Constraints on the lexicons of human languages have cognitive roots present in baboons (*Papio papio*)

Emmanuel Chemla[1] · Isabelle Dautriche[2] · Brian Buccola[1] · Joel Fagot[3,4]

[1]Laboratoire de Sciences Cognitives et Psycholinguistique (ENS, EHESS, CNRS), Département d'Études Cognitives, École Normale Supérieure, PSL University, Paris, France
[2]Centre for Language Evolution, University of Edinburgh, Edinburgh, UK
[3]Laboratory of Cognitive Psychology, Aix-Marseille University, CNRS, Marseille, France
[4]Institute of Language, Communication and the Brain, Aix-Marseille University, CNRS, Aix-en-Provence, France

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Abstract

Using a pattern extraction task, we show that baboons, like humans, have a learning bias that helps them discover *connected* patterns more easily than disconnected ones, i.e. they favor rules like 'contains between 20% and 60% red' over rules like 'contains less than 20% or more than 60% red'. The task was made as similar as possible to a task previously run on humans, which was argued to reveal a bias that is responsible for shaping the lexicons of human languages, both content words (nouns and adjectives) and logical words (quantifiers). The current baboon result thus suggests that the cognitive roots responsible for regularities across the content and logical lexicons of human languages are present in a similar form in other species.

Keywords: connectedness, human languages and their lexicons, primate semantics

1 Connectedness: constraints on natural classes and pattern extraction

Humans and animals categorize objects in the world into natural classes based on various criteria. A prominent example of a criterion that has been hypothesized for humans is *connectedness*. Informally, connectedness requires that whenever two objects a and c belong to a certain class, and a third object b is 'between' a and c, then b must also belong to that class. The traces of connectedness are twofold. First, content words (nouns and adjectives) in the world's natural languages are generally connected (Gärdenfors, 2004). For example, the set of all flying, feathered animals is a natural, connected class, for which many languages have a single word (e.g. *bird*); however, the set of all objects that are either red or a bird is not a natural class — it is too disconnected (e.g. it includes both raspberries, which are red, and blue jays, which are birds, but not blueberries, even though blueberries are, intuitively, 'between' raspberries and blue jays) — and indeed no language has a single word meaning 'red or bird'. Second, connectedness creates a learning bias: new nouns are more readily associated with connected meanings than with non-connected ones (Dautriche and Chemla, 2016; Xu and Tenenbaum, 2007).

Recently, Chemla et al. (2018) have generalized the notion of connectedness from the domain of content words (in which the relevant notion of betweenness is often difficult to specify; see

Murphy and Medin, 1985) to the domain of logical words, specifically quantifiers (in which a precise, canonical notion of betweenness naturally arises based on the mathematical subset relation between sets).[1] They show that connectedness is a weak version of *monotonicity*, a classic notion in formal semantics: a quantifier q is monotonic just in case both q and its negation are connected. Examples of monotonic quantifiers include *somebody*, *everybody*, and *more than five people*. Connected but non-monotonic quantifiers include *some but not all people* and *between three and five people*. Non-connected quantifiers include *all or no people* and *fewer than three or more than five people*. As in the domain of content words, connected quantifiers appear to be privileged across the lexicons of the world's languages: most lexicalized quantifiers are connected, if not monotone, and conversely, non-connected concepts generally require compositional machinery to be expressed (e.g. via overt disjunction, or with the help of a non-connected content word, as in *an odd number of people*; see Keenan and Paperno, 2017 for a survey). Furthermore, Chemla et al. show that humans have corresponding learning biases favoring connected quantifiers, as evidenced by performance on rule learning, or pattern extraction, tasks: it is easier to discover connected rules than non-connected ones, and easier still to discover monotone ones.

