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# Committing to an Ontology: A Connectionist Account

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## Abstract

Young children generalize nouns in systematic ways. They generalize names for solid things by shape and names for non-solid things by material. Recent evidence suggests that the source of these biases is in the children's lexicon: the bias becomes apparent only after they know names for things that are solid and have a similar shape and they know names for things that are non-solid and similar in material. In Experiment 1, we train a simple connectionist network with the regularities present in early noun vocabularies and show that this network shows generalization patterns comparable to those of young children. In Experiment 2 we look for other possible biases coming from statistical regularities and find that the network predicts that children will not cross ontological boundaries in their word generalizations. In Experiment 3 we test this prediction in 30-36 month-old children. We explain this finding in terms of the statistical regularities present in young children's noun vocabularies.

## Introduction

Young children are excellent learners of object names. After hearing a noun used once to name one object, they seem to know the scope of the whole category. To explain this proficiency people have proposed several mechanisms in the form of constraints or biases (Landau, Smith & Jones, 1988; Markman, 1989; Soja, Carey & Spelke, 1991). This paper is about the shape and material biases and about a new "bias", what one might call an "ontology bias". In the end, we propose that all these biases and constraints reduce to associative learning and generalization by similarity.

Our starting point is a recent study by Samuelson & Smith (1999). They examined the similarity structure of 300 object categories, the names of which are typically known by 30 month-olds. They found many nouns that name things that are solid and similar in shape and fewer nouns that refer to non-solid substances similar in material. They also showed that children do generalize novel nouns for solids by shape and for non-solids by material, but only after they know many of these words. These results suggest that these biases may be the product of statistical learning. In other words, children's noun generalizations are themselves generalizations over the nouns the child already knows.

In this paper we show that a simple statistical learner, when trained with the regularities present in early noun vo-

cabularies, generalizes novel nouns like children do. In Experiment 1 we train connectionist networks on the regularities found in early vocabulary by Samuelson and Smith (1999) and show that, like children, the networks generalize by shape for solid objects and by material for non-solid substances. In Experiment 2 we examine this early lexicon for other regularities that might create biases in a statistical learner and find that networks trained on this set exhibit what we call an "ontology bias". In Experiment 3 we test for this bias in children.

## Experiment 1

The goal of Experiment 1 is to determine if the regularities present in early noun vocabularies are sufficient to create word learning biases in a simple associative learner. If this is the case, it would support the idea that the biases are learned as part of learning the regularities in the lexicon. To do this we trained simple connectionist networks with a vocabulary organized using the regularities found in early lexicon by Samuelson and Smith (1999) and then we tested the network's performance on an adaptation of the novel noun generalization task.

## Architecture

We used a Hopfield network, which is a simple settling network. The network was trained using Contrastive Hebbian Learning (Movellan, 1990), an algorithm which adjusts weights on the basis of correlations between unit activations. Figure 1. shows the architecture of the network. The network has a Word Layer, in which words are represented locally. That is, each unit corresponds to one word in the network's vocabulary. Individual objects are represented on what we call the Dimension layer. Activation patterns on this layer represent the shape and material of each individual object or substance presented to the network. More specifically, the shape and material of an object (say the roundness of a particular ball and its yellow rubbery material) are represented by an activation pattern along the whole layer, in a distributed fashion. In the Solidity layer one unit stands for Solid and another for Non-Solid. Finally, there is a hidden layer that is connected to all the other layers and recurrently with itself. Note that the Word Layer and the Dimension and Solidity layers are only connected through the hidden layer, there are no direct connections among them.

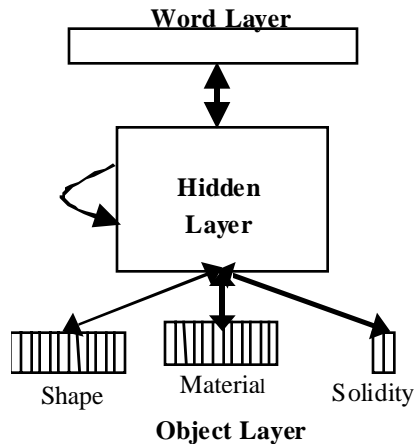


Figure 1. Architecture of the network used in Experiments 1 and 2.

