Object naming on steroids

Anonymous ACL submission

Abstract

1 Introduction

The real-world objects that we interact with in our every-day life can be categorized into many thousands and maybe millions of categories. And even a single object can be member of many categories, i.e. at different taxonomical levels or in different parts of a taxonomy. For instance, both objects in Figure 1 are at once instances of CAKE, CHEESECAKE, DESSERT, SWEET, PASTRY, FOOD etc.

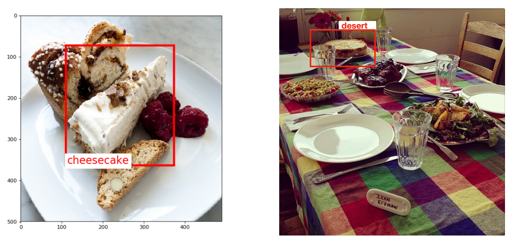

Figure 1: Two objects of the same type of cake, with different names in VisualGenome

Given the abundance of concepts available in language, the act of *naming* a visual object is not just a labeling of visible properties, it amounts to selecting a name from a complex network of concepts and competing lexical alternatives. Hence, research on cognition and language production has relied on object naming as a basic paradigm for investigating the processes that underly formation and organization of concepts in the human mind (Rosch et al., 1976) *//sz: cite more here//*, though mostly using idealized, graphical objects from specific domains (plants, animals) as visual stimuli. Complementary to that, research in computer vision has (successfully) focused on automatically recognizing *real-world* objects in images or videos, but using simplified categorization schemes where each object is assigned a single correct label or name, cf. (Szegedy et al., 2015).

In NLP, to date, research on object naming is relatively scarce despite the fact that there has been a recent explosion of interest in various, and even complex, language & vision tasks ranging from image captioning (Fang et al., 2015; Devlin et al., 2015; Bernardi et al., 2016) to e.g. visual dialogue (Das et al., 2017; De Vries et al., 2017). Massive data collections for applications in language & vision (L&V) are nowadays available and, in principle, these should also constitute an excellent, large-scale test bed for assessing theories such as, e.g. , the claim that objects have a preferred entry-level when being named (Rosch et al., 1976).

The goal of this paper is to extend Visual Genome (Krishna et al., 2016), a well-known, large-scale resource in language & vision research, in a way that it can serve as a broad empirical basis for systematic and linguistically motivated investigations into object naming. We argue that object naming is an interesting, core phenomenon in itself as it occurs in virtually every L&V task, but our approach can also support more systematic analysis of broader tasks, such as e.g. modeling referring expressions.

Even though VisualGenome is one of the most exhaustively annotated resources to date, providing dense object annotations and descriptions in real-world images, it suffers from two important shortcomings if one is interested in linguistic analysis of object naming: First, it only provides a single, manually annotated object description (including a single name) per object which makes it impossible to assess how representative the annotated naming choices are, e.g. whether speakers tend to generally prefer *cheesecake* for the highlighted object in Figure 1. Second, it does not provide consistent taxonomic information on objects and their categories, as names have been automatically linked to WordNet synsets. This makes it difficult to assess how naming depends on the taxonomic properties of the object, e.g. that both objects in Figure 1 are instances of CHEESECAKE, but one is named *cheesecake* and the other one is named *desert*. It is important to note here that these shortcomings exist for basically all large-scale resources currently used in L &V research (see Section 2 below).

In this work, we address these two shortcomings and present a crowdsourcing-based and light-weight experimental set-up for eliciting representative and taxonomically consistent (*//sz: more complete?//*) naming data. We compare our collected data against names annotated in Visual Genome, and calculate various measures assessing agreement, naming preferences etc.

The main idea is to elicit names in (i) in a standard naming task (phase 0) where participants simply give the most straightforward name to an object they can immediately think of, and then in (ii) a taboo-like naming task where frequent names collected initially are blocked and participants have to provide alternative names. We show that this simple, two-stage approach gives us taxonomically rich data that allows us to study object naming empirically, without adopting costly annotation procedures involving complex hierarchical object annotation schemes.

2 Related Work

Cognition: Concepts and categorization 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*) (Rosch et al., 1976), 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*) (Jolicoeur, 1984). 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 in their choice of the level of specificity. Scenarios where multiple objects (of the same category) are present induce a pressure for generating names which uniquely identify the target (Olson, 1970), such that sub-level names can be systematically elicited in these cases (Rohde et al., 2012; Graf et al., 2016).