A natural hypothesis is that the source of the regularity of the world's lexicons, for both content and logical words, is a learning bias for connectedness. Can the roots of this bias be found independently of language proper, and do other animals show the same bias? The object/noun version of the connectedness constraint has been explored with animals, often under the name of 'pseudo-categorization' (e.g. Huber, 1999; Wasserman et al., 1988; Zentall et al., 2008). Here, we report on an experiment that explores a variation on these experiments, to prompt more directly the rule/quantifier version of connectedness with animals. We presented baboons with a pattern extraction task, which is as close as possible to the task used to argue for a human learning bias favoring connected quantifiers. We do not need to wonder whether this requires high-level reasoning abilities (Call, 2006; Tomasello, 2014), and surely there is no claim that a 'word'-like element has this high logical type in an animal's repertoire. We thus ask whether the connectedness constraint is active for an animal's *potential* 'functional vocabulary'. If the answer is positive, it may suggest that the shape of the world's lexicons, including logical lexicons, has roots in general, non-linguistic cognitive biases, which may have evolved in other animals, too, independently of language.

2 Method

The data and the script for their analysis are available here: `https://tinyurl.com/y96bctb5`.

1 For instance, the set of all Berliners (B) is a subset of the set of all Germans (G), which in turn is a subset of the set of all Europeans (E); thus, G is between B and E in the sense that $B \subseteq G \subseteq E$. To check whether a quantifier q is connected, one can therefore check whether the truth of $q(B)$ and $q(E)$ (q applied to the extreme sets) entails the truth of $q(G)$ (q applied to the in-between set). Take, for example, *between three and five people* (assume that *people* refers to the people here in this room). If between three and five people here are Berliners, and moreover between three and five people here are Europeans, then it follows that between three and five people here are Germans. (The smallest possible number of Germans is three, since there are at least three Berliners, and the largest possible number of Germans is five, since there are at most five Europeans.) Thus, *between three and five people* is connected. By contrast, *fewer than three or more than five people* is non-connected: if fewer than three or more than five people here are Berliners, and moreover fewer than three or more than five people here are Europeans, it does *not* follow that fewer than three or more than five people here are German. (A counterexample: exactly two people here are Berliners, exactly two people here are Hamburgers, exactly two people here are Parisians, and nobody else is European. Then there are exactly two Berliners, exactly six Europeans, but exactly four Germans.)

Ethical standards. This research conformed to the Standard of the American Psychological Association's Ethical Principles of Psychologist and Code of Conduct, and received ethical approval from the French Ministry of Education (approval APAFIS #2717-2015111708173794 v3).

Participants and apparatus. 13 Guinea baboons (*Papio papio*, 10 females; age range: 2-20 years) from the CNRS primate facility (Rousset-sur-Arc, France) participated in the study. An additional 10 participants started the study but were not included in the final sample because they did not reach the learning criteria for the first condition they were assigned in (see Inclusion criterion below). This is the maximal number of participants that we could test. The participants were tested using ten automatic computerized learning devices for monkeys (see Fagot and Bonté, 2010), each comprising a touch screen and food dispenser, which were freely accessible from the baboons' living enclosures. The procedure used an automated radio frequency identification of the subjects within each test system, making it possible to test the individuals without capturing them. Use of this procedure improves animal welfare in experimental research (Fagot et al., 2013).

Stimuli. There were 3 sets of 6 stimuli, represented in Table 1. A stimulus was a picture of a circle filled by X% of a color α and by $(100 - X)$% of a color β on a black background. X had 6 possible values (0, 20, 40, 60, 80, 100), such that each stimulus in its set may be described by its proportion of color α. The 3 stimuli sets differed in the α/β colors they featured (i.e. purple/white; blue/orange; grey/pink), in the orientation of the line separating the two colors (i.e. horizontal, diagonal, vertical), and in the set of two response buttons provided to the participants to arrange the stimuli in two groups. Each response button featured a yellow digit on a black background. All participants saw the three sets of stimuli in the same order, but associated with different conditions. Each image was created as a bitmap file with 250×250 pixels and presented on the screen as a square of 6cm, corresponding to a visual angle of 11.4° at a distance of 30cm.

