

Object naming is context dependent - A case study on testing linguistic hypotheses on real-world image corpora

Anonymous ECCV submission

Paper ID ***

Abstract. The abstract should summarize the contents of the paper. LNCS guidelines indicate it should be at least 70 and at most 150 words. It should be set in 9-point font size and should be inset 1.0 cm from the right and left margins. ...

Keywords: We would like to encourage you to list your keywords within the abstract section

@Carina TODO:

- requirements:
 - add most specific name; (possible ways to obtain information: taxonomy, object detectors)
 - add unconstrained object co-occurrences / unbiased as far as possible; rename R1? (lexical alternatives? candidate names?)
- title?

1 Introduction

Understanding and modeling the way humans converse about their environment using natural language has been a long-standing goal of research in various fields related to artificial intelligence and linguistics. With recent developments in computer vision and a range of massive data collections in particular, there has been a veritable explosion of interest in language & vision tasks, ranging from image captioning [1,2,3,4,5], referring expression resolution and generation [6,7,8,9], to multi-modal summarization or visual dialogue [10,11]. In principle, the underlying data collections here should not only spur computational, application-oriented research aimed at implementing systems for very specific tasks – they should also constitute extremely valuable resources for research aimed at deriving linguistic generalizations about various phenomena related to language grounding, reference and situated interaction which, for a long time, have been investigated mostly in very controlled and small-domain experimental settings, cf. [?, ?, 12, ?, ?] for some examples of traditional data collections related to reference and grounding. In turn, these linguistic generalizations could inform

computational modeling, architecture design and future data collections. However, so far, studies that have tested linguistic hypotheses on large-scale vision & language resources have been relatively rare.

In this paper, we take a look at object naming, a core phenomenon that occurs in virtually every language & vision task and is, at the same time, subject of ongoing research in language grounding and pragmatics. Our starting point is a particular linguistic hypothesis related to object naming - namely that the choice of a name for an object is dependent on other objects in its visual context - which has been tested recently in a classical experimental setting [13]. We discuss how this hypothesis could be tested based on recent data sets that pair images and object descriptions, referring expressions or captions (all containing object names) and define a set of requirements for obtaining a theoretically informed model for object naming. In sum, this discussion will show that specific requirements are met by particular resources, but none of the available corpora consistently satisfies all of the requirements. We believe that this is a perfect showcase illustrating the challenges for linguistically motivated research in language and vision, and we derive a proposal for obtaining more consistently designed and annotated data collections for object naming.

2 Naming Objects (in Context)

The act of naming an object amounts to that of picking out a nominal to be employed to refer to it (e.g., “the *dog*”, “the white *dog* to the left”). Since an object is simultaneously a member of multiple categories (e.g., a young beagle is at once a dog, a beagle, an animal, a puppy etc.), all the various names that lexicalize these constitute a valid alternative, meaning that the same object can be named with more or less **specific names** [14,15]. Seminal work on concepts by Rosch suggests that object names typically exhibit a preferred level of specificity called the **entry-level**. This typically corresponds to an intermediate level of specificity, i.e., **basic level** (e.g., *bird*, *car*) [16], as opposed to more generic (i.e., **super-level**; e.g., *animal*, *vehicle*) or specific categories (i.e., **sub-level**; e.g., *sparrow*, *convertible*). However, less prototypical members of basic-level categories tend to be instead identified with sub-level categories (e.g., a penguin is typically called a *penguin* and not a *bird*) [17]. This out-of-context preference towards a certain taxonomic level is often referred to as **lexical availability**.

While the traditional notion of entry-level categories suggests that objects tend to be named by a *single* preferred concept, research on pragmatics has found that speakers are flexible with respect to the chosen level of specificity. Scenarios where multiple objects (of the same category) are present induce a pressure for generating names which uniquely identify the target [18], such that sub-level names can be systematically elicited in these cases [19] [13]. For example, in presence of more than one dog, the name *dog* is ambiguous and a sub-level category (e.g., *rottweiler*, *beagle*) is more informative and potentially preferred by speakers, though additional factors such as cost (which is typically approximated by frequency) or saliency also come into play [13] [20].

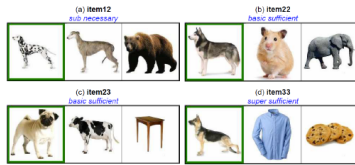


Fig. 1. Experimental and real-world visual scenes showing dogs (GET MORE IMAGES OF DOGS FROM VG???)

So far, research in computer vision, and vision & language, has mostly worked around the fact that objects can be categorized and named at different levels of specificity. State-of-the-art object recognizers are typically trained on a flat set of categories taken from ImageNet (REF!!), though see work by Deng et al. on trading off object recognition accuracy and level of specificity [21]. [22] present one of the few explicit studies on naming in computer vision and operationalize the task as translating between leaf nodes in the ImageNet hierarchy and entry-level concepts, adopting the traditional view that there is a single preferred name for a given object. Thus, establishing whether object naming is context dependent in realistic, large-scale data sets would not only be of interest to theoretical work on concepts and pragmatics, it would also be of great importance for the design of models in computer vision, object recognition and vision & language.

