LANGUAGE, COGNITION AND NEUROSCIENCE, 2016
http://dx.doi.org/10.1080/23273798.2016.1236978

COMMENTARY

Zebras and antelopes: category sparsity as the result of the relations between objects and within categories*

Paulo F. Carvalho[a] and Robert L. Goldstone[b]

[a]Human-Computer Interaction Institute, Carnegie Mellon University, Pittsburgh, PA, USA; [b]Department of Psychological and Brain Sciences, Indiana University, Bloomington, IN, USA

ARTICLE HISTORY Received 20 May 2016; Accepted 11 September 2016

In their paper "Recognizing a zebra from its stripes and the stripes from 'zebra': the role of verbal labels in selecting category relevant information", Perry and Lupyan (P&L) argue that sparse categories impose high selective attention demands, requiring one to choose what to attend to, compared to dense categories for which several dimensions can or must be used. Furthermore, P&L argue that labels are more useful for sparse categories because they "tune" perception towards the *discriminative* properties of objects. P&L show that categories for which there is substantial agreement by participants on what the common feature of that category is, have lower selective attention demands and benefit more from the inclusion of a label.

In this commentary we focus on what constitutes a sparse category. We will attempt to make the case for the importance of considering both how many discriminative features as well as how many common but not discriminative features a category has in order to evaluate category sparsity. We propose that for a complete understanding of the selective attention processes and labelling effects on category learning one must take the categorisation space, rather than each isolated category, into account.

A sparse category is a category for which there are only one or few discriminative features and various irrelevant ones. Increasing the variability in the features among items of the same category (the number of features irrelevant for categorisation) increases sparsity, whereas increasing the number of features varying between the categories (the number of features relevant for categorisation) reduces it (Kloos & Sloutsky, 2008). To identify the sparsity of a category, P&aL asked participants to list the common features to a set of 10 items of the same category, for example 10 pictures of zebras. When asked to list the features of a set of zebras, people are likely to list stripes. Stripes could be a good discriminative feature of zebras (not many animals have stripes), and also a highly characteristic property of that category (all zebras have stripes). However, this might not always be the case, depending on the properties of the contrasting categories and the variability among items of the same category. We believe this is an important consideration because P&L's measure of sparsity takes into account each category in isolation (thus it is not clear how many discriminating features the categories possess), and does not take into account how many features vary among items of the same category.

To illustrate the importance of considering the relation between categories for their sparsity, take the following example using different contrasting categories for the category zebra. One would agree that stripes are a good descriptor of zebras (Figure 1(a)), constituting a sufficient and necessary feature to describe this category – therefore zebra would be considered a sparse category. This would also be the case when one thinks of horses (Figure 1(b)) as a contrast group for the zebra category. However, when contrasting zebras with antelopes (Figure 1(c)) or okapis (Figure 1(d)) stripes are probably not the only good descriptor. In this case, zebra would constitute a denser category. Although people could still frequently list stripes as a commonality, they would also list a series of other features (potentially colour, horns and size), as well as one or more discriminating features. People might still agree that stripes is a good descriptor of zebra but it would no longer be the only or most frequently listed feature. Importantly, the category zebra did not change, it was the space of categories that changed,

CONTACT Paulo F. Carvalho pcarvalh@andrew.cmu.edu

*Commentary on Perry & Lupyan (2016). Recognizing a zebra from its stripes and the stripes from "zebra": the role of verbal labels in selecting category relevant information.

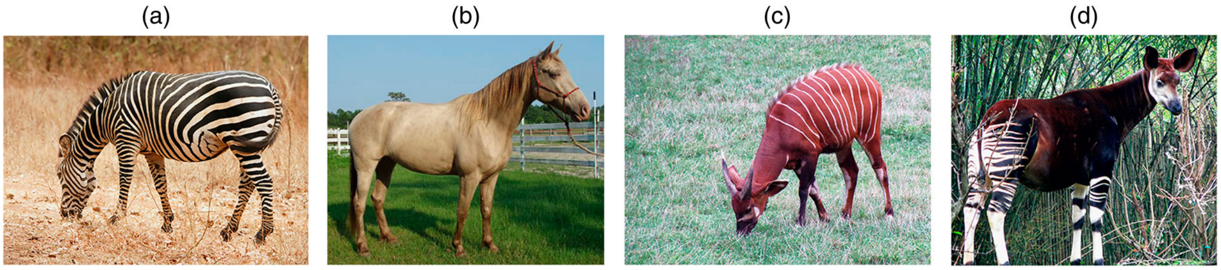

Figure 1. Images of a Zebra (a), a Horse (b), an Antelope (c), and an Okapi (d). Images retrieved from Wikimedia Commons.

