Modeling developmental and linguistic relativity effects in color term acquisition

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Abstract

We model two patterns related to the acquisition of color terms in Russian and English: children produce overextension errors for some colors but not others, and language-specific distinctions affect color discrimination in a non-linguistic task. Both effects, as well as a reasonable convergence with adult linguistic behavior, are shown by a Self-Organizing Map trained on naturalistic input. We investigate the effect of different ways of representing colors, i.e., as perceptual features or in terms of the cognitive biases on categorization extracted from crosslinguistic color naming data. We also consider the influence of color term frequency. Our results suggest effects of all three of term frequency, cognitive biases, and perceptual features.

Keywords: color terms, language acquisition, linguistic relativity, Typological Prevalence Hypothesis

Introduction

Languages vary in how they carve up lexical semantic domains; e.g., for situations where English uses the preposition *on*, Dutch uses *aan* and *op*. The crosslinguistic variation in lexical semantic divisions raises two interesting questions regarding the language user. First, are these various divisions all equally easy to learn, and if not, what drives the difference in ease of acquisition? Second, does acquiring a language-specific system affect other parts of cognition, a position known as 'linguistic relativity' (Gumperz & Levinson, 1996)? The two questions are related, as the acquisition of language-specific semantic divisions can be expected to go hand in hand with any extra-linguistic effects of acquiring such systems.

In this paper, we use a computational model to study both the acquisition of color terms and behavior on a non-verbal color discrimination task. Our goal is to propose a unified account of these two phenomena by simulating them within a single computational word-learning model. We explore what factors drive the two phenomena, considering both the features with which we represent color in the model and the varying frequencies of the color terms.

As there is an understanding of how color is represented on a perceptual level (e.g., Fairchild, 1998), we can use perceptual features as one representation of color. We also explore features motivated by the Typological Prevalence Hypothesis, which holds that crosslinguistically more common divisions are more cognitively accessible and thus easier to learn (Gentner & Bowerman, 2009). This exploration is motivated by positive results of this approach in the domain of spatial adpositions (Beekhuizen, Fazly, & Stevenson, 2014). Specifically, we use a representation based on the crosslinguistic biases in the divisions of the color space, derived from elicitation data (Kay, Berlin, Maffi, Merrifield, & Cook, 2009).

We find that both types of features yield a good fit to the developmental pattern of color term acquisition as well as to the behavioral pattern, with term frequency having an impact on some results. In some cases, we find that using the features together produces a better fit to human data, indicating that both perceptual properties and crosslinguistic biases may play a complementary role in learning a system of color terms.

Empirical findings and related work

Color term acquisition The development of children's use of color terms is slow, and across languages displays many errors where children use one color term where adults would use another ('overextension errors') (e.g. Harkness, 1973; Roberson, Davidoff, Davies, & Shapiro, 2004). In line with the Typological Prevalence Hypothesis, it has also been argued that the crosslinguistic patterns in color systems are reflected in the pattern of acquisition – i.e., children learn crosslinguistically rarer divisions later than more common ones (Dougherty, 1978). Here, we look at two languages for which detailed developmental color naming data is available, English (Bateman, 1915) and Russian (Davies, Corbett, McGurk, & MacDermid, 1998).

Color discrimination Winawer et al. (2007) (henceforth: W07) ask whether having two primary color terms (*sinij* 'dark blue' and *goluboj* 'light blue' in Russian) versus one (*blue* in English) affects non-linguistic color discrimination. They presented adult monolingual speakers of Russian and English with triplets of a stimulus color chip, an identical target chip and a different distracter. Participants were asked to decide which of the target and distracter was identical to the stimulus, and response latency was measured. On each trial, the distracter was either 'within' the same (participant-determined) category of dark or light blue as the stimulus, or 'across' the category boundary. Each distracter was also either 'near' or 'far' from the stimulus chip on the color scale.

