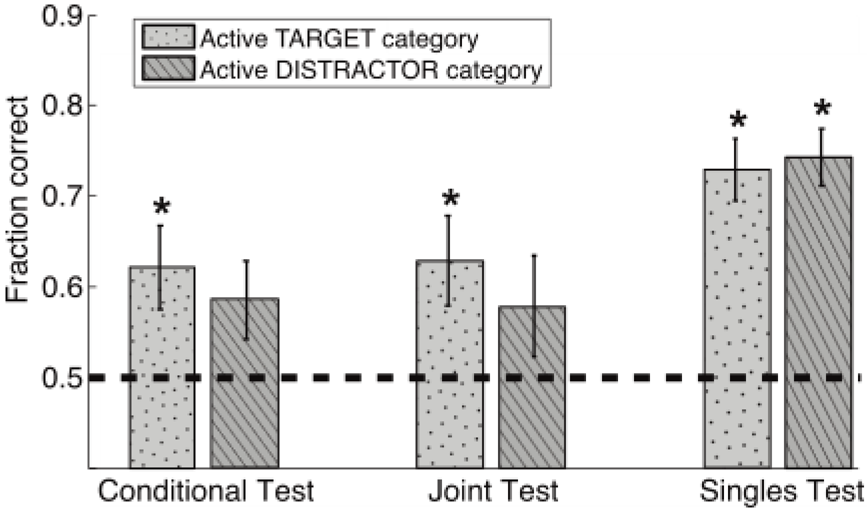

Figure S1. The test results obtained with Target vs. Distractor stimuli in the Active condition of the Human Baseline experiment. As attested by Table S1, there was no significant difference between the two conditions in any of the tests.

Test type	N	z-value	p
Conditional test	35	.62	.53
Joint test	35	.89	.37
Single test	35	-.27	.79

Table S2. Comparing human performance statistically in three tests performed with Target vs. Distractor stimuli in the Active condition of the Human Baseline experiment. There was no significant difference between the two conditions in any of the tests.

Test type	N	z-value	p
Conditional test	72	-.88	.38
Joint test	70	2.27	.023 *
Single test	70	1.62	.11

Table S3. Comparing human performance in three statistical tasks performed in the Active and Passive Task conditions of the Human Baseline experiment. In the Joint Test condition, performing an active discrimination task during the familiarization significantly reduced the performance of human participants. Nevertheless, performance in the Active condition remained significantly above chance.

Reference:

1. K. Janacsek, J. Fiser, & D. Nemeth, The best time to acquire new skills: Age-related differences in implicit sequence learning across the human lifespan. *Dev Sci* **15**(4):496-505 (2012). 10.1111/j.1467-7687.2012.01150.x

Counterbalancing in the human experiments

We confirmed in a pilot run that there was a carry-over effect between the three tests of the human experiments (Joint, Conditional and Single) due to altered appearance frequencies in the conditional test. In order to control for this effect, we run both the Active and Passive tasks with two different groups of participants. One group from each of the task conditions completed the conditional test, while another group only completed the singles and joint tests without the conditional test. Since the familiarization session was exactly the same in the two versions, we used all familiarization data combined (N=70) for measuring task learning.

Computational modeling:

The Counting-based model: In the counting-based model (CB), we stored the single shape occurrence frequencies (single-counting model M_1) and the co-occurrence frequencies of the shapes (pair-counting model M_2) during training with an additional assumption regarding a baseline probability of any shape to occur.

$$P(T\ test\ scene \mid M_i\ model) = P(\text{shape(s) in } T \text{ occur} \mid M_i)$$
$$= 1 - (1-\epsilon)^n (1 - P(T|M_i))$$

where

ϵ is the baseline probability of a shape being spontaneously presented, independently of the training period's statistics, defined by model fitting

n is the number of shapes in the scene

$P(T|M_i)$ is the T test scene's shape(s) occurrence/co-occurrence frequency calculated during the training period based on the single-counting or the pair-counting model M_i.

Such a model is a typical example of treating learning as a process that accumulates the averaged sum of memory traces.

Computing Choice probability: For each test trial, the choice probability was calculated for the two models in the same manner. For calculating the choice probabilities during the test trials, the obtained probabilities of shapes and pairs of the CB model and the scene probabilities calculated by the PC model were treated similarly. The only difference was adding a training-length-dependent "capacity" parameter to the CB model (see below), which represented the model's weighting of summary traces obtained from the single-counting and pair-counting modules. In a test trial with T_1 and T_2 test stimuli, the choice was computed as:

$$P(\text{prefer test scene } \mathrm{T_1} \text{over test scene } \mathrm{T_2})$$
$$= (1-\kappa) \cdot \left(\frac{P(T_1|M_1)}{P(T_1|M_1) + P(T_2|M_1)} w_1 + \frac{P(T_1|M_2)}{P(T_1|M_2) + P(T_2|M_2)} w_2 \right) + \frac{\kappa}{2}$$

where

κ is the lapse parameter, subject of model fitting

w_1 is the weight of the model for element-representation/single-counting and it is given by the posteriors and an lapse parameter defined for the weights, κ_w. As discussed above, there is an additional capacity parameter in case of the CB model – more precisely, w_1 is calculated as below in case of the PC and CB models.

In case of the PC model:

$$w_1 = (1-\kappa_w) \cdot \left(\frac{P(T_1,T_2|M_1)P(M_1)}{P(T_1,T_2|M_1)P(M_1) + P(T_1,T_2|M_2)P(M_2)} \right) + \frac{\kappa_w}{2}.$$

In case of the CB model there is an additional capacity parameter, depending on the training time t:

$$w_1 = (1-\kappa_w)\cdot\left(\frac{P(T_1,T_2|M_1)P(M_1)c_1}{P(T_1,T_2|M_1)P(M_1)c_1+P(T_1,T_2|M_2)P(M_2)c_2}\right)+\frac{\kappa_w}{2},$$

$$c_1 = Min\left(1,\frac{capacity_{system}}{requirement_1}\cdot r_t\right),$$

$$c_2 = Min\left(1,\frac{capacity_{system}}{requirement_2}\cdot (1-r_t)\right).$$

$capacity_{system}$ and r_t-s are subjects of model fitting ($t = 100, 200, 300$), while $requirement_1 = 6, requirement_2 = 60$ based on the number of parameters the given counting model needs to store (6 elements in case of the single-counting and $\binom{6}{2}\cdot 4 = 60$ in case of the pair-counting model),

$P(M_1) = P(M_2) = 0.5$, representing a uniform prior on the two models,

κ_w is the lapse parameter for the model weights, subject of model fitting.

All the parameters were fitted separately for the human data and for the honeybee data. For each experiment, the same parameters were fitted for all the test scenarios (conditional, joint, singles) used in the Test session.