Differences in distributional structure can lead to differences in similarity biases

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Some people think a beaver is more similar to a chimp than a turtle, while others think the opposite. What are the consequences of such differences in concepts/word-meanings on communication? And where might these differences come from? We conducted an experiment investigating whether exposure to different word co-occurrence patterns affects people's biases to rely on more taxonomic or thematic relations. English-speaking participants were asked to learn novel words (pseudo-words) in different co-occurring contexts (taxonomic, thematic, and neutral), and their similarity biases were measured over the learning process for each word group and across groups. Context exposure increases similarity biases for the matching context. Learned similarity biases persisted to novel lexical items. Overall, our findings show a causal link between being exposed to different distributional data and people's subsequent similarity ratings, providing a possible mechanism behind previously observed cross-linguistic differences in similarity biases.

1. Introduction

It is generally assumed that for a language to function as an effective communication system, both the forms and meanings must be closely aligned among speakers (e.g., Hutchins & Hazlehurst, 2006). However, different language users may have somewhat different word-meanings. These differences can be partially revealed by comparing people's similarity judgments, e.g., some people think a beaver to be more similar to a chimp than a turtle–prioritizing the common biological taxonomy of beaver and chimp. Others indicate that a beaver is more similar to a turtle, emphasizing the thematic relationship, in this case presumably the strong association with aquatic habitats (Martí, Wu, Piantadosi, & Kidd, 2023; Duan & Lupyan, 2023). These differences in some cases lead to communication misalignment (Duan & Lupyan, 2023). These findings raise a number of interesting questions such as where these differences come from, how languages adapt to tolerate them, and to what extent people's word-meanings (and even conceptual structure) diverge while maintaining communicative success? Here, we focus on the first question.

There is a long history of studying people's reliance on thematic and taxonomic factors in judging similarity relationships (e.g. Markman & Hutchinson, 1984; Lin & Murphy, 2001). One commonly observed trend is an increase then decrease in bias for taxonomic similarity with age (Smiley & Brown, 1979; Borghi & Caramelli, 2003; Brooks, Seiger-Gardner, & Sailor, 2014). Additionally, individual differences in similarity biases also vary with education (Luriia, 1976), language skills (Nation & Snowling, 1999), and the items being judged (Whitmore, Shore, & Smith, 2004). Another contributor is cultural and linguistic differences. People from Eastern cultures show more thematic bias compared to those from Western cultures (Nisbett & Masuda, 2003).

However, the mechanism through which these factors lead to individual differences in similarity biases is less understood. In a recent study, Le, Gao, Frank, and Carstensen (2023) point out that cross-cultural differences in similarity biases (such as those reported in Ji, Zhang, & Nisbett, 2004) may be explained by different statistical patterns in languages spoken by these people. They found that word similarity inferred by language models trained on different languages correlated with human similarity biases from the corresponding language. However, the correlational nature of this study fails to elucidate the extent to which language, as opposed to culture, contributes to human similarity biases. Additionally, the mechanism through which cross-cultural differences in language statistics produce differences in human similarity biases has not been investigated.

Our study addresses these gaps by using a word-learning experiment in which we manipulate linguistic patterns in which pseudo-words are embedded to examine the resulting patterns of similarity judgments. Following the results in Le et al. (2023), we hypothesize that individuals who are exposed to different word co-occurrence patterns will form different similarity biases. Specifically, our research questions are: (Q1) Do different inputs of word co-occurrence patterns (taxonomic, thematic, neutral) result in changes in the corresponding similarity biases? (Q2) Do changes in similarity biases caused by exposure to language patterns generalize to novel words?

2. Methods

2.1. *Materials*

The study focused on second-order word co-occurrences[1], which has been suggested to be the main source of model simulation of human similarity ratings (Paridon, Liu, & Lupyan, 2021). We generated three groups of pseudo-words consisting of a target word and three co-occurring words in taxonomic, thematic and neutral contexts, and five pairs of second-order co-occurring sentences for

[1]Occurrences in the same contexts. Consider 2 sentences: "A chicken looks like a duck" and "A goose looks like a duck". "Chicken" and "goose" is an example of second-order co-occurrence because they both occur in the context of "looks like a duck", even if they do not co-occur within the same sentence.

each context. Taxonomic contexts focus on attributes and categories[2], thematic contexts focus on spatial and temporal occurrences[3], while neutral contexts are contexts that do not fall under taxonomic or thematic, serving as a baseline[4]. Nouns in the contexts were replaced with pseudo-words to minimize reliance on prior knowledge. All pseudo-words were generated by ChatGPT, and manually checked by two English speakers to ensure they were not in English dictionaries and had no phonetic similarity to other pseudo-words in the set.