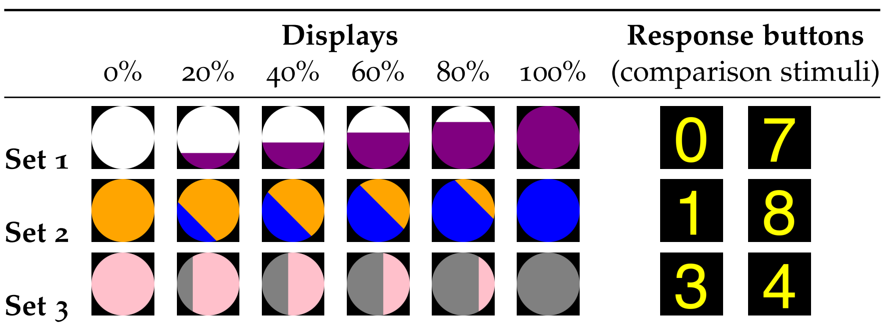

Table 1. Each stimulus was a circle characterized by the proportion of color α (e.g. for set 1, white vs. purple) of its total area, varying from 0% to 100% by increments of 20. Each set was presented with a different pair of response buttons (i.e. arbitrary digits).

Task and conditions. Participants were tested in a matching-to-sample task: in each trial an item selected from a given stimulus set was used as a sample, and two distinctive shapes A and B (i.e. digits) as comparison stimuli. The task was to learn a rule where half of the 6 stimuli in a set correspond to a response A, and the other half to a response B. There were 3 conditions, described schematically in Table 2. In the *monotone* condition, the 3 stimuli associated with A were clustered at one extreme (and the stimuli associated with B were thus clustered at the other extreme). In the *connected* condition, the 3 stimuli associated with A were all contiguous, but not clustered at an extreme. Finally, in the *non-connected* condition, the 3 stimuli associated with A were spread non-continuously, and so were the stimuli associated with B.

The 3 conditions were implemented in a different order to three different groups of participants. The order of the conditions was determined such that group 1 saw the conditions in increasing order of difficulty (*a priori*), group 2 in decreasing order, and group 3 started with the connected condition so that all conditions occurred first across groups. The stimuli sets were implemented in the same order to the different participants (so that they would be matched with different conditions across groups).

Conditions	0%	20%	40%	60%	80%	100%
Monotone	A	A	A	B	B	B
Connected	B	B	A	A	A	B
Non-connected	B	A	A	B	B	A

Table 2. The 3 conditions were determined by whether a particular stimulus should be matched with the first response button (A) or the second response button (B). Monotonicity and connectedness of the resulting pattern are determined based on the way the As and Bs are entangled.

Procedure and learning criteria. Stimuli were presented in blocks of 6 trials containing all proportions, with random order within each block. A trial started with the presentation of a stimulus centered in the middle of the screen. Once participants touched the stimulus picture, the two response buttons A and B appeared on each side of the screen. The left-right location of the response buttons was fixed within each learning condition. Touching the correct button cleared the screen and delivered a food reward. Touching the incorrect button triggered a 3-second timeout indicated by a green screen. Participants were allowed a maximum of 5 seconds to respond. The inter-trial interval was set to 3 seconds. A rule was considered to be learned when the participants made no more than 1 error per block for three consecutive blocks (a general accuracy criterion), and no 2 of such errors were on the same stimulus (to ensure that each item could be counted as learned).

Inclusion criterion. We included all participants who learned at least one rule and in our analysis only considered the rules for which the learning criteria were reached. Of the 13 participants included in our sample, 9 participants (3 per group) learned the 3 proposed rules (one in each condition), 2 learned 2 rules (connected and monotone), and 2 learned a single rule (one in the non-connected condition and the other in the monotone condition). Excluding participants who did not finish the experiment (i.e. who could not reach the learning criteria in each of the 3 proposed conditions) does not change the pattern of results.

3 Results

We reproduced the two analyses already used in a human version of the task (Chemla et al., 2018).

Analysis 1: Learning performance. Participants took on average 2,888 trials to reach the learning criteria across conditions (SE_{trials} = 330; min_{trials} = 162; max_{trials} = 7,392). Figure 1 reports the average number of blocks of trials needed to learn a rule per Condition (monotone, connected, and non-connected).

