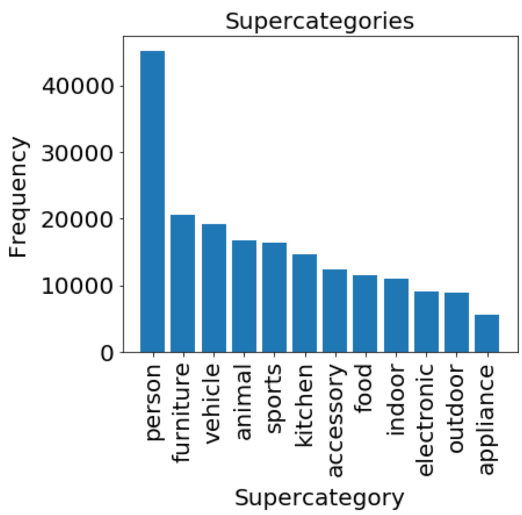
Object-Based Summary

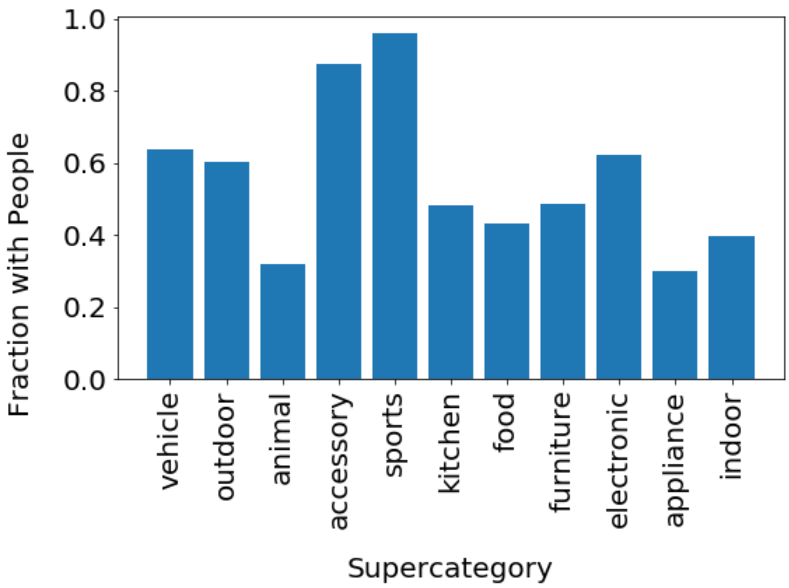
Overview Statistics

(M0) Distribution of object categories that appear in dataset.

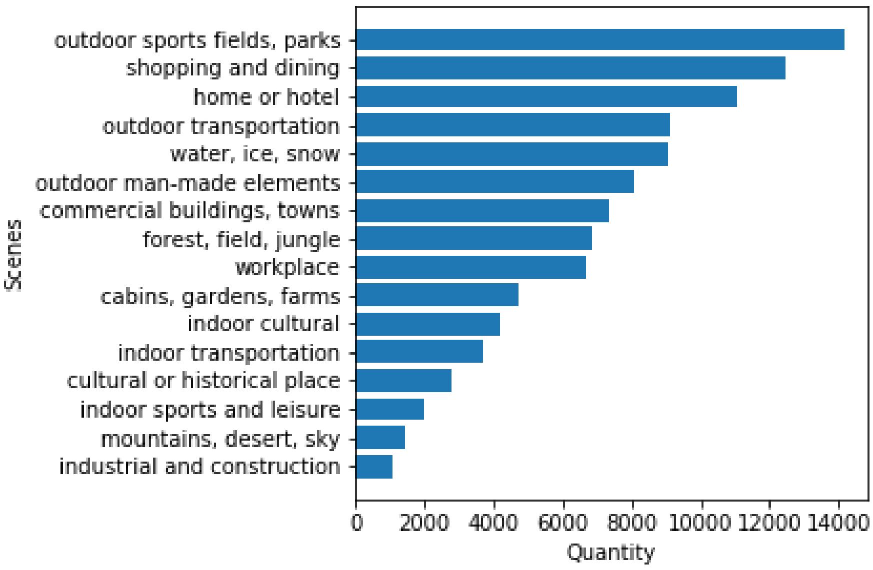


Not all datasets contain supercategories like these that the objects are sorted into, so if these statistics are wanted, manual labeling may be required.

(M8) Distribution of how often object categories are represented with people.

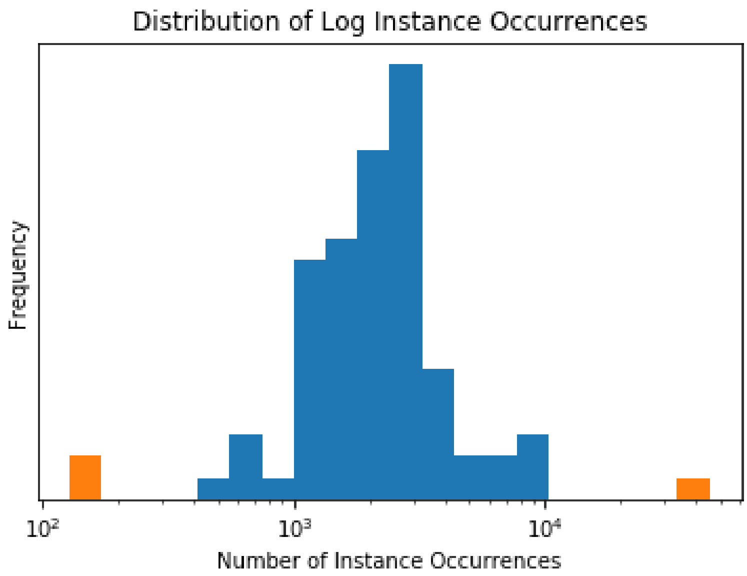


(M9) Distribution of scenes that appear in dataset.

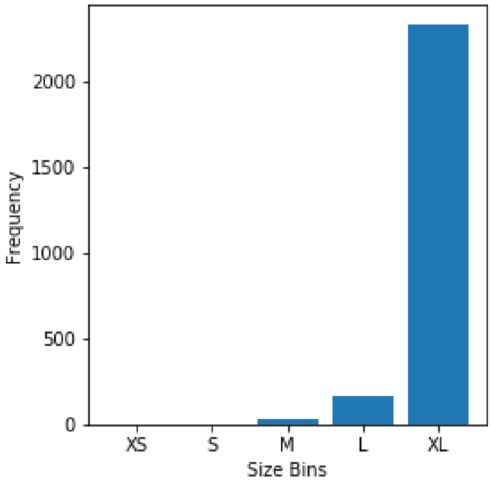


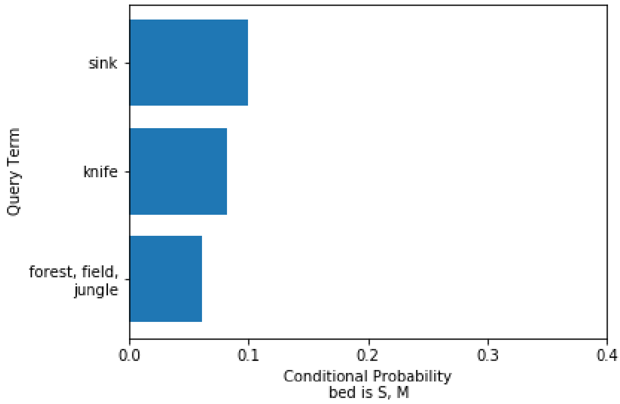
Sample Interesting Findings

(M0) The outliers shown on the graph for instance count are:
person: 45174
toaster: 151
hair drier: 128



(M7) bed has the least uniform size distribution.
Shown below is the size distribution for this object, what kinds of pairwise queries are recommended to augment the dataset for more uniform sizing, and qualitative examples of these pairs.
Pairwise queries take the form of "[Object 1] + [Object 2]"





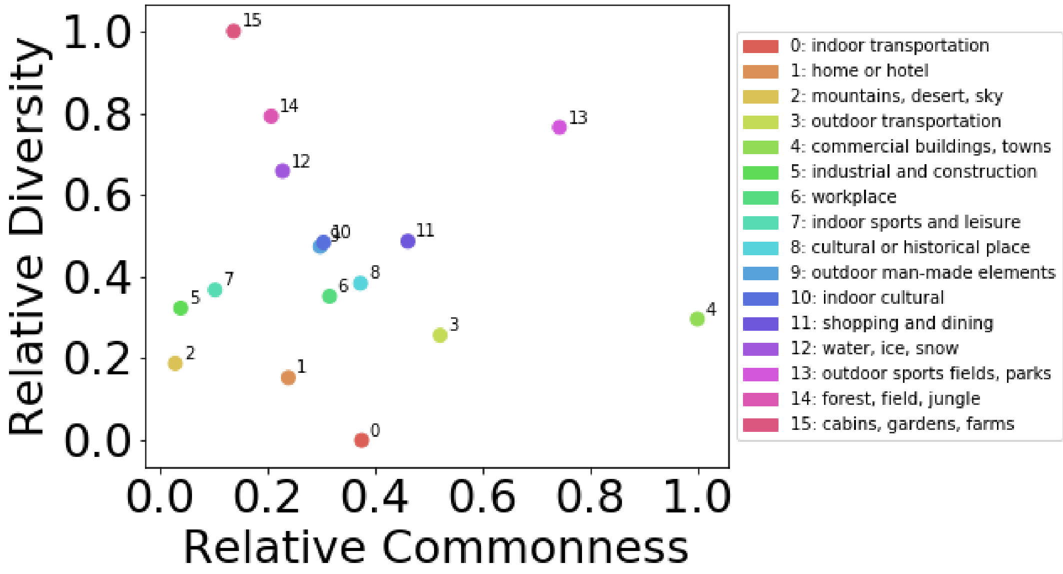
These pairwise queries are generated automatically based on cooccurrences in the dataset, which may not be representative of real-world cooccurrences, and scene classification, which may not always be accurate. This leaves it up to the user to ultimately decide which pairwise queries actually make the most sense. For example, trying to collect images of smaller beds by querying for them in the “forest, field, jungle” scenes may not make the most sense.

(M8) The strongest deviations of an object from its category being represented with people. The first fraction is this object's representation with people, and the second is the object category's:

toilet is underrepresented with people within furniture: 0.12, 0.49
horse is overrepresented with people within animal: 0.68, 0.32
chair is overrepresented with people within furniture: 0.64, 0.49
airplane is underrepresented with people within vehicle: 0.35, 0.64

Human judgment is required to determine whether these are actually problematic; for example, we might actually be happy toilets are imaged with people less than other furniture.

(M9) An example of how to diversify the appearance diversity of the "accessory" category by augmenting the dataset with images in different scenes. Appearance diversity can thought of as something like intra-class variation, which is an important feature for object detection. However, there is a tradeoff between the amount of appearance diversity an object in a particular scene brings, and how common this object-scene combination is, which contributes to how easy it is to collect this kind of image.



From looking at this, it appears as if collecting more images of appliances from the “outdoor sports fields, parks” scene would be the best balance of increasing the appearance diversity without having too obscure of an object-scene combination to find.

Some of the other metrics in the notebook

- (M0) Cooccurrences of objects as a hierarchical graph
- (M0) Finer grained look at distribution within each object category
- (M7) Size of each object category
- (M9) Qualitative look at what each object's scenes are like
- (M9) Highest/lowest cooccurrences between object categories and scenes