Three conditions were explored: with a verbal dual task, a spatial dual task, or no interfering task. In the latter two conditions, Russian speakers picked the target faster when it was located 'across' the category boundary from the distracter, but only in the 'near' (harder discrimination) cases. (Participants in both languages are slower at picking the target chip when it is 'near' the distracter compared to when it is 'far.') The across-category advantage in Russian was not found under the verbal interference task, and English speakers showed no effect of category in any condition, indicating that the Russian category-advantage is a linguistic influence on lower-level processing.

Related modeling work To our knowledge, the only other attempt at modeling linguistic relativity is Colunga and Gasser (1998), who train a neural network on artificial languages and semantic domains to study both the effects of ease of acquisition and cognitive consequences of acquiring semantic divisions. Our model has a similar architecture and displays similar effects, but is trained on naturalistic data.

An earlier attempt at modelling color term acquisition is Belpaeme and Bleys (2005), who present a multi-agent model that represents color in an $L^*a^*b^*$ space (see below), although they do not focus on the developmental trajectories of learners or on behavioral linguistic relativity effects. Our approach can be considered as complementary, focusing on the cognition and behavior of an individual learner rather than on biases in the emergence of community-wide systems.

Beekhuizen and Stevenson (2015) used the Generalized Context Model (GCM; Nosofsky, 1987) to simulate the developmental English color naming data of Bateman (1915). While this approach showed interesting preliminary results, GCM is limited in its ability to acquire language-specific attention weighting. We require a model able to incrementally acquire and represent varying attentional weights over subintervals of the values of a dimension, possibly independently of values on other dimensions. The Russian 'blue's are a case where such representational potential is needed: attention to a part of the luminance scale is heightened, but only for blue hues. Self-Organizing Maps (SOMs; Kohonen, Schroeder, & Huang, 2001), explored for language acquisition by, e.g., Li and Zhao (2013), constitute a class of models that can capture such effects, while also having the potential to show developmental effects due to their incremental nature.

Our Computational Model

Self-Organizing Map

A Self-Organizing Map M is a neural network consisting of an $m \times n$ grid of neuron cells $[c_{11}, c_{12}, \dots c_{mn}]$, where every cell consists of a vector of feature values. At every iteration i of training, an input stimulus s, with values for the same set of features, is compared to all cells $c \in M$, and is subsequently mapped to the cell to which it is most similar, called the Best Matching Unit (BMU) cell for s, or c_s. The values of c_s as well as its neighboring cells are then updated with the values of s. This way, M will come to display a topology that reflects the similarity among the input items.

Formally, $c_s = \arg\min_{c \in M} d_{\text{feat}}(c,s)$ where $d_{\text{feat}}(c,s)$ is the Euclidean distance between the feature values of c and s. All cells are updated in proportion to their map distance from c_s:

$$c^{i+1}_{jk} = c^i_{jk} + h^i_{jk} \times (s - c^i_{jk}) \tag{1}$$

$$h^i_{jk} = \alpha \cdot \exp\Big(- \frac{d_{\text{map}}(c_{jk}, c_s)}{2 \times {\sigma_i}^2} \Big) \tag{2}$$

That is, h^i_{jk} yields the excitation of the neuron cell c_{jk} given a center of activation at the coordinates of c_s, taking into account their distance in the map grid given by d_{map}. Here $\alpha = [0,1]$ is a learning rate parameter, and σ_i the neighborhood radius of c_s, given by the exponential function $\sigma_i = \sigma_0 \times \exp(-\frac{i}{\lambda_\sigma})$; σ_0 and λ_σ are constants defining the intercept and slope of the function yielding the neighborhood radius. To observe developmental effects, slow learning is needed, and therefore we set $\alpha = .05$, $\sigma_0 = 1$, $\lambda_\sigma = 2000$, and train 8×8 maps.

Feature Representations

We formulate acquisition of color vocabulary as a categorization task that associates a color term (category label) with a color stimulus (a set of color property features). An input item consists of a representation of the properties of a Munsell color chip (a property-feature vector) paired with a color term (a term-feature vector). Each cell of the SOM represents a learned association between a set of property-feature values and a distribution over the terms in the term-feature vector.

