A connectionist account of ontological boundary shifting

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Abstract. Previous research on children's categorizations has suggested that children use perceptual and conceptual knowledge to generalize object names. Especially, the relation between ontological categories and linguistic categories appears to be a critical cue to learning object categories. However, its underlying mechanism remains unclear. In this paper, we propose a connectionist model that can acquire ontological knowledge by learning linguistic categories of entities. The results suggest that linguistic cues help children attend to specific perceptual properties.

1 Introduction

Categorization is an essential cognitive ability. Categorization, which involves compression of information, is one solution to handle an almost infinite number of entities efficiently. To categorize entities and learn words is basic linguistic ability. Quine [7] suggested the difficulty of word learning in the situation including many possible interpretations. This problem occurs when children acquire the word meaning in the early stage. Parent's daily words to their children will be spoken with many possible interpretations. How do children learn word meanings in that situation? Children have to logically reject many useless possibilities, so they can not acquire the meaning once. However, in effect, children do not consider useless possibilities. Therefore, they can acquire temporary word meaning from words presented only once.

Landau, Smith and Jones [5] claimed that children could learn words so quickly because they use the prior knowledge about vocabulary and entities as constraints. They showed that shape is an important property to categorize objects and they called this 'shape bias'. Colunga & Smith [1] and Samuelson [8] suggested that children attended to perceptual features depending on the solidity of objects. In other words, children know the nature of entities and use them to generalize the novel words. We focus on how children acquire knowledge about the nature of entities and ontological categories.

Some researchers suggested a deep relation between ontological categories and linguistic categories. In particular, the relation between count/ mass noun syntax in English and objects/ substance ontology is typical.

Imai & Gentner [3] expanded upon the experiments of Soja, Carey and Spelke [9] to verify the difference between English and Japanese speakers. English has syntax compatible with ontological distinction between objects and substance, but Japanese do not have such syntax, so their comparison will reveal the influence of count/ mass syntax to ontological category. The results suggested the different categorization of simple objects between English and Japanese speakers. Imai & Gentner considered these simple objects to be near the boundary between objects and substance, since they were objects but they also resembled substances in that parts of the object were similar to the whole. Their experiments showed the linguistic influence on ontological categories of ambiguous entities.

Japanese has animacy syntax by verb form. For example, in sentences, (1) '*Animates*-ga **iru**,' and (2) '*Inanimates*-ga **aru**,' 'iru' and 'aru' have almost the same meaning as 'be' in English, but an animate subject needs 'iru' and an inanimate one needs 'aru'. In this paper, we call this syntax 'iru'/ 'aru' syntax. Yoshida & Smith [10] verified the influence of Japanese syntax by using objects simulating animates. The results suggested that English and Japanese speakers had different categorical criterion. They proposed 'the boundary shift hypothesis' (BSH). This hypothesis states that the linguistic cues influence the ontological boundaries on 'individuation continuum' , which explains ontological categories by individuation [6]. However, the mechanism of boundary shifting is still unclear.

1.1 Previous work

Hidaka & Saiki [2] proposed a computational model explaining BSH. They quantified the common feature space by English and Japanese adults' vocabulary rating (see also Figure 1). They asked adults to rate the applicability of 16 adjective pairs to 48 nouns (e.g., "a monkey is (very dynamic, dynamic, neither, static, very static)."). Furthermore, they estimated English- and Japanese-specific ontological space using a principal component analysis (PCA)-based model including specific syntactical categories (i.e. count/ mass and 'iru'/ 'aru' syntax), and they simulated the experiment of Yoshida & Smith [10] using the results of this estimation. We believe that feature attention learning is powerful enough to change ontological knowledge and explain BSH. Therefore, in this work, we show ALCOVE [4] which, is successful in simulating adult's category learning can also explain children's attentional shift.

