

From ImageNet to Image Classification: Contextualizing Progress on Benchmarks

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Abstract

Building rich machine learning datasets in a scalable manner often necessitates a crowd-sourced data collection pipeline. In this work, we use human studies to investigate the consequences of employing such a pipeline, focusing on the popular ImageNet dataset. We study how specific design choices in the ImageNet creation process impact the fidelity of the resulting dataset—including the introduction of biases that state-of-the-art models exploit. Our analysis pinpoints how a noisy data collection pipeline can lead to a systematic misalignment between the resulting benchmark and the real-world task it serves as a proxy for. Finally, our findings emphasize the need to augment our current model training and evaluation toolkit to take such misalignments into account.¹

1 Introduction

Large-scale vision datasets and their associated benchmarks [Eve+10; Den+09; Lin+14; Rus+15] have been instrumental in guiding the development of machine learning models [KSH12; Sze+16; He+16]. At the same time, while the progress made on these benchmarks is undeniable, they are only proxies for real-world tasks that we actually care about—e.g., object recognition or localization in the wild. Thus, it is natural to wonder:

How aligned are existing benchmarks with their motivating real-world tasks?

On one hand, significant design effort goes towards ensuring that these benchmarks accurately model real-world challenges [Pon+06; TE11; Eve+10; Rus+15]. On the other hand, the sheer size of machine learning datasets makes meticulous data curation virtually impossible. Dataset creators thus resort to scalable methods such as automated data retrieval and crowd-sourced annotation [Eve+10; Rus+15; Lin+14; Zho+17], often at the cost of faithfulness to the task being modeled. As a result, the dataset and its corresponding annotations can sometimes be ambiguous, incorrect, or otherwise misaligned with ground truth (cf. Figure 1). Still, despite our awareness of these issues [Rus+15; Rec+19; Hoo+19; NJC19], we lack a precise characterization of their pervasiveness and impact, even for widely-used datasets.

Our contributions

We develop a methodology for obtaining fine-grained data annotations via large-scale human studies. These annotations allow us to precisely quantify ways in which typical object recognition benchmarks fall short of capturing the underlying ground truth. We then study how such *benchmark-task misalignment* impacts

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¹To facilitate further research, we release our refined ImageNet annotations at <https://github.com/MadryLab/ImageNetMultiLabel>.

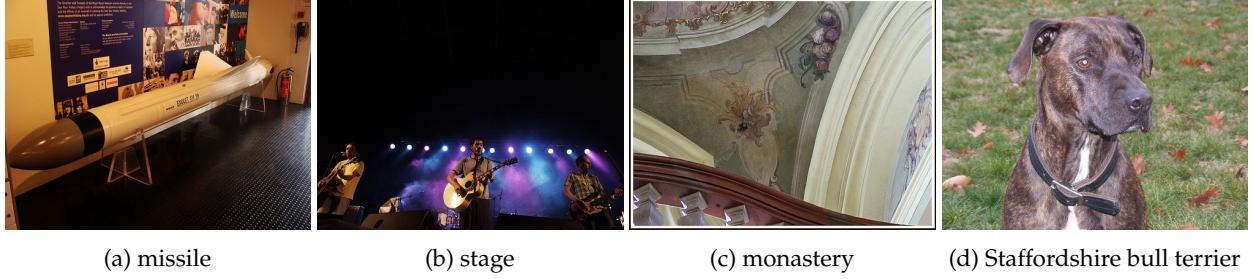


Figure 1: Judging the correctness of ImageNet labels may not be straightforward. While the labels shown above appear valid for the corresponding images, *none* of them actually match the ImageNet labels (which are “projectile”, “acoustic guitar”, “church”, and “American Staffordshire terrier”, respectively).

state-of-the-art models—after all, models are often developed in a way that treats existing datasets as the ground truth. We focus our exploration on the ImageNet dataset [Den+09] (specifically, the ILSVRC2012 object recognition task [Rus+15]), one of the most widely used benchmarks in computer vision.

Quantifying benchmark-task alignment. We find that systematic annotation issues pervade ImageNet, and can often be attributed to design choices in the dataset collection pipeline itself. For example, during the ImageNet labeling process, annotators were not asked to classify images, but rather to validate a specific automatically-obtained candidate label without knowledge of other classes in the dataset. This leads to:

- *Multi-object images* (Section 4.1): Each image in ImageNet is associated with a single label. Yet, we find that more than one fifth of ImageNet images contain objects from *multiple* classes. In fact, the ImageNet label often does not even correspond to what humans deem the “main object” in the image. Nevertheless, models still achieve significantly-better-than-chance prediction performance on these images, indicating that they must exploit idiosyncrasies of the dataset that humans are oblivious to.
 - *Bias in label validation* (Section 4.2): Even when there is only one object in an image, collectively, annotators often end up validating several mutually exclusive labels. These correspond, for example, to images that are ambiguous or difficult to label, or instances where two or more classes have synonymous labels. The ImageNet label in these cases is determined not by annotators themselves, but rather by the fidelity of the automated image retrieval process. In general, given that annotators are ineffective at filtering out errors under this setup, the automated component of the data pipeline may have a disproportionate impact on the quality of ImageNet annotations.

More broadly, these issues point an inherent tension between the goal of building large-scale benchmarks that are realistic and the scalable data collection pipelines needed to achieve this goal. Hence, for benchmarks created using such pipelines, the current standard for model evaluation—accuracy with respect to a single, fixed dataset label—may be insufficient to correctly judge model performance.

Human-based performance evaluation. In light of this, we use our annotation pipeline to more directly measure human-model alignment. We find that more accurate ImageNet models also make predictions that annotators are more likely to agree with. In fact, we find that models have reached a level where non-expert annotators are largely unable to distinguish between predicted labels and ImageNet labels (i.e., even model predictions that don't match the dataset labels are often judged valid as by annotators). While reassuring, this finding highlights a different challenge: non-expert annotations may no longer suffice to tell apart further progress from overfitting to idiosyncrasies of the ImageNet distribution.

2 A Closer Look at the ImageNet Dataset

We start by briefly describing the original ImageNet data collection and annotation process. As it turns out, several—seemingly innocuous—details of this process have a significant impact on the resulting dataset.

The ImageNet creation pipeline. ImageNet is a prototypical example of a large-scale dataset (1000 classes and more than million images) created through automated data collection and crowd-sourced filtering. At a high level, this creation process comprised two stages [Den+09]:

1. *Image and label collection:* The ImageNet creators first selected a set of classes using the WordNet hierarchy [Mil95]. Then, for each class, they sourced images by querying several search engines with the WordNet synonyms of the class, augmented with synonyms of its WordNet parent node(s). For example, the query for class “whippet” (parent: “dog”) would also include “whippet dog” [Rus+15]. To further expand the image pool, the dataset creators also performed queries in several languages. Note that for each of the retrieved images, the label—which we will refer to as the *proposed label*—that will be assigned to this image should it be included in the dataset, is already determined. That is, the label is simply given by the WordNet node that was used for the corresponding search query.
2. *Image validation via the CONTAINS task.* To validate the image-label pairs retrieved in the previous stage, the ImageNet creators employed annotators via the Mechanical Turk (MTurk) crowd-sourcing platform. Specifically, for every class, annotators were presented with its description (along with links to the relevant Wikipedia pages) and a grid of candidate images. Their task was then to select all images in that grid that contained an object of that class (with *explicit* instructions to ignore clutter and occlusions). The grids were shown to multiple annotators and only images that received a “convincing majority” of votes (based on per-class thresholds estimated using a small pool of annotators) were included in ImageNet. In what follows, we will refer to this filtering procedure as the *CONTAINS* task.

Revisiting the ImageNet labels

The automated process described above is a natural method for creating a large-scale dataset, especially if it involves a wide range of classes (as is the case for ImageNet). However, even putting aside occasional annotator errors, the resulting dataset might not accurately capture the ground truth (see Figure 1). Indeed, as we discuss below, this pipeline design itself can lead to certain *systematic* errors in the dataset. The root cause for many of these errors is that the image validation stage (i.e., the *CONTAINS* task) asks annotators only to verify if a *specific* proposed label (i.e., WordNet node for which the image was retrieved), shown in isolation, is valid for a given image. Crucially, annotators are never asked to choose among different possible labels for the image and, in fact, have no knowledge of what the other classes even are. This can introduce discrepancies in the dataset in two ways:

Images with multiple objects. Annotators are instructed to *ignore* the presence of other objects when validating a particular ImageNet label for an image. However, these objects could themselves correspond to other ImageNet classes. This can lead to the selection of images with multiple valid labels or even to images where the dataset label does not correspond to the most prominent object in the image.