The term-feature vector has length $|T|$, where T is the set of primary color terms in a language. To represent term t_i in an input item, the ith feature is set to a value a in $[0,1]$, and all others set to 0; e.g., in a system with 4 terms, input $t_2 = [0,a,0,0]$. The parameter a (in our experiments set to .2) reflects the relative importance of term features in training. The term-feature vector of each cell of the SOM will come to hold a distribution over terms, which we normalize to arrive at a probability of a term for a cell, $P(t|c)$ (see below).

The property-feature vector represents the set of stimuli of Munsell color chips, S, in one of two forms. First, we test the idea that the cross-linguistic tendencies in the semantic distinctions are telling of the extra- or pre-linguistic cognitive biases of language learners (cf. the Typological Prevalence Hypothesis). As in Beekhuizen and Stevenson (2015), we operationalize this idea with Principal Component Analysis (PCA) over the World Color Survey data (Kay et al., 2009), which contains color terms for 330 Munsell color chips in 110 languages. The closeness of a pair of chips in the resulting space reflects the frequency with which they are labeled with the same term, and the space thereby represents the crosslinguistic tendencies to group chips under a particular term. (More details can be found in Beekhuizen & Stevenson, 2015.) If the extension of a color term – i.e., the set of chips labeled with that term – is spread widely over the PCA space, it is assumed to be harder to learn than if a set of the same size were spread less widely over the PCA space. We refer to property features based on the PCA components as the conceptual, or `conc`, features.

We also can represent the various color chips at a purely perceptual level. We use the coordinates of the chips in $L^*a^*b^*$ space, which is thought to encode the perceptual dissimilarity between colors (Fairchild, 1998). This feature set will be referred to as the perceptual, or `perc`, features.

Both the property-feature spaces were normalized such that the mean for each feature is .5 and the values are in $[0,1]$. SOMs are initialized with values of 0 for term features and .5± a very small random value for property features.

Sampling for training data

Input items are sampled as a pair of a color term $t \in T$ and a stimulus color chip $s \in S$ from the distribution $P(t,s) = P(s|t)P(t)$. We obtain the conditional probability distributions for $P(s|t)$ from adult elicitation data in English (Berlin & Kay, 1969) and in Russian (Davies & Corbett, 1994).[1] (For the latter data in Yxy coordinates, we convert those coordinates into $L^*a^*b^*$, and identify the Munsell chip with the closest $L^*a^*b^*$ value.)

As one estimation of $P(t)$, we used the relative term frequency over all color terms. For English, these were taken from the child-directed speech portion of the Manchester corpus (Theakston, Lieven, Pine, & Rowland, 2001) of CHILDES (MacWhinney, 2000). For Russian, lacking a corpus of child-directed speech of suitable size, we use the relative term frequencies reported in Vamling (1986).[2] We also assess sampling according to a uniform distribution for $P(t)$. These two conditions are called `corpus` and `uniform`.

Experimental Methods

For all experiments, we run 30 simulations for each of the six combinations of `features={perc,conc,perc+conc}` and `sampling={corpus,uniform}`. At every test moment (every 100 input items), we present the model with an unlabelled color chip s (i.e., a property-feature vector with no term features) and extract the most probable term that the model associates with those property features. We obtain the Best Matching Unit for s as $c_s = \arg\min_{c \in M} d_{\text{feat}}(c,s)$, where only the property features of c are compared to those of s. The model response for s, term t_s, is extracted from the probability distribution over the terms T for c_s:

$$t_s = \arg\max_{t \in T} P(t|c_s) \tag{3}$$

$$P(t|c_s) = \frac{\text{value}(t,c_s)}{\sum_{t' \in T} \text{value}(t',c_s)} \tag{4}$$

where $\text{value}(t,c_s)$ is the value for feature t in cell c_s.