2 Simulation

We simulated Yoshida & Smith [10]'s experiment, known as "novel word generalization task", suggesting BSH. They conducted three experiments showing ontology difference between Japanese and English monolingual children. Following is a brief summary of their second experiment, which we simulated. Participants

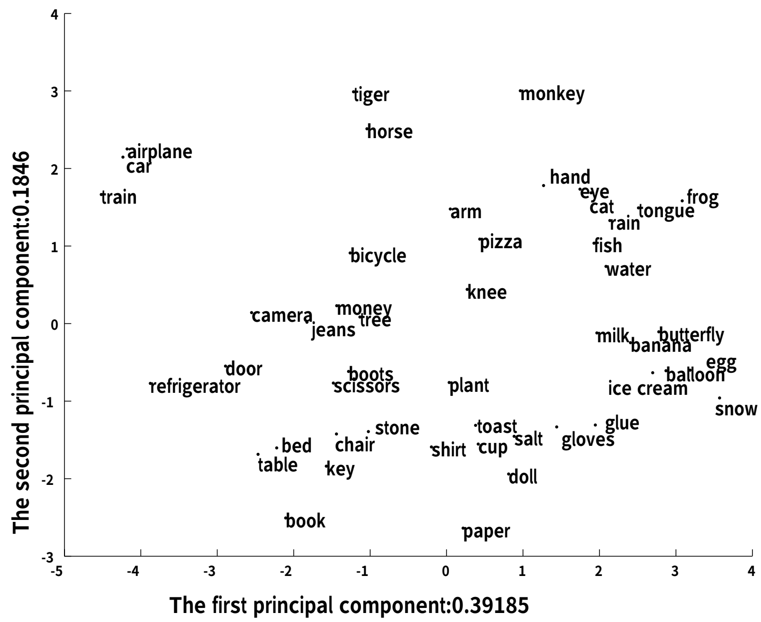

Fig. 1. The result of adults' vocabulary rating (Hidaka & Saiki, 2004). The first two principal components of the vocabulary rating. The first principal component (x axis) was interpreted as 'solidity' or 'size' of objects. The second principal component (y axis) was interpreted as 'animacy' or 'movement' of objects.

of Yoshida & Smith's experiment were 3-year-old English and Japanese monolingual children. Experimenters presented them exemplars with pipes resembling animal legs and named it a novel label (e.g. in Japanese 'Kore-wa __ dayo', in English 'This is __.'). Experimenters did not give any syntactic cue like 'iru/aru' which tells children the animacy of the label. Then experimenters presented them test objects and asked them whether the test object had a novel label (e.g. in Japanese 'Kore-wa __-kana?', in English 'Is this __ ?'). Exemplars and test objects were controlled to be matched or not matched in three perceptual features (Table 1). The results showed different responses between English speakers and Japanese speakers. English speakers tended to generalize novel labels to test objects matched in shape, but Japanese speaker did not.

2.1 Method

In this experiment, we used ALCOVE (Attention Learning COVEring map; [4]) to simulate Yoshida & Smith's experiment. ALCOVE is an exemplar-based neural network model. It has an input layer which receives attentional modulation, a hidden layer with exemplar units and an output layer with category units. It has

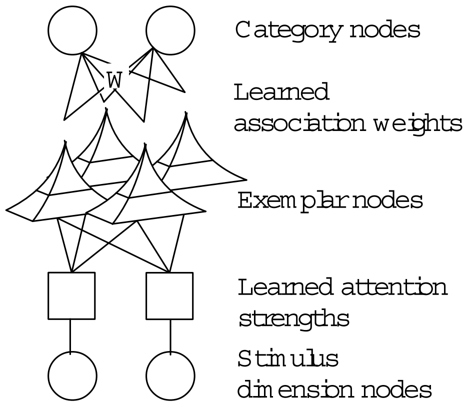

Fig. 2. ALCOVE (revised from Kruschke, (1992) [4])

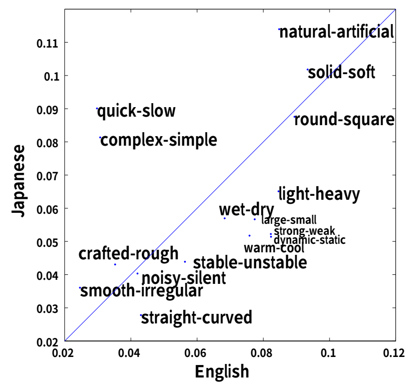

Fig. 3. The attention weight of English and Japanese condition

an error-driven learning algorithm to optimize its attention and weights between the hidden layer and output layer. In this simulation, the input layer had 16 units representing the psychological features of Hidaka & Saiki [2] and attentions initialized to one. The hidden layer had 48 exemplar units representing each of the 48 entities by holding the mean value of each category. The output layer had two units representing linguistic category. The output layer represented count/ mass category and 'iru'/ 'aru' category in the English and Japanese condition respectively. The model performed novel word genralization task simulating Yoshida & Smith's experiment after learning linguistic categories in 40 epochs.