Biases in image filtering. Since annotators have no knowledge of what the other classes are, they do not have a sense of the granularity of image features they should pay attention to (e.g., the labels in Figure 1 appear reasonable until one becomes aware of the other possible classes in ImageNet). Moreover, the task itself does not necessary account for their expertise (or the lack of thereof). Indeed, one cannot reasonably expect non-experts to distinguish, e.g., between all the 24 terrier breeds that are present in ImageNet. As a result, if annotators are shown images containing objects of a different, yet similar class, they are likely to select them as valid. This implies that potential errors in the collection process (e.g., automated search retrieving images that do not match the query label) are unlikely to be corrected during validation (via the *CONTAINS* task) and thus can propagate to the final dataset.

In the light of the above, it is clear that eliciting ground truth information from annotators using the ImageNet creation pipeline may not be straightforward. In the following sections, we present a framework for improving this elicitation (by bootstrapping from and refining the existing labels) and then use that framework to investigate the discrepancies highlighted above (Section 3) and their impact on ImageNet-trained models (Section 4).

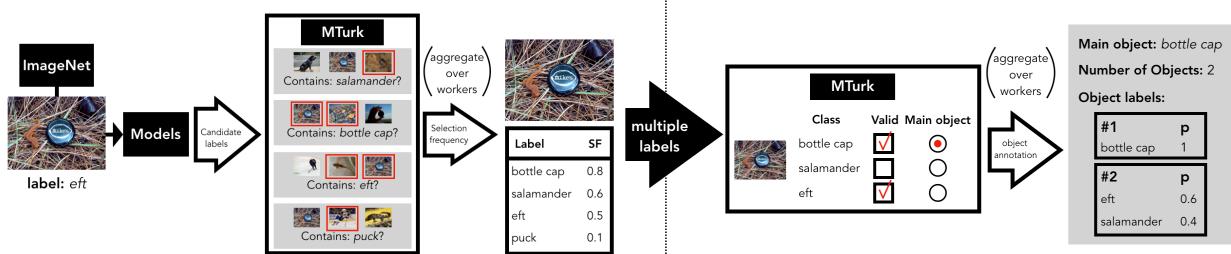


Figure 2: Overview of our data annotation pipeline. First, we collect a pool of potential labels for each image using the top-5 predictions of multiple models (Section 3.1). Then, we ask annotators to gauge the validity of each label (in isolation) using the `CONTAINS` task (described in Section 2). Next, we present all highly selected labels for each image to a new set of annotators and ask them to select *one* label for every distinct object in the image, as well as a label for the main object according to their judgement, i.e., the `CLASSIFY` task (Section 3.2). Finally, we aggregate their responses to obtain fine-grained image annotations (Section 3.2).

3 From Label Validation to Image Classification

We begin our study by obtaining a better understanding of the ground truth for ImageNet data. To achieve this, rather than asking annotators to *validate* a single proposed label for an image (as in the original pipeline), we would like them to *classify* the image, selecting *all* the relevant labels for it. However, asking (untrained) annotators to choose from among all 1,000 ImageNet classes is infeasible.

To circumvent this difficulty, our pipeline consists of two phases, illustrated in Figure 2. First, we obtain a small set of (potentially) relevant *candidate labels* for each image (Section 3.1). Then, we present these labels to annotators and ask them to select one of them for *each* distinct object using what we call the `CLASSIFY` task (Section 3.2). These phases are described in more detail below, with additional information in Appendix B.

For our analysis, we use 10,000 images from the ImageNet validation set—i.e., 10 randomly selected images per class. Note that since both ImageNet training and ImageNet validation sets were created using the same procedure, analyzing the latter is sufficient to understand systematic issues in that dataset.

3.1 Obtaining candidate labels

To ensure that the per-image annotation task is manageable, we narrow down the candidate labels to a small set. To this end, we first obtain *potential labels* for each image by simply combining the top-5 predictions of 10 models from different parts of the accuracy spectrum with the existing ImageNet label (yields approximately 14 labels per image; cf. Appendix Figure 13). Then, to prune this set further, we reuse the ImageNet `CONTAINS` task—asking annotators whether an image contains a particular class (Section 2)—but for *all* potential labels. The outcome of this experiment is a *selection frequency* for each image-label pair, i.e., the fraction of annotators that selected the image as containing the corresponding label.² We find that, although images were often selected as valid for many labels, relatively few of these labels had high selection frequency (typically less than five per image). Thus, restricting potential labels to this smaller set of *candidate labels* allows us to hone in on the most likely ones, while ensuring that the resulting annotation task is still cognitively tractable.

3.2 Image classification via the `CLASSIFY` task

Once we have identified a small set of candidate labels for each image, we present them to annotators to obtain fine-grained label information. Specifically, we ask annotators to identify: (a) *all* labels that correspond to objects in the image, and (b) the label for the *main object* (according to their judgment). Crucially, we explicitly instruct annotators to select *only one label per distinct object*—i.e., in case they are confused about the correct label for a specific object, to pick the one they consider most likely. Moreover, since ImageNet

²Note that this notion of selection frequency (introduced by Recht et al. [Rec+19]) essentially mimics the majority voting process used to create ImageNet (cf. Section 2), except that it uses a fixed number of annotators per grid instead of the original adaptive process.

contains classes that could describe parts or attributes of a single physical entity (e.g., "car" and "car wheel"), we ask annotators to treat these as distinct objects, since they are not mutually exclusive. We present each image to multiple annotators and then aggregate their responses (per-image) as described below. In the rest of the paper, we refer to this annotation setup as the *CLASSIFY* task.

Identifying the main label and number of objects. From each annotator's response, we learn what they consider to be the label of the main object, as well as how many objects they think are present in the image. By aggregating these two quantities based on a majority vote over annotators, we can get an estimate of the number of objects in the image, as well as of the main label for that image.

Partitioning labels into objects. Different annotators may choose different labels for the same object and thus we need to map their selections to a single set of distinct objects. To illustrate this, consider an image of a soccer ball and a terrier, where one annotator has selected "Scotch terrier" and "soccer ball" and another "Toy terrier" and "soccer ball". We would like to partition these selections into objects as ["soccer ball"] and ["Scotch terrier" or "Toy terrier"] since both responses indicate that there are two objects in the image and that the soccer ball and the terrier are distinct objects. More generally, we would like to partition selections in a way that avoids grouping labels together if annotators identified them as distinct objects. To this end, we employ exhaustive search to find a partition that optimizes for this criterion (since there exist only a few possible partitions to begin with). Finally, we label each distinct object with its most frequently selected label.

The resulting annotations characterize the content of an image in a more fine-grained manner compared to the original ImageNet labels. Note that these annotations may still not perfectly match the ground truth. After all, we also employ untrained, non-expert annotators, that make occasional errors, and moreover, some images are inherently ambiguous without further context (e.g., Figure 1c). Nevertheless, as we will see, these annotations are already sufficient for our examination of ImageNet.

4 Quantifying the Benchmark-Task Alignment of ImageNet

Our goal in this section is two-fold. First, we would like to examine potential sources of discrepancy between ImageNet and the motivating object recognition task, using our refined image annotations.³ Next, we want to assess the impact these deviations have on models developed using this benchmark. To this end, we will measure how the accuracy of a diverse set of models (see Appendix A.2 for a list), is affected when they are evaluated on different sets of images.

4.1 Multi-object images

We start by taking a closer look at images which contain objects from more than one ImageNet class—how often these additional objects appear and how salient they are. (Recall that if two labels are both simultaneously valid for an image—i.e., they are not mutually exclusive—we refer to them as different objects (e.g., "car" and "car wheel").) In Figure 3a, we observe that a significant fraction of images—more than a fifth—contains *at least two* objects. In fact, there are pairs of classes which *consistently co-occur* (see Figure 3b). This indicates that multi-object images in ImageNet are not caused solely by irrelevant clutter, but also due to systemic issues with the class selection process. Even though ImageNet classes, in principle, correspond to distinct objects, these objects overlap greatly in terms of where they occur in the real-world.

