Journal of Memory and Language 133 (2023) 104459

Contents lists available at ScienceDirect

Journal of Memory and Language

journal homepage: www.elsevier.com/locate/jml

What's in a name? A large-scale computational study on how competition between names affects naming variation

Eleonora Gualdoni [a,*], Thomas Brochhagen [a], Andreas Mädebach [a], Gemma Boleda [a,b]

[a] Universitat Pompeu Fabra, Roc Boronat 138, Barcelona, 08018, Spain
[b] Catalan Institution for Research and Advanced Studies (ICREA), Passeig Lluis Companys 23, Barcelona, 08010, Spain

ARTICLE INFO

Dataset link: https://github.com/amore-upf/manynames, https://osf.io/s7h9f/, https://colab.research.google.com/drive/1o63vmYlVNTcp7RIvzP4cpijKwLkhJdZs?usp=sharing, https://colab.research.google.com/drive/18r7UuVTGMZJ1ay4bmM0HaVe3WICwctuY?usp=share_link

Keywords:
Object naming
Naming variation
Visual typicality
Object typicality
Context typicality
Computational method

ABSTRACT

Different speakers often use different names to refer to the same entity (e.g., "woman" vs. "tennis player" for a given woman playing tennis). We study how visual typicality affects variation in naming behavior. We use a novel computational approach to estimate visual typicality from images, and analyze a large dataset containing naming data for realistic images. In contrast to previous work, we take into account the visual properties of both the object and the scene in which it appears; and factor in multiple candidate names. We show that visual typicality mediates competition between candidate names: high competition, induced by the relationship between the visual properties of the object and the visual representations associated to names, predicts higher naming variation. On a methodological level, we demonstrate the potential of using large-scale datasets with realistic images in conjunction with computational methods to shed light on how people name objects.

Introduction

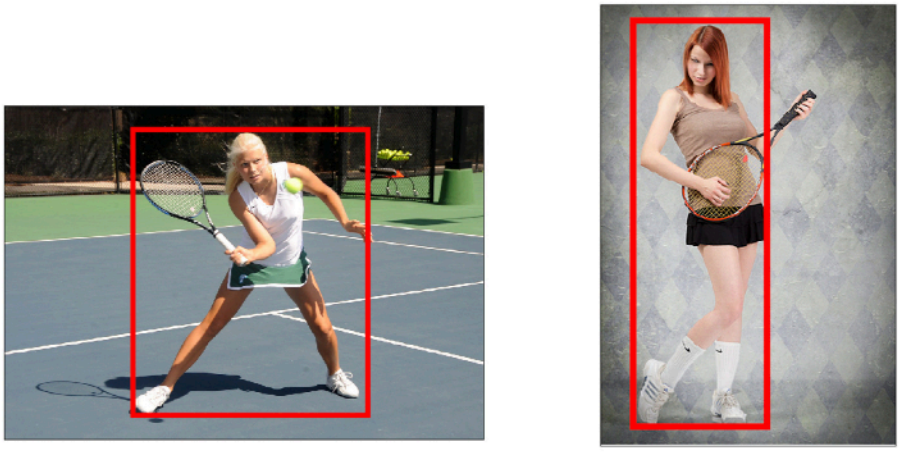
We refer to objects in most interactions. In doing so, we usually choose a word in our lexicon to name them, such as "woman" or "tennis player" for the persons in Fig. 1. This involves cognitive processes that link the properties of the object with the lexicon. The mapping of an object's properties to the lexicon is, however, not one-to-one: different names can be used for the same object. In this article, we examine how the visual properties of objects and the contexts they appear in influence how varied speakers' choices are when naming them. In particular, we focus on the role of **visual typicality**, and on how different name alternatives **compete** as a function of typicality. In contrast to most previous studies, we analyze data from realistic images (i.e., real-world objects seen in meaningful contexts like those of Fig. 1) and use computational methods adapted from the field of Computer Vision to estimate visual typicality. Our work is thus part of a very recent line of research that proposes using state-of-the-art Computer Vision representations to address questions about human language (Ahn et al., 2021; Battleday et al., 2020; Günther et al., 2022).

Naming variation has so far received relatively little attention in the literature. Naming norms, encompassing hundreds of objects, are available for a number of languages (e.g., Alario & Ferrand, 1999; Brodeur et al., 2010; Duñabeitia et al., 2022, 2018; Krautz & Keuleers, 2021; Snodgrass & Vanderwart, 1980; Tsaparina-Guillemard et al., 2011). These norms were collected by asking subjects to freely produce a name for visually presented single objects in standardized image sets –i.e., in descriptive settings. In naming norms, the image sets are usually preselected with the goal to minimize naming variation by choosing easily identifiable and stylized depictions of a given object category (see Figs. 2(a), 2(b), 2(c) and 2(d) for examples. Of note, the THINGS dataset (Hebart et al., 2019) – Fig. 2(e) – constitutes a recent exception to this trend, collecting realistic images aiming for more ecological validity, but still without a rich visual context). Indeed, naming variation is often regarded as a nuisance variable in need of control for a given experimental task, not as a variable of interest (Alario & Ferrand, 1999; Brodeur et al., 2010, 2014). However, even in this scenario of prototypical objects presented in isolation, pervasive variation is still attested in subject responses. In our study, we look at naming variation as the variable of interest.

There is also a sizable literature focused on discriminative tasks, with the standard paradigm consisting of an artificial scene constituted by different objects (Graf et al., 2016; Jescheniak et al., 2005, see Fig. 2(f) for an example). The task of human participants is to produce

* Corresponding author.
E-mail address: eleonora.gualdoni@upf.edu (E. Gualdoni).

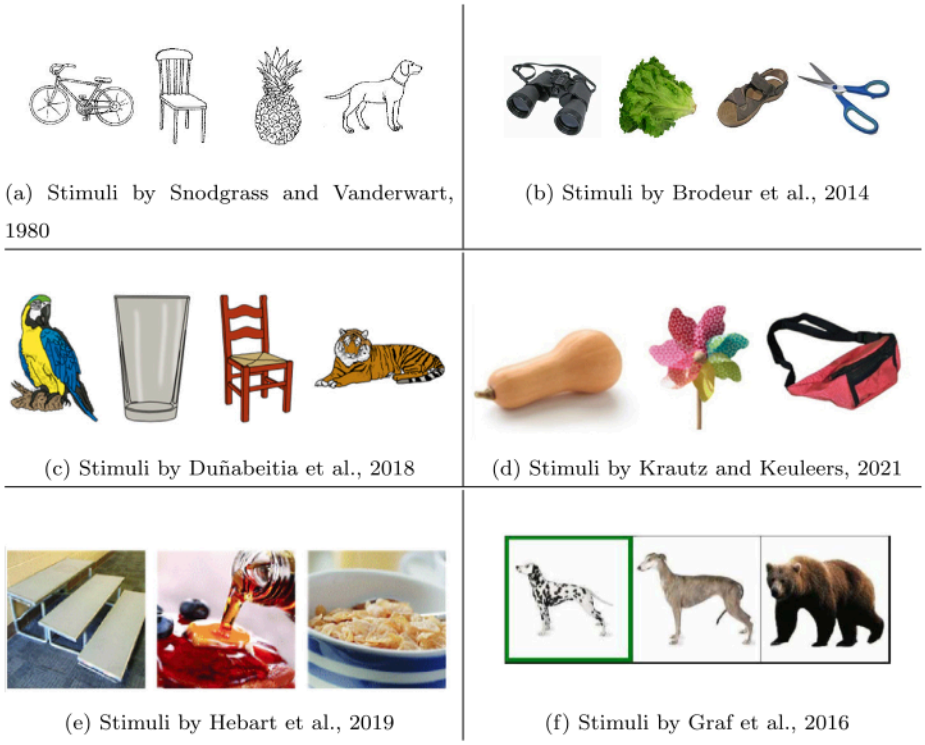
https://doi.org/10.1016/j.jml.2023.104459
Received 14 October 2022; Received in revised form 12 July 2023; Accepted 14 August 2023
Available online 31 August 2023



(a)
NAMES: **woman (17)**, tennis player (8), player (4), athlete (2).
VARIATION (H): 1.62

(b)
NAMES: **woman (30)**, tennis player (3), girl (2).
VARIATION (H): 0.73

Fig. 1. Examples of images with top name "woman" and alternative name "tennis player" in ManyNames (Silberer, Zarrieß, & Boleda, 2020) (in parentheses, response counts; in bold face, the most frequent name, or *top name*). Image 1(a) exhibits more naming variation, expressed by the information statistic H (see Section b).



(a) Stimuli by Snodgrass and Vanderwart, 1980

(b) Stimuli by Brodeur et al., 2014

(c) Stimuli by Duñabeitia et al., 2018

(d) Stimuli by Krautz and Keuleers, 2021

(e) Stimuli by Hebart et al., 2019

(f) Stimuli by Graf et al., 2016

Fig. 2. Examples of stimuli employed in naming studies. In panel (a), the stylized black-and-white stimuli used by Snodgrass and Vanderwart (1980). In panels (b), (c) and (d), the colored images used by Brodeur et al. (2014), Duñabeitia et al. (2018), and Krautz and Keuleers (2021): Objects are more realistic but without any context. In panel (e) the more realistic images used in Hebart et al. (2019): Images are realistic pictures, with an object clearly salient but without a rich visual context. In panel (f), the stimuli used in the study by Graf et al. (2016): Here simple colored stimuli are arranged in grids to artificially generate a context for the object to name, highlighted in green. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a linguistic expression that uniquely identifies a target object. The focus of this line of research has been on how expressions for the same object vary as a function of which other objects are present in the scene (Graf et al., 2016; Jescheniak et al., 2005); or across interactions between interlocutors (Brennan & Clark, 1996; Haber et al., 2019). We instead analyze inter-speaker variation for the same object; and we do so in a descriptive setting akin to that of naming norms.

Lexical choices in object naming are tightly linked to the way humans categorize and conceptualize objects. Different speakers may arrive at different conceptualizations, resulting in naming variation. Early seminal studies on object categorization and naming (e.g., Jolicoeur et al., 1984; Rosch & Mervis, 1975; Rosch et al., 1976) concentrate on the level of specificity chosen in a taxonomy of categories; for instance, the choice between "animal", "dog", and "Dalmatian" for a given dog. This early work has been enormously influential, and

subsequent research in Cognitive Science, both on categorization and on naming, has overwhelmingly focused on taxonomic aspects (Graf et al., 2016; Jescheniak et al., 2005). However, the names that speakers give to objects reflect not only their preferred taxonomic level, but also how they conceptualize them more broadly. This includes different conceptualizations of the same object (e.g. "woman" vs. "tennis player" in Fig. 1; Ross & Murphy, 1999) and even disagreements as to which category an object belongs to in the first place (e.g. "woman" vs. "man" for the same person seen from afar; Silberer, Zarrieß, & Boleda, 2020). Our use of a large-scale dataset of realistic images enables us to encompass different sources of naming variation.

The body of research discussed above highlighted the role of typicality in categorization and naming. The term "typicality" in this case is usually applied to concepts (or categories). For example, ducks, in general, are atypical birds. However, typicality has also been shown to be relevant for instances (e.g., different images of ducks). Recall from above that naming norms are based on visually depicted objects –that is, specific graphical instantiations of a given concept, even if they are designed to be prototypical. Snodgrass and Vanderwart (1980) reported a significant correlation between naming variation and subjective ratings of image agreement, with the latter being defined as the resemblance between an experimental item and the mental image for this type of object. Thus, image agreement is arguably typicality applied to instances. In this paper, we use "visual typicality" instead of the more obscure "image agreement", to highlight the connection to typicality more generally.

In Snodgrass and Vanderwart's work, image agreement correlated negatively with naming variation: the less typical an object was for the target category, the higher the observed variation in subject responses. This result has been replicated in several subsequent studies (Alario et al., 2004; Brodeur et al., 2010; Liu et al., 2011; Shao & Stiegert, 2016; Tsaparina et al., 2011).[1] However, there are two important limitations when relating these findings to human naming variation in realistic scenarios, besides the aforementioned fact that they consist of highly idealized stimuli. The first is the fact that naming norms typically include only one instance for each category, which does not allow for an analysis of intra-category variation. The second is that typicality ratings have so far been collected only for the top name – the name most frequently produced by subjects –, and thus most analyses ignored other produced names.[2] An important reason for excluding less frequent names is that gathering subjective ratings for multiple object names per image is costly. Another – and related – reason is that norming data were usually collected and analyzed with the final goal of modeling latencies of *names* in object naming, e.g. "chair" or "apple" (e.g., Alario et al., 2004; Barry et al., 1997; Shao & Stiegert, 2016). Ratings for objects' candidate names beyond the top name were only of limited relevance for this goal. However, this exclusion is not conducive to explaining naming variation.

Finally, while previous work has focused only on the typicality of the object, we also analyze the typicality of the context in which the object appears. We define *context* as the scene the object is in (e.g., the tennis court in Fig. 1(a)), which requires working with objects in realistic images.

To sum up, the present study investigates naming variation as a phenomenon in its own right. We aim at better characterizing variation in object naming by analyzing multiple, varied, and realistic images for a given object category (as opposed to a single, stylized depiction), as well as multiple candidate names competing for lexical choice. Large part of the variation in our data results from inter-individual differences in object identification and conceptualization (e.g., deciding whether to highlight gender or action-related information when naming people, or which taxonomic level to use; Silberer, Zarrieß, & Boleda, 2020). We hypothesize that visual typicality impacts the degree of competition between candidate names, which is reflected in the amount of variation in speakers' naming choices. For instance, being fairly typical for the names "woman", "tennis player", and "athlete", like the person in Fig. 1(a), can trigger competition between candidate names, resulting in higher naming variation than in the case where the person is less typical for "tennis player" and "athlete" (Fig. 1(b)). We expect similar effects for object and context typicality, although they may be less pronounced for the latter because contexts are likely less informative for a given name than the object itself.