Evaluating linguistic convergence

To evaluate whether the model obtains an adult level of understanding of the color terms, we test it with color stimuli corresponding to the complete set of color chips S_{adult} for which we have adult responses ($|S_{\text{adult}}| = 49, |T| = 12$ for Russian; $|S_{\text{adult}}| = 211, |T| = 11$ for English). Model convergence with adult linguistic behavior is then given by:

$$\mathbf{score_C} = \frac{|S_{\text{correct}}|}{|S_{\text{adult}}|} \tag{5}$$

at each test moment, where S_{correct} is the set of test stimuli for which $t_s = t_{\text{correct}}$, and t_{correct} is the modal adult response for the given chip. To avoid accidental local optima, we average $\mathbf{score_C}$ over the most recent 20 test moments. We let the model run until it ceases to improve $\mathbf{score_C}$ for 10K inputs.

Evaluating linguistic development

In the child color naming data, several types of patterns are observed: For some color stimuli, children produce hardly any or no errors, whereas for others, overextensions are observed, sometimes even more frequently than the correct term. Our goal is to assess the fit between the model's distribution over terms, $P(t|c_s)$ (Eqn. 4), for each stimulus s at various points in learning, and the relative dominance of terms exhibited by children at various points in development.

To that end, we compare the ranking of terms based on $P(t|c_s)$ to a ranking derived from child elicitation data (ranked by the number of children producing an error for that color in Bateman, 1915 and Davies et al., 1998). For every color stimulus presented to children from n age groups, we find the n consecutive, equal-sized bins of test moments for which the predicted ranking for that stimulus matches optimally the observed ranking of each age group for that color.[3] Each bin contains at least 5 test moments, to avoid finding unrealistically narrow 'age groups' in the model data. The model ranking of terms is given by $P(t|c_s)$ averaged over all test moments in that bin, across 30 simulations. The low values in this pooled probability distribution ($P(t|c_s) < .05$) are rounded down to 0 to avoid diluting the ranking metric with insignificant predictions; similarly, we consider only errors occurring a minimum of 3 times in the child data. The two – model and observed – rankings are then compared using Kendall's τ_b, which we use as our evaluation measure.

Evaluating color discrimination

We take the final state of the SOM to correspond to adult organization of the color terms. Reflecting the hypothesis that linguistic knowledge affects the extra-linguistic task of color discrimination, we take the closeness between the BMUs of two stimuli in our learned SOM to correspond to the degree of difficulty people show in discriminating them. We convert the 20 stimuli of W07 into our representation of color properties, yielding the vector $S_{\text{disc}} = [s_1, \ldots, s_{20}]$. Following W07, we consider two stimuli s_i and s_j to be 'near' if $j = i+2$, and 'far' if $j = i+4$. To find the perceived distance between the target and distracter, $s_{\text{t}}, s_{\text{d}} \in S_{\text{disc}}$, we take their SOM distance $d_{\text{map}}(c_{s_t}, c_{s_d})$ (as defined above). The greater the distance, the easier to discriminate the target from the distracter.

We find the category boundary in the model by having it predict the most likely Russian term per stimulus in S_{disc}, and placing the boundary between the last light blue (*goluboj*)

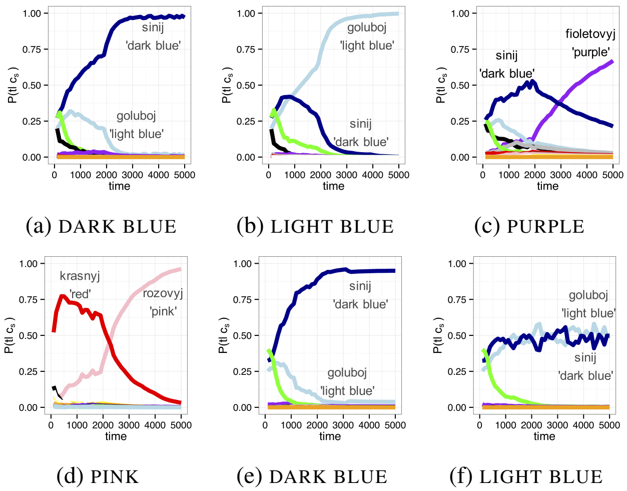
[1] This formulation of $P(s|t)$ is informative about the mapping of terms to colors: a chip s_1 labeled half the time as *blue* is less likely to be sampled for the term *blue* than a chip s_2 labeled 100% of the time as *blue*. However, $P(s|t)$ says nothing about how frequently the colors are discussed with that label: if s_1 is more frequent in the world, usages of *blue* may refer to it more than to s_2. At this point we know of no way to estimate a sampling of colors people refer to.