Model accuracy on multi-object images. Model performance is typically measured using (top-1 or top-5) accuracy with respect to a *single* ImageNet label, treating it as the ground truth. However, it is not clear what the right notion of ground truth annotation even is when classifying multi-object images. Indeed, we find that models perform significantly worse on multi-label images based on top-1 accuracy (measured w.r.t. ImageNet labels): accuracy drops by more than 10% across all models—see Figure 4a. In fact, we observe in Appendix Figure 21 that model accuracy is especially low on certain classes that systematically co-occur.

³Our primary focus is on studying systematic issues in ImageNet. Thus we defer discussing clear mislabelings to Appendix C.3.

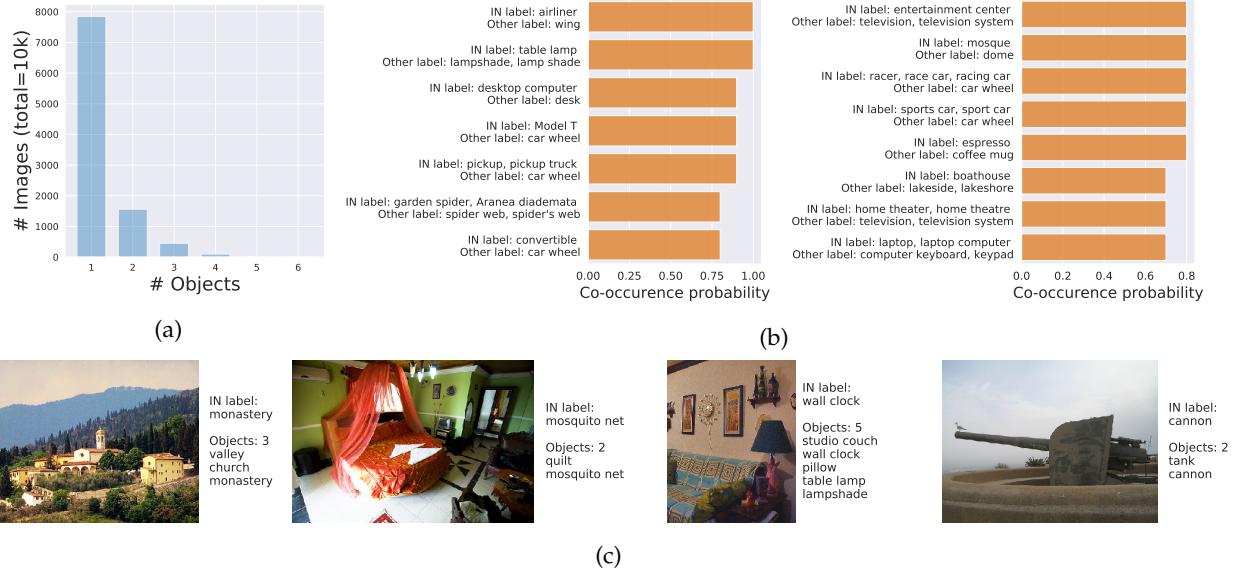


Figure 3: (a) Number of objects per image—more than a fifth of the images contains two or more objects from ImageNet classes. (b) Pairs of classes which consistently co-occur as distinct objects. Here, we visualize the top 15 ImageNet classes based on how often their images contain another *fixed* object (“Other label”). (c) Random examples of multi-label ImageNet images (cf. Appendix Figure 17 for additional samples).

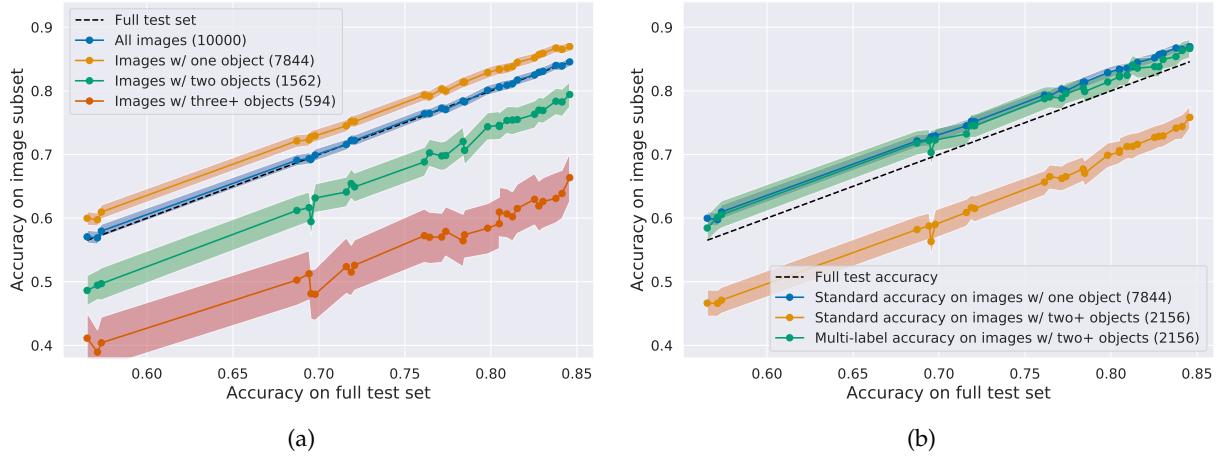


Figure 4: (a) Top-1 model accuracy on multi-object images (as a function of overall test accuracy). Accuracy drops by roughly 10% across all models. (b) Evaluating multi-label accuracy on ImageNet: the fraction of images where the model predicts the label of *any* object in the image. Based on this metric, the performance gap between single- and multi-object images virtually vanishes. Confidence intervals: 95% via bootstrap.

In light of this, a more natural notion of accuracy for multi-object images would be to consider a model prediction to be correct if it matches the label of *any* object in the image. On this metric, we find that the aforementioned performance drop essentially disappears—models perform similarly on single- and multi-object images (see Figure 4b). This indicates that the way we typically measure accuracy, i.e., with respect to a single label, can be overly pessimistic, as it penalizes the model for predicting the label of another valid object in the image. Note that while evaluating top-5 accuracy also accounts for most of these multi-object confusions (which was after all its original motivation [Rus+15]), it tends to inflate accuracy on *single object* images, by treating several erroneous predictions as valid (cf. Appendix C.1).

Human-label disagreement. Although models suffer a sizeable accuracy drop on multi-object images, they are still relatively good at predicting the ImageNet label—much better than the baseline of choosing the label of one object at random. This bias could be justified whenever there is a distinct main object in the image and it corresponds to the ImageNet label. However, we find that for nearly a third of the multi-object images, the ImageNet label *does not* denote the most likely main object as judged by human annotators—see Figure 5. Nevertheless, model accuracy (w.r.t. the ImageNet label) on these images is still high—see Figure 6a.

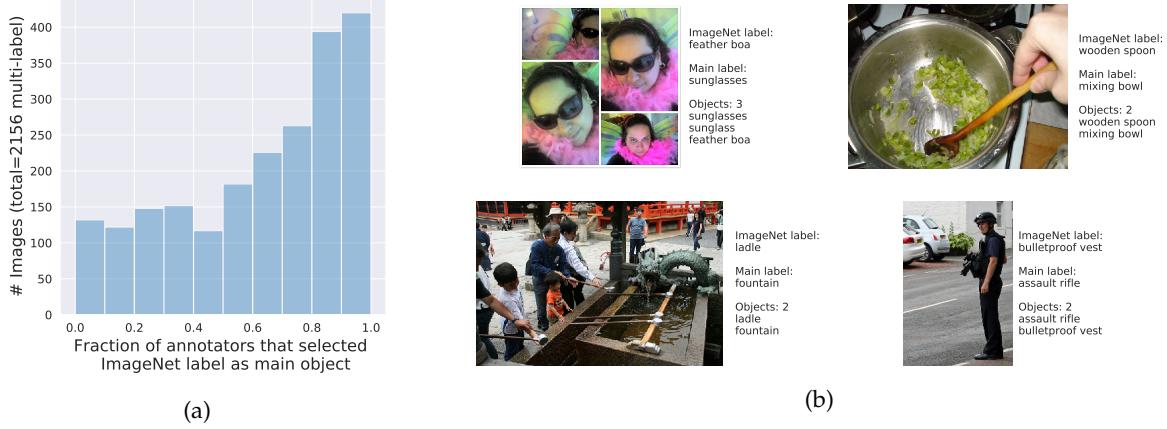


Figure 5: (a) Fraction of annotators that selected the ImageNet label as denoting the main image object. For 650 images (out of 2156 multi-object images), the majority of annotators select a label *other* than the ImageNet one as the main object. (b) Random examples of images where the main label as per annotators contradicts the ImageNet label (cf. Appendix Figure 19 for additional samples).