### Training

The goal of the training phase was to mimic in the network the vocabulary learning that a child brings into a novel noun generalization experiment. We trained the networks on a subset of the nouns studied by Samuelson and Smith (1999). We specifically selected the names for objects and substances, excluding names for people, animals, places and abstract objects (e.g. wind). There were 149 training nouns. For each of these noun categories we used the adult judgments from Samuelson and Smith (199) to construct category exemplars. Importantly, although adults judged most solid things to be categorized by shape, there were exceptions and complications – e.g. muffins are judged to be alike in both shape and material and bubbles are judged to be non-solid but similar in shape. Our training instantiated the structures attributed to these words by adults.

More specifically, the statistical regularities across the noun vocabularies were built into the network’s training set in the following way. First, for each word that the network was to be taught, a pattern was generated to represent its value along the *relevant* dimension -- the dimension on which objects named by that noun were found to be similar. Second, at each presentation of the word, the value along the *irrelevant* dimension was varied randomly. For example, the word “ball” was judged to refer to things that are similar in shape; thus, a particular pattern of activation was randomly chosen and then assigned to represent ball-shape. All balls presented to the network were defined as having this shape, although each ball presented to the network also consisted of a unique and randomly generated pattern defining the material. So, each time the unit representing the word “ball” was turned on during training, the pattern representing ball-shape was presented along the shape dimension and a different, randomly generated pattern was presented along the material dimension.

Solid objects were assumed to have a bigger range of values along the shape dimension. This assumption is in line with the fact that solid things can hold more varied and complex shapes than non-solid things.

### Testing

We tested the networks in an analog of the novel noun generalization task used with children. Our approach is based on our conceptualization of the novel noun generalization task. In that task, the child sees an exemplar and hears its name. If, for example, the child attends exclusively to the shape of the named exemplar, then a test object that matches the exemplar in shape (although different from the exemplar in material) should be perceived as highly similar to the exemplar. Thus, we asked if the network’s internal representations – the patterns of activations on the hidden layer -- of a named exemplar and a test object were similar.

The novel noun generalization task used with children is typically a forced choice task in which the child must choose between an object matching the named exemplar in shape and one matching in material. Accordingly, on each simulated test trial, we measured the similarity of the internal patterns of representation for two test objects –one matching the exemplar in shape and one matching the exemplar in material.

More specifically, on each test trial, we created a novel exemplar object by randomly generating an activation pattern along the shape and material dimensions. Then we combined the exemplar’s shape pattern with a novel randomly generated material pattern to create a novel shape-matching test object. A similarity measure of the exemplar and the shape match was computed using the Euclidean distance between the activation patterns in the Hidden Layer after the exemplar and its shape match had been presented.

Similarly, we generated a novel material-matching test object by combining the exemplar’s material pattern with a new randomly generated shape pattern and then computed the similarity between exemplar and material match. Finally, we used these similarity measures between the emergent patterns of activation on the hidden layer to calculate the probability of choosing the shape and the material matches using Luce’s Forced Choice Rule.

In this way, we trained 10 networks (with 10 different randomly generated initial connection weights) with the object and substance terms young children know. During training, we presented multiple instances of each trained noun until the network stably produced the right noun when presented an instance of each kind. We then tested each of these networks in the novel noun generalization task using 20 novel exemplars. Half of these exemplars were defined by patterns of activation representing solid things and half by patterns representing nonsolid things. If the statistical regularities in early child vocabulary are sufficient to create learning biases then the networks should present a shape bias when the exemplar is solid and a material bias when the exemplar is non-solid.

### Results

Figure 2 shows the networks’ performance in the novel noun generalization task. As is apparent, the connectionist networks prefer the shape match in the solid trials and the material match in the non-solid trials. This supports the idea that the statistical regularities in the lexicon are sufficient to