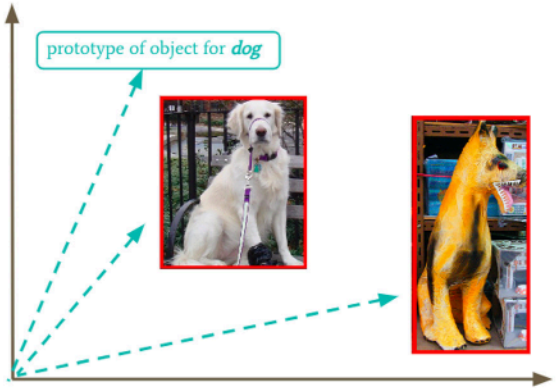


Fig. 3. Computational method to estimate the typicality of a given image for a given name. High-dimensional vector representations of objects (in the figure, 2-D, for illustration) are averaged to obtain a visual prototype for a name. Typicality for a given image is the cosine similarity between the representation of the image and the name prototype. In this case, the golden retriever is closer to the prototype, so it is deemed more typical for the name "dog" than the toy dog on the right. The procedure to obtain typicality estimates for contexts is similar — see text.

Typicality estimation

As mentioned in the introduction, subjective ratings of visual typicality in naming norms are based on the similarity of the mental image evoked by a name and the image being evaluated. We use a computational equivalent of this procedure, also independently proposed by Günther et al. (2022). The procedure is summarized in Fig. 3 and detailed next.

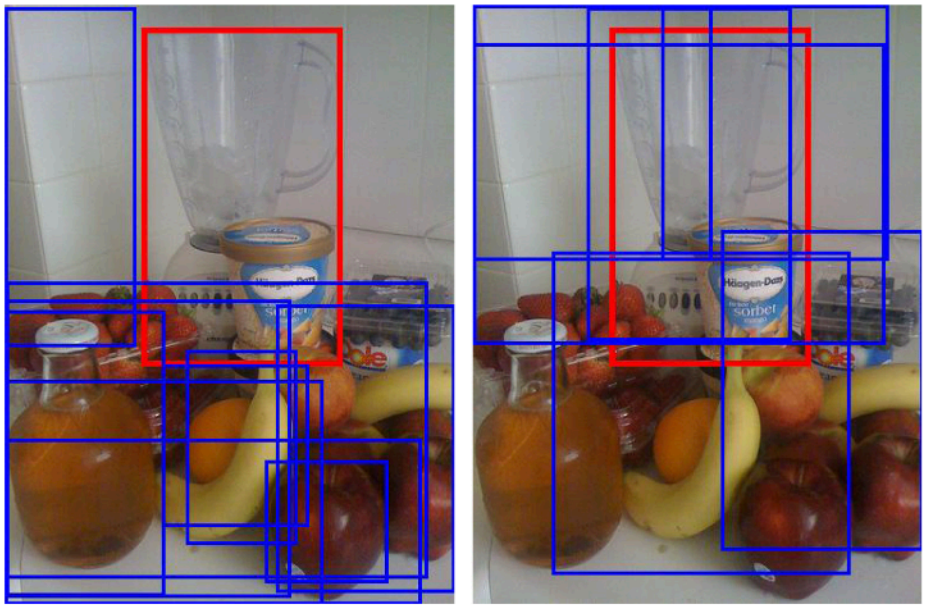
Data: ManyNames

We use the ManyNames dataset (Silberer, Zarrieß, & Boleda, 2020), a large-scale resource containing up to 36 naming annotations for 25K objects in real-world images. We distinguish between the top name (the name most frequently used by the subjects) and the remaining, alternative names. The images in ManyNames were selected from VisualGenome (Krishna et al., 2017), a collection of 100K images often used for Computer Vision tasks. Naming annotations in ManyNames were collected by asking human participants to freely produce a name to describe the object outlined by the red frame in each image (one object per image), as illustrated in Fig. 1.[3] To avoid sparsity in our computational representations, we only considered objects for which at least 20 naming annotations are available, resulting in 24.5 K images.

[1] Of note, other variables have also been repeatedly shown to correlate with naming variation in at least some studies, most notably familiarity and age-of-acquisition (Alario et al., 2004; Liu et al., 2011; Moreno-Martínez & Montoro, 2012; Tsaparina et al., 2011).

[2] Koranda et al. (2018) and Vitkovitch and Tyrrell (1995) do analyze multiple alternative names, although not for typicality, but to assess how lexical choice and naming latencies, respectively, are affected by the availability of multiple candidate object names.

[3] Note that names that were used only once are not included in the dataset, due to constraints in the validation phase of the dataset (see Silberer, Zarrieß, Westera, and Boleda 2020 for details), except for those that are synonyms or hypernyms of the top name.



(a) (b)

Fig. 4. In blue bounding boxes, objects as detected by Anderson et al. (2018) in an image from ManyNames. The red bounding box outlines the target object, which received the following naming annotations: "blender" (32), "mixer" (1). In panel (a), the context objects we use to compute the blender's context representation. That is, this blender's visual context is computed as the average of the blue detections in panel (a); In panel (b), the detections discarded due to high overlap with the target area. To obtain the context prototype for "blender" we average the context representation of multiple blender instances. The resulting context prototype will represent the typical scene an object named "blender" appears in. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

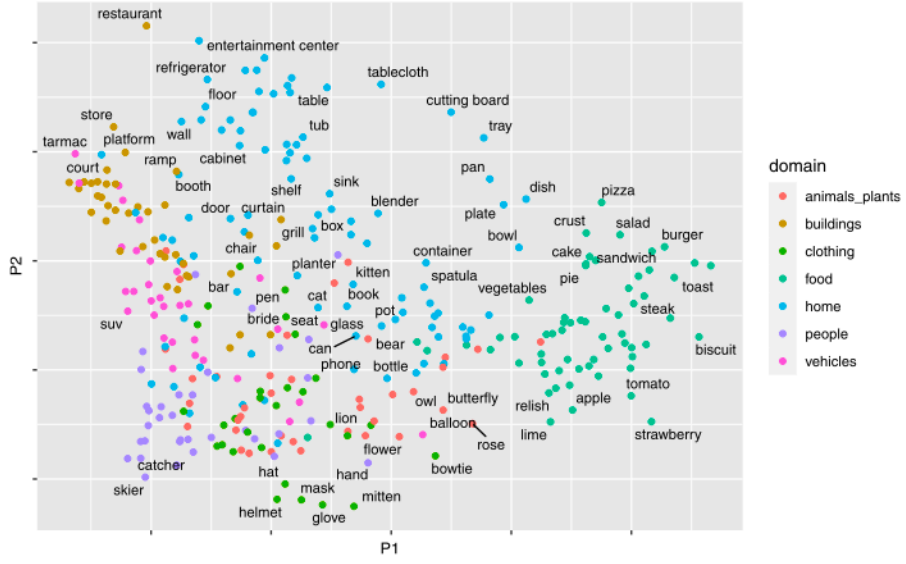


Fig. 5. 2-D reduction of our space of object visual prototypes. For ease of visualization, only prototypes of top names are shown. Colors correspond to ManyNames domains. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Visual features

To obtain visual representations of the objects in our dataset and of the contexts they appear in, we use a deep learning model from the field of Computer Vision (Anderson et al., 2018). Computer Vision models are trained to perform a task given an image, such as object classification or image captioning; as they learn to perform the task, they also learn to recognize progressively more complex visual features of the image, from edges of some orientation to for instance faces, such that they produce synthetic high-level representations of the input that go beyond the information encoded in raw pixels. These are high-dimensional vectors that can be seen as distributed representations, similar in nature to those for words in models such as Latent Semantic Analysis (Landauer et al., 1998) and distributional models more generally. Recent work (Günther et al., 2022; Jozwik et al., 2017; Peterson et al., 2018; Roads & Love, 2020; Zhang et al., 2018) has shown that representations learnt by this kind of deep learning models correlate positively with human perceptual similarity judgments, such that similar objects obtain similar representations.

Analyses of the representations encoded by the layers of deep neural networks have shown that the first layers encode low-level perceptual information, such as line orientations or color blobs. Then, gradually going towards the final layers, more complex representation are formed that will be used by the model as basis to accomplish its task (LeCun

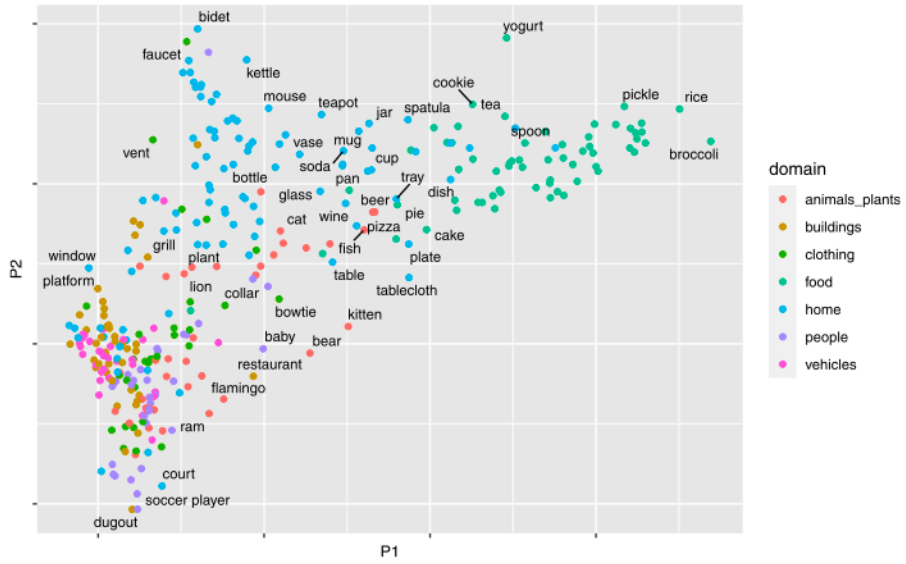


Fig. 6. 2-D reduction of our space of context visual prototypes. For ease of visualization, only prototypes of top names are shown. Colors correspond to ManyNames domains. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

et al., 2015; Mahendran & Vedaldi, 2014; Zeiler & Fergus, 2013). Indeed, Günther et al. (2022) carry out an extensive evaluation of the information encoded by various layers of deep learning models, by comparing them against human behavioral data, and conclude that deeper layers, capturing high-level information, are the best choice when trying to model general-purpose mental representations. We use the visual features output of the Region Of Interest Pooler of the Computer Vision model by Anderson et al. (2018). The Region of Interest Pooler is a very deep layer, and the model by Anderson et al. (2018) has been trained on VisualGenome, which is the dataset from which ManyNames images were sampled.

Anderson et al. (2018)'s model is trained to perform object detection and recognition, among other tasks, that is, the localization and classification of objects within an image. As part of carrying out this task, it learns to encode robust object representations that can support the learning of multiple additional tasks (Ackermann et al., 2022; Anderson et al., 2018). For instance, Anderson et al. (2018) successfully train an image captioning model (i.e., a model that outputs a textual description of an image), on top of their object detector by feeding it the high-level visual features of multiple objects present in the scene. More details about (Anderson et al., 2018)'s architecture can be found in Appendix B.

Object typicality

Our computational estimate of the typicality of a given object for a given name is based on the distance between a visual representation of the object and a visual prototype for the name. We define the visual prototype of a name as the average of the visual representations of objects with that name. This operationalization follows the assumption that the prototypical exemplar of a category is the mental image of an average member of all the class exemplars (Gärdenfors & Williams, 2001; Rosch et al., 1976). It is consistent with image agreement as defined in naming norms, and in line with what has been done in recent computational studies on related phenomena (Ahn et al., 2021; Battleday et al., 2020; Günther et al., 2022; Westera et al., 2021; Xu et al., 2021).

We obtained the visual features of the objects with the Computer Vision model described in the previous section, and used VisualGenome as the source of objects for our prototypes. We excluded objects that also appear in ManyNames in the computation of prototypes, to avoid circularity; this way, the visual space is fully independent from the data that we analyze with it. Of the 1618 distinct object names in ManyNames, we built prototypes for the 874 that have at least 30 instances in VisualGenome after excluding instances that also appear in ManyNames.[4] We then define the visual typicality of a ManyNames object for a name as the cosine similarity between the visual features of the object and the prototype for this name.

Exemplifying the whole pipeline: To obtain the object prototype for "tennis player", we (1) extracted all VisualGenome objects labeled "tennis player" (excluding images that are in ManyNames), where each object corresponds to a region in the image, such as the region marked in red in Fig. 1(a); (2) processed the objects – that is, the image region corresponding to the object as outlined by the bounding box – with the Computer Vision model to obtain their feature representations; (3) computed the prototype of "tennis player" by averaging all these feature representations. Then we (4) obtained estimates of typicality for individual instances by computing the cosine similarity between their feature representation[5] and the visual prototype. For example, the object typicality scores obtained for Figs. 1(a) and 1(b) for the name "tennis player" are, respectively, 0.77 and 0.67 (the maximum cosine similarity is 1).[6]

Context typicality

We obtained context typicality scores in an analogous fashion to the object typicality scores. The only difference is how we obtained the representation of object contexts. We aimed at a notion of context that synthesizes the global scene an object appears in – that is, for instance a representation of the scene a given "tennis player" object appears in – and adapted the procedure used by Anderson et al. (2018) for that purpose (see also Takmaz et al., 2022, for a similar approach).

[4] Note, that, due to Zipf's law, the majority of excluded names are very rare (see Appendix A for their frequency distribution).

[5] Feature representations for the objects in ManyNames are obtained by cropping the images at the object bounding box and by processing only this region with the Computer Vision model.

[6] Günther et al. (2022) independently proposed this measure of typicality and successfully evaluated model-derived typicality scores against human typicality judgments for a different set of images than ours. While the analysis reported in that article is not directly comparable, Günther (p.c.) reports that the Spearman correlation between their model scores (best layer, n. 7) and human ratings is r = .37.