[2] The different sources of frequency data may differentially affect outcomes in the two languages, an issue for future research.

[3] Since the actual frequencies of colors and their co-occurrence with terms is unknown (see footnote 1), and such patterns will certainly affect learning, we think it overly strict to require the model to align all test stimuli in parallel. Future work will explore more directly the impact of color frequencies on our model's results.

	Russian		English	
	`corpus`	`uniform`	`corpus`	`uniform`
`perc`	.84 (.04)	.89 (.03)	.91 (.03)	.93 (.02)
`conc`	.86 (.03)	.87 (.02)	.92 (.02)	.93 (.02)
`perc+conc`	.89 (.03)	.92 (.03)	.95 (.02)	.97 (.01)

Table 1: Results for convergence: mean and standard deviation of $\textbf{score}_\textbf{C}$ (Eqn. 5), over 30 simulations.



(a) DARK BLUE (b) LIGHT BLUE (c) PURPLE

(d) PINK (e) DARK BLUE (f) LIGHT BLUE

Figure 1: $P(t|s)$ over time for example stimuli in Russian for `(perc+conc,corpus)` (a-d) and `(conc,corpus)` (e-f).

response and the first dark blue (*sinij*) response.[4] English does not have these distinct terms, but the observed category boundaries for Russian and English hardly differ according to W07. We thus use as the English boundary the mean location of the Russian category boundary under the given combination of `features` × `sampling`. A target–distracter pair, s_t–s_d, is considered 'within'-category if s_t and s_d are on the same side of the boundary, and 'across'-category otherwise. Analogously to W07, the map distances for the 8 'near' and 8 'far' pairs closest to the category boundary were calculated from the model for all simulations.

We evaluate whether the model's behavior corresponds to human behavior in W07 by seeing if the same significant effects are found: we compare the $d_\mathrm{map}(c_{s_t}, c_{s_d})$ values (using t-tests) between near and far cases, and between within- and across-category cases, and see whether these two interact.

Results: convergence and development

The model reaches its closest fit to adult behavior after some 20K (Russian) or 30K (English) input items. Table 1 shows that the model captures adult behavior well; a naive baseline always guessing the most frequent term would reach a $\textbf{score}_\textbf{C}$ of .20 (English) or .22 (Russian). We find that `uniform` sampling achieves slightly closer to adult naming behavior. With `sampling=corpus`, more frequent terms take up more of the SOM, leaving less space for less frequent terms to capture their full extension (and hence they are often mislabeled by more frequent neighboring terms). One area for further exploration is whether learners have to be relatively immune to frequency when processing color terms, as otherwise less frequent color terms may not be strongly represented.

	Russian		English	
	`corpus`	`uniform`	`corpus`	`uniform`
`perc`	.91	.86	.96	.95
`conc`	.91	.89	.91	.90
`perc+conc`	.90	.89	.98	.96
error-free learner	.81	.81	.95	.95

Table 2: Results for development (mean τ_b over stimuli and age groups).

Furthermore, we find that there is little difference in $\textbf{score}_\textbf{C}$ in either language between the `perc` and `conc` features alone. However, the model performs somewhat better with both used together. This suggest that the cross-linguistic conceptual space and the perceptual features are complementary, contributing somewhat different information to learning.

Turning to the development results next (Table 2), we find that the model has a good fit to observed patterns of developmental behavior. An error-free learner – one always predicting the correct term with a probability of 1 – has average τ_b values of .81 (Russian) and .95 (English), and so a large part of the global score comes from the model correctly simulating adult behavior rather than the overextension patterns. In most cases, however, the model surpasses these scores, indicating that it does capture some overextension patterns, especially in Russian, which has many more such errors.

