Constraining the search space in cross-situational learning:
Different models make different predictions

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1. Cross-situational learning

How do children map sound sequences to objects?

The hypothesis is that children track word-referent co-occurrences over many different situations, which allows to filter noise. However, **missing co-occurrences are equally important:** knowing that a word doesn't occur with an object matters as much as knowing that it does.

We took 4 prominent computational models of cross-situational learning and checked whether their predictions **fit with the behavioral data from children and adults**.

2. Computational Models

Hebbian learner: two layer neural network that learns word-referent associations using Hebb's rule

Naïve Discriminative Learner (NDL): two layer neural network that learns word-referent associations using Rescorla-Wagner equations

Probabilistic Learner: computes a probability distribution over words for each referent

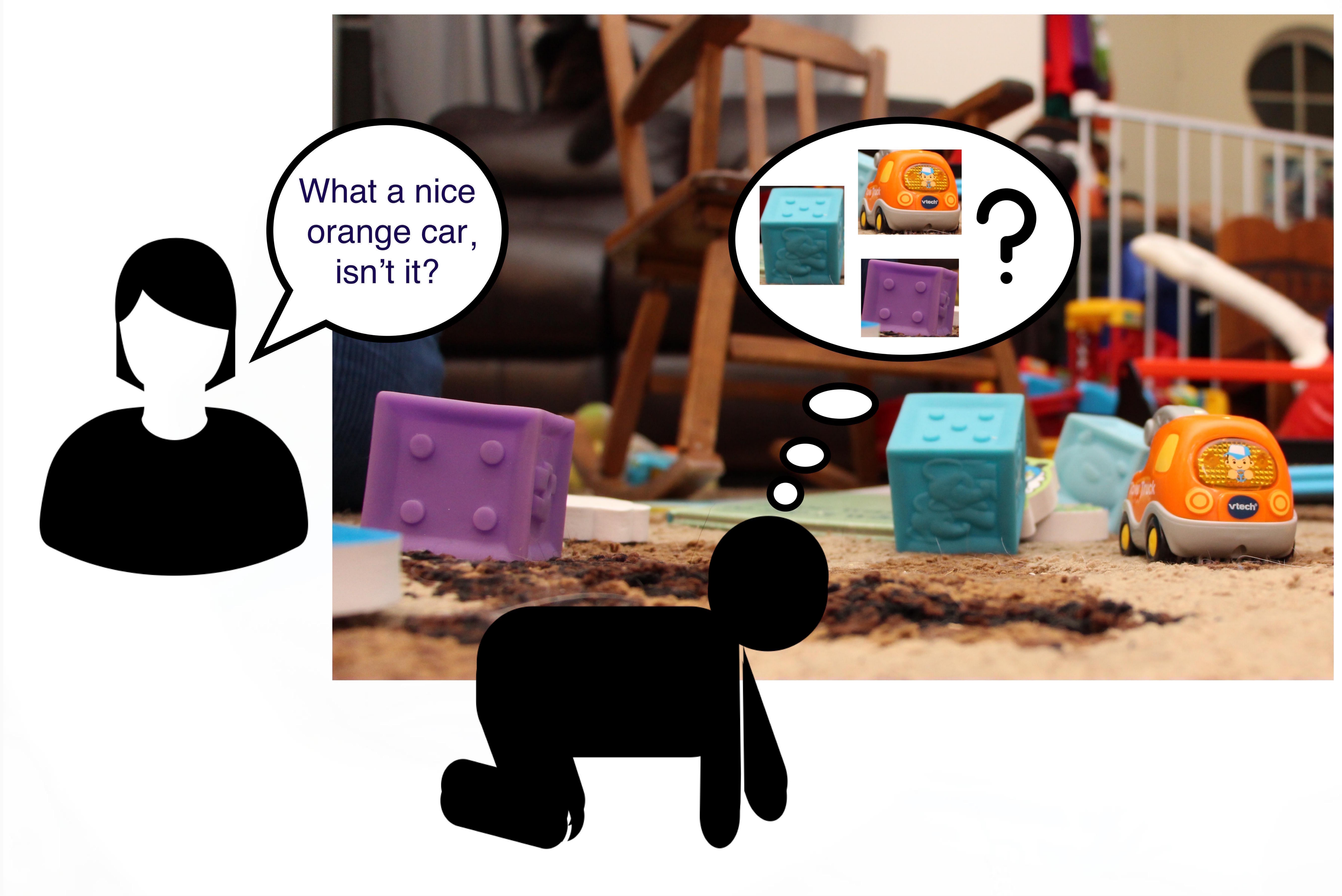
Hypothesis Testing Model (HTM): on the first trial, it picks a single word-referent hypothesis. On subsequent trials, it retrieves a formed hypothesis (with probability p, increasing on every successful retrieval) and checks whether the current trial supports it. If it does not, a new hypothesis is formed at random.