(Anderson et al., 2018) use their object detection module to detect 36 regions in an image, and average their visual features to obtain a representation of the whole scene to feed an image captioning model to. These regions include what one would commonly call an object (like a cat or a table), and also background elements like patches of grass, sky, or walls; see Fig. 4 for example regions localized by the object detection model. We followed the same procedure as Anderson et al., except that we excluded regions corresponding to the target object, since we wanted a representation of the context only (compare panels (a) and (b) of Fig. 4 for example regions that were included and excluded, respectively).

To exclude regions corresponding to the target object, we computed the intersection over union between the target and each of the 36 regions detected by the model. Intersection over union is the ratio between the overlapping area of two objects and their joint total area. This metric is commonly used in Computer Vision to evaluate object detection algorithms (Rezatofighi et al., 2019). We kept only regions with an intersection over union smaller than 0.1. We used the same metric to identify objects *without* context as well, i.e. objects that are almost as big as the entire image and for which a context typicality score would not be meaningful. We labeled all the objects whose bounding box had an intersection over union with the entire image higher than 0.77 as "objects without context". This threshold was chosen through visual inspection: a value between 0.75 and 0.80 captures the majority of these cases.

Then, except for the differences relating to the definition of a context representation vs. an object representation, the pipeline for calculating context typicality is the same as that for object typicality. This implies decoupling step (2) above into two steps. For instance, to obtain the context prototype for "tennis player", we first detected the objects present in each "tennis player" image and extracted their corresponding visual features as explained above; and then averaged the visual features of the detected objects to obtain the representation of the global scene each "tennis player" instance appears in. This gives us one context representation per image. To obtain the context prototype, we average the context representations of all the "tennis player" images, analogously to step (3) for object representations. The context prototype obtained with this procedure represents the prototypical scene that objects called "tennis player" appear in. The computation of context typicality for an image and a name is also analogous to the one for objects: it is the cosine similarity between the context representation of the image and the context prototype of the name. For example, context typicality scores for Figs. 1a and 1b for the name "tennis player" are, respectively, 0.82 and 0.43, aligning with our intuition about the typicality of the respective contexts. for the name "tennis player" are, respectively, 0.82 and 0.43, aligning with our intuition about the typicality of the respective contexts.

Properties of the visual space

Figs. 5 and 6 illustrate the relative positions of the object and the context name prototypes in a space defined by their visual features (reduced to 2D via Principal Component Analysis for plotting). The figures illustrate that the prototypes cluster meaningfully: Visual prototypes of semantically similar objects – and of contexts of semantically similar objects – tend to be similar to each other. Indeed, Günther et al. (2022) find a high correlation (ρ = .79) between the similarities of visual prototypes for objects (computed as in the present article, on different data) and human judgments on the semantic relatedness of their associated names. Also note that, according to the context space, vehicles and buildings appear in the same contexts. This agrees with our intuitions.

Moreover, our computational estimates of object typicality seem to incorporate the typicality of the viewpoint, as the visual representations of objects with atypical viewpoint tend to be further from the prototype than the ones of objects with typical viewpoint — see Appendix C for example images. Some previous studies have teased apart the specific contribution of object viewpoint typicality from the role of object typicality in naming tasks (Brodeur et al., 2014; Johnson et al., 1996); future work should check how the two aspects can be differentiated computationally.

An exploration of typicality scores for the ManyNames objects additionally revealed systematic differences between object names from different levels of specificity, as could be expected from classic work on categorization (Rosch & Mervis, 1975; Rosch et al., 1976). This relation is illustrated in Fig. 7. For this illustration, we focus on the domain *people*, for which ManyNames contains many data points at different levels of specificity. The figure shows the cluster spread in both the object and the context visual spaces for the names in this domain. Cluster spread was defined as the average pairwise cosine distance between visual features of objects with the same top name — respectively, between visual features of contexts of objects with the same top name. We manually annotated the level of specificity of the names, ranging from the very general "person" (level 1) to more specific names, such as "umpire" or "catcher" (level 5). As shown in Fig. 7, higher levels of specificity correspond to lower cluster spread — that is, objects with a specific name, like "skateboarder" or "catcher", are visually more similar to each other than objects with a less specific name like "woman" or "person". This mirrors the fact that more general names can be used for a more diverse set of objects than more specific names. Similarly, contexts for objects named "woman" or "person" are likely to be more diverse than the contexts in which skateboarders and catchers appear. These findings suggest that visual spaces embed interesting semantic properties whose exploration is a promising direction for future research aimed at studying the structure of categories and the relationship between names at different level of specificity. For instance, along these lines, De Deyne et al. (2021) analyzed the extent to which linguistic, visual, and multimodal representations capture the meaning of abstract and concrete words at different levels of specificity, while Gualdoni et al. (2023) studied the relationship between name informativeness, name specificity, category homogeneity, and category contrast by leveraging the information encoded in the visual space of a deep-learning model.

Taking stock, the exploration of the prototype space suggests that its geometry relates to properties of object names represented in it, and that it could be taken as a surrogate for the human visual space of categories denoted by names. This suggests that the typicality scores and the relative position of prototypes may relate to the mapping between the visual features of an object and potential names for this object. This is further supported by the fact that, in 61% of the cases, at least one of the names produced by the subjects is among the 3 closest prototypes. See Appendix D for further data on the relationship between the space and lexical choice.

Analysis I: Naming variation and typicality

In this first analysis, we investigate how naming variation relates to the visual typicality of objects and their contexts. We restrict this analysis to the top name and the most frequent alternative name, e.g. "woman" and "tennis player" for the images in Fig. 1. Analysis I seeks to test the computationally derived typicality scores by checking whether they replicate the result obtained in prior work (Alario et al., 2004; Brodeur et al., 2010; Liu et al., 2011; Shao & Stiegert, 2016; Snodgrass & Vanderwart, 1980; Tsaparina et al., 2011) that lower variation is found for objects that are more typical of their top name. It also served as a first exploration of the role of alternative names and context typicality.

Our hypothesis was that the typicality of the alternative name would have an effect opposite to that of the top name. That is, we expected higher naming variation for objects that are more typical of their alternative name. This is because, assuming the same typicality for the most frequent name, relatively higher typicality for an alternative name

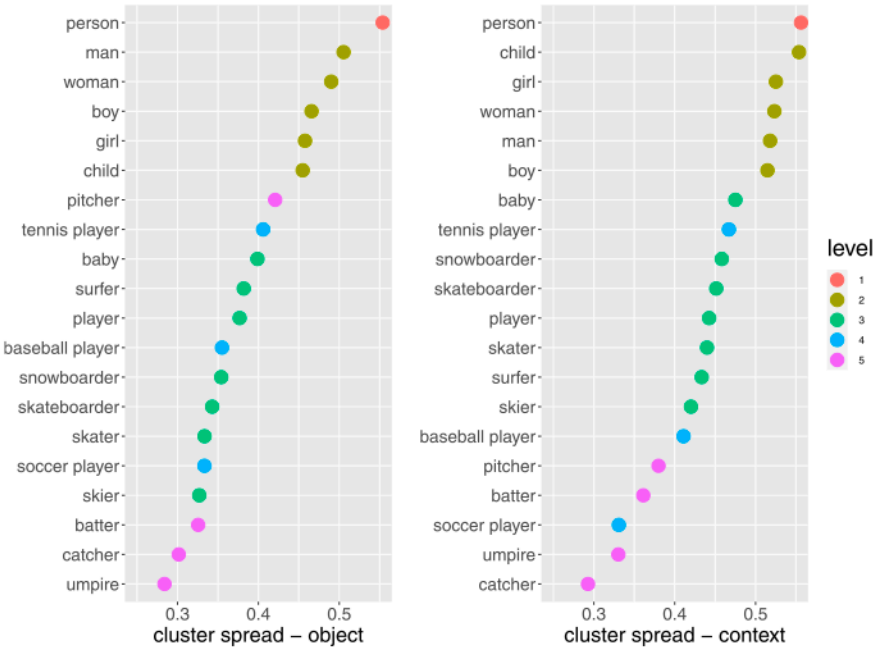


Fig. 7. Cluster spread for names belonging to the domain *people*, computed as average pairwise distance between visual features of objects with that name as top name. Left: objects, right: contexts. Colors correspond to different levels of name specificity, from low ("person") to high ("umpire" / "catcher"). Note that "pitcher" is a polysemic word, which explains a higher cluster spread compared to words from the save level of specificity.

should broaden the lexical options available for speakers, resulting in more inter-speaker variation. To illustrate, person (a) in Fig. 1 is a more typical tennis player than person (b). Accordingly, more subjects use "tennis player" when naming her.[7]

With regard to context typicality, we expected to find the same pattern: A higher context typicality of the top name would have a negative effect on naming variation, and conversely for the alternative name. For instance, in Fig. 1, the context of person (a) (a tennis court) is more typical for the alternative name "tennis player" than the context of person (b). This may contribute to the higher naming variation observed for person (a) compared to person (b).

Data and measures. We worked on the subset of ManyNames objects for which at least two different names were provided (17K out of 25K). Typicality estimates were derived as described above in Section "Typicality estimation" . Naming variation was estimated in terms of entropy (Shannon, 1948), as expressed by the information statistic H (Snodgrass & Vanderwart, 1980), defined as:

$$H = \sum_{i=1}^{k} p_i \ log_2(1/p_i), \tag{1}$$

where k refers to the number of different names given to each object and p_i is the proportion of annotators giving each name. This measure captures information about the distribution of names across annotators. As exemplified in Fig. 1, the person in panel (a) has a higher H score than that in panel (b) because she elicits more naming variation; both in terms of evoking more names and of having a more even spread of counts.

Regression model. We fitted a linear mixed-effects model with naming variation as the outcome variable and fixed effects for standardized object typicality and context typicality, each for both the top name and the alternative name. This made for four main effects in total. In the case of objects without context (see Section "Typicality estimation"; 684 images in this analysis), we imputed context typicality with the average value in the data.[8] Top names and alternative names were treated as random effects. By-topname and by-alternative name random slopes were included for object typicality and context typicality. Models were fit in R using *brms* (Bürkner, 2017; R. Core Team, 2022), and diagnosed to rule out issues with our estimates. All diagnostics suggest a reliable model fit. Among others, all parameters have an $\hat{R} < 1.1$ (Gelman & Rubin, 1992); no saturated trajectories; and a large enough effective sample size (> 0.001 effective samples per transition).

Results

Fixed effect estimates are shown in Fig. 8; numerical results are reported in Appendix F. In what follows, we discuss results of the model fitted with the first imputation method (imputing context typicality with the average value). Naming variation is higher the less typical an object is for its top name. For what concerns the alternative name, the model reports no significant effect. Similarly, when it comes to context typicality, counter to our expectations, we find no effect. This is true of both top and alternative names.[9]

Discussion

Analysis I replicates previous findings in showing a negative relationship between naming variation and object typicality (Brodeur et al., 2010, 2014; Liu et al., 2011; Moreno-Martínez & Montoro, 2012;

[7] Notably, the top name for Fig. 1(a) is still "woman". An effect of lexical frequency, as a proxy of lexical accessibility, may be at play in this case, as shown by Gualdoni et al. (2022). Moreover, Harrison (2022) reported a gender bias in ManyNames: annotators used sports-related names like "tennis player" much less for women than for men.

[8] An alternative imputation method, namely discarding the 684 objects without context, did not alter results.

[9] See Appendix G for the results of a model fitted on the same data with the additional information of name frequency, as a proxy of ease of lexical access, a factor that is likely to affect lexical choice (Alario & Ferrand, 1999; Gualdoni et al., 2022; Koranda et al., 2018). Interestingly, this model reports a significant negative effect of the typicality of the alternative name on naming variation, as well as a positive effect of the top name frequency, showing a more complex picture of the phenomenon, where multiple factors interact.

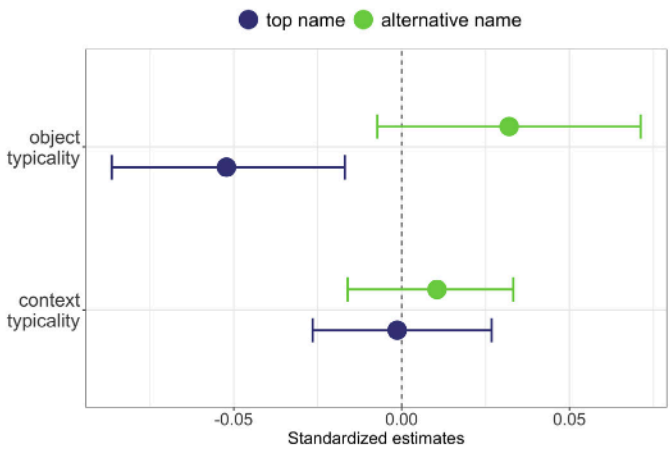


Fig. 8. Fixed effect estimates. Bars correspond to 95% CIs. Positive vs. negative estimates show, respectively, the increase and decrease in naming variation for a one point difference in standard deviation of the predictor variable. The regression's R^2 is 0.59.

Snodgrass & Vanderwart, 1980; Tsaparina-Guillemard et al., 2011). That is, people tend to choose the same name for an object when the object is very typical for that name. Importantly, we show this using a computational approach to estimate typicality. This suggests that our method offers a sensible and scalable way to address questions that, so far, had been approached with smaller data sets and more costly methodologies (i.e., human ratings).

One of the benefits of our computational approach is that it enabled us to investigate the way in which multiple candidate names jointly affect naming variation. Recall from the introduction that this aspect was neglected by previous studies that took into account the properties of only one name per object (Alario & Ferrand, 1999; Brodeur et al., 2010, 2014; Liu et al., 2011; Moreno-Martínez & Montoro, 2012; Snodgrass & Vanderwart, 1980; Tsaparina-Guillemard et al., 2011). Our hypothesis was that the object typicality for an alternative name has the opposite effect than for the top name: The more typical an image is for an alternative name, the more likely it is that this name gets chosen over the top name. This would be in line with the idea that names compete for lexical selection. However, our Analysis I does not find such an effect. In Analysis I, we restricted ourselves to considering only the most frequent alternative name. Since, in most cases, more than one name competes for lexical selection, considering the full range of competing names may yield a clearer picture. We address this issue in Analysis II.