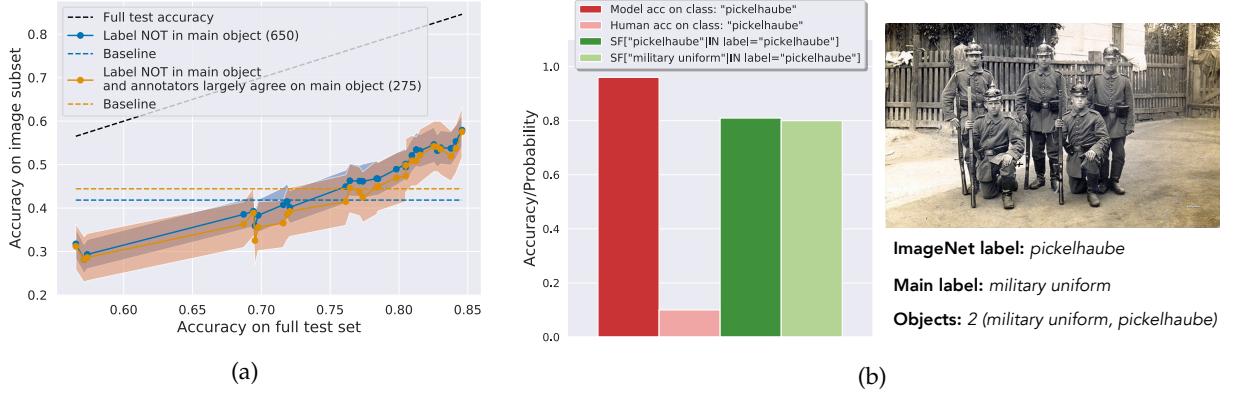


Figure 6: (a) Model accuracy on images where the annotator-selected main object does not match the ImageNet label. Models perform much better than the baseline of randomly choosing one of the objects in the image (dashed line)—potentially by exploiting dataset biases. (b) Example of a class where humans disagree with the label as to the main object, yet models still predict the ImageNet label. Here, for images of that class, we plot both model and annotator accuracy as well as the selection frequency (SF) of both labels.

On these samples, models must base their predictions on some features that humans do not consider salient. For instance, we find that these disagreements often arise when the ImageNet label corresponds to a very distinctive object (e.g., “*pickelhaube*”), but the image also contain another more prominent object (e.g., “*military uniform*”)—see Figure 6b. To do well on these classes, the model likely picks up on ImageNet-specific biases, e.g., detecting that military uniforms often occur in images of class “*pickelhaube*” but not vice versa. While this might be a valid strategy for improving ImageNet accuracy (cf. Appendix Figure 20), it causes models to rely on features that may not generalize to the real-world.

4.2 Bias in label validation

We now turn our attention to assessing the quality of the ImageNet filtering process discussed in Section 2. Our goal is to understand how likely annotators are to detect incorrect samples during the image validation process. Recall that annotators are asked a somewhat leading question, of whether a specific label is present in the image, making them prone to answering positively even for images of a different, yet similar, class.

Indeed, we find that, under the original task setup (i.e., the `CONTAINS` task), annotators consistently select multiple labels, *in addition to* the ImageNet label, as being valid for an image. In fact, for nearly 40% of the images, another label is selected *at least as often* as the ImageNet label (cf. Figure 7). Moreover, this phenomenon does not occur only when multiple objects are present in the image—even when annotators perceive a single object, they often select as many as 10 classes (cf. Figure 8a). Thus, even for images where a single ground truth label exists, the ImageNet validation process may fail to elicit this label from annotators.⁴

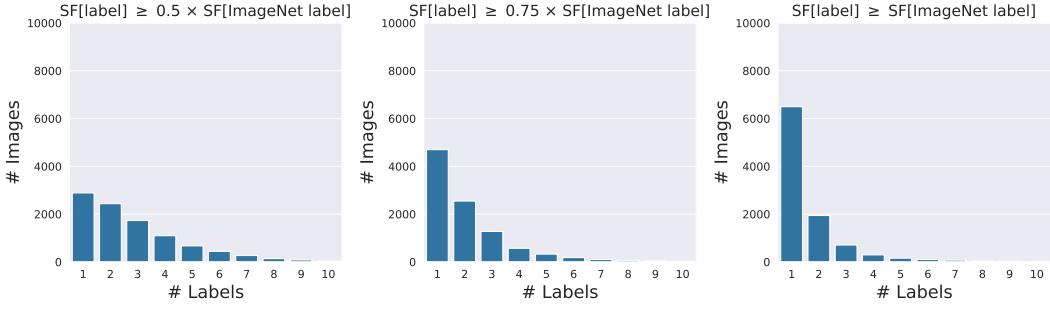


Figure 7: Number of labels per image that annotators selected as valid in isolation (determined by the selection frequency of the label relative to that of the ImageNet label). For more than 70% of images, annotators select another label at least half as often as they select the ImageNet label (*leftmost*).

In fact, we find that this confusion is not just a consequence of using non-expert annotators, but also of the `CONTAINS` task setup itself. If instead of asking annotators to judge the validity of a specific label(s) in isolation, we ask them to choose the main object among several possible labels simultaneously (i.e., via the `CLASSIFY` task), they select substantially fewer labels—see Figure 8b.

These findings highlight how sensitive annotators are to the data collection and validation pipeline setup, even to aspects of it that may not seem significant at first glance. It also indicates that the existing ImageNet annotations may not have been vetted as carefully as one might expect. ImageNet annotators might have been unable to correct certain errors, and consequently, the resulting class distributions may be determined, to a large extent, by the fidelity (and biases) of the automated image retrieval process.

Confusing class pairs. We find that there are several pairs of ImageNet classes that annotators have trouble telling apart—they consistently select both labels as valid for images of either class—see Figure 9a. On some of these pairs we see that models still perform well—likely because the search results from the automated image retrieval process are sufficiently error-free (i.e., the overlap in the image search results for the two classes is not significant) to disambiguate between these pairs.

However, for other pairs, even state-of-the-art models have poor accuracy (below 40%)—see Figure 9b. In fact, we can attribute this poor performance to model confusion *within* these pairs—*none* of the models we examined do much better than chance at distinguishing between the two classes. The apparent performance barrier on these *ambiguous classes* could thus be due to an inherent overlap in their ImageNet distributions. It is likely that the automated image retrieval caused mixups in the images for the two classes, and annotators were unable to rectify these. If that is indeed the case, it is natural to wonder whether accuracy on ambiguous classes can be improved without overfitting to the ImageNet test set.

⁴Note that our estimates for the selection frequency of image-ImageNet label pairs may be biased (underestimates) [Eng+20] as these specific pairs have already been filtered during dataset creation based on their selection frequency. However, we can effectively ignore this bias since: a) our results seem to be robust to varying the number of annotators (Appendix C.2), b) most of our results are based on the follow-up `CLASSIFY` task for which this bias does not apply.

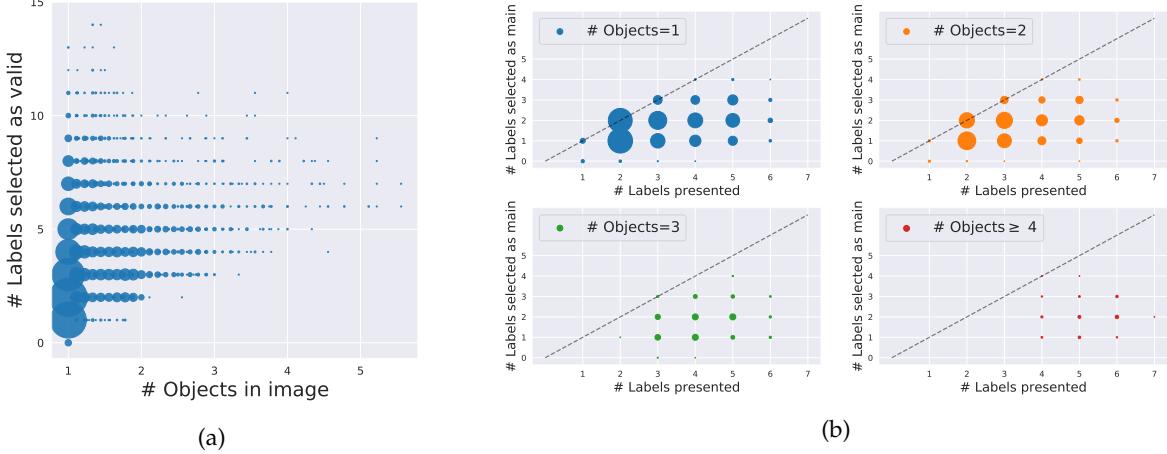


Figure 8: (a) Number of labels selected in the CONTAINS task: the y-axis measures the number of labels that were selected by at least two annotators; the x-axis measures the average number of objects indicated to be present in the image during the CLASSIFY task; the dot size represents the number of images in each 2D bin. Even when annotators perceive an images as depicting a single object, they often select multiple labels as valid. (b) Number of labels that at least two annotators selected for the main image object (in the CLASSIFY task; cf. Section 3.2) as a function of the number of labels presented to them. Annotator confusion decreases significantly when the task setup explicitly involves choosing between multiple labels *simultaneously*.