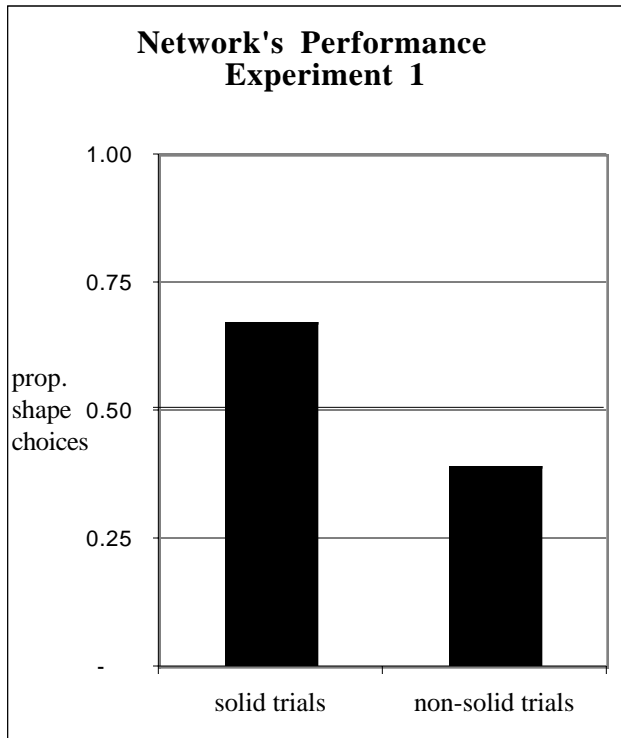


Figure 2. Network's performance in Experiment 1. The networks show shape and material biases comparable to those of children.

create word-learning biases in a statistical learner. If this is true, then other regularities present in the language should create their own "biases". One ubiquitous regularity that became obvious to us is that things that share a name share their solidity value. In other words, names do not refer to categories that span across ontological boundaries. This is true for all words in children's vocabulary except one – egg, which adults judged to have both solid and non-solid forms. If noun generalizations by the network are generalizations over the structures of already learned noun categories, then the network's generalizations of new names for novel things should adhere to this constraint. Given a solid exemplar, sameness in shape should not count if the test object is non-solid; given a non-solid exemplar, sameness in material should not count if that material is now solid. In Experiment 2 give this tests to the networks.

### Experiment 2

The goal of Experiment 2 is to test the network on the ontology bias. The network architecture and training procedure were the same as in Experiment 1. Ten networks were trained using the same testing procedure as in Experiment 1 except for the kinds of test objects used.

As in Experiment 1, on each test trial, we created a novel exemplar object by randomly generating an activation pattern along the shape and material dimensions and then created shape and material matches combining the exemplar's shape and material patterns with novel randomly generated material and shape patterns. Again, the networks were tested

on 20 novel exemplars; half of them defined as solid and half of them defined as non-solid. However, to make the ontology violating test, the shape match for solid exemplars was defined as non-solid and the material match for non-solid exemplars was defined as solid. So for the solid trials, we computed forced choice probability between a non-solid shape match and a solid material match, while in non-solid trials we compared a non-solid shape match with a solid shape match.

### Results

Figure 3 shows the proportion of shape choices predicted by the networks for solid exemplar trials and for non-solid exemplar trials. As predicted from the regularities in the training set, the networks chose the test item that matches the exemplar in solidity. That is, when the exemplar is solid the network prefers the solid test object, (even though it does not match in shape) and when the exemplar is non-solid the network prefers the non-solid test item (even though it does not match in material). Thus, the pattern of generalization observed in Experiment 1 (and typical in experimental tests of children) is now reversed: the networks exhibit a shape bias in non-solid trials and a material bias in solid trials. In Experiment 3 we look for this effect in children.

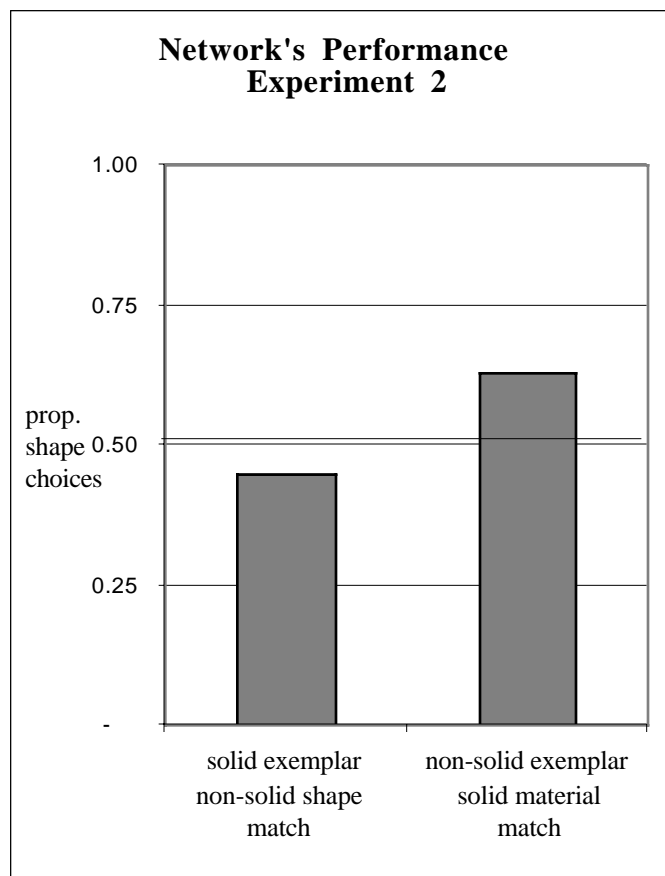


Figure 3. Network's performance in Experiment 2. The networks preferences are reversed when the shape match for the solid exemplar is made non-solid and the material match for the non-solid exemplars is made solid.