Contrary to our expectations, Analysis I suggests that context typicality does not have an effect on naming variation in a descriptive object naming task such as the one the from ManyNames. The nature of the task may be key, since, when asked to freely produce a name for an object, speakers may not be influenced by the visual properties of the scene like they are in discrimination tasks (e.g., Graf et al., 2016). Furthermore, prototypical contexts for different candidate names may also often be too similar as to affect name variation. For instance, the names "armchair" and "chair" are often naming alternatives for the same object, but the prototypical contexts for these two names are alike.

However, there is also the possibility that we merely fail to detect a true effect of context typicality due to how we represent contexts. The computational procedure we chose is robust in the sense that it has been shown to be a successful strategy to represent a scene for automatic image captioning and visual question answering tasks (Anderson et al., 2018). These tasks require a comprehensive representation of images. Additionally, the effectiveness of Anderson et al. (2018)'s model in extracting relevant visual features from images is supported by the fact that our results for object typicality replicate previous findings. However, due to the lack of previous research on context typicality, we cannot benchmark our computational estimates of context typicality using previous findings.

We thus turned to a comparison between subjective ratings of context typicality and our estimates. We collected human typicality judgments through crowdsourcing (see Appendix E for details) and obtained a positive correlation between computationally-derived scores and the scores of randomly sampled human annotators ($\rho = 0.32$). The average correlation between random pairs of participants is not very far (0.48).[10] These results suggest that the computational scores for context typicality are moderately close to human behavior; however, humans themselves agree only partially as to what counts as a typical context for an object. Further work is needed to experimentally elicit the same notion of visual typicality from humans, and for computational models to approximate this notion even more.

Finally, it could be that we fail to detect an effect of context typicality because of our limitation to two names per image — analogously to a potential explanation for the lack of a effect of alternative names. If the effect of context typicality is not very strong, its signal may not be picked up by this restrictive setup. We address this concern in Analysis II, where we indeed find support for this explanation.

Analysis II: Competition between names

Analysis I, while improving on previous work by including alternative names and context, is still based on a partial picture of naming behavior: on the one hand, for 39% of the objects in MN, speakers produced more than 2 different names; and, on the other, the analysis excluded the 31% of objects in ManyNames that received only one name.

In addition, Analysis I relied on knowing the names for a given image a priori. Therefore, model estimates from Analysis I cannot be used to predict naming variation without already knowing which names are used for the object. Finally, and importantly, the notions *top name* and *alternative name* are not static features of objects. They are themselves the result of competition.

In Analysis II we addressed these issues in the following way. Our general assumption is that the probability of selecting a given name for an image is a function of its visual similarity to the visual prototype of that name — that is, its typicality for the name.[11] Naming variation is then expected to vary as a function of the number of viable (i.e., sufficiently typical) name candidates, with a larger number of viable candidate names leading to more naming variation due to higher competition. Fig. 9 provides an illustration. Objects A and B are placed in different positions in the object visual space, based on their visual features. In particular, object A is much closer to the prototype "bench" than to any other candidate name. In contrast, object B is similarly close to 4 prototypes: "couch", "sofa", "chair", and "bench" (note that "couch" and "sofa" have almost overlapping prototypes, since they are synonyms). According to our model, specified below, this has consequences for the object names that speakers produce. For object A, the competition between names is dominated by "bench", as reflected in the object names showing no variation ($H = 0$). For object B, all 4 viable candidates are produced, resulting in higher naming variation ($H = 2.4$).

[10] Interestingly, for objects we find a lower correlation between random pairs of human annotators (0.26); the correlations with the computational scores are also lower ($\rho = 0.12$ when compared to random participants). See Appendix E for further discussion.

[11] Other factors have been shown to affect lexical choice, such as ease of lexical access, age of acquisition, or visual context (Alario & Ferrand, 1999; Brodeur et al., 2010; Snodgrass & Vanderwart, 1980; Tsaparina-Guillemard et al., 2011). Therefore, it cannot be expected that typicality alone determines lexical choice.

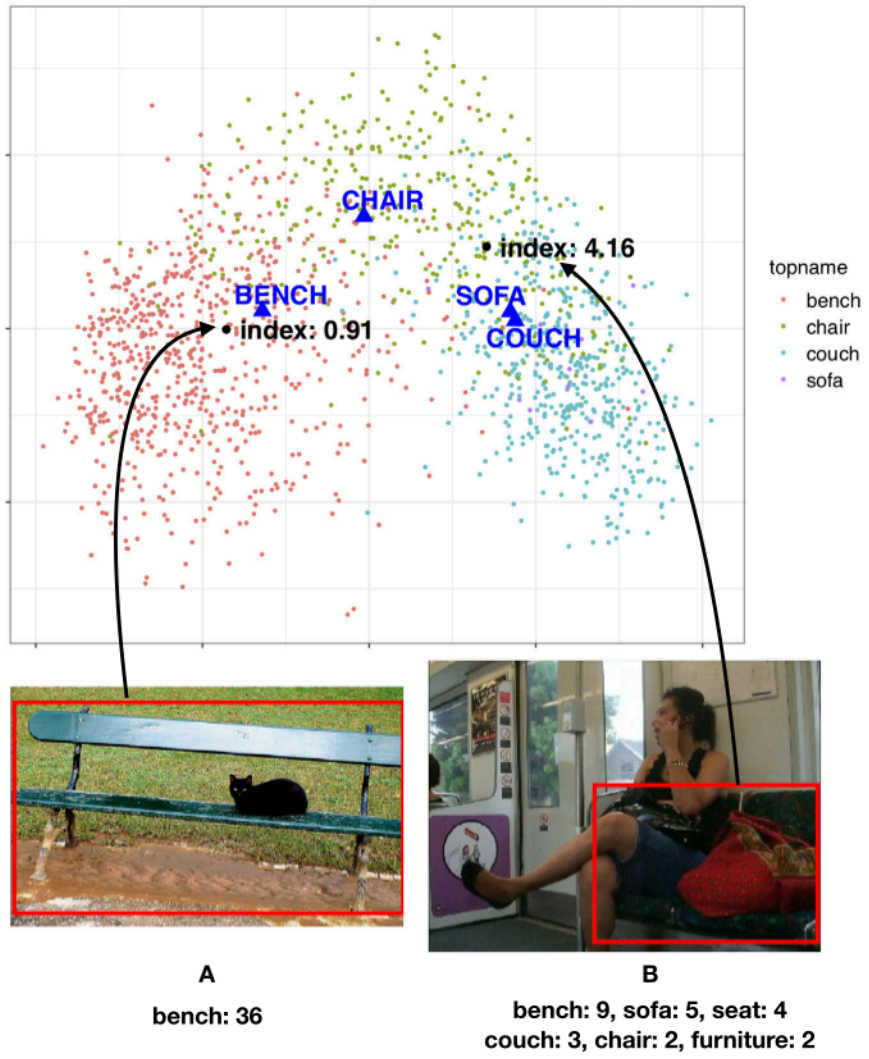


Fig. 9. Visualization of the model proposed in Analysis II, obtained via a 2-D reduction of the region of our object visual space corresponding to images named "bench", "couch", "sofa", and "chair". Prototypes are represented by blue triangles. Dots represent objects. They are colored based on their top name. Images A and B show two ManyNames objects framed in a red bounding box. They are positioned in the visual space based on their visual features. Their index of object crowdedness is written in black. The names produced for the objects are listed below the images, followed by response counts. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

We implemented this idea using the prototypes in our visual space as potential attractors when naming an object. The position of the target object relative to each of the prototypes in this visual space of attractors was then used to predict naming variation: The closer the image is to multiple visual prototypes for names, the more naming variation it is expected to evoke.

Methods

Data. We included the 24.5 K ManyNames data points with more than 20 naming annotations available, to ensure robust estimates. We used the visual space populated by 874 prototypes and all the 24.5 K individual images (see Section "Typicality estimation").

Index of crowdedness. We formalized competition via an *index of crowdedness*. This index quantifies, for each object image, the crowdedness of the area where it is located in our visual space. The crowdedness value for an image depends on how close the image is to each prototype in the visual space (see Fig. 9). Importantly, and by contrast to Analysis I, our index if crowdedness allowed us to treat all names in our visual space as possible candidates of an object. The closer more prototypes p are to a target image i, the higher the crowdedness for i. For instance, for object A in Fig. 9 crowdedness is lower (0.91) than for object B (4.16). More concretely, the index is defined as:

$$crowdedness_i = \sum_p sim(i,p)^\gamma, \tag{2}$$

where i is an object in the data set, p is a prototype in our visual space, $sim(\cdot,\cdot)$ is cosine similarity, and $\gamma \geq 1$ is a temperature parameter. If $\gamma = 1$, then all prototypes contribute the same to the index, as a function of their distance to the image. As γ increases, closer prototypes exert more influence. This follows our intuition that competition may be non-linear in visual space ($\gamma > 1$), with competition between prototypes close to the target mattering more. This intuition is in line with the seminal work by Luce (1959) and Shepard (1957, 1987) showing that human choice and generalization behaviors follow exponential laws grounded in the distances between the stimuli in a "psychological space". Tenenbaum and Griffiths (2001) added evidence for the universality of the exponential law, as governing a diverse set of cognitive and perceptual phenomena; see also Sims (2018) for an understanding of this law in terms of efficient information compression.

In analogy to Analysis I, we used both an *index of object crowdedness*, considering object visual features and object prototypes; and an *index of context crowdedness*, considering context visual features and context

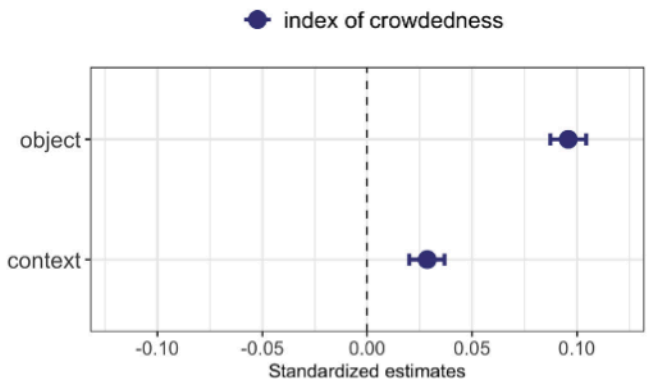


Fig. 10. Effect estimates, showing the decrease or increase in naming variation for a one point difference in standard deviation of the predictor. Bars correspond to 95% CIs. The regression's R^2 is 0.03.

prototypes. We expected the same effect for both object and context crowdedness: Objects/contexts in more crowded areas should elicit more naming variation. However, we expected a weaker effect in the case of contexts, since they may generally be more similar to each other than objects themselves, as discussed in Section "Analysis II: Competition between names".

Regression models. We identified the best γ-value for each index by fitting linear models with naming variation as outcome and the standardized index of object crowdedness as the sole predictor, for a sample of γ-values (1, 2, 5, 8, 10, 20, 30, 50). We selected the best γ-value through leave-one-out cross-validation, in terms of expected log predictive densities (Vehtari et al., 2019, 2017). Details and full model rankings for both object and context crowdedness are in Appendix H.

The best γ-value for the object index is 8, with values between 5 and 10 outperforming the rest by a large margin. This suggests a non-linear contribution of object prototypes to the competition between name, in line with Luce (1959), Shepard (1957, 1987), Tenenbaum and Griffiths (2001)'s tradition. That is, prototypes near the target indeed contribute more than prototypes that are further away, corresponding to the intuition outlined above. Instead, for contexts the contribution of prototypes seems to be linear in visual space, with the highest ranked model being the one with $\gamma = 1$. More research is needed to elucidate whether this difference between visual prototype spaces is due to our particular operationalization, as discussed further below, or whether there is a true difference between how object and context typicality interact with naming choices. In what follows, we focus on the best models for each index, and we refer to the estimate derived from the best object/context γ-value simply as "index of object/context crowdedness".

We fitted a linear model with naming variation as outcome and both the index of object crowdedness and that of context crowdedness as predictors. This model outperforms single-predictor models with only object or only context crowdedness (see Table H.5 in Appendix H). As before, the model was diagnosed to rule out issues with the estimates. All diagnostics suggest reliable results.

Results

Estimates are shown in Fig. 10; Numerical results are reported in Appendix I. Crowdedness affects variation in the way we expected: Naming variation is higher the more crowded the area is, in terms of name prototypes. Albeit to a lesser degree, the same is true of the object context: Context features that are close to many context prototypes elicit more naming variation. Taken together, this result suggests that, indeed, subjects tend to choose the same name for an object when there is less competition between naming alternatives; and that this competition is based on the visual properties of both the object and of the context in which it appears.

Discussion

Our second analysis expands the findings of the first one, considering all the candidate names in our lexicon as attraction points in a multidimensional visual space, and showing that naming variation increases with an increase in the competition of multiple candidate names. The approach in Analysis II has the additional advantage that there is no need to know the object names in advance to predict naming variation: The visual space has all the necessary information.

In contrast to Analysis I, Analysis II suggests that the visual features of the context, and specifically how typical the context is for an object with a given name, do affect naming variation after all (for a qualitative example, recall the case of the two women in Fig. 1, where the tennis court is a more typical context for a tennis player). We hypothesize that the structure of Analysis I, which considered only the properties of the first and second most frequent names, may have led to too weak of a signal to detect the effect of context on naming. Analysis II instead considers all the names. Note, however, that in Analysis II context effects are still much weaker than object effects.

The same may be at play when it comes to the effect of the object typicality of alternative names: The fact that the index of object crowdedness is a good predictor of naming variation suggests that, indeed, many naming alternatives compete for lexical selection, not just the top name and the most frequent alternative name.