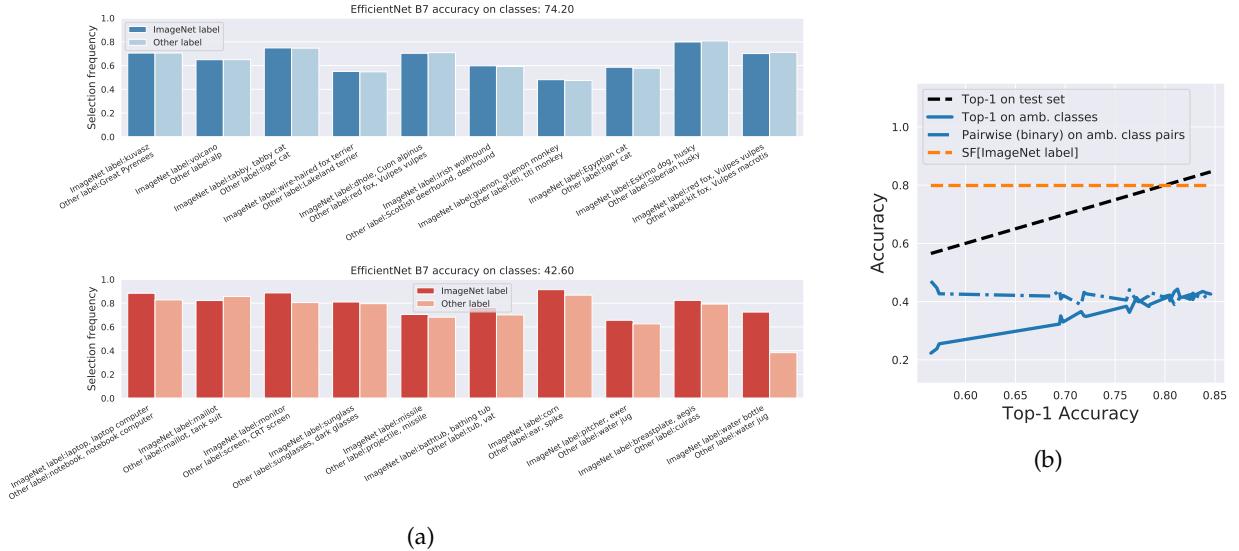


Figure 9: (a) ImageNet class pairs for which annotators often deem both classes as valid. We visualize the top 10 pairs split based on the accuracy of EfficientNet B7 on these pairs being high (*top*) or low (*bottom*). (b) Model progress on ambiguous class pairs (from (a) *bottom*) has been largely stagnant—possibly due to substantial overlap in the class distributions. In fact, models are unable to distinguish between these pairs better than chance (cf. pairwise accuracy).

The annotators’ inability to remedy overlaps in the case of ambiguous class pairs could be due to the presence of classes that are semantically quite similar, e.g., “rifle” and “assault rifle”—which is problematic under the CONTAINS task as discussed before. In some cases, we find that there also were errors in the task setup. For instance, there were occasional overlaps in the class names (e.g., “maillot” and “maillot, tank suit”) and Wikipedia links (e.g., “laptop computer” and “notebook computer”) presented to the annotators.

This highlights that choosing labels that are in principle disjoint (e.g., using WordNet) might not be sufficient to ensure that the resulting dataset has non-overlapping classes—when using noisy validation pipelines, we need to factor human confusion into class selection and description.

5 Beyond Test Accuracy: Human-In-The-Loop Model Evaluation

Based on our analysis of the ImageNet dataset so far, it is clear that using top-1 accuracy as a standalone performance metric can be problematic—issues such as multi-object images and ambiguous classes make ImageNet labels an imperfect proxy for the ground truth. Taking these issues into consideration, we now turn our focus to augmenting the model evaluation toolkit with metrics that are better aligned with the underlying goal of object recognition.

5.1 Human assessment of model predictions

To gain a broader understanding of model performance we start by *directly* employing annotators to assess how good model predictions are. Intuitively, this should not only help account for imperfections in ImageNet labels but also to capture improvements in models (e.g., predicting a similar dog breed) that are not reflected in accuracy alone. Specifically, given a model prediction for a specific image, we measure:

- **Selection frequency of the prediction:** How often annotators select the predicted label as being present in the image (determined using the CONTAINS task). Note that this metric accommodates for multiple objects or ambiguous classes as annotators will confirm all valid labels.
- **Accuracy based on main label annotation:** How frequently the prediction matches the main label for the image, as obtained using our CLASSIFY task (cf. Section 3.2). This metric penalizes models that exploit dataset biases to predict ImageNet labels even when these do not correspond to the main object. At the same time, it only measures accuracy as non-experts perceive it—if annotators cannot distinguish between two classes (e.g., different dog breeds), models can do no better than random chance on this metric, even if their predictions actually match the ground truth.

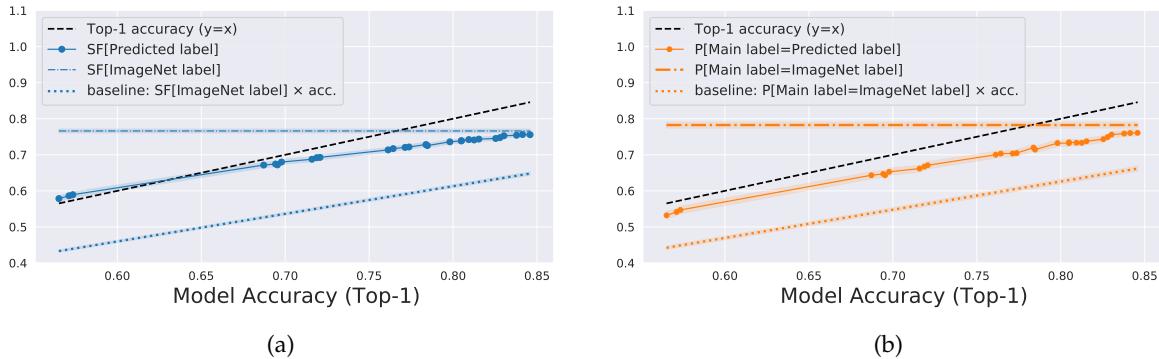


Figure 10: Using humans to assess model predictions—we measure how often annotators select the predicted/ImageNet label: (a) to be contained in the image (*selection frequency* [SF] from Section 3.1), and (b) to denote the *main* image object (cf. Section 3.2), along with 95% confidence intervals via bootstrap (shaded). We find that though state-of-the-art models have imperfect top-1 accuracy, their predictions are, on average, almost indistinguishable according to our annotators from the ImageNet labels themselves.

Comparing model predictions and ImageNet labels along these axes would allow us to assess the (top-1 accuracy) gap in model performance from a human perspective. Concretely, we want to understand whether more accurate models also make higher-quality predictions, i.e., if the labels they predict (including erroneous ones) also appear more reasonable to humans? We find that models improve consistently along

these axes as well (cf. Figure 10)—faster than improvements in accuracy can explain (i.e., more predictions matching the ImageNet label). Moreover, we observe that the predictions of state-of-the-art models have gotten, on average, quite close to ImageNet labels with respect to these metrics. That is, annotators are almost *equally likely* to select the predicted label as being present in the image (or being the main object) as the ImageNet label. This indicates that model predictions might be closer to what non-expert annotators can recognize as the ground truth than accuracy alone suggests.