Vision: Object Recognition State-of-the-art computer vision systems are able to classify images into thousands of different categories (e.g. Szegedy et al. (2015)). These object recognition systems are now widely used in vision & language research. Nevertheless, the way the treat object recognition is conceptually very simple (if not to say, naive): standard object classification schemes are inherently "flat", and treat object labels as mutually exclusive (Deng et al., 2014), ignoring all kinds of linguistic relations between these labels and ignoring the fact that an object can easily be an instance of several categories.*//cs: I would make this statement stronger and argue that* ***object recognition is merely a labeling of objects with human interpretable symbols****, and that a system would probably fail if it had to decide whether an object labeled as, e.g. fig may also be labeled as food.//*

Vision & language: Naming and Referring Ordonez et al. (2016) have studied the problem of deriving appropriate object names, or so-called entry-level categories, from the output of an object recognizer. Their approach focusses on linking abstract object categories in ImageNet to actual words via translation procedures that e.g. involve corpus frequencies. Zarrieß and Schlangen (2017) learn a model of object naming on a corpus of referring expressions paired with objects in real-world images, but focus on combining visual and distributional information and on zero-shot learning. Thus, object naming is an important task for referring expression generation, though most research in this area has focussed on content and attribute selection (Kazemzadeh et al., 2014; Gkatzia et al., 2015; Zarrieß and Schlangen, 2016; Mao et al., 2015).

Existing resources and their shortcomings Moreover, existing resources in L&V hardly provide any consistent taxonomic information on objects and their categories, e.g. object labels are typically quite general as in Flickr30k (Plummer et al., 2015, e.g., PEOPLE, ANIMALS, BODYPARTS, CLOTHING) or taxonomically heterogeneous as in MS COCO (Lin et al., 2014, e.g., PEOPLE, BASEBALL GLOVE, BIRD).

3 Data Collection

describe the task here

3.1 Materials

describe sampling of images, category selection

Table with:

- rows: domains (if we go for long paper: then one row per collection node?)
- columns:
  1. # collection nodes
  2. collection nodes (list)
  3. # unique VG names
  4. example VG names
  5. # unique objects
  6. # unique images (? not sure if necessary; maybe only one of unique objects, images)

3.2 Procedure

describe the crowdsourcing set-up and the task

3.3 Data

give an overview of the collected data

4 Analysis

//gb: Note: the structure below is not supposed to be the one in the paper; it was the easiest way for me to plan the analysis a bit//

4.1 Agreement, basic-level and entry-level names

analyse data from Phase 0

Items:

- to what extent do people agree when their task is to give the most straightforward name they can think of to a visual object? (see 4.1.1)
- is the level of agreement the same for all categories? (see 4.1.1)
- how specific are the most familiar names? link names to WordNet, show that WordNet might not be ideal to assess specificity
- assess how representative name annotations in Visual Genome are, when compared to our names (see 4.1.2)

4.1.1 Agreement: Snowgrad's measure

Note: I (Gemma) will use three levels of analysis: ALL (all data lumped together), DOMAIN (Gemma's reorganization of Carina's "supercategories"; see doc 0_object_naming_taboo), COLLECTION NODE (Carina's "synset / collection node").

Plans for analysis (then we see what to put in the paper):

1. compute snowgrad measure and do a:
   - histogram ALL
   - boxplot by DOMAIN
   - dataframe with mean and sd by COLLECTION NODE

   → This will tell us how much agreement there is among subjects about how to name objects in general and within each domain/"subcategory".
2. can we find generalizations about tendencies in agreement? (open: how to go about it)

4.1.2 How representative are VG names?

Compute the most frequent name for each image and see how often that name coincides with the one given by the VG annotator.

4.2 Cases of disagreement

when and why do people give different names to the same object? this will probably happen in phase 0, and even more so in the later round *//sz: this is what I expect//*

//gb: Maybe we can fuse this analysis with the one in the next subsection (taxonomic relations). The way I would put it is, instead of disagreement and taxonomy, "sources of variation"//

- analyse naming disagreement using WordNet, how do names for the same object relate to each other according to WordNet?Overarching question:
- can we identify instances of cross-classification? so objects that are systematically part of several classes (e.g. cake/dessert)
- *//cs: Wrt points 1+2: Show that WordNet, again, is not ideal for retrieving all possible names of an object from a single synset.//*

- we might need to do some manual annotation here and try to carefully describe the phenomena

4.3 Taxonomic relations

can we elicit natural sub-ordinate, super-ordinate concepts?

5 Conclusion

We have presented a systematic, large-scale study on object naming with real-world images and crowdsourced data.

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