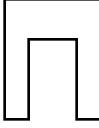



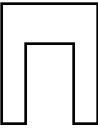
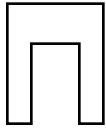

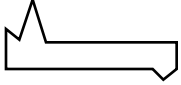
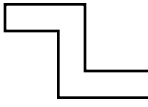



	Exemplar	Material Match	Shape Match	
			Ontology Violating	Traditional
TEEMA	 red sand paint	red sand paint   	 toothpaste with glitter shaving cream purple hair gel	 metallic blue clay burlap
WAZZLE	 blue cheese cloth	blue cheese cloth   	 toothpaste with glitter shaving cream purple hair gel	 pink felt with bumps purple foam green fur

Figure 4. Stimuli for Experiment 3A..

### Experiment 3

The goal of Experiment 3 is to test the prediction made by the network in Experiment 1. Given a solid object, will children refuse to generalize its name to an object of the same shape if the test object is not solid? Given a non-solid object, will children refuse to generalize its name to a material match if the test object is solid? Experiment 3A tests the first question using solid exemplars and Experiment 3B tests the second question using non-solid exemplars. Constructing stimuli for Experiment 3A (shape matches that differ in solidity) was easy; we can create the same shape out of hardened clay and shaving cream. Constructing stimuli for the second question (material matches that differ in solidity) required more creativity. What we did was use translucent gel and translucent hardened plastic for one set and off-white hand lotion and off-white hardened paint for the other. In both cases the material looked to be the same and was judged by adults to be the non-solid and hardened versions of the same material.

### Method

**Subjects** Twenty-four children between the ages of 30 and 36 months participated in this study. Half of them were ran-

domly assigned to Experiment 3A and half of them were assigned to Experiment 3B.

**Stimuli** The stimuli for Experiment 3A are shown in Figure 4. There were two exemplar objects. The exemplar for one set, the Teema, was a “U” shape covered with red sand-paint. The exemplar for the other set, the Wazzle, was an irregular “M” shape covered with blue cheese-cloth. For each exemplar there were three objects matching in material and two sets of items matching in shape. The Traditional set consisted of three solid objects that matched the exemplar in shape and differed in material (e.g. metallic clay, styrofoam covered with fur). The Ontology Violating set consisted of shape matches made out of non-solid materials (e.g. shaving cream, hair gel).

The stimuli for Experiment 3B are shown in Figure 5. There were two exemplar objects. The exemplar for one set, the Teema, was a “V” shape made out of translucent gel. The exemplar for the other set, the Wazzle, was an irregular “M” shape made out of hand lotion. For each exemplar there was a set of shape matches made out of three different non-solid substances. For the Teema, the shape matches were made out of wax, glitter and noxzema mixed with sand; for the Wazzle, the shape matches were made out of green sand, toothpaste with glitter and shaving cream. For each exemplar there were also two sets of “material” matches: a Traditional set and an Ontology Violating set. For the Teema the


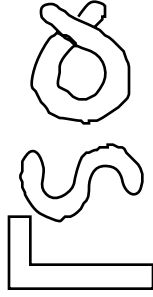
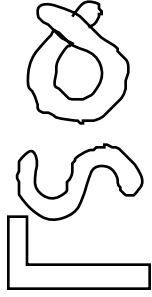


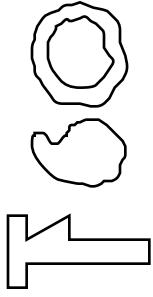
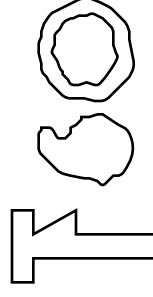

	Exemplar	Material Match		Shape Match
		Ontology Violating	Traditional	
TEEMA	 translucent gel	translucent plastic 	translucent gel 	 noxzema with sand glitter wax crystals
WAZZLE	 hand lotion	hardened paint 	hand lotion 	 toothpaste with glitter fine sand shaving cream

Figure 5. Stimuli for Experiment 3B.