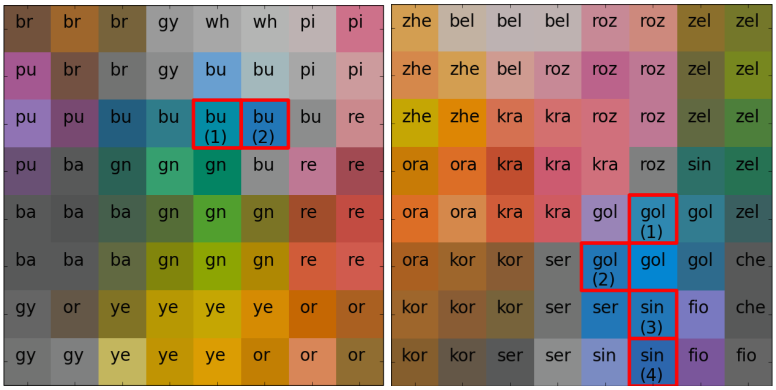
For English, the two `perc` settings give a better fit than the `conc` settings. Considering the match with children's development on particular colors helps understand why. For English, Bateman (1915) presented children (age 6–12) with 8 color chips. The model only displays the correct overextensions of *blue* to PURPLE with `(perc+conc, corpus)` and `(perc, corpus)`, and fails to simulate the correct pattern for ORANGE in both `conc` settings. The other color terms were learned with the correct developmental pattern under all settings: For BLACK, WHITE, RED, and BLUE, no or hardly any overextensions were found either in children or in the model, and the few observed overextensions for YELLOW and GREEN were predicted in any parameter setting.

For Russian, we observe a difference between `corpus` and `uniform` sampling. Davies et al. (1998) presented 3- to 5-year-olds with 12 color chips. 3-year-olds label LIGHT BLUE and PURPLE more frequently *sinij* 'dark blue' than the correct terms, but do not label DARK BLUE as *goluboj* 'light blue' or *fioletovyj* 'purple' as often. Furthermore, 3-year-olds more frequently use *krasnyj* 'red' than *rozovyj* 'pink' for PINK. The model predicts these effects completely under

[4] We discard 4% of Russian simulations which did not have a sequence of only *goluboj* followed by only *sinij*.

	W07	model
Russian	near > far	✓
	within > across	✓
	near-within > near-across	✓
	far-within ≈ far-across	✗
English	near > far	✓
	within ≈ across	✓
	near-within ≈ near-across	✓
	far-within ≈ far-across	✓

(a) Model match to W07; ✓/✗ indicate a match/non-match, respectively, across all 6 feature/sampling settings for Russian, and for 5 of 6 settings in English.



(b) Converged maps for English (left) and Russian (right). S_{disc} stimuli are mapped to the highlighted cells. Cell labels are taken from the first few letters of the most likely term for the cell. bu=*blue*; gol=*goluboj*, sin=*sinij*.

Figure 2: Results for modeling the discrimination experiment.

(perc+conc, corpus) (Fig. 1a-d), and generally predicts the observed ranking better when using corpus, suggesting that term frequencies explain some of the error pattern.

Feature sets display a subtle effect for Russian as well. The asymmetry for DARK BLUE and LIGHT BLUE disappears when we train on perc, as DARK BLUE and LIGHT BLUE are (too) easily discriminated in the perceptual space. This is different for the conceptual features: as many languages group DARK BLUE and LIGHT BLUE under one term, the inferred cognitive bias is to group them together. Figures 1e-f show that for conc, the asymmetry is present, but *goluboj* never gets fully learned. A combination of both feature sets thus seems necessary to understand this effect: perceptual dissimilarity is needed to discriminate them, but cognitive biases bias the learner against forming two categories. The asymmetry may then emerge because of the slightly higher term frequency of *sinij* (.08) over *goluboj* (.06).

Results: discrimination

Figure 2a summarizes the findings of W07 in their color discrimination task (1st column), along with an indication of whether the model results match those findings (2nd column). For example, the entry for Russian of "near-within > near-across" means that people found the near-within cases harder to discriminate than the far-within cases (a statistically-significant difference); "far-within ≈ far-across" means the difference between those two cases for people was not statistically significant. For the former, our model also found a statistically significant effect in the same direction, and for the latter, the lack of an effect in the same direction.[5]

The fact that the model matches "near > far" for both languages supports our assumption that map distance in the learned SOM is a good proxy for discriminability of stimuli. Importantly, the model matches the main finding of W07 that distracters in a different category from the target are more easily discriminated than distracters in the same category, for Russian but not for English (the "within > across" and "within ≈ across" rows in Figure 2a).