affecting the sparsity of the category zebra. The same category can be more or less sparse depending on what other categories and images one sees in the same situation/task.

Taking into account the relation between the categories and among items of the same category is not only important for defining category sparsity, but also has consequences for thinking about how verbal labels might influence categorisation. When people hear the word "zebra" and have to say whether the image that is displayed is or is not a zebra, the nature of the other categories and items (i.e. the foils) participants are simultaneously studying will affect whether the property "stripes" is activated or not. For example, seeing images of both dogs and birds in the same task might emphasise what discriminates these two types of animals as would seeing an image of a feather duster and a cow (the foils used in P&L picture verification tasks). Additionally, and perhaps more importantly, features that do not discriminate between the categories being studied might not be emphasised by this task, leading to the conclusion that naming brings to mind discriminating, unique, and simple features and not a constellation of characteristic features. We will return to this point later.

Taking into account the whole stimuli space, including the items from contrasting categories, is important because it allows for a detailed description of the role that different features play for categorisation. This detailed description will allow for a more complete characterisation of the category space being learned, the selective attention demands of the task, and the effects that labelling exerts on this process. For instance, the feature distributions within and between categories affect how characteristic and discriminative that feature is. A feature might be characteristic of a category – that is, have high category validity, defined as p (feature | category) – the probability of having a feature given that an object belongs to a category. The feature would also be discriminative if it allows one to categorise an item as belonging to one from among a set of categories – that is, it may have high cue validity, defined as p (category | feature). However, it is possible that a characteristic feature has low or no discriminative value (e.g. having stripes and being a zebra when compared to okapis). Thus, how diagnostic a feature is will depend not only on whether that feature is expected given a category, but also to which degree the category can be predicted given the feature. Both of these factors have been shown to influence several aspects of categorisation, including category acquisition (e.g. Medin, 1983; Murphy & Ross, 2005; Rosch & Mervis, 1975; Wisniewski, 1995), how attention should be deployed during categorisation (e.g. Carvalho & Goldstone, 2014, 2015), the role of category labels (Markman & Ross, 2003), and how categories are represented (e.g. Ashby & Maddox, 2005; Goldstone, 1996; Kloos & Sloutsky, 2008; Markman & Ross, 2003).

Going back to the definition of sparse categories, the number of discriminative and characteristic features a given category contains will be related to how sparse the category is; sparser categories are likely to have a few highly discriminative features, whereas denser categories will have more characteristic features, each with lower discriminative value. Thus, the selective attention demands of a categorisation task will depend not only on the discriminability of the feature but also on the characteristic value of that feature and how many low discriminability features exist in the space. A category defined by six features in which one of them has high discriminative value and five have no discriminative value but are highly characteristic of the category will require greater selective attention than a similar category in which five of the six features are not discriminative and not characteristic of the category (e.g. they randomly vary).

We defined and recruited the concepts of cue and category validity because we believe these notions can help to clarify, going forwards, what might be meant by category sparsity and how labelling might be expected to differentially influence the categorisation of sparse and dense categories. By one account, what a category label does is to bring to mind a prototypical example of a category. This prototypical example would be expected to possess the characteristic features of the category. For the category *dog* these features would include barking, having four legs, and a tail that wags, and can be determined without knowing the contrast category. By another account, what a category label does is to prime the features that discriminate the category from other relevant categories. If the other categories are *horse, donkey,* and *deer*, this account predicts that presenting the label "zebra" will emphasise the feature *stripes*.

