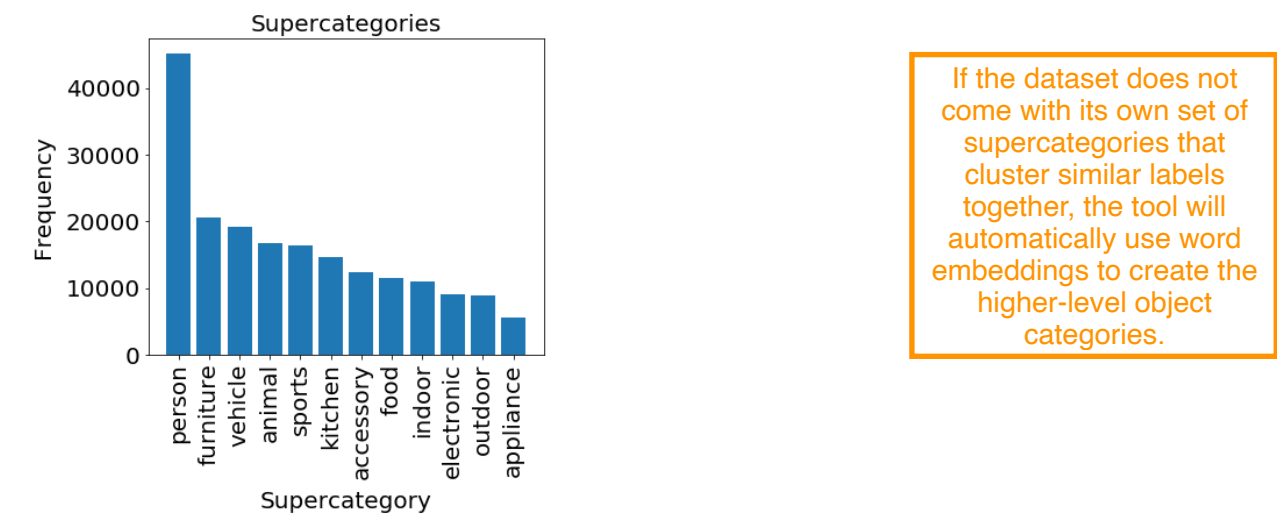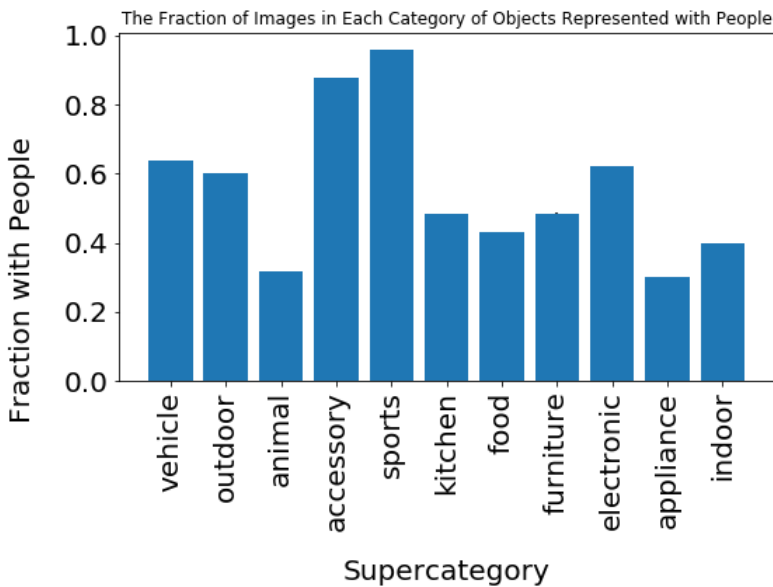# Object-Based Summary

Overview Statistics
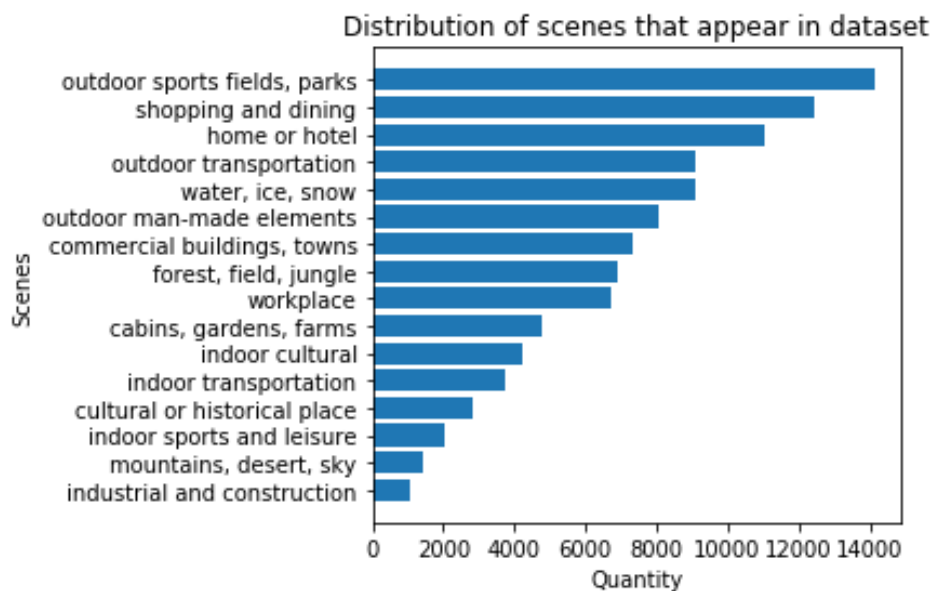
(obj_cnt) Distribution of object categories that appear in dataset.

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

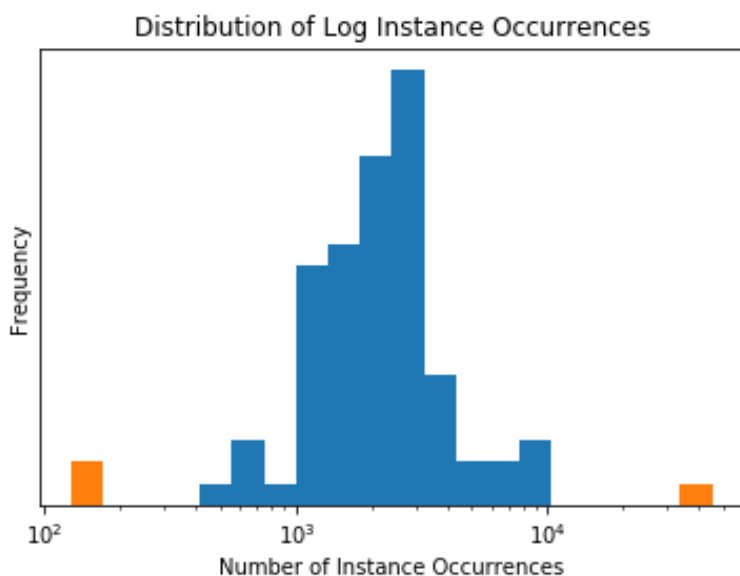
(obj_scn) Distribution of scenes that appear in dataset.

Distribution of scenes that appear in dataset

Sample Interesting Findings

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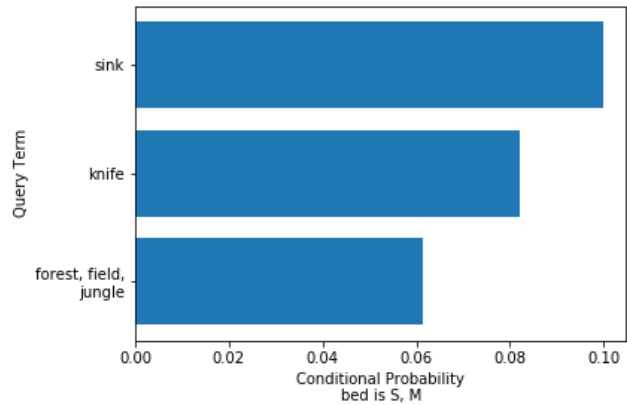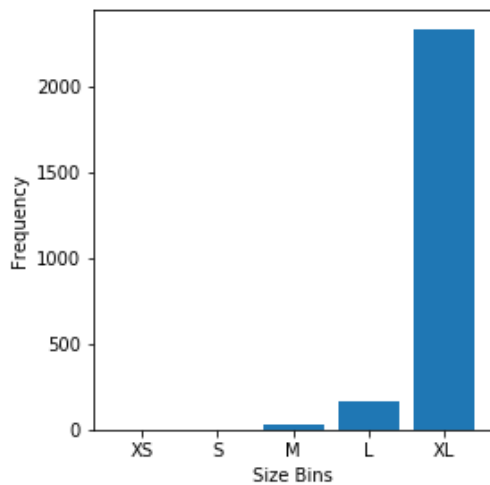person: 45174
toaster: 151
hair drier: 128

(obj_siz) 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]"

(obj_ppl) 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:
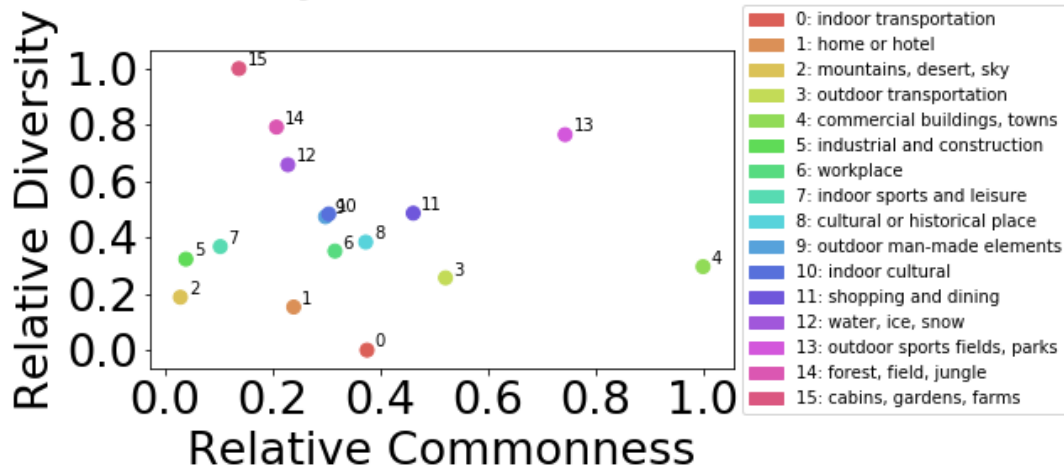
- HORSE is overrepresented with people within ANIMAL: 0.68, 0.32
- CHAIR is overrepresented with people within FURNITURE: 0.64, 0.49
- CELL PHONE is overrepresented with people within ELECTRONIC: 0.8, 0.62
- BICYCLE is overrepresented with people within VEHICLE: 0.83, 0.64

- TOILET is underrepresented with people within FURNITURE: 0.12, 0.49
- AIRPLANE is underrepresented with people within VEHICLE: 0.35, 0.64
- MOUSE is underrepresented with people within ELECTRONIC: 0.25, 0.62
- KEYBOARD is underrepresented with people within ELECTRONIC: 0.29, 0.62

(obj_scn) 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.

accessory scene contributions

0: indoor transportation	
1: home or hotel	
2: mountains, desert, sky	
3: outdoor transportation	
4: commercial buildings, towns	
5: industrial and construction	
6: workplace	
7: indoor sports and leisure	
8: cultural or historical place	
9: outdoor man-made elements	
10: indoor cultural	
11: shopping and dining	
12: water, ice, snow	
13: outdoor sports fields, parks	
14: forest, field, jungle	
15: cabins, gardens, farms	

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

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