4. Conclusions & future work

The **Hebbian Learner** and the **HTM** failed to fit the behavioral data. The **NDL model** and the **Probabilistic Learner** learned correct associations.

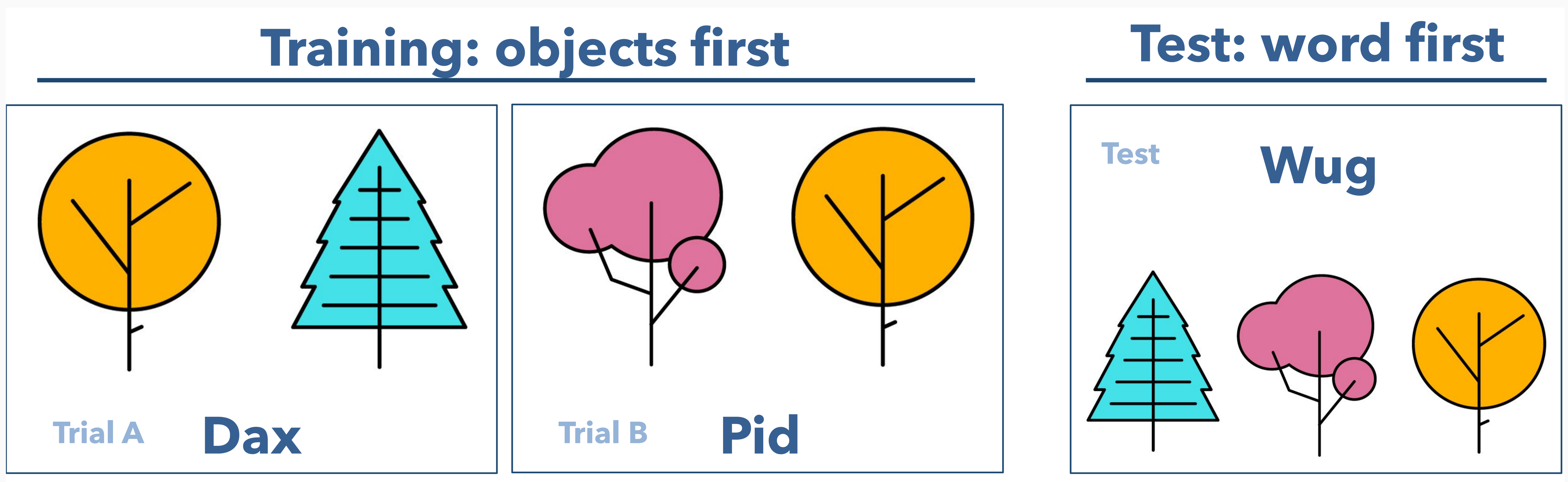
Crucially, the successful models learn from **missing co-occurrences** as well, unlike the unsuccessful ones.

Given that, in the experimental design, spurious word-referent co-occurrences occur as often as correct ones in the data, an unambiguous mapping can only be formed by noting that **certain referents fail to co-occur with certain words**.