3 Requirements

In this Section we discuss requirements for scaling experimental studies on object names as in [13] to real-world images. The difference between these two approaches is illustrated in Figure 1, showing [13]’s carefully controlled experimental conditions with isolated objects arranged in a collage, and a real-world scene where multiple objects occur in a natural context. Thus, in contrast to [13] we do not aim for assembling controlled and, to some extent, artificial scenes, but we aim for studying object naming as prompted by real-world images. Therefore, we not only need access to names naturally generated by speakers, but also, we need to be able to quantify those factors whose interaction with naming we want to analyze.

Given a natural scene with multiple objects and a target object that a speaker referred to, we need to be able to answer the following questions:

(1) **Lexical choice:**

Which name did the speaker use to refer to the target object?

(2) **Lexical candidates:** *//cs: "candidate" does not exclude the chosen name in contrast to "alternative"//*

Which names are available for the target objects? And how are they taxonomically related? For instance, if we want to check whether a convertible is more often referred to with a basic-level category (e.g., *car*) or a more specific one (e.g., *convertible*) we need to know that a given object is a CONVERTIBLE, and that CONVERTIBLE is a sub-level concept of CAR (and VEHICLE, etc.). In [13], the authors manually group object names used by speakers in terms of three levels (sub-level, basic-level, super-level). Thus, ideally, lexical candidates would be grouped according to their taxonomic relations.

(3) **Contextual informativeness:**

Which names are available for the other objects in the scene (i.e. distractors)? For instance, when the target is a CONVERTIBLE, we need to know that there are multiple CONVERTIBLES, CARS, etc. to judge whether these concepts are ambiguous.

//cs: Should the following be here or at the beginning of Sect. 4?// //cs: We could also call below requirements "Desiderata"// In practical terms, the prerequisite for Requirements (2) and (3) is, given an image, the information on **R1: the most specific category of each object** which is depicted in the image. A taxonomy, such as WordNet [23], could then be queried with these categories to retrieve their individual lexical candidates arranged by their taxonomic relations.

Furthermore, the information on the **R2: entry-level category** of an object could be used as a pivot to taxonomically group its lexical candidates.

With respect to linguistic data-driven experiments, the range of linguistic phenomena under study (see, e.g., Section 2 for phenomena in object naming) need to be observable in the data in order to study the interaction of their underlying factors. Hence, a further practical requirement is that the data, first, captures ideally all possible combinations of the factor values across all factors¹, and second, that it has been naturally produced in that speakers were not constraint in their choice of a name by external factors. We summarize this requirement by the term **R3: unconstraint**. Note that this requirement XXX *//cs: @Sina ref to bias and paper you mentioned?//*.

4 Resources: What Do We Have?

ImageNet and ILSVRC

¹ For example, data that contains only images where target and distractor objects do not share any lexical candidates would not be appropriate

4.1 RefCOCO and RefCOCO+ [8]

Both datasets are extensions of ReferIt [6], a large-scale collection of referring expressions (RE) for natural objects in real-world images, and are built on top of the MS COCO image collection [?], a dataset of images of natural scenes of 91 common object categories (e.g., DOG, PIZZA, CHAIR). The REs were collected via crowdsourcing in a two-player game, which was designed to obtain REs uniquely referring to the target objects in an image. Specifically, a director and a matcher are presented with an image, and the director produces a RE for an outlined target object in the image. The matcher must click on the object he thinks the RE refers to. If the matcher’s prediction is correct, the RE is considered valid.

Shortcomings REs in RefCOCO and RefCOCO+ were collected under the constraints that (i) all images contain at least two objects of the same category (80 COCO categories), which prompts the players to avoid the mere object category as RE, and (ii) in RefCOCO+ the players must not use location words, urging them to refer to the appearance of objects. Another critical property of the data is that, (iii), not all objects in an image were annotated with REs, may it due to the frequency constraint (i), or due to the object not being part of the 80 COCO categories. Finally, the 80 COCO categories tend to be entry-level categories and are not linked to the ImageNet taxonomy. *//cs: TODO: EX / ANALYSIS//*

- (R1) **Lexical choice:** is mostly met by both data sets, though it is unclear how the additional constraints in RefCOCO+ impact on the naturalness of object naming
- (2) **Lexical candidates:** is not met, as we only have access to basic-level categories and cannot retrieve the most specific category or name for each object
- (3) **Contextual informativeness:** is not met, as not all objects were annotated with REs and corresponding categories

Flickr30k Entities

The Flickr30k Entities dataset [?]² augments Flickr30k, a dataset of 30k images and five sentence-level captions for each of the images, with region-level annotations. Specifically, mentions of the same entities across the five captions of an image are linked to the bounding boxes of the objects they refer to. The dataset was designed to advance image description generation and phrase localization in particular (e.g., [?, ?, ?]).

5 Proposal

² Available at web.engr.illinois.edu/~bplumme2/Flickr30kEntities

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