Traditional set consisted of shapes made out of translucent hair gel and the Ontology Violating set consisted of shapes made out of translucent hard plastic. For the Wazzle the Traditional set consisted of shapes made out of off-white hand lotion and the Ontology Violating set consisted of shapes made out of off-white hardened fabric paint.

**Procedure** The procedure used was a forced choice task. The child were shown an exemplar (i.e., the Teema) and told its name (“this is the Teema”). The child was then presented with pairs of objects, a shape match and a material match, and asked “Can you show me the Teema?”. Each child was presented with the Traditional set of one exemplar and the Ontology Violating set of the other. Half of the children were assigned at random to judge the Traditional version of one exemplar and the Ontology Violating version of the other. The two exemplars were presented in separate blocks. Each shape-match/material-match pair was presented twice in random order for a total of 12 trials. The order of the sets was counterbalanced across subjects; the position of the choices was counterbalanced across trials.

### Results

Figure 6 shows the proportion of shape choices for the solid exemplar (Experiment 3A) and for the non-solid exemplar (Experiment 3B) Ontological Violating and Traditional sets respectively. In the Traditional sets, children’s performance replicates previous findings: they present a clear shape bias for the trials with solid exemplars (Experiment 3A) and

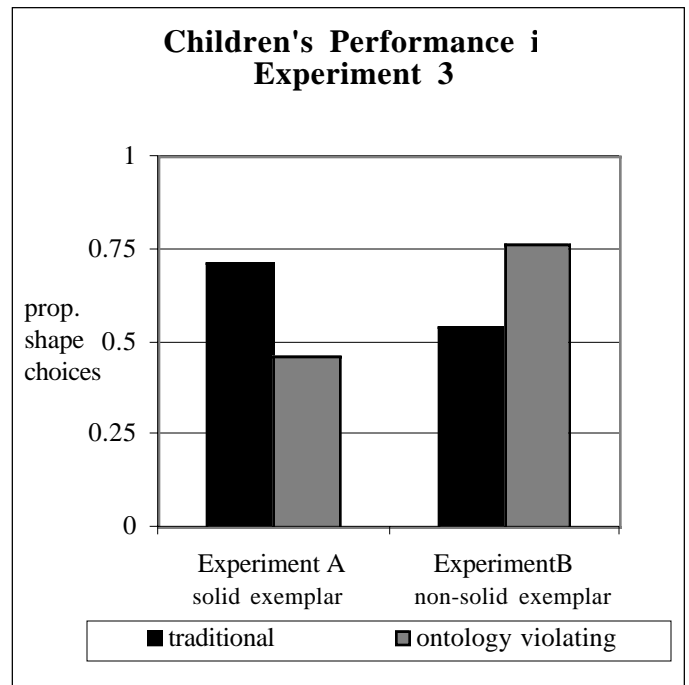


Figure 6. Results of Experiment 3.

show increased attention to the material of non-solid exemplars (Experiment 3B). In the Ontology Violating sets, as

the network simulations predicted, children's shape bias decreased to chance levels in solid trials and increased to above chance in the non-solid trials.

Although these results are consistent with a bias in children to extend category names only within ontological boundaries, there is an alternative explanation. Children's preference for the same-solidity item could be a result of the way the ontological violating choices alter the exemplar-test items' similarity. For example, in the case of the solid exemplar, the material match matches in both material and solidity, while the shape match now only matches in shape (and imperfectly at that, given the change of solidity). While we can't be sure of which explanation is the case in children, we know for a fact that it is more than just similarity for the networks.

## Conclusions

Learning a first language is a hard problem. However, the task appears less daunting when we consider that the kinds of words children know early present an organized structure. A smart learner could learn to exploit this structure to its advantage. In this paper we have shown that a simple statistical learner, with no other mechanisms than associative learning and generalization by similarity, will learn shape and material biases to match the systematic regularities present in its training set. We have also documented a new bias, one which could be taken as evidence of an underlying ontology, but that also makes sense in terms of the statistical regularities present in the language. This suggests that word-learning biases and constraints could be a product of learning. While the evidence presented here is consistent with this account, it does not provide conclusive proof; the regularities found in children's vocabularies could be a product of pre-existing biases. However, the fact that we have demonstrated the computational plausibility of the learning account and simple parsimony suggest that this is not the case.

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