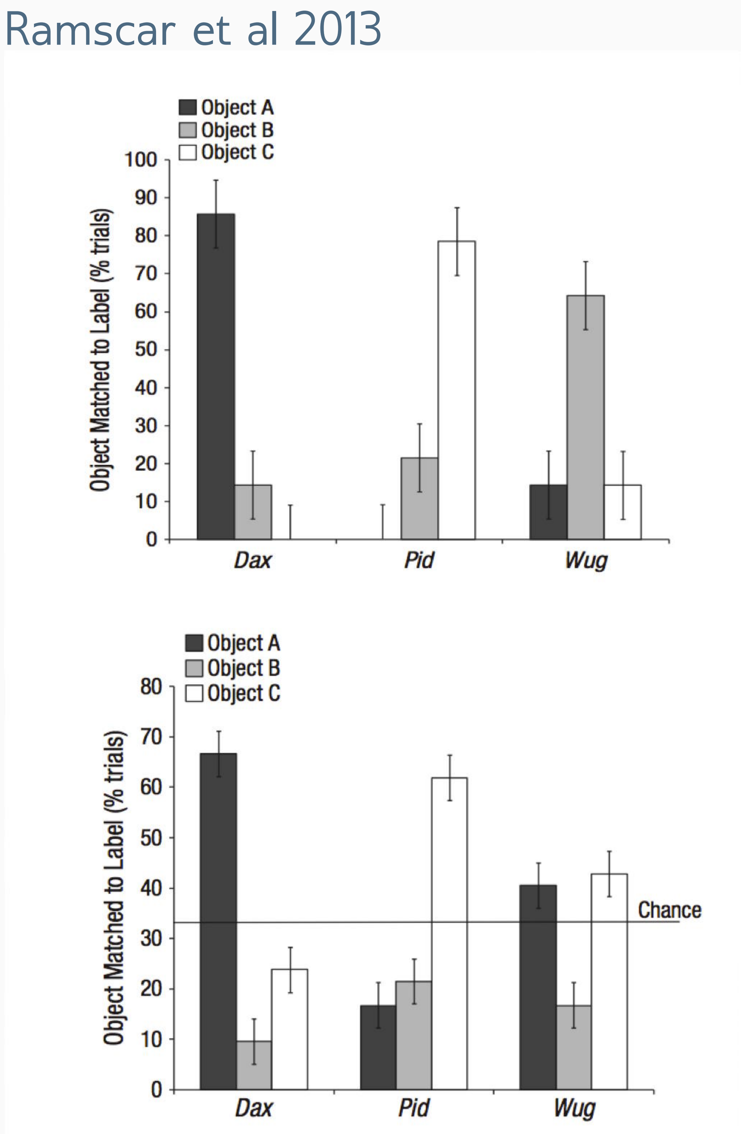


3. Experimental design & results

Experimental design from Ramscar and colleagues (2013): Over 18 trials, object B is always present, 9 times with object A and 9 times with object C. When object A is present, the word *Dax* is always present, while when object C is present, the word *Pid* is also present. A third word, *Wug*, is only presented at test. At test, one of the three words is presented and subjects are asked to retrieve the associated object.
CAVEAT: the images do not depict the objects used during the experiment, we simply use them for descriptive purposes.



Behavioral responses from **undergrads** (top) and **children** (bottom) - plots from Ramscar et al 2013



Model	Cue	DAX	PID
Hebbian Learner	ObjA	**9**	.
	ObjB	**9**	**9**
	ObjC	.	**9**
NDL	ObjA	.134 $\pm$.001	-.021 $\pm$.005
	ObjB	.113 $\pm$.005	.113 $\pm$.005
	ObjC	-.021 $\pm$.005	.134 $\pm$.001
Probabilistic Learner	ObjA	.967 $\pm$.003	.
	ObjB	.483 $\pm$.082	.486 $\pm$.082
	ObjC	.	.967 $\pm$.003
HTM	ObjA	**.455**	.
	ObjB	**.545**	**.485**
	ObjC	.	**.515**

Table 1: Simulated responses The table shows word-referent mappings induced by the 4 simulated learners. In red, we highlighted successful matches, i.e. the highest value column-wise; in **bold** we highlighted learners that would have to guess at random when retrieving the object matching a given label.

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