To illustrate why this happens, Figure 2b presents a typical converged map for English and for Russian. For English, chips s_1:s_4 are mapped to the cell marked with (2), and chips s_5:s_{20} to the cell marked with (1). Because the category boundary is placed between s_{11} and s_{12} of S_{disc}, all pairs of targets and distracters are mapped to the same cell (1), whether across-category *or* within, and such pairs are indiscriminable for the learner. For Russian, the different shades of blue cannot be compressed on the SOM as much as in English, because there are two terms that need to be discriminated: English *blue* is the most likely term in 5 cells, whereas Russian *sinij* and *goluboj* combined are the most likely terms in 10 cells. Thus in Russian, we see that the 20 S_{disc} stimuli are mapped to a larger part of the SOM (cells (1)–(4) in that map) than the English stimuli, and distances across the categories – from cells (1)-(2) to (3)-(4) – are further than within categories (within (1)-(2) or within (3)-(4)).

Finally, the model generally fails to predict the empirical interaction whereby Russian displays a significant within-across difference for near but not far cases. Under all settings, the model predicts both differences to be significant. We do find a trend in the right direction: for all settings, the within-across difference is greater in the model for the near cases than for the far cases.

Discussion

In this paper, we looked at the developmental pathway of color term acquisition and the effects of acquiring the color term system of a particular language on a non-verbal discrimination task. A Self-Organizing Map (SOM) trained on naturalistic input models three effects: (1) some patterns of overextension errors in linguistic development and (2) subsequent convergence in Russian and English, as well as (3) a higher ability to discriminate light blue from dark blue stimuli in Russian, but not English. Our model thus provides a

[5] Recall that a closer SOM distance, $d_{\text{map}}(c_{s_t}, c_{s_d})$, means the target and distracter stimuli s_t, s_d are "harder to discriminate".

mechanistic conception of learning that gives a unified explanation of both linguistic development and linguistic relativity. The idea that between-language variation is represented by the varying amount of information compression on the SOM (due to the different patterns of words with stimuli across languages) gives us an explanatory principle that could be applied to domains beyond color.

We asked whether possible cognitive biases inferred from crosslinguistic categorization tendencies (cf. Gentner & Bowerman, 2009, reflected in our 'conceptual features', play a role, or whether perceptual features of color best explain the effects. Both feature sets contribute to the explanation of linguistic development: in some cases (naming PURPLE in English), the error pattern is predicted only when the perceptual features are present. For others, leaving out the conceptual features hurts the fit with the observed data (naming DARK BLUE in Russian), suggesting that these biases do play a role.

We also investigated frequency effects: The model fails to predict common overextension patterns in both languages when not taking term frequency into account. Nonetheless, sampling on the basis of corpus frequencies makes the model converge less well to adult behavior for infrequent terms, suggesting that, over development, learners may need to be decreasingly sensitive to term frequency.

One issue we did not explore is different initializations of the SOMs. As children experience color prior to acquiring terms for them, it is possible that the map is already 'preorganized' by exposure to color stimuli without associated color terms. We plan on studying further whether such prelinguistic exposure affects the developmental patterns.

Finally, we looked at the converged states of the SOMs in predicting color discrimination behavior across languages, finding a weak preference for models trained on perceptual features. Since we are able to track the development of the SOM, we can also investigate the effect of language-specific lexical semantic systems on extra-linguistic behavior over developmental time (see, e.g., McDonough, Choi, & Mandler, 2003, for such developmental effects in another domain). In the future, we plan to explore suitable semantic domains for evaluating how well our model simulates linguistic relativity effects over the course of acquisition.

Acknowledgements

We acknowledge the support of NSERC of Canada and thank the four CogSci reviewers for helpful suggestions.

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