The novel word generalization task in the simulation is to say 'yes' to a test stimulus similar to the exemplar. Three features (shape, color and texture) were manipulated in the behavioral experiment, but we handled only shape and texture in this simulation. We selected the shape and texture dimensions based on the perceptual expressivity [2].The shape dimensions were 'round-square' (.83), 'straight-curved' (.67) and 'large-small' (.63), and the texture dimensions were 'smooth-irregular' (.25), 'complex-simple' (.17) and 'finely crafted-rough hewn' (.13).[1] At first we presented the model with novel exemplars which have uniform random values as feature dimensions. Then the model was presented with a feature-controlled test stimuli and it would classify the stimuli as being similar to the novel exemplar ('yes') or different ('no'). We defined the probability of a 'yes' response (P_{yes}) based on the Euclidean distance δ between the two output vectors corresponding to the exemplar and the test stimulus (see equation 1). $b > 0$ is the scaling parameter of the conversion from a distance to a similarity.

$$P_{yes} = exp(-b\delta) \tag{1}$$

[1] We selected the three most expressive dimensions. These values in parentheses represent expressivity of shape or texture. The range of expressivity is from 1 (the most appropriate) to -1 (the least appropriate)

Table 1. Experimental conditions of Yoshida & Smith (2003). 'm' means feature match between exemplar and test object, and 'N' means non-match

condition	S+T+C	S+C	C
shape	m	m	N
texture	m	N	N
color	m	m	m

2.2 Results

We show the learned attention weights of English (learning count /mass category) and Japanese (learning 'iru' /'aru' category) (Figure 3) normalized by the total sum of the weights. The result suggested the network in the English condition attended to shape dimension more (e.g. straight-curved, large-small) and that in the Japanese condition it attended to material and movement dimension more (e.g. smooth-irregular, quick-slow). The model results (Figure 5) reproduced the results of Yoshida & Smith [10] (Figure 4). Using a Monte Carlo simulation, we estimated that the scaling parameter b is 1.8. In the behavioral experiment, the English speakers categorized the stimuli based on shape and the Japanese speakers categorized them based on multiple features. These results provided evidence for BSH because they suggested the difference of criteria between English and Japanese. From this point of view, our model fitted the behavioral results well ($R^2 = .96$).

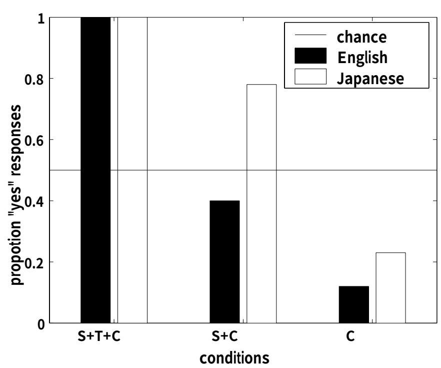

Fig. 4. The result of Yoshida & Smith [10]

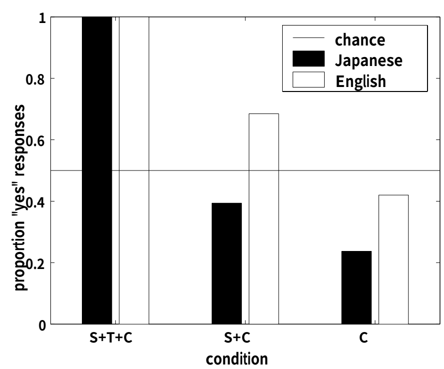

Fig. 5. The result of the simulation

2.3 Discussion

This research showed that the connectionist model could simulate behavioral data by learning linguistic categories. Therefore, this work implemented a computational model expanding BSH proposed by Hidaka & Saiki [2] in the form of connectionist network model. One contribution of this work is to provide associational "learnablity" to the previous computational model. The model learned language-specific linguistic categories of entities. The result (Figure 3) suggested that the linguistic categories influenced learners' attention. In the English condition, the model attended shape dimension. This is consistent with Colunga & Smith [1] and Samuelson [8] showing that American children attended more to the shape of objects during object categorization. On the other hand, in the Japanese condition, the model attended to material and movement dimensions. This is consistent with Yoshida & Smith [10] showing that Japanese children attended to multiple features and animacy of objects. In addition to qualitative matches with previous data, our model could make a good quantitative fit to the behavioral data of Yoshida & Smith [10]. We showed that a general category learning model can account for crosslinguistic differences in object categorization, known as ontological boundary shifting, that is intimately related to children's word learning bias.

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