To quantify the ease with which different rules are learned, we fit the number of blocks of 6 trials needed to learn the rule using a mixed model in R (`lme4` package, Bates et al., 2015). The model included a categorical predictor Condition (monotone, connected, non-connected) as well as a random intercept for each participant. The model was specified as: `Nblocks ~ Condition + (1 | Participant)` and compared to a model without the predictor Condition to establish the effect of connectedness on learning difficulty.[2] Condition was a significant predictor of learning performance ($\chi^2(2) = 16.76$; $p < 0.001$) with the monotone and the connected rules learned the fastest ($M_{monotone} = 367$ blocks; $SE_{monotone} = 75$; $M_{connected} = 319$ blocks; $SE_{connected} = 66$) and the non-connected rule learned the slowest ($M = 741$ blocks; $SE = 70$).[3]

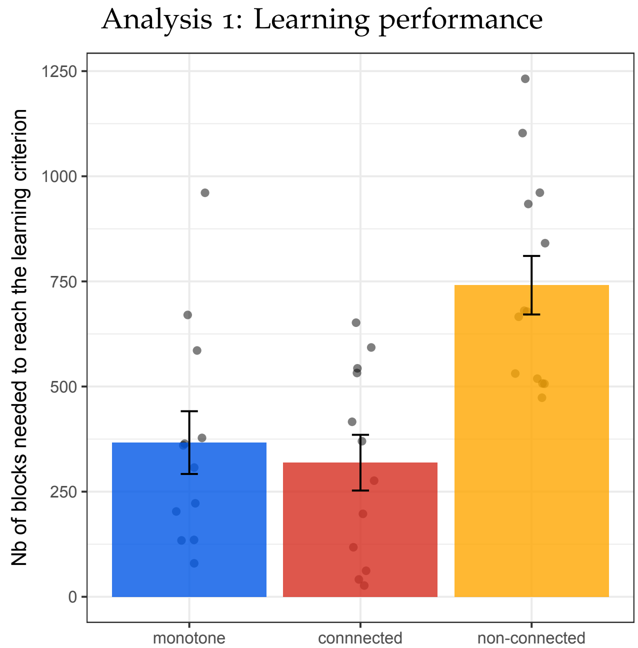

Figure 1. Results corresponding to Analysis 1: the Figure represents the average number of blocks needed to reach the learning criterion for each Connectedness condition (monotone, connected, non-connected). Error bars indicate standard errors of the mean. Dots represent individual data points.

Analysis 2: Bias for connectedness. We explore here the role of a learning bias for connectedness across all conditions: do responses adhere to connectedness, whether or not these responses are correct or incorrect? To quantify the role of connectedness independently of the conditions in which participants were tested, we inspected the responses within all blocks of trials and asked whether these responses correspond to a connected guess about the underlying rule. For this, we looked at whether participants' response for a stimulus (characterized by X% of its area colored) is dependent on their responses for the two 'contiguous' stimuli (filled by $X - 20\%$ and $X + 20\%$ of the same color) within the same block of trials. The idea is that if participants responded in one way to both $X - 20\%$ and $X + 20\%$, they should respond in the same way to

2 Since adding a predictor Condition Order (and its interaction with Condition) did not improve the model fit significantly ($\chi^2(4) = 6.96$; $p = 0.14$), this predictor was removed from the final model.

3 In some cases the non-connected rule could not be learned at all: 2 participants did not succeed in reaching the learning criteria in the non-connected condition despite receiving a high number of blocks (> 1675) and despite succeeding in learning in the two other conditions. Note that these two unfinished learning conditions are not included in our analysis (see Inclusion criterion).

the central case X%. We modeled participants' A response (coded as 0/1) for a given stimulus using a mixed logit model specified as `response ~ NContiguousResponses + Condition + (NContiguousResponses + Condition | Participant)`[4] where the predictor NContiguousResponses is the sum of responses A (0 to 2) for both contiguous stimuli within the same block.