2.2. *Participants*

We recruited 90 participants from Mechanical Turk, assigning them evenly to a taxonomic, neutral, or thematic condition. All participants indicated that their first language was English and that they resided in the US. The average age of participants is 40.2 (SD=11.7) and the average education level was 4.1 (SD=1.37)[5], with no significant differences among conditions.

2.3. *Procedure*

Participants were randomly assigned to one of three conditions: taxonomic, thematic, and neutral. In all conditions, participants completed a practice set of trials that familiarized them with the study, and three experimental sets of trials each of which consisted of a *prior* trial block and a *critical* trial block (see Figure 1).

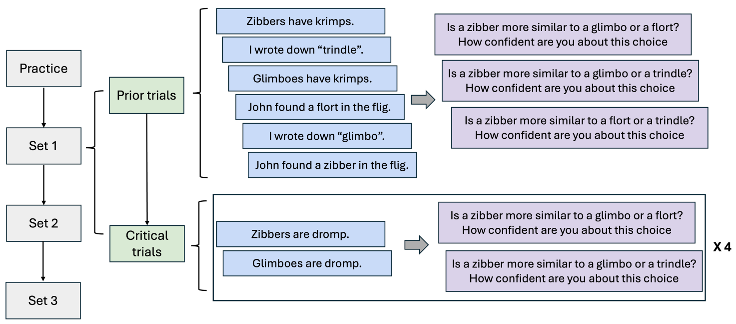

Figure 1. Procedure schematic for the taxonomic condition

Participants were asked to make a series of similarity judgments in which they

[2]For e.g., Zibbers have krimps. / Glimboes have krimps.
[3]For e.g., John found a zibber in the flig. / John found a flort in the flig.
[4]For e.g., I wrote down "zibber". / I wrote down "trindle".
[5]1 = Less than high school, 2 = High school diploma, 3 = Some college, no degree, 4 = 2-year/associate's degree, 5 = Bachelor's degree, 6 = Master's degree, 7 = PhD, law, or medical degree.

chose which of two wordswas more similar to the target word, and then indicated their confidence on a 10-point Likert scale.

Prior trial block. Participants read three pairs of sentences (one in each context type). They then completed three similarity judgments (as described above) pitting pairs of co-occurring words against one another (taxonomic-thematic, taxonomic-neutral, and thematic-neutral).

Critical trial block. Participants saw four pairs of co-occurrence sentences corresponding to their assigned condition (e.g., in the taxonomic condition they only saw sentences involving the target word and the taxonomic match). The order of sentences was randomized, which could result in a delay between pairs of co-occurring sentences. After viewing each co-occurring sentence, they completed two similarity judgments pitting the co-occurring word they had just seen with the other co-occurring choices (e.g., in the taxonomic condition, the judgments pit the taxonomic match against the neutral and thematic match respectively).

After reading each sentence, participants saw a multiple-choice question that served as an attention check[6]. Participants who failed more than two attention checks were excluded from analysis. Participants' age and education level were collected at the end of the experiment for analysis. Pseudo-words, sentence order and set order were randomized across participants.

2.4. *Analytic Procedure*

We analyzed our data using two linear mixed-effects models. To answer Q1, we examined the effect of sequence order (order of four co-occurrences in each block) for each experimental block, age and education (all scaled), as well as their interactions with different types of comparison (neutral against taxonomic as the reference level). We used the following 'lmer' syntax: `bias ∼ (sequence order + age + education) * Comparison Type + (1 | participant ID)`. Sequence order refers to one prior trial plus four critical trials within each set ($1 \sim 5$). There were six comparison types in total: for each condition, we used two comparison types – the similarity of the target word to the co-occurring word in this conditional type, compared to its similarity to the other two co-occurring words in prior trials. For example, in the taxonomic condition, we compared taxonomic against thematic, and taxonomic against neutral. Participants' biases were coded as positive if they preferred the condition-aligning choice and negative otherwise. We used their confidence rating for the absolute value of their bias. To answer Q2, we focused on how people's prior bias (bias for new pseudo-words) changed over the course of three sets. We therefore only considered the prior trial in each set. The model was `bias ∼ (set order + age + education) * Comparison Type + (1 | participant ID)`.

[6] For e.g., after reading "John found a zibber in the flig", participants needed to choose whether the zibber was found "in the flig", "on the flig", or "under the flig".

3. Results

Clear evidence of learning is indicated by the main effect of sequence order (b=1.59, p<0.005), which means when people saw more pairs of sentences containing co-occurrence of two words in the corresponding type of context, their similarity bias for that type increased (Table 1 and Figure 2). While this learning slope didn't differ between different conditions, overall, people had a stronger taxonomic bias than thematic and neutral bias, and a stronger thematic than neutral bias (type[taxonomic against neutral]: b=4.04, p<0.005; type[taxonomic against thematic]: b=3.81, p<0.005; type[thematic against neutral]: b=2.51, p<0.01).