These findings do not imply that all of the remaining gap between state-of-the-art model performance and perfect top-1 accuracy is inconsequential. After all, for many images, the labels shown to annotators during the ImageNet creation process (based on automated data retrieval) could have been the ground truth. In these cases, striving for higher accuracy on ImageNet would actually extend to real-world object recognition settings. However, the results in Figure 10 hint at a different issue: we are at a point where we may no longer be able to easily identify (e.g., using crowd-sourcing) the extent to which further gains in accuracy correspond to such improvements, as opposed to models simply matching the ImageNet distribution better.

Incorrect predictions. We can also use these metrics to examine model mistakes, i.e., predictions that deviate from the ImageNet label, more closely. Specifically, we can treat human assessment of these labels (based on the metrics above) as a proxy for how much these predictions deviate from the ground truth. We find that recent, more accurate ImageNet models make progressively fewer mistakes that would be judged by humans as such (i.e., with low selection frequency or low probability of being the main object)—see Figure 11. This indicates that models are not only getting better at predicting the ImageNet label, but are also making fewer blatant mistakes, at least according to *non-expert* humans. At the same time, we observe that for *all* models, a large fraction of the seemingly incorrect predictions are actually valid labels according to human annotators. This suggests that using a single ImageNet label alone to determine the correctness of these predictions, may, at times, be pessimistic (e.g., multi-object images or ambiguous classes).

When viewed from a different perspective, Figure 11 also highlights the pitfalls of using selection frequency as the sole filtering criteria during dataset collection. Images with high selection frequency (w.r.t., the dataset label) can still be challenging for models (cf. Appendix Figure 24).

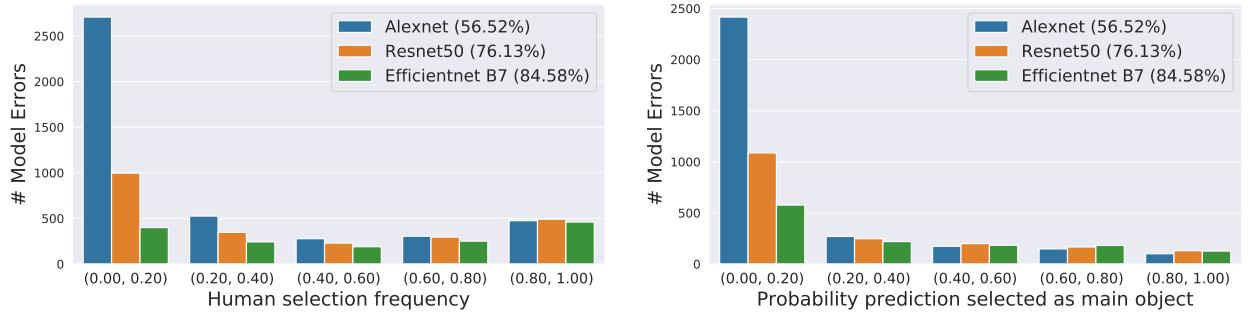


Figure 11: Distribution of annotator selection frequencies (cf. Section 3.1) for model predictions deemed incorrect w.r.t. the ImageNet label. Models that are more accurate also seem to make fewer mistakes that have low human selection frequency (for the corresponding image-prediction pair).

5.2 Fine-grained comparison of human vs. model performance

Next, we can get a more fine-grained understanding of model predictions by comparing them to the ones humans make. To do this, we use the image annotations we collect (cf. Section 3)—specifically the main label—as a proxy for (non-expert) human predictions. (Note that, the human prediction matches the ImageNet label only on about 80% of the images, despite the fact that annotators are directly presented with a few relevant labels (including the ImageNet label) to choose from—see Figure 10b.)

Confusion matrix. We start by comparing the confusion matrices for models and humans. Since it is hard to manually inspect the full 1000-by-1000 matrices (cf. Appendix C.4), we partition ImageNet classes into 11

superclasses (Appendix A.1.1). This allows us to study confusions *between* and *within* superclasses separately.

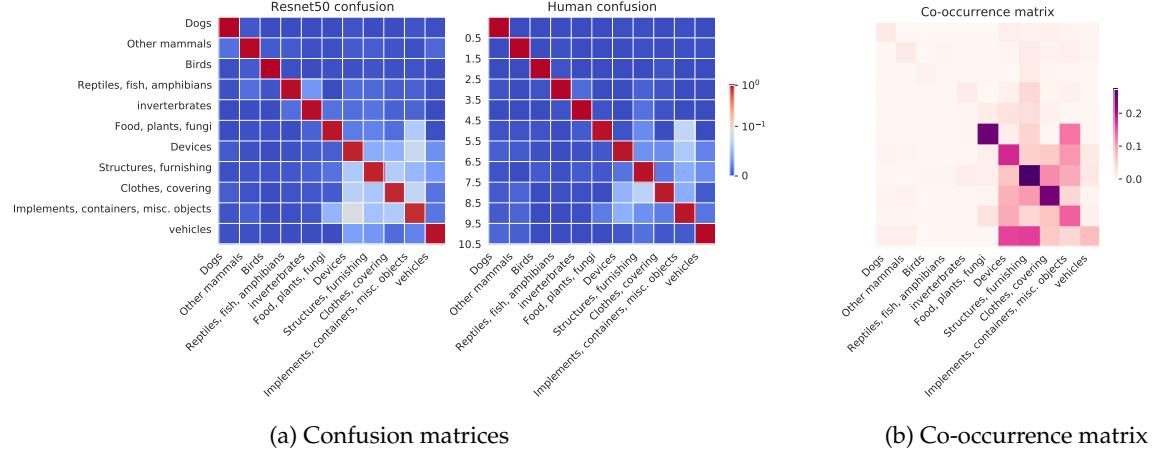


Figure 12: Characterizing similarity between model and human predictions (indicated by main object selection in the CONTAINS task): (a) Model (ResNet-50) and human confusion matrices on 11 ImageNet superclasses (cf. Section A.1.1). (b) Superclass co-occurrence matrix: how likely a specific pair of superclasses is to occur together (based on annotation from Section 3.2).

In the cross-superclass confusion matrix (cf. Figure 12a), we observe a block where both human and model is high—this is particularly striking given that these superclasses are semantically quite different. To understand these confusions better, we compare the superclass confusion matrix with the superclass *co-occurrence* matrix, i.e., how often an image of superclass i (w.r.t. the ImageNet label) also contains an object of superclass j according to annotators (cf. Figure 12b). Indeed, we find that the two matrices are quite aligned—indicating that model and human confusion between superclasses might be stemming from multi-object images. We also observe that the intra-superclass confusions are more significant for humans compared to models (cf. Appendix Figure 29), particularly on fine-grained classes (e.g., dog breeds).

6 Related Work

Identifying ImageNet issues. Some of the ImageNet label issues we study have been already been identified in prior work. Specifically, Recht et al. [Rec+19], Northcutt, Jiang, and Chuang [NJC19], and Hooker et al. [Hoo+19] demonstrate the existence of classes that might be inherently ambiguous (similar to our findings in Section 4.2). Moreover, the existence of cluttered images was discussed by Russakovsky et al. [Rus+15] as an indication that the dataset mirrors real-world conditions—hence being desirable—and by Stock and Cisse [SC18], Northcutt, Jiang, and Chuang [NJC19], and Hooker et al. [Hoo+19] as a source of label ambiguity (similar to our findings in Section 4.1). Additionally, Stock and Cisse [SC18], motivated by the multi-label nature of images, perform human-based model evaluation, similar to our experiments in Section 5.1. Finally, Stock and Cisse [SC18] use manual data collection and saliency maps to identify racial biases that models rely on to make their predictions. However, the focus of all these studies is not to characterize ImageNet issues and hence they only provide coarse estimates for their pervasiveness. In particular, none of these studies evaluate how these issues affect model performance, nor do they obtain annotations that are sufficient to rigorously draw per-class conclusions (either due to granularity or scale).

Human performance on ImageNet. Rigorously studying human accuracy on the full ImageNet classification task is challenging, mainly due to the fact that annotators need to be mindful of all the 1000 ImageNet classes that are potentially present. The original ImageNet challenge paper contained results for two trained annotators [Rus+15], while Karpathy [Kar14] reports result based on evaluating themselves. An MTurk study using a subset of the ImageNet classes is presented in Dodge and Karam [DK17].