In fact, an intriguing possibility is that the relative density of the different areas of the lexical space play a role in lexical choice, and consequently also in naming variation. A densely populated part of the lexicon (e.g. the *people* area) could trigger a more complex search that makes different people land on different names for the same object, resulting in higher naming variation. Future work should empirically explore this possibility.

An effect of competition between names due to the visual features of objects is indirectly reported in Battleday et al. (2020). In this study, aimed at modeling human categorization choices with a dataset of real-world images, the performances of deep-learning object classification models in predicting naming distributions for images are compared to those of cognitively inspired models, in which the information provided by deep-learning visual features is augmented with measures of reciprocal similarity in visual spaces governed by cognitive rules of exponential nature (Shepard, 1987). Results show that the cognitive models outperform their counterparts especially for images with high naming variation (performances are comparable for images with high name agreement). As our own research, this suggests that a good model for predicting naming distributions needs to factor in a measure of competition, as expressed by the reciprocal visual similarities between candidate categories.

The fact that the effect of context typicality is weaker than that of object typicality suggests that context prototypes are less informative than our object prototypes. This may be due to different reasons. First, as shown in Fig. 11, the visual space of contexts is less spread out than the visual space of objects, possibly providing less discriminating information. Second, context prototypes of alternative names for the same object tend be more similar to each other ($M = 0.94$, $SD = 0.05$) than the corresponding object prototypes ($M = 0.81$, $SD = 0.14$), again pointing to the fact that they may carry less information (see Fig. 12 for the full distributions). As discussed in Section "Analysis II: Competition between names", these properties could be an inherent property of contexts. These findings open promising avenues for future research.

Finally, recall that, with the index of object crowdedness, a non-linear version clearly characterizes the data better than a linear version. This confirms our intuition that closer prototypes should contribute more to the competition for a name than prototypes that are farther away. However, this prediction is not borne out in the case of context. At present, we have no hypothesis as to why this may be the case.

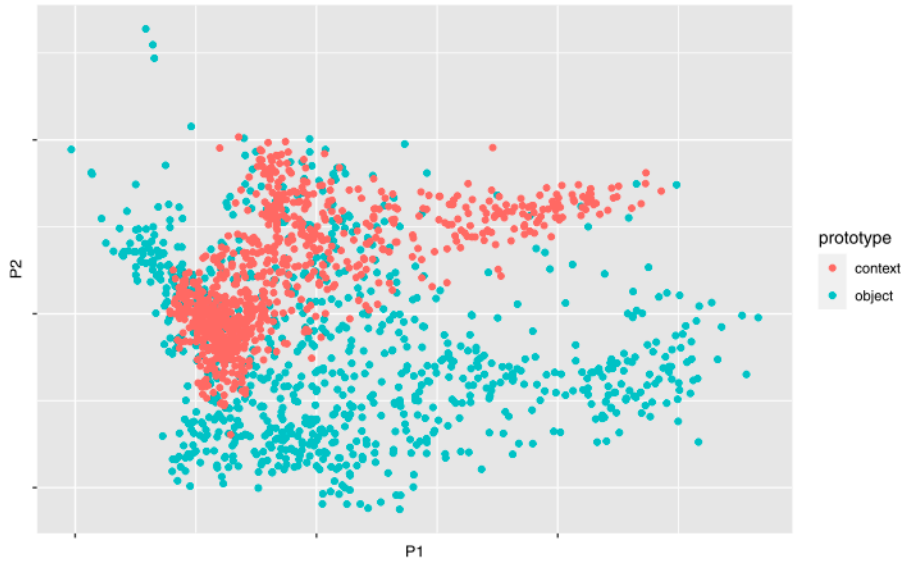


Fig. 11. Visual object and context prototype spaces, after reduction to 2 dimensions.

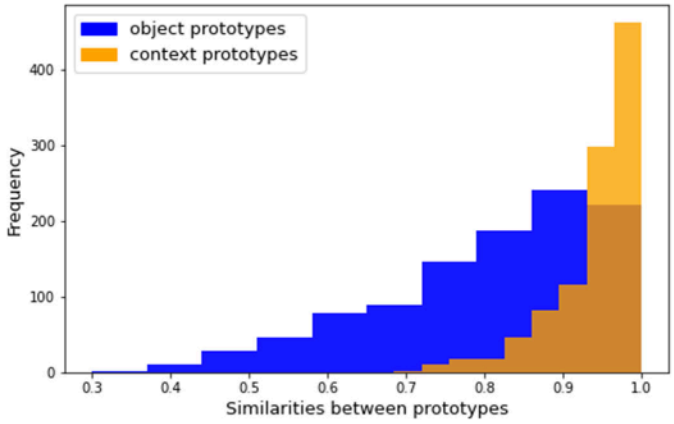


Fig. 12. Histograms of prototypes' similarity between top name — alternative name pairs.

General discussion

Objects can be called by many names. And yet, naming variation – inter-speaker variability in the names produced for a given object – has been either overlooked or considered as noise in most work in Cognitive Science (Alario & Ferrand, 1999; Brodeur et al., 2014; Tsaparina-Guillemard et al., 2011). Our work puts naming variation center stage, adding it to the repertoire of research questions in Cognitive Science. We believe that this is important because naming variation provides a window into how conceptual and linguistic knowledge interact in human behavior. Exploring naming variation thus promises to advance our knowledge of human naming behavior, and consequently also of language and cognition.

There are many different sources for naming variation. Some are conceptual, such as the different choices speakers face when categorizing an object ("woman" vs. "tennis player"), and others have more to do with the linguistic system, such as whether the lexicon offers (near-)synonyms to express a given concept ("sofa" and "couch"). We have tapped into one particularly relevant source of naming variation: How visually typical an object is for different names. Our hypothesis was that, because names compete for selection, when an object is visually typical for several names, higher variation would be observed. Conversely, lower variation would be observed when the object is typical for a single name (or simply fewer names). We tested this hypothesis using large-scale naming data for concrete objects in realistic images. The results support the hypothesis.

In particular, we replicate results from previous work about the role of typicality for a single name (Alario et al., 2004; Brodeur et al., 2010; Liu et al., 2011; Shao & Stiegert, 2016; Tsaparina et al., 2011), and add new insights on the role of typicality for multiple names, as well as on that of context typicality. We find that, in relation to the competition between names that they elicit, object and context typicality both have an effect on naming variation. The directionality of these effects is the same, with higher competition yielding higher variation, possibly for the same reasons. The effect of context, modeled as the scene in which an object appears, is however less strong, possibly because the visual context is less informative about the object than the visual features of the object itself.

We propose computational estimates of visual typicality as a less costly, time effective, and scalable alternative to the subjective ratings of visual typicality used in previous work on naming. More specifically, we have used data-driven distributed representations of images obtained through a Computer Vision model. Cognitive scientists have been successfully using data-driven distributed representations of words for decades, since the seminal work of Landauer and Dumais (1997) and Lund and Burgess (1996), among others. Classical word representations were generic lexical representations, and often used as surrogates for concepts[12] –i.e., they encode knowledge such as the fact that cats are more similar to dogs than to chairs. Computer Vision methods have developed over the last decade so as to be able to extract useful representations from images, that is, specific object *instances*: A given blond woman playing tennis in a tennis court, another one holding a racket against a gray background, etc. This affords new modeling possibilities, such as the ones explored here.

In particular, we used these representations to build both instance-like and concept-like visual representations: individual visual representations for object instances given particular names, and generic visual representations for names by averaging individual representations, creating a prototype (Gärdenfors & Williams, 2001; Rosch et al., 1976). In this way, we could explore the interplay between instance-specific and concept-general aspects of naming, yielding a rich picture about the relationship between instances and concepts. This is key when

[12] The relationship between word representations and concepts is nuanced; see Westera and Boleda 2019, Westera et al. 2021 for discussion.

conducting research on naming, since it is often the case that instances do not neatly fall into only one category, and the relationship between names and categories is not straightforward (Malt et al., 1999).

Our operationalization of prototypes and typicality, which is also found in recent computational approaches that leverage the information embedded in vector spaces (Ahn et al., 2021; Battleday et al., 2020; Günther et al., 2022; Xu et al., 2021), is only one of many possible operationalizations. We do not intend it to be taken as a proposal reflecting the internal human processes at play when naming (see, for instance, Battleday et al., 2020; Singh et al., 2020, for cognitively oriented analyses of the role of deep-learning visual features and computationally derived prototypes in the study of human category learning). Rather, its usefulness lies in its generality and its predictive acumen.

While we show that computational estimates of typicality are informative and can be used to predict naming variation, our analyses also show that model estimates show some degree of difference from human-rated typicality. Future work should delve deeper into how they differ and what that teaches us: Are the differences mainly due to issues in the definition of the annotation task for humans? Or to limits in the data that the model was trained on, the architecture of the model, or the specific operationalization of visual prototypes (Battleday et al., 2020)? Or to humans using non-visual knowledge as well as visual knowledge in their estimates, as suggested in Appendix E and previous work on shape bias (Malhotra et al., 2022, 2020)? It is for instance plausible that, in typicality judgments, humans rely less on size or view-point dependent visual information than machines.

These different options suggest different ways forward. Possibilities that we deem especially worth exploring are models that are trained on both text and images, providing a more comprehensive representation of objects (Radford et al., 2021), and alternative operationalizations of name prototypes (Battleday et al., 2020; Singh et al., 2020; Westera et al., 2021).

Finally, previous work has shown that multiple factors besides visual typicality, such as lexical frequency, age of acquisition, or visual complexity, influence speakers' production choices (Alario & Ferrand, 1999; Gualdoni et al., 2022; Koranda et al., 2018; Snodgrass & Vanderwart, 1980). While enriching our Analysis I with new factors is relatively easy – see Appendix G –, as the parameter exploration task is performed by the model, it is not trivial to augment Analysis II with additional sources of information: It would require a new formulation of the index of crowdedness that accounts for the new variables while still expressing visual information, and, crucially, assigning the proper weight to the different components. We thus leave the exploration of this aspect to future work.

Conclusion

In this work, we have presented a large-scale computational analysis of how people name objects, using naturalistic stimuli to investigate how visual typicality affects variation in naming. With respect to previous work, we have broadened the empirical coverage of our analysis along three axes: first, the amount of data (24.5 K images and 874 names); second, the object names themselves, by including in the analysis all the names produced for a given object (as opposed to only the most frequent name); and third, the kinds of typicality explored, encompassing the typicality of both the objects and the scenes in which they occur. This increased coverage of factors affecting naming was achieved by adapting computational methods from Computer Vision to estimate visual typicality, instead of relying on subjective human ratings as done in previous work on naming.

We modeled visual prototypes as attraction points in a multi-dimensional space and found that naming variation can be predicted using the position of a given object in the visual space. Naming variation increases as a function of the density of suitable name candidates, with a larger number of similarly viable (i.e., similarly close) prototypes predicting higher naming variation. The same pattern was found for both object and context typicality, although less pronounced for context typicality.

Our results suggest that competition between candidate names is mediated by visual properties, and that this competition can be modeled using computational methods. Our approach provides a more flexible and less costly alternative to human rating data: It can be scaled to model large data sets and may facilitate research into aspects of human object naming that have not received sufficient attention to date, as we have done in the current paper for naming variation. More generally, our work is part of a budding strand of research showcasing the potential of new Computer Vision methods for the study of human language (Ahn et al., 2021; Battleday et al., 2020; Günther et al., 2022).

CRediT authorship contribution statement

Eleonora Gualdoni: Conceptualization, Methodology/Study design, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Thomas Brochhagen:** Conceptualization, Methodology/Study design, Software, Writing – original draft, Writing – review & editing, Supervision. **Andreas Mädebach:** Conceptualization, Methodology/Study design, Software, Data curation, Writing – original draft, Visualization, Supervision. **Gemma Boleda:** Conceptualization, Methodology/Study design, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The original ManyNames data are available at https://github.com/amore-upf/manynames. Data and scripts for our analyses are available at https://osf.io/s7h9f/.

Google Colab demos are available at:

Demo object visual properties: https://colab.research.google.com/drive/1o63vmYlVNTcp7RIvzP4cpijKwLkhJdZs?usp=sharing;

Demo context visual properties: https://colab.research.google.com/drive/18r7UuVTGMZJ1ay4bmM0HaVe3WICwctuY?usp=share_link.

Acknowledgments

The authors thank the editors Adrian Staub and Kathleen Rastle, the reviewers Fritz Günther and Marc Brysbaert, and the COLT research group for their useful feedback, as well as Carina Silberer for advice regarding Computer Vision models. This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No. 715154) and Ministerio de Ciencia e Innovación and the Agencia Estatal de Investigación (Spain; ref. PID2020-112602GB-I00/MICIN/AEI/10.13039/501100011033). This paper reflects the authors' view only, and the funding agencies are not responsible for any use that may be made of the information it contains.

Appendix A. Histogram of occurrences of missing names

See Fig. A.13.

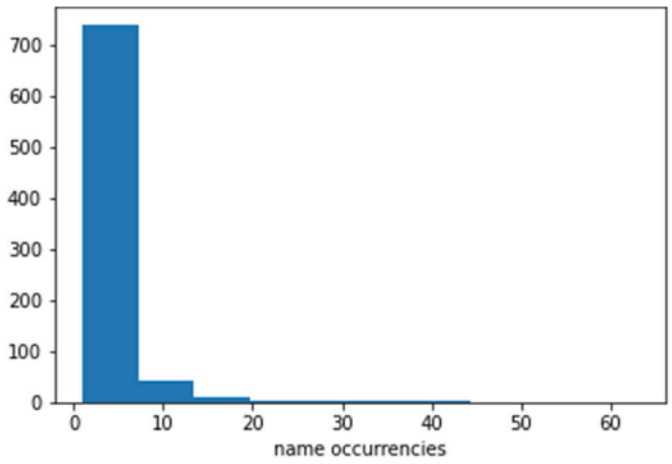


Fig. A.13. Histogram of occurrences of names in ManyNames for which we lack prototypes.