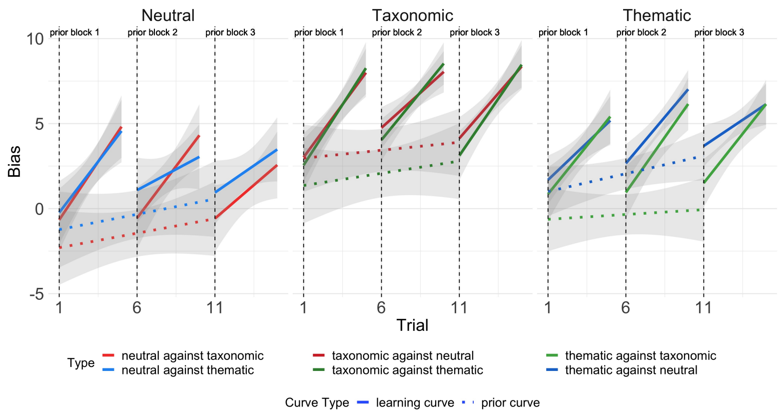

Figure 2. Learning and prior curves for each condition. Dashed vertical lines indicate the beginning of new experimental sets with new words. Learning curves reflect change of bias within each set. Prior curves reflect change of prior bias across three sets.

Higher education level was associated with a stronger thematic bias against both taxonomic and neutral choices. A closer investigation revealed that although thematic biases (against neutral and taxonomic choices) increased more with education, even at the highest education level, they did not surpass taxonomic biases. Taxonomic biases remained high across education levels. One possible reason is that taxonomic biases are easier to learn, and people become better at learning from diverse contexts to exhibit a broader ranger of biases (including thematic biases) with more education.

The only significant effect of age was in the neutral condition: older participants acquired less neutral bias against thematic choice versus against taxonomic choice (i.e., interactive effects between age and type), which provided tentative supporting evidence of the theory that elderly people re-increase their thematic bias (Smiley & Brown, 1979).

Table 1. Coefficient estimates for significant predictors. (*: $p < 0.05$,**: $p < 0.01$,***: $p < 0.005$, reference level of type: neutral against taxonomic)

Model	Variables	Predictor coefficient	95% CI
conditional learning effect	(Intercept)	1.98**	[0,78, 3.18]
	sequence order	1.59***	[1.18, 2.00]
	education	-2.00**	[-3.27, -0.73]
	type(taxonomic against neutral)	4.04***	[2.35, 5.73]
	type(taxonomic against thematic)	3.81***	[2.12, 5.50]
	type(thematic against neutral)	2.51**	[0.82, 4.19]
	education : type(thematic against neutral)	2.96**	[1.22, 4.69]
	education : type(thematic against taxonomic)	3.87***	[2.13, 5.60]
	age : type(neutral against thematic)	-1.02**	[-1.67, -0.38]
prior generalization effect	set order	0.58**	[0.15, 1.02]
	type(taxonomic against neutral)	4.70***	[2.54, 6.86]
	type(taxonomic against thematic)	3.34**	[1.18, 5.50]
	type(thematic against neutral)	3.45**	[1.29, 5.60]

In the prior generalization model, since there were no significant interactive effects, we removed these from the model and found a significant generalization effect: people increased their prior bias for the condition they were assigned to learn, and generalized the bias they learned from previous sets to a new set with novel lexical items (i.e., set order effects). We also found the same comparison type effects as found in the conditional learning effect model (Table 1).

4. Discussion

Our findings provide evidence supporting the hypothesis that exposure to different linguistic patterns cause individual differences in similarity biases. The observed learning effects across all conditions (e.g., taxonomic bias increases with more exposure to taxonomic co-occurrences) underscore that individuals indeed mold their similarity biases based on the word co-occurrence patterns they encounter. Furthermore, biases learned from language inputs can be generalized to novel lexical items, which suggests that exposure to language patterns in different co-occurrence contexts is a possible mechanism through which individual differences in similarity biases emerge. Altogether, our findings endorse the idea that our judgment of lexical and conceptual similarities can be guided by linguistic statistics, corroborating with prior studies that demonstrated such relationships in cross-cultural linguistic patterns and human similarity judgments (Le et al., 2023). Future research should investigate how different languages might naturally evolve to favor certain word co-occurrence contexts over others, to further shed light on how cross-cultural differences in similarity biases develop.

In conclusion, our study elucidates how linguistic patterns shape cognitive biases. The results underscore the importance of exploring language statistics exposure as a contributor to lexical representation and effective communication.

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