Generalization beyond the test set. The topic of designing large-scale vision datasets that allow generalization beyond the narrow benchmark task has been an active topic of discussion in the computer vision community [Pon+06; Eve+10; TE11; Rus+15]. Torralba and Efros [TE11] propose evaluating cross-dataset generalization—testing the performance of a model on a different dataset which shares a similar class structure. Recht et al. [Rec+19] focus on reproducing the ImageNet validation set process to measure potential adaptive overfitting or over-reliance on the exact dataset creation conditions. Kornblith, Shlens, and Le [KSL19] investigate the extent to which better ImageNet performance implies better feature extraction as measured by the suitability of internal model representations for transfer learning [Don+14; Sha+14].

Adversarial testing. Beyond the benign shift in test distribution discussed above, there has been significant work on measuring model performance from a worst-case perspective. A large body of work on adversarial examples [Big+13; Sze+14] demonstrates that models are extremely brittle to imperceptible pixel-wise perturbations—every image can be arbitrarily misclassified. Similar, yet less severe, brittleness can be observed for a number of more natural perturbations, such as: worst-case spatial transformation (e.g., rotations) [FF15; Eng+19], common image corruptions [HD19], adversarial texture manipulation [Gei+19], adversarial data collection [Bar+19; Hen+19].

7 Conclusion

In this paper, we take a step towards understanding how closely widely-used vision benchmarks align with the real-world tasks they are meant to approximate, focusing on the ImageNet object recognition dataset. Our analysis uncovers systemic—and fairly pervasive—ways in which ImageNet annotations deviate from the ground truth—such as the wide presence of images with multiple valid labels, and ambiguous classes.

Crucially, we find that these deviations significantly impact what ImageNet-trained models learn (and don’t learn), and how we perceive model progress. For instance, top-1 accuracy often underestimates the performance of models by unduly penalizing them for predicting the label of a different, but also valid, image object. Further, current models seem to derive part of their accuracy by exploiting ImageNet-specific features that humans are oblivious to, and hence may not generalize to the real world. Such issues make it clear that measuring accuracy alone may give us only an imperfect view of model performance on the underlying object recognition task.

Taking a step towards evaluation metrics that circumvent these issues, we utilize human annotators to directly judge the correctness of model predictions. On the positive side, we find that models that are more accurate on ImageNet also tend to be more human-aligned in their errors. In fact, on average, (non-expert) annotators turn out to be unable to distinguish the (potentially incorrect) predictions of state-of-the-art models from the ImageNet labels themselves. While this might be reassuring, it also indicates that we are at a point where we cannot easily gauge (e.g., via simple crowd-sourcing) whether further progress on the ImageNet benchmark is meaningful, or is simply a result of overfitting to this benchmarks’ idiosyncrasies.

More broadly, our findings highlight an inherent conflict between the goal of building rich datasets that capture complexities of the real world and the need for the annotation process to be scalable. Indeed, in the context of ImageNet, we found that some of the very reasons that make the collection pipeline scalable (e.g., resorting to the CONTAINS task, employing non-expert annotators) were also at the crux of the afore-mentioned annotation issues. We believe that developing annotation pipelines that better capture the ground truth while remaining scalable is an important avenue for future research.

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A Experimental setup

A.1 Datasets

We perform our analysis on the ImageNet dataset [Rus+15]. A full description of the data creation process can be found in Deng et al. [Den+09] and Russakovsky et al. [Rus+15]. For the purposes of our human studies, we use a random subset of the validation set—10,000 images chosen by sampling 10 random images from each of the 1,000 classes. (Model performance on this subset closely mirrors overall test accuracy, as shown in Figure 4b.) In our analysis, we refer to the original dataset labels as “ImageNet labels” or “IN labels”.

A.1.1 ImageNet superclasses

We construct 11 superclasses by manually grouping together semantically similar 1000 ImageNet classes (in parenthesis), with the assistance of the WordNet hierarchy—*Dogs* (130), *Other mammals* (88), *Bird* (59), *Reptiles, fish, amphibians* (60), *Invertebrates* (61), *Food, plants, fungi* (63), *Devices* (172), *Structures, furnishing* (90), *Clothes, covering* (92), *Implements, containers, misc. objects* (117), *Vehicles* (68).

A.2 Models

We perform our evaluation on various standard ImageNet-trained models—see Appendix Table 1 for a full list. We use open-source pre-trained implementations from github.com/Cadene/pretrained-models.pytorch and/or github.com/rwightman/pytorch-image-models/tree/master/timm for all architectures.

Table 1: Models used in our analysis with the corresponding ImageNet top-1/5 accuracies.

Model	Top-1	Top-5	Model	Top-1	Top-5
alexnet [KSH12]	56.52	79.07	efficientnet_b1 [TL19]	78.38	94.04
squeezezenet1_1 [Ian+16]	57.12	80.13	wide_resnet50_2 [ZK16]	78.47	94.09
squeezeNet1_0 [Ian+16]	57.35	79.89	efficientnet_b2 [TL19]	79.81	94.73
vgg11 [SZ15]	68.72	88.66	gluon_resnet152_v1d [He+19]	80.49	95.17
vgg13 [SZ15]	69.43	89.03	inceptionresnetv2 [Sze+17]	80.49	95.27
inception_v3 [Sze+16]	69.54	88.65	gluon_resnet152_v1s [He+19]	80.93	95.31
googlenet [Sze+15]	69.78	89.53	senet154 [HSS18]	81.25	95.30
vgg16 [SZ15]	71.59	90.38	efficientnet_b3 [TL19]	81.53	95.65
mobilenet_v2 [San+18]	71.88	90.29	nasnetalarge [Zop+18]	82.54	96.01
vgg19 [SZ15]	72.07	90.74	pnasnet5large [Liu+18]	82.79	96.16
resnet50 [He+16]	76.13	92.86	efficientnet_b4 [TL19]	83.03	96.34
efficientnet_b0 [TL19]	76.43	93.05	efficientnet_b5 [TL19]	83.78	96.71
densenet161 [Hua+17]	77.14	93.56	efficientnet_b6 [TL19]	84.13	96.96
resnet101 [He+16]	77.37	93.55	efficientnet_b7 [TL19]	84.58	97.00

B Obtaining Image Annotations

Our goal is to use human annotators to obtain labels for each distinct object in ImageNet images (provided it corresponds to a valid ImageNet class). To make this classification task feasible, we first identify a small set of relevant candidate labels per image to present to annotators.

B.1 Obtaining candidate labels

As discussed in Section 3.1, we narrow down the candidate labels for each image by (1) restricting to the predictions of a set of pre-trained ImageNet models, and then (2) repeating the CONTAINS task (cf. Section 2) on human annotators using the labels from (1) to identify the most reasonable ones.

B.1.1 Pre-filtering using model predictions

We use the top-5 predictions of models with varying ImageNet (validation) accuracies (10 in total): `alexnet`, `resnet101`, `densenet161`, `resnet50`, `googlenet`, `efficientnet_b7` `inception_v3`, `vgg16`, `mobilenet_v2`, `wide_resnet50_2` (cf. Table 1) to identify a set of *potential labels*. Since model predictions tend to overlap, we end up with ~ 14 potential labels per image on average (see full histogram in Figure 13). We always include the ImageNet label in the set of potential labels, even if it is absent in all the model predictions.

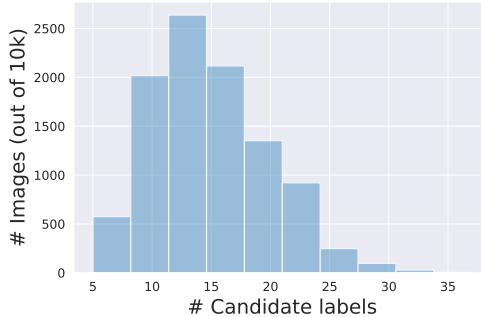


Figure 13: Distribution of labels per image obtained from the predictions of ImageNet-trained models (plus the ImageNet label). We present these labels (in separate grids) to annotators via the CONTAINS task (cf. Section 3.1) to identify a small set of relevant candidate labels for the classification task in Section 3.2.