As can be seen in Figure 2, there was a significant effect of responses to the contiguous stimuli on the response participants gave ($\chi^2(2) = 14.79$; $p < 0.001$): participants were more likely to give a response A when they responded A to both contiguous stimuli than if they responded A to only one of them ($\beta = -0.80$; $z = -6.35$; $p < .001$), in which case they were at chance, or to none ($\beta = -1.41$; $z = -5.96$; $p < .001$), in which case they were more likely to respond B. This was presumably true in all three conditions (there was no effect of Condition, $\chi^2(2) = 2.39$; $p = 0.30$, despite the presence of feedback inducing participants' response towards connectedness or non-connectedness).

Analysis 2: Bias for connectedness

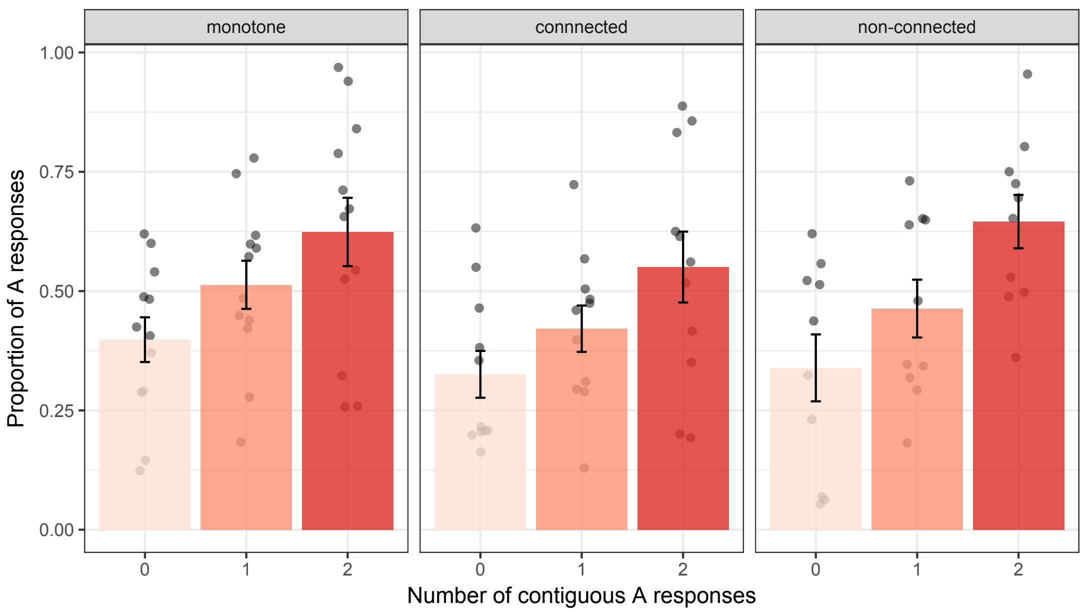

Figure 2. Results corresponding to Analysis 2: the Figure represents the proportion of A responses as a function of the number of A responses given on the contiguous stimuli. Error bars indicate standard errors of the mean. Dots represent individual data points.

4 Discussion

On first glance, our results may not seem so surprising: the patterns we described as connected (and monotonic) are, in an obvious sense, more 'complex' than those we described as non-connected, and so perhaps all that we have shown is that baboons learn less complex patterns more easily. However, it is important to note that one needs to establish a metric of complexity in order for such a conclusion to be meaningful: in precisely what sense is one pattern more or less complex than another? Responses to this question may be more or less simple (see, e.g., Feldman, 2000). We argue that connectedness provides one such metric. One way of interpreting our results, then, is to say that the complexity to which baboons are sensitive, in pattern extraction tasks like the ones we used, crucially involves connectedness, since connectedness is what distinguishes the

4 A model with the interaction between NContiguousResponses and Condition did not converge.

different conditions. Thus, we conclude that baboons have learning biases that favor connectedness, just like humans.

It is worth emphasizing that our results closely resemble well-established results about so-called 'pseudo-categorization' (Huber, 1999; Wasserman et al., 1988; Zentall et al., 2008), which has been explored very broadly, with very consistent findings. On this basis, we trust that our results are solid and novel, even if they may not necessarily be surprising on their own. Rather, we see our contribution as showing that what has been said for pseudo-categorization and object concepts can be replicated for *logical* concepts. We furthermore hope that our results are framed in a way that may open up interesting new developments, in particular the possibility of exporting many discussions about object concepts to logical concepts in the animal kingdom.

Finally, returning to our starting point, we reiterate that the meanings of words in natural languages are, by and large, subject to a connectedness constraint. This constraint could be the fossilization in language of more general, non-linguistic biases: in a large hypothesis space for the meaning of a new word, connected meanings are at an advantage because the patterns they correspond to are more salient to humans. These biases may not have a linguistic source, however, and they could thus be present even in non-human animals without an extended lexicon. Strikingly, even if both content words and logical words may show the traces of these biases for humans, the biases themselves may be found in species without a communication system like human language, certainly without logical words. The evidence shows that indeed baboons, just like humans, find it easier to discover connected patterns than non-connected patterns. The connectedness constraint is thus active in these species in a form that can explain how the referential and functional lexicons of human languages are shaped.

Author contributions

B. B., E. C., and I. D. developed the study concept. J. F. adapted it to non-human primates, wrote the test program, and performed the testing and data collection. I. D. performed the data analysis. B. B. and E. C. wrote the introductory and discussion sections of the manuscript, and I. D. wrote the method and results sections. J. F. provided comments on initial drafts. All authors edited and approved the final version of the manuscript for submission.

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References

Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting linear mixed-effect models using lme4. *Journal of Statistical Software*, 67(1):1–48.

Call, J. (2006). Descartes' two errors: Reason and reflection in the great apes. In Hurley, S. and Nudds, M., editors, *Rational Animals?*, pages 219–234. Oxford University Press.

Chemla, E., Buccola, B., and Dautriche, I. (2018). Connecting content and logical words. *Journal of Semantics*. In press.

Dautriche, I. and Chemla, E. (2016). What homophones say about words. *PLoS ONE*, 11(9):e0162176.

Fagot, J. and Bonté, E. (2010). Automated testing of cognitive performance in monkeys: Use of a battery of computerized test systems by a troop of semi-free-ranging baboons (*Papio papio*). *Behavior Research Methods*, 42(2):507–516.

Fagot, J., Gullstrand, J., Kemp, C., Defilles, C., and Mekaouche, M. (2013). Effects of freely accessible computerized test systems on the spontaneous behaviors and stress level of guinea baboons (*Papio papio*). *American Journal of Primatology*, 76:56–64.

Feldman, J. (2000). Minimization of boolean complexity in human concept learning. *Nature*, 407(6804):630.

Gärdenfors, P. (2004). *Conceptual spaces: The geometry of thought*. MIT press.

Huber, L. (1999). *Visual categorization in pigeons*. Cook RG (ed) Avian visual cognition [On-line].

Keenan, E. L. and Paperno, D. (2017). *Handbook of Quantifiers in Natural Language: Volume II*, volume 97. Springer.

Murphy, G. L. and Medin, D. L. (1985). The role of theories in conceptual coherence. *Psychological review*, 92(3):289.

Tomasello, M. (2014). *A Natural History of Human Thinking*. Harvard University Press.

Wasserman, E., Kiedinger, R., and Bhatt, R. (1988). Conceptual behavior in pigeons: Categories, subcategories, and pseudocategories. *Journal of Experimental Psychology: Animal Behavior Processes*, 14(3):235.

Xu, F. and Tenenbaum, J. B. (2007). Word learning as Bayesian inference. *Psychological review*, 114(2):245–272.

Zentall, T. R., Wasserman, E. A., Lazareva, O. F., Thompson, R. K. R., and Rattermann, M. J. (2008). Concept learning in animals. *Comparative Cognition & Behavior Reviews*, 3:13–45.