L&P are somewhat ambiguous about which of these accounts they are endorsing. Their operationalisation of category sparsity derives from asking participants to list all of the features shared by objects from a particular category, and measuring the proportion of participants that listed a particular feature, integrating across all listed features. On the surface, this measure sounds like it is measuring category validity because it focuses on the features that are shared by members of a single category considered on its own. However, in the same way that people rarely list "two eyes" as a feature of *robin* because that feature does not discriminate robins from other birds and many animals, people may be editing the features that they decide to list to emphasise the features of a category that discriminate one category from others being presented around the same time. If participants were not thus editing, after all, they would be listing features like *takes up space*, *is an object*, and *can be thought about* for all of the categories.

Determining whether labels bring to mind category valid or cue valid features would be a valuable direction for future work in this research line. It would help resolve the nature of the relation between labels and categorisation. Are *stripes* brought to mind for *zebra* because most zebras have stripes, or because stripes distinguish zebras from horses? Our bets are on the former, but if so, then category labels are acting to bring to mind a possible entire constellation of characteristic features associated with the objects from a category, not necessarily to focus only on discriminating features that act like rules. The link between category sparsity and participants' ability to ignore flankers when attending a central object (shown in L&P's Figure 4) is suggestive of a discriminative, selective influence of labels, but only weakly suggestive in our opinions because neither of the interactions in Figure 4 (b or c) are overwhelming, and arguably the most relevant flanker task comparison, the performance cost for incongruent relative to neutral trials (measuring how well can participants ignore irrelevant information), shown in Figure 4(c), is barely related to category sparsity in terms of determining category verification ease.

We agree with L&P's final comments on the potential influence of the category space (beyond a single category) for category sparsity. Here we argued that this influence is not only important for understanding category sparsity, but might also be crucial for a complete understanding of the role of labels in category learning. Considering both the discriminative and characteristic values of each of the stimuli features and how frequent each of these are can prove valuable in the effort to specifying the role of labels in categorisation and its relation to attentional demands and category representation.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

Preparation of this commentary was supported by Graduate Training Fellowship from the Portuguese Foundation for Science and Technology (FCT) [SFRH/BD/78083/2011] to PFC.

References

Ashby, F. G., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology*, *56*, 149–178. doi:10.1146/annurev.psych.56.091103.070217

Carvalho, P. F., & Goldstone, R. L. (2014). Putting category learning in order: Category structure and temporal arrangement affect the benefit of interleaved over blocked study. *Memory & Cognition*, *42*(3), 481–495. doi:10.3758/s13421-013-0371-0

Carvalho, P. F., & Goldstone, R. L. (2015). The benefits of interleaved and blocked study: Different tasks benefit from different schedules of study. *Psychonomic Bulletin & Review*, *22*(1), 281–288. doi:10.3758/s13423-014-0676-4

Goldstone, R. L. (1996). Isolated and interrelated concepts. *Memory & Cognition*, *24*(5), 608–628. doi:10.3758/BF03201087

Kloos, H., & Sloutsky, V. M. (2008). What's behind different kinds of kinds: Effects of statistical density on learning and representation of categories. *Journal of Experimental Psychology: General*, *137*(1), 52–72. doi:10.1037/0096-3445.137.1.52

Markman, A. B., & Ross, B. H. (2003). Category use and category learning. *Psychological Bulletin*, *129*(4), 592–613. doi:10.1037/0033-2909.129.4.592

Medin, D. L. (1983). Structural principles in categorization. In T. J. Tighe & B. E. Shepp (Eds.), *Perception, cognition, and development: Interactional analyses* (pp. 203–230). Hillsdale, NJ: Lawrence Erlbaum Associates.

Murphy, G. L., & Ross, B. H. (2005). The two faces of typicality in category-based induction. *Cognition*, *95*(2), 175–200. doi:10.1016/j.cognition.2004.01.009

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology*, *7*(4), 573–605. doi:10.1016/0010-0285(75)90024-9

Wisniewski, E. J. (1995). Prior knowledge and functionally relevant features in concept learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *21*(2), 449–468. doi:10.1037/0278-7393.21.2.449