Appendix B. Details on Anderson et al. 2018's model

Anderson et al. (2018)'s architecture has two main components; we use the one called *Bottom-Up*. Bottom-Up works as an object detector: it is designed to identify instances of objects belonging to certain classes and localize them with bounding boxes in images, while extracting corresponding visual representations. Bottom-Up's object detection is based on the Faster R-CNN architecture (Ren et al., 2015) –substituted with Detectron2 (Wu et al., 2019) in a recent release–[13] with a ResNet-101 (He et al., 2016) as backbone model responsible for visual features extraction. This ResNet-101 is pre-trained for object classification on ImageNet (Deng et al., 2009) and fine-tuned on VisualGenome (Krishna et al., 2017). This fine-tuning step on VisualGenome ensures that the model returns good quality visual features for objects in ManyNames (recall that ManyNames images are a sample of VisualGenome images). We use the version of Bottom-Up based on Detectron2 to extract visual representations from our images.

Fig. B.14 shows a schematic representation of our architecture of choice. To obtain high-level visual features for specific objects in images, it is possible to use the Region Of Interest (ROI) Pooler module that, given the coordinates of an image region, returns a vector that corresponds to the visual features as extracted by the backbone ResNet architecture for that specific area.[14] When the goal is to use the model as an object detector (which we do not do here, as we already have the coordinates of the target objects), the ROI Pooler is fed the object locations proposed by the Region Proposal Network – that proposes bounding boxes –, and extracts the corresponding visual features.

Appendix C. Visual inspection of images with high/low computationally-derived typicality scores

C.1. Object typicality

See Fig. C.15

C.2. Context typicality

See Fig. C.16.

[13] Available at https://github.com/airsplay/py-bottom-up-attention

[14] It is also possible to get from the model a vector of probabilities over a set of class labels, which is not of our interest here.

Appendix D. Further analyses on the visual space

Here we complement and discuss the data on the relationship between the visual space and lexical choice. In 24 % of the cases, the closest prototype to the object corresponds to the object top name (chance level 0.1%); and the mean rank of the top name in the prototype space is 12.8, out of 874 options. We have also run a correlation analysis: For each object in the dataset, we computed the correlation between the typicalities for the 10 closest prototypes and the number of annotators producing the corresponding names. The average correlation is 0.32 (the average correlation when randomly shuffling prototypes in the visual space is expectedly 0).

The presence of prototypes of names not produced by speakers close to the objects can be explained in terms of what our visual space represents; that is, a surrogate of the human visual space of categories as denoted by names. ManyNames does not list, for each object, all the possible adequate names. Given the multiple factors affecting lexical choice, it is to be expected that some names, even if plausible for an object, have nevertheless not been produced (for instance, the images in Fig. 1 depicting women holding tennis rackets could be called "person", "human", or "female"; we expect the prototypes of these names to be close to the images). We cannot even exclude that semantically related, but not plausible, names for an object compete with plausible names, and that this affects variation. It could be, for instance, that a densely populated part of the lexicon (e.g. the *people* area) triggers a more complex search that makes different people land on different names, resulting in higher naming variation. We have no data for this hypothesis (though see Caramazza and Hillis (1990), Nickels and Howard (1994) for data on semantic errors in patients), but this adds to the reasons why we cannot expect all and only the produced names to be closest to a given target object in the visual space.

Appendix E. Details on typicality judgment data collection

Design. We collected human judgments for object and context typicality to compare them with our computationally-derived typicality scores. We chose the subset to annotate as follows: For both objects and contexts, we selected 100 images by dividing the ManyNames images into 10 bins based on their computationally-derived typicality score (i.e. 10 percentiles). We sampled 10 images per bin, making sure that we did not repeat image top names; and avoiding to sample images whose top name is very frequent all from the same bin (to do so, we randomly sampled one image from the first bin, one image from the second, and so on).

Participants saw, in each screen, a single image with a name written above it. They were asked to give a typicality rating for it. Participants could give a score from 1 to 5 by clicking on radio buttons below the image, as illustrated in Fig. E.17. In the object typicality task, subjects were presented with the cropped objects from ManyNames. They were instructed to give a score for how much the object looked like what they would expect when hearing or reading the corresponding object name. In the context typicality task, subjects were presented with the entire image from ManyNames; but with the object blurred so that they could focus primarily on the context. In the instructions, they were asked to give a score for how much the object surroundings looked like what they would expect to see for an object carrying the name written above. They could see one example before starting the task.

We collected 40 annotations for the context task, and 41 for the object task. Each participant annotated the entire set of 100 images, plus 5 randomly placed control items. The control items were chosen to monitor if annotators were paying attention to the task. They were intentionally picked to be very simple: We randomly sampled 5 object/context prototypes whose name did not appear in the list of top names previously selected as stimuli, and, for each of them, picked the furthermost object/context in terms of cosine distance (making sure we

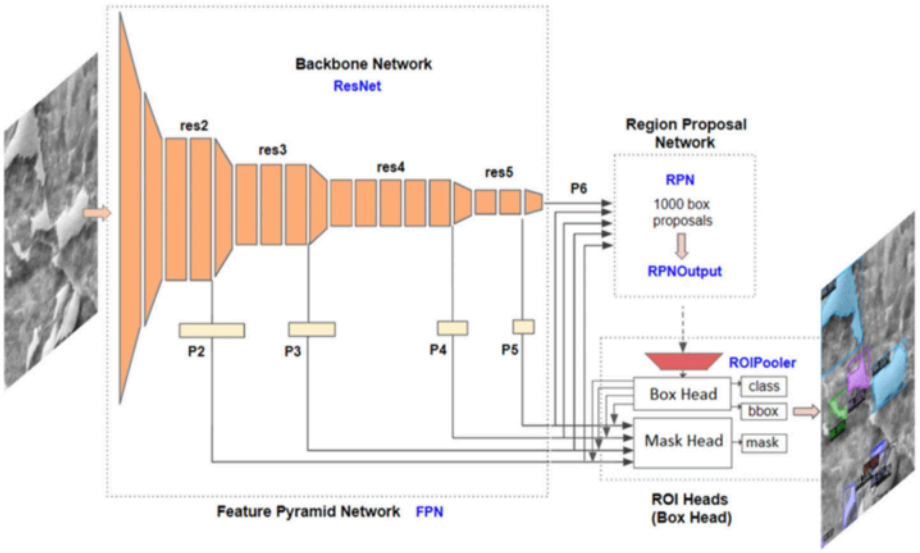


Fig. B.14. Schematic representation of the Detectron2 architecture from Ackermann et al. (2022). The backbone model ResNet-101 provides visual feature maps (P1–P5) to a region proposal network (RPN) that is used for the object detection phase. The ROI heads locate objects and output the corresponding classes after ROI Pooling. When using the model to obtain visual features for a specific object of choice, it is possible to skip the region proposal phase, and pool the visual features corresponding to the object by providing its coordinates.

did not repeat items from the same category). This yielded, for instance, the picture of a train, associated with the prototype "penguin"; the furthermost image from the prototype. Accordingly, these controls were expected to receive a very low score of typicality; serving as a benchmark of attentiveness. For the context control items, an additional step of manual selection was added to ensure their quality.

The data collection routine was written in Psychopy (Peirce et al., 2019) and launched through Pavlovia.[15] Participants were recruited via Amazon Mechanical Turk.[16] We only accepted annotators from the US, with HIT approval rate higher than 89% and number of approved HITs higher than 1000. We informed them that we would not collect any personal data (except for their workerID, that we would not make public), and that the goal of the experiment was to study how well certain names and images of everyday objects fit together. Moreover, they were informed that the task contained some control items designed to ensure the quality of the annotation. Before being able to access the link to the experiment, participants had to complete an informed consent form. They were able to quit the experiment at any time. There was no time limit. We paid participants $3 for completing the task. The experiment was approved by the ethical board of Universitat Pompeu Fabra.

Results of the data collection. We excluded the data of participants that failed to give a low score (either 1 or 2) to more than one control, as this suggests that they were not paying enough attention to the task. This resulted in 41 out of 65 annotations being accepted for the object task; and 40 out of 84 annotations being accepted for the context task. For both object and context ratings, we computed the reliability of our study with the *performance* and the *psych* package (Lüdecke et al., 2021; R. Core Team, 2022; Revelle, 2023). Both our studies obtained a high reliability level: With Spearman–Brown correction we obtain a reliability score of 0.92 for the object typicality scores and of 0.97 for the context typicality scores. Considering Cronbach's α, we obtain a value of 0.95 for the object ratings and of 0.98 for the context ratings. These numbers show that our norming study is reliable.

To assess the correlation between human and computationally-derived typicality scores, we followed two methods. We computed the average correlation between computational scores and randomly sampled participants. This leads to $R = 0.12$ for object typicality ratings and $R = 0.32$ for context typicality ratings (see Figs. E.18 and E.19).

As a baseline for comparison, we computed the correlation between random pairs of participants, and averaged the resulting 20 correlations. When judging object typicality, the average correlation between randomly paired human annotators is 0.26, which is substantially higher than model-human correlations but still low. In the case of context typicality, this number grows to 0.48. These baselines put our results in perspective. They suggest that human participants disagree substantially when judging the visual typicality of naturalistic images. Interestingly, this disagreement is higher when judging objects than contexts, as was the case in the model-human comparison.

In general, human judgments about objects tend to be more skewed towards high typicality (see Fig. E.20); and humans and models tend to agree more on what is *atypical* rather than on what is typical. A manual inspection of the annotations revealed that humans seem to take into account some non-visual information as well, which models have no access to. For instance, a raw pizza is judged by humans as atypical. However, since it is visually similar to a cooked pizza, the computational judgment leans towards higher typicality. Moreover, human judgments are not affected by the object being occluded or incomplete (humans "complete" the object in their head), while computational judgments clearly are: A dog seen through a net remains a fairly typical dog for humans, while it is judged atypical by the models — see Fig. E.21 for other examples of this kind.

Table F.1
Estimates of standardized fixed effects when predicting naming variation (H) as a function of object and context typicality. $R^2 = 0.59$.

	Estimate	Est.Error	l-95% CI	u-95% CI
Intercept	1.33	0.03	1.27	1.39
Obj typ top name	−0.05	0.02	−0.09	−0.02
Obj typ alt name	0.03	0.02	−0.01	0.07
Ctx typ top name	−0.00	0.01	−0.03	0.03
Ctx typ alt name	0.01	0.01	−0.02	0.03

Appendix F. Numerical results of Analysis I

See Table F.1

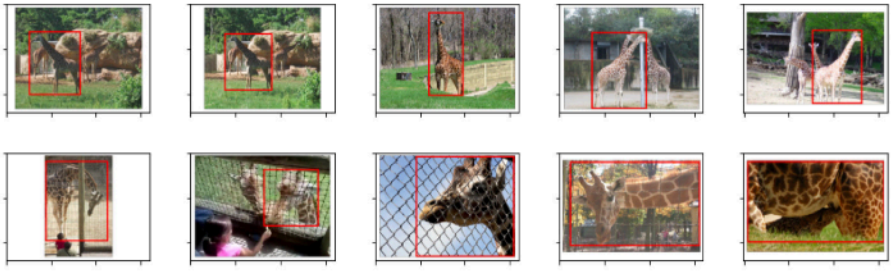
[15] https://pavlovia.org/
[16] https://www.mturk.com/

(a) woman

(b) man

(c) train

(d) shirt

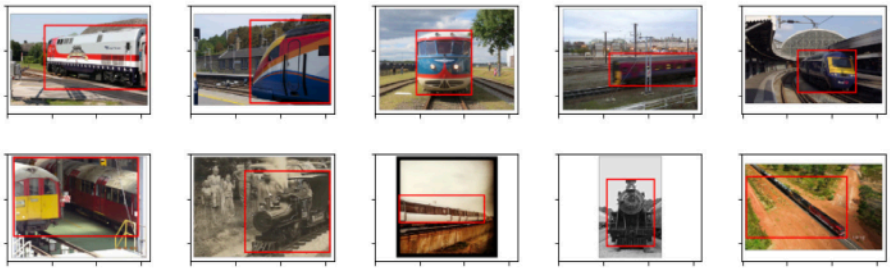


(e) giraffe

Fig. C.15. The 5 most typical (first row of each panel) and the 5 most atypical objects (second row of each panel) based on our computationally-derived scores, for the 5 most frequently attested names in ManyNames. Typicality and atypicality grow going from left to right. (There are pairs of very similar images: of note, these are not repeated images. Small differences can be noticed displaying them in bigger dimensions — they are often different frames extracted from the same video.).

(a) woman

(b) man

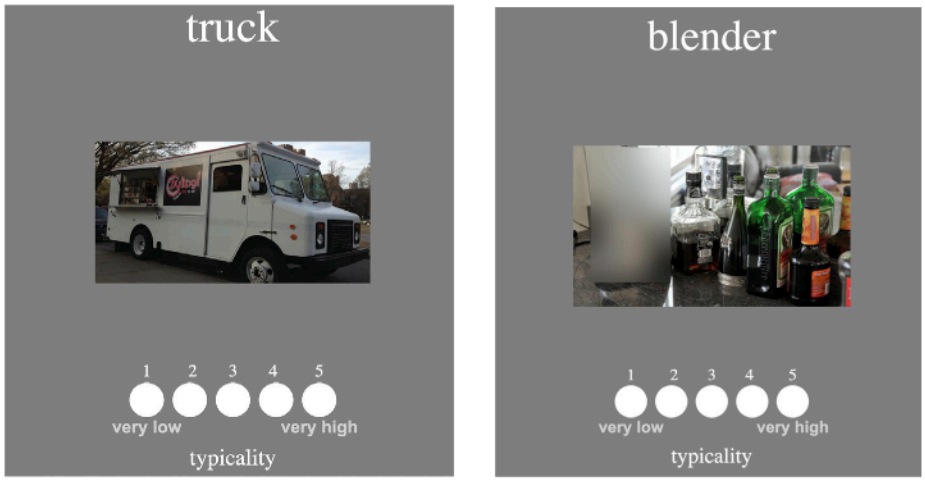


(c) train

(d) shirt

(e) giraffe

Fig. C.16. The 5 most typical (first row of each panel) and the 5 most atypical context (second row of each panel) based on our computationally-derived scores, for the 5 most frequently attested names in ManyNames. Typicality and atypicality grow going from left to right. (There are pairs of very similar images: of note, these are not repeated images. Small differences can be noticed displaying them in bigger dimensions — they are often different frames extracted from the same video.).



(a) (b)

Fig. E.17. Examples of screens shown to the participants. Panel (a) exemplifies the object typicality task. Panel (b) exemplifies the context typicality task.

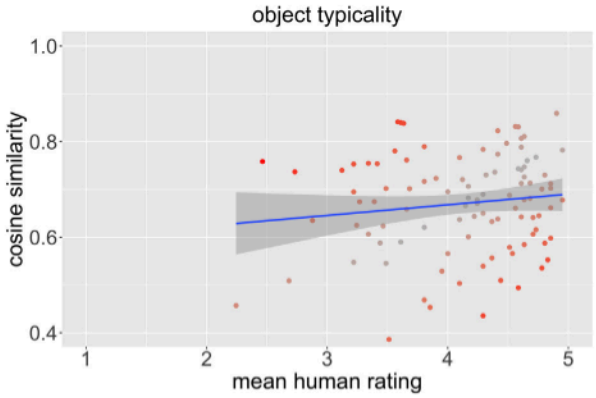


Fig. E.18. Relationship between our computationally-derived typicality scores for objects (y-axis) and average human typicality scores (x-axis). The color gradient depicts the difference between the two ratings. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

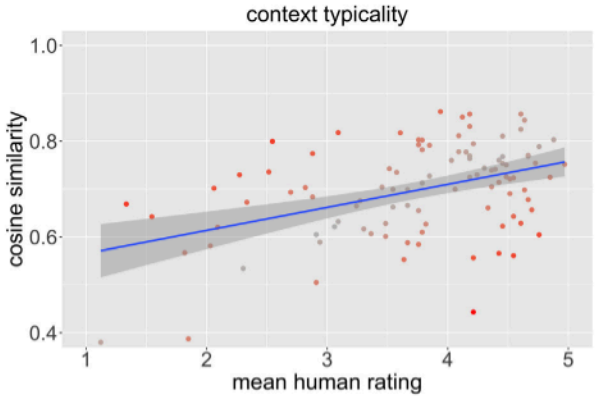


Fig. E.19. Relationship between our computationally-derived typicality scores for contexts (y-axis) and average human typicality scores (x-axis). The color gradient depicts the difference between the two ratings. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Appendix G. Variant of Analysis I including frequency information

Lexical frequency – as a proxy of ease of lexical access – is one of the factors expected to affect naming variation and lexical choice (Alario & Ferrand, 1999; Koranda et al., 2018). We report here the results of the same model described in Analysis I, fitted with additional information about top name and alternative name frequency. Frequency estimates for names were extracted from SUBTLEX-US, a subtitle corpus of American English (Brysbaert & New, 2009).

Table G.2
Estimates of standardized fixed effects when predicting naming variation (H) as a function of object and context typicality, as well as name frequency (as extracted from SUBTLEX-US Brysbaert & New, 2009)

	Estimate	Est.Error	l-95% CI	u-95% CI
Intercept	1.27	0.04	1.20	1.33
Obj typ top	−0.09	0.02	−0.12	−0.06
Obj typ alt	0.09	0.02	0.05	0.12
Ctx typ top	0.00	0.01	−0.02	0.03
Ctx typ alt	0.00	0.01	−0.02	0.03
Log freq top	−0.11	0.03	−0.18	−0.05
Log freq alt	0.02	0.02	−0.02	0.07

In addition to the findings reported in Analysis I, this augmented model shows that higher typicality for the alternative name predicts higher naming variation; and a more frequent top name is predictive of lower naming variation. When it comes to the effect of the frequency of alternative names, results are not significant (see Fig. G.22 for a visualization of the model estimates). Taking stock, these results suggest that more people tend to choose the same name for an object when the object is very typical for that name, not very typical for the alternative name, and if that name is very frequent. For further discussion, see Gualdoni et al. (2022).

Appendix H. Analysis II: model evaluations

We report here the model rankings based on leave-one-out cross-validation. Table H.3 and Table H.4 show, respectively, the rankings of models with index of object crowdedness and index of context crowdedness across γ parameters. Table H.5 shows the ranking of models with the best γ parameters, including the multi-variate model.

H.1. Index of object crowdedness: evaluation for best γ

See Table H.3

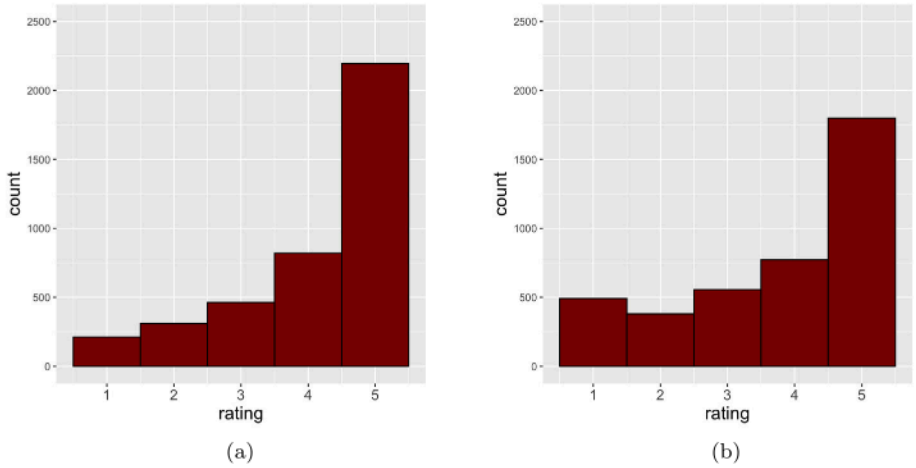


Fig. E.20. Histograms of human ratings in the object typicality task – panel (a) – and in the context typicality task — panel (b).

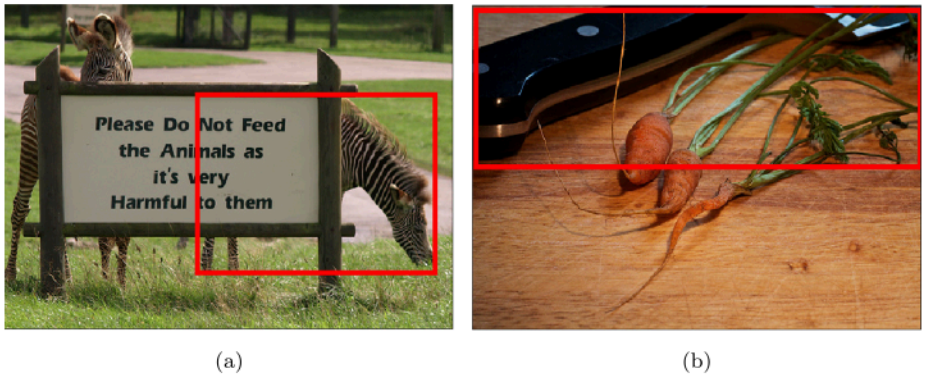


Fig. E.21. Examples of occluded/incomplete objects. Panel (a): An object with top name "zebra"; with a human typicality score of 4.58 and a computational score of 0.61 (the average computational typicality for objects with top name "zebra" is 0.68). Panel (b): An object with top name "knife"; with human typicality score of 3.39 and a computational score of 0.38 (average computational typicality for objects with top name "knife" is 0.61).

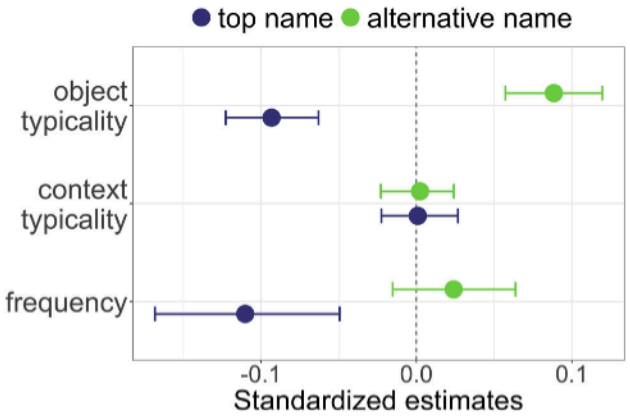


Fig. G.22. Visualization of fixed effect estimates for the model in Table G.2. Bars correspond to 95% CIs. Positive vs. negative estimates show, respectively, the increase and decrease in naming variation for a one point difference in standard deviation of the predictor variable.

H.2. Index of context crowdedness: evaluation for best γ

See Table H.4

Table H.3
Ranking, based on leave-one-out cross-validation, of models fitted with index of object crowdedness with different values of γ (values of γ are made explicit in the model names). The second column shows differences in expected log-predictive densities to the highest ranked model; the third columns shows the standard error. The best model is boldfaced.

Model	ELPD difference	SE difference
idx obj 8	0.0	0.0
idx obj 5	−63.7	11.8
idx obj 10	−75.0	6.5
idx obj 2	−227.8	19.5
idx obj 1	−251.7	20.7
idx obj 30	−255.2	27.8
idx obj 50	−267.8	26.2
idx obj 20	−285.9	24.1

H.3. Index of crowdedness: evaluation for best model

See Table H.5.

Appendix I. Numerical results of Analysis II

See Table I.6.

Table H.4
Ranking, based on leave-one-out cross-validation, of models fitted with index context of crowdedness with different values of γ (values of γ are made explicit in the model names). The second column shows differences in expected log-predictive densities to the highest ranked model; the third columns shows the standard error. The best model is boldfaced.

Model	ELPD difference	SE difference
idx ctx 1	0.0	0.0
idx ctx 2	−2.6	1.2
idx ctx 5	−12.5	3.7
idx ctx 8	−20.3	5.3
idx ctx 10	−24.0	6.1
idx ctx 20	−32.9	8.5
idx ctx 30	−38.5	9.7
idx ctx 50	−53.9	10.6

Table H.5
Ranking, based on leave-one-out evaluation, of the best unifactorial models fitted with index of crowdedness and the multifactorial model (here referred to as "idx obj + ctx"). The second column shows differences in expected log-predictive densities to the highest ranked model; the third columns shows the standard error. The best model is boldfaced.

Model	ELPD difference	SE difference
idx obj + ctx	0.0	0.0
idx obj	−21.4	6.6
idx ctx	−249.0	21.9

Table I.6
Estimates of effects when predicting naming variation (H) using both indices of crowdedness. R^2 equals 0.025.

	Estimate	Est.Error	l-95% CI	u-95% CI
Intercept	0.71	0.004	0.70	0.71
Index of obj crowd	0.10	0.004	0.09	0.10
Index of ctx crowd	0.03	0.004	0.02	0.04

References

Ackermann, M., İren, D., Wesselmecking, S., Shetty, D., & Krupp, U. (2022). Automated segmentation of martensite-austenite islands in bainitic steel. *Materials Characterization*, *191*, Article 112091. http://dx.doi.org/10.1016/j.matchar.2022.112091.

Ahn, S., Zelinsky, G. J., & Lupyan, G. (2021). Use of superordinate labels yields more robust and human-like visual representations in convolutional neural networks. *Journal of Vision*, *21*(13), 13. http://dx.doi.org/10.1167/jov.21.13.13.

Alario, F. X., & Ferrand, L. (1999). A set of 400 pictures standardized for French: Norms for name agreement, image agreement, familiarity, visual complexity, image variability, and age of acquisition. *Behavior Research Methods, Instruments, & Computers*, *31*, 531–552.

Alario, F. X., Ferrand, L., Laganaro, M., New, B., Frauenfelder, U. H., & Segui, J. (2004). Predictors of picture naming speed. *Behavior Research Methods, Instruments, & Computers*, *36*(1), 140–155. http://dx.doi.org/10.3758/BF03195559.

Anderson, P., He, X., Buehler, C., Teney, D., Johnson, M., Gould, S., & Zhang, L. (2018). Bottom-up and top-down attention for image captioning and visual question answering. In *Proceedings of CVPR*. arXiv:1707.07998.

Barry, C., Morrison, C. M., & Ellis, A. W. (1997). Naming the Snodgrass and Vanderwart pictures: Effects of age of acquisition, frequency, and name agreement. *The Quarterly Journal of Experimental Psychology Section A*, *50*(3), 560–585. http://dx.doi.org/10.1080/783663595.

Battleday, R. M., Peterson, J. C., & Griffiths, T. L. (2020). Capturing human categorization of natural images by combining deep networks and cognitive models. *Nature Communications*, *11*(1), http://dx.doi.org/10.1038/s41467-020-18946-z.

Brennan, S., & Clark, H. H. (1996). Conceptual pacts and lexical choice in conversation. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *22 6*, 1482–1493.

Brodeur, M., Dionne-Dostie, E., Montreuil, T., & Lepage, M. (2010). The Bank of Standardized Stimuli (BOSS), a new set of 480 normative photos of objects to be used as visual stimuli in cognitive research. *PLoS One*, *5*, Article e10773.

Brodeur, M., Guérard, K., & Bouras, M. (2014). Bank of Standardized Stimuli (BOSS) phase II: 930 new normative photos. *PLoS One*, *9*, Article e106953.

Brysbaert, M., & New, B. (2009). Moving beyond Kucera and Francis: A critical evaluation of current word frequency norms and the introduction of a new and improved word frequency measure for American English. *Behavior Research Methods*, *41*, 977–990. http://dx.doi.org/10.3758/BRM.41.4.977.

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. http://dx.doi.org/10.18637/jss.v080.i01.

Caramazza, A., & Hillis, A. E. (1990). Where do semantic errors come from? *Cortex*, *26*, 95–122.

De Deyne, S., Navarro, D., Collell, G., & Perfors, A. (2021). Visual and affective multimodal models of word meaning in language and mind. *Cognitive Science*, *45*, http://dx.doi.org/10.1111/cogs.12922.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. (2009). Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition* (pp. 248–255). Ieee.

Duñabeitia, J. A., Baciero, A., Antoniou, K., Antoniou, M., Ataman, E., Baus, C., Ben-Shachar, M., Çağlar, O., Chromý, J., Comesaña, M., Filip, M., Filipovic Durdevic, D., Dowens, M., Hatzidaki, A., Januška, Z., Kanj, R., Kim, S. Y., Kırkıcı, B., & Pliatsikas, C. (2022). The multilingual picture database. *Scientific Data*, *9*, http://dx.doi.org/10.1038/s41597-022-01552-7.

Duñabeitia, J. A., Crepaldi, D., Meyer, A., New, B., Pliatsikas, C., Smolka, E., & Brysbaert, M. (2018). MultiPic: A standardized set of 750 drawings with norms for six European languages. *The Quarterly Journal of Experimental Psychology*, *71*, 808–816. http://dx.doi.org/10.1080/17470218.2017.1310261.

Gärdenfors, P., & Williams, M.-A. (2001). Reasoning about categories in conceptual spaces. In *Proceedings of the IJCAI* (pp. 385–392).

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*(4), 457–472. http://dx.doi.org/10.1214/ss/1177011136.

Graf, C., Degen, J., Hawkins, R. X. D., & Goodman, N. D. (2016). Animal, dog, or dalmatian? Level of abstraction in nominal referring expressions. *Cognitive Science*.

Gualdoni, E., Brochhagen, T., Mädebach, A., & Boleda, G. (2022). Woman or tennis player? Visual typicality and lexical frequency affect variation in object naming.. In J. Culbertson, A. Perfors, H. Rabagliati, & V. Ramenzoni (Eds.), *Proceedings of the 44th annual conference of the cognitive science society*. Cognitive Science Society, http://dx.doi.org/10.31234/osf.io/34ckf.

Gualdoni, E., Kemp, C., Xu, Y., & Boleda, G. (2023). Quantifying informativeness of names in visual space. In *Proceedings of the 45th annual conference of the cognitive science society*. Cognitive Science Society.

Günther, F., Marelli, M., Tureski, S., & Petilli, M. A. (2022). ViSpa (Vision Spaces): A computer-vision-based representation system for individual images and concept prototypes, with large-scale evaluation. *Psychological Review*, *Advance online publication*, https://psycnet.apa.org/doi/10.1037/rev0000392.

Haber, J., Baumgärtner, T., Takmaz, E., Gelderloos, L., Bruni, E., & Fernández, R. (2019). The PhotoBook dataset: Building common ground through visually-grounded dialogue. In *Proceedings of the 57th annual meeting of the association for computational linguistics* (pp. 1895–1910).

Harrison, S. (2022). *Run like a girl: Sports-related gender bias in language and vision*. Universitat Pompeu Fabra.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *2016 IEEE conference on computer vision and pattern recognition* (pp. 770–778).

Hebart, M. N., Dickter, A. H., Kidder, A., Kwok, W. Y., Corriveau, A., Van Wicklin, C., & Baker, C. I. (2019). Things: A database of 1,854 object concepts and more than 26,000 naturalistic object images. *PLoS One*, *14*(10), 1–24. http://dx.doi.org/10.1371/journal.pone.0223792.

Jescheniak, J., Hantsch, A., & Schriefers, H. (2005). Context effects on lexical choice and lexical activation. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *31*, 905–920.

Johnson, C. J., Paivio, A., & Clark, J. M. (1996). Cognitive components of picture naming. *Psychological Bulletin*, *120*(1), 13–139.

Jolicoeur, P., Gluck, M. A., & Kosslyn, S. M. (1984). Pictures and names: Making the connection. *Cognitive Psychology*, *16*(2), 243–275.

Jozwik, K. M., Kriegeskorte, N., Storrs, K. R., & Mur, M. (2017). Deep convolutional neural networks outperform feature-based but not categorical models in explaining object similarity judgments. *Frontiers in Psychology*, *8*.

Koranda, M., Zettersten, M., & MacDonald, M. C. (2018). Word frequency can affect what you choose to say. *Cognitive Science*.

Krautz, A., & Keuleers, E. (2021). LinguaPix database: A megastudy of picture-naming norms. *Behavior Research Methods*, *54*, http://dx.doi.org/10.3758/s13428-021-01651-0.

Krishna, R., Zhu, Y., Groth, O., Johnson, J., Hata, K., Kravitz, J., Chen, S., Kalantidis, Y., Li, L.-J., Shamma, D., Bernstein, M., & Li, F.-F. (2017). Visual genome: Connecting language and vision using crowdsourced dense image annotations. *International Journal of Computer Vision*, *123*.

Landauer, T. K., & Dumais, S. T. (1997). A solution to plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review*, *104*, 211–240.

Landauer, T. K., Foltz, P. W., & Laham, D. (1998). An introduction to latent semantic analysis. *Discourse Processes*, *25*, 259–284.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*, 436–444. http://dx.doi.org/10.1038/nature14539.

Liu, Y., Hao, M., li, P., & Shu, H. (2011). Timed picture naming norms for mandarin Chinese. *PLoS One*, *6*, Article e16505. http://dx.doi.org/10.1371/journal.pone.0016505.

Luce, R. D. (1959). *Individual choice behavior: A theoretical analysis*. New York, NY, USA: Wiley.

Lüdecke, D., Ben-Shachar, M. S., Patil, I., Waggoner, P., & Makowski, D. (2021). performance: An R package for assessment, comparison and testing of statistical models. *Journal of Open Source Software*, *6*(60), 3139. http://dx.doi.org/10.21105/joss.03139.

Lund, K., & Burgess, C. (1996). Producing high-dimensional semantic space from lexical co-occurence. *Behavior Research Methods Instruments & Computers*, *28*, 203–208. http://dx.doi.org/10.3758/BF03204766.

Mahendran, A., & Vedaldi, A. (2014). Understanding deep image representations by inverting them. arXiv:1412.0035.

Malhotra, G., Dujmović, M., & Bowers, J. S. (2022). Feature blindness: A challenge for understanding and modelling visual object recognition. *PLoS Computational Biology*, *18*(5), 1–27. http://dx.doi.org/10.1371/journal.pcbi.1009572.

Malhotra, G., Evans, B. D., & Bowers, J. S. (2020). Hiding a plane with a pixel: examining shape-bias in CNNs and the benefit of building in biological constraints. *Vision Research*, *174*, 57–68. http://dx.doi.org/10.1016/j.visres.2020.04.013, URL https://www.sciencedirect.com/science/article/pii/S0042698920300742.

Malt, B. C., Sloman, S. A., Gennari, S., Shi, M., & Wang, Y. (1999). Knowing versus naming: Similarity and the linguistic categorization of artifacts. *Journal of Memory and Language*, *40*(2), 230–262. http://dx.doi.org/10.1006/jmla.1998.2593, URL https://www.sciencedirect.com/science/article/pii/S0749596X98925931.

Moreno-Martínez, F., & Montoro, P. (2012). An ecological alternative to Snodgrass & Vanderwart: 360 high quality colour images with norms for seven psycholinguistic variables. *PLoS One*, *7*, Article e37527.

Nickels, L., & Howard, D. (1994). A frequent occurrence? factors affecting the production of semantic errors in aphasic naming. *Cognitive Neuropsychology*, *11*, 289–320.

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods*, *51*(1), 195–203. http://dx.doi.org/10.3758/s13428-018-01193-y.

Peterson, J. C., Abbott, J. T., & Griffiths, T. L. (2018). Evaluating (and improving) the correspondence between deep neural networks and human representations. arXiv:1706.02417.

R. Core Team (2022). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing, URL https://www.R-project.org/.

Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., Krueger, G., & Sutskever, I. (2021). Learning transferable visual models from natural language supervision. arXiv:2103.00020.

Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. In *IEEE transactions on pattern analysis and machine intelligence, vol. 39*.

Revelle, W. (2023). *psych: Procedures for psychological, psychometric, and personality research*. Evanston, Illinois: Northwestern University, URL https://CRAN.R-project.org/package=psych R package version 2.3.3.

Rezatofighi, H., Tsoi, N., Gwak, J., Sadeghian, A., Reid, I., & Savarese, S. (2019). Generalized intersection over union: A metric and a loss for bounding box regression. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*.

Roads, B. D., & Love, B. C. (2020). Enriching ImageNet with human similarity judgments and psychological embeddings. arXiv:2011.11015.

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology*, *7*(4), 573–605.

Rosch, E., Mervis, C. B., Gray, W. D., Johnson, D. M., & Boyes-Braem, P. (1976). Basic objects in natural categories. *Cognitive Psychology*, *8*, 382–439.

Ross, B., & Murphy, G. L. (1999). Food for thought: Cross-classification and category organization in a complex real-world domain. *Cognitive Psychology*, *38*, 495–553.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*, 379–423, URL http://plan9.bell-labs.com/cm/ms/what/shannonday/shannon1948.pdf.

Shao, Z., & Stiegert, J. (2016). Predictors of photo naming: Dutch norms for 327 photos. *Behavior Research Methods*, *48*(2), 577–584. http://dx.doi.org/10.3758/s13428-015-0613-0.

Shepard, R. N. (1957). Stimulus and response generalization: A stochastic model relating generalization to distance in psychological space. *Psychometrika*, *22*, 325–345.

Shepard, R. N. (1987). Toward a universal law of generalization for psychological science. *Science*, *237 4820*, 1317–1323.

Silberer, C., Zarrieß, S., & Boleda, G. (2020). Object naming in language and vision: A survey and a new dataset. In *Proceedings of the 12th language resources and evaluation conference* (pp. 5792–5801). Marseille, France: European Language Resources Association.

Silberer, C., Zarrieß, S., Westera, M., & Boleda, G. (2020). Humans meet models on object naming: A new dataset and analysis. In *Proceedings of the 28th international conference on computational linguistics* (pp. 1893–1905). Barcelona, Spain (Online): International Committee on Computational Linguistics.

Sims, C. R. (2018). Efficient coding explains the universal law of generalization in human perception. *Science*, *360*, 652–656.

Singh, P., Peterson, J. C., Battleday, R. M., & Griffiths, T. L. (2020). End-to-end deep prototype and exemplar models for predicting human behavior. In *Proceedings of the 42nd annual conference of the cognitive science society*. Cognitive Science Society.

Snodgrass, J. G., & Vanderwart, M. (1980). A standardized set of 260 pictures: norms for name agreement, image agreement, familiarity, and visual complexity.. *Journal of Experimental Psychology. Human Learning and Memory*, *6*(2), 174–215.

Takmaz, E., Pezzelle, S., & Fernández, R. (2022). Less descriptive yet discriminative: Quantifying the properties of multimodal referring utterances via CLIP. In *Proceedings of the workshop on cognitive modeling and computational linguistics*.

Tenenbaum, J. B., & Griffiths, T. L. (2001). Generalization, similarity, and Bayesian inference.. *The Behavioral and Brain Sciences*, *24*(4), 629–40; discussion 652–791.

Tsaparina, D., Bonin, P., & Méot, A. (2011). Russian norms for name agreement, image agreement for the colorized version of the Snodgrass and Vanderwart pictures and age of acquisition, conceptual familiarity, and imageability scores for modal object names. *Behavior Research Methods*, *43*(4), 1085–1099. http://dx.doi.org/10.3758/s13428-011-0121-9.

Tsaparina-Guillemard, D., Bonin, P., & Méot, A. (2011). Russian norms for name agreement, image agreement for the colorized version of the snodgrass and vanderwart pictures and age of acquisition, conceptual familiarity, and imageability scores for modal object names. *Behavior Research Methods*, *43*, 1085–1099. http://dx.doi.org/10.3758/s13428-011-0121-9.

Vehtari, A., Gabry, J., Magnusson, M., Yao, Y., & Gelman, A. (2019). loo: Efficient leave-one-out cross-validation and WAIC for Bayesian models. URL https://mc-stan.org/loo R package version 2.2.0.

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, *27*(5), 1413–1432.

Vitkovitch, M., & Tyrrell, L. (1995). Sources of disagreement in object naming. *The Quarterly Journal of Experimental Psychology Section A*, *48*(4), 822–848. http://dx.doi.org/10.1080/14640749508401419.

Westera, M., & Boleda, G. (2019). Don't blame distributional semantics if it can't do entailment. In *Proceedings of the 13th International Conference on Computational Semantics - Long Papers* (pp. 120–133). Gothenburg, Sweden: Association for Computational Linguistics, http://dx.doi.org/10.18653/v1/W19-0410, URL https://aclanthology.org/W19-0410.

Westera, M., Gupta, A., Boleda, G., & Padó, S. (2021). Distributional models of category concepts based on names of category members. *Cognitive Science*, *45*, http://dx.doi.org/10.1111/cogs.13029.

Wu, Y., Kirillov, A., Massa, F., Lo, W.-Y., & Girshick, R. (2019). Detectron2. https://github.com/facebookresearch/detectron2.

Xu, A., Stellar, J., & Xu, Y. (2021). Evolution of emotion semantics. *Cognition*, *217*, Article 104875. http://dx.doi.org/10.1016/j.cognition.2021.104875.

Zeiler, M. D., & Fergus, R. (2013). Visualizing and understanding convolutional networks. arXiv:1311.2901.

Zhang, R., Isola, P., Efros, A. A., Shechtman, E., & Wang, O. (2018). The unreasonable effectiveness of deep features as a perceptual metric. arXiv:1801.03924.