B.1.2 Multi-label validation task

We then use human annotators to go through these potential labels and identify the most reasonable ones via the CONTAINS task. Recall that in CONTAINS task, annotators are shown a grid of images and asked to select the ones that contain an object corresponding to the specified query label (cf. Section 2). In our case, each image appears in multiple such grids—one for each potential label. By presenting these grids to multiple annotators, we can then obtain a selection frequency for every image-potential label pair, i.e., the number of annotators that perceive the label as being contained in the image (cf. Figure 7). Using these selection frequencies, we identify the most relevant *candidate labels* for each image.

Grid setup. The grids used in our study contains 48 images, at least 5 of which are *controls*—obtained by randomly sampling from validation set images labeled as the query class. Along with the images, annotators are provided with a description of the query label in terms of (a) WordNet synsets and (b) the relevant Wikipedia link—see Figure 14 for an example. (Our MTurk interface is based on a modified version of the code made publicly available by Recht et al. [Rec+19]⁵.) We find that a total of 3,934 grids suffice to obtain selection frequencies for all 10k images used in our analysis (w.r.t. all potential labels). Every grid was shown to 9 annotators, compensated \$0.20 per task.

⁵<https://github.com/modestyachts/ImageNetV2>

Which of these images contain at least one object of type
Lhasa or Lhasa apso

Definition: a breed of terrier having a long heavy coat raised in Tibet as watchdogs

If you are unsure about the object meaning, please also consult the following Wikipedia page(s): https://en.wikipedia.org/wiki/Lhasa_Apso

Task:
For each of the following images, check the box next to an image if it contains at least one object of type *Lhasa or Lhasa apso*.

Select an image if it contains the object **regardless of occlusions, other objects, and clutter or text** in the scene. Only select images that are photographs (**no drawings or paintings**).

Please make accurate selections!

If it is impossible to complete a HIT due to missing data or other problems, please return the HIT. Blatantly incorrect answers might cause the HIT to be rejected.

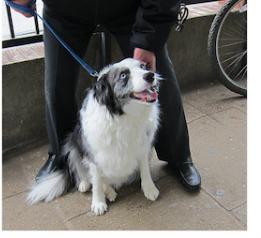
<input type="checkbox"/>		<input type="checkbox"/>		<input type="checkbox"/>	
<input type="checkbox"/>		<input type="checkbox"/>		<input type="checkbox"/>	
<input type="checkbox"/>		<input type="checkbox"/>		<input type="checkbox"/>	

Figure 14: Sample interface of the CONTAINS task we use for label validation: annotators are shown a grid of 48 images and asked to select all images that correspond to a specific label (Section 3.1).

Quality control. We filtered low-quality responses on a per-annotator and per-task basis. First, we completely omitted results from annotators who selected less than 20% of the control images on half or more of the tasks they completed: a total of 10 annotators and the corresponding 513 tasks. Then we omitted tasks for which less than 40% of the controls were selected: a total of 3,104 tasks. Overall, we omitted 3,617 tasks in total out of the total 35,406. As a result, the selection frequency of some image-label pairs will be computed with fewer than 9 annotators.

B.1.3 Final candidate label selection

We then obtain the most relevant candidate labels by selecting the potential labels with high human selection frequency. To construct this set, we consider (in order):

1. The existing ImageNet label, irrespective of its selection frequency.
2. All the highly selected potential labels: for which annotator selection frequency is at least 0.5.
3. All potential labels with non-zero selection frequency that are semantically very different from the ImageNet label—so as to include labels that may correspond to different objects. Concretely, we select candidate labels that are more than 5 nodes away from the ImageNet label in the WordNet graph.
4. If an image has fewer than 5 candidates, we also consider other potential labels after sorting them based on their selection frequency (if non-zero).

- To keep the number of candidates relatively small, we truncate the resulting set size to 6 if the excess labels have selection frequencies lower than the ImageNet label, or the ImageNet label itself has selection frequency $\leq 1/8$. During this truncation, we explicitly ensure that the ImageNet label is retained.

In Figure 15, we visualize the distribution of number of candidate labels per image, over the set of images.



Figure 15: Distribution of the number of candidate labels used per image presented to annotators during the classification task in Section 3.2.

B.2 Image classification

The candidate labels are then presented to annotators during the CLASSIFY task (cf. Section 3.2). Specifically, annotators are shown images, and their corresponding candidate labels and asked to select: a) all valid labels for that image, b) a label for the main object of the image—see Figure 16 for a sample task interface. We instruct annotators to pick multiple labels as valid, only if they correspond to different objects in the image and are not mutually exclusive. In particular, in case of confusion about a specific object label, we explicitly ask them to pick a single label making their best guess. Each task was presented to 9 annotators, compensated at \$0.08 per task.

Images included. We only conduct this experiment on images that annotators identified as having *at least* one candidate label outside the existing ImageNet label (based on experiment in Appendix B.1). To this end, we omitted images for which the ImageNet label was clearly the most likely: out of all the labels seen by 6 or more of the 9 annotators, the original label had more than double the selection frequency of any other class. Note that since we discard some tasks as part of quality control, it is possible that for some image-label pairs, we have the results of fewer than 9 annotators. Furthermore, we also omitted images which were not selected by any annotator as containing their ImageNet label (150 images total)—cf. Appendix Figure 25 for examples. These likely corresponds to labeling mistakes in the dataset creation process and do not reflect the systemic error we aim to study. The remaining 6,761 images that are part of our follow-up study have at least 1 label, in addition to the ImageNet label, that annotators think could be valid.

Quality control. Performing stringent quality checks for this task is challenging since we do not have ground truth annotations to compare against—which was after all the original task motivation. Thus, we instead perform basic sanity checks for quality control—we ignore tasks where annotators did not select *any* valid labels or selected a main label that they did not indicate as valid. In addition, if the tasks of specific annotators are consistently flagged based on these criteria (more than a third of the tasks), we ignore all their annotations. Overall, we omitted 1,269 out of the total 59,580 tasks.

The responses of multiple annotators are aggregated as described in Section 3.2.

Select which labels appear in the image
 (Please read the instructions carefully as they are somewhat unusual)

Task:

1. Valid labels: select ALL labels that correspond to DISTINCT objects in the image. If for a single thing you cannot decide between multiple labels (which cannot all be true at the same time--e.g., different animal breeds), select the one that seems most likely.

Example: Select ONLY ONE dog breed for a single dog and ONE shoe type for a single shoe (even if you are unsure about the correct breed/type--just pick one). BUT select BOTH "car" and "car wheel" for a car with visible wheels, BOTH "fur" and "coat" for a fur coat, BOTH "grocery store" and "orange" for oranges inside a grocery store (as these correspond to distinct things in the image).

2. Main object: from the chosen labels, select the one corresponding to the MAIN OBJECT in the image by clicking the appropriate radio button. (If you cannot decide which object is the main one, pick your best guess.)

If unsure about what a label means, you can consult the corresponding Wikipedia pages.

Examples:

Image	Main object	Valid labels
	<input checked="" type="radio"/>	<input checked="" type="checkbox"/> Car <input checked="" type="checkbox"/> Car wheel <input type="checkbox"/> Truck
	<input type="radio"/> <input checked="" type="radio"/>	<input checked="" type="checkbox"/> Fur <input type="checkbox"/> Wool <input checked="" type="checkbox"/> Fur coat
	<input checked="" type="radio"/>	<input checked="" type="checkbox"/> Collie <input type="checkbox"/> Terrier

Image Main object Valid Labels



Main object Valid Labels

<input type="radio"/>	<input type="checkbox"/> pedestal or plinth or footstall Definition: an architectural support or base (as for a column or statue) Wikipedia: https://en.wikipedia.org/wiki/Pedestal
<input type="radio"/>	<input type="checkbox"/> obelisk Definition: a stone pillar having a rectangular cross section tapering towards a pyramidal top Wikipedia: https://en.wikipedia.org/wiki/Obelisk
<input type="radio"/>	<input type="checkbox"/> pirate or pirate ship Definition: a ship that is manned by pirates Wikipedia: https://en.wikipedia.org/wiki/Piracy

Submit

Figure 16: Screenshot of a sample image annotation task. (Section 3.2). Annotators are presented with an image and multiple candidate labels. They are asked to select all valid labels (selecting only one of mutually exclusive labels in the case of confusion) and indicate the main object of the image.

C Additional experimental results

C.1 Multi-object Images

Additional (random) multi-object images are shown in Figure 17. We observe that annotators tend to agree on the number of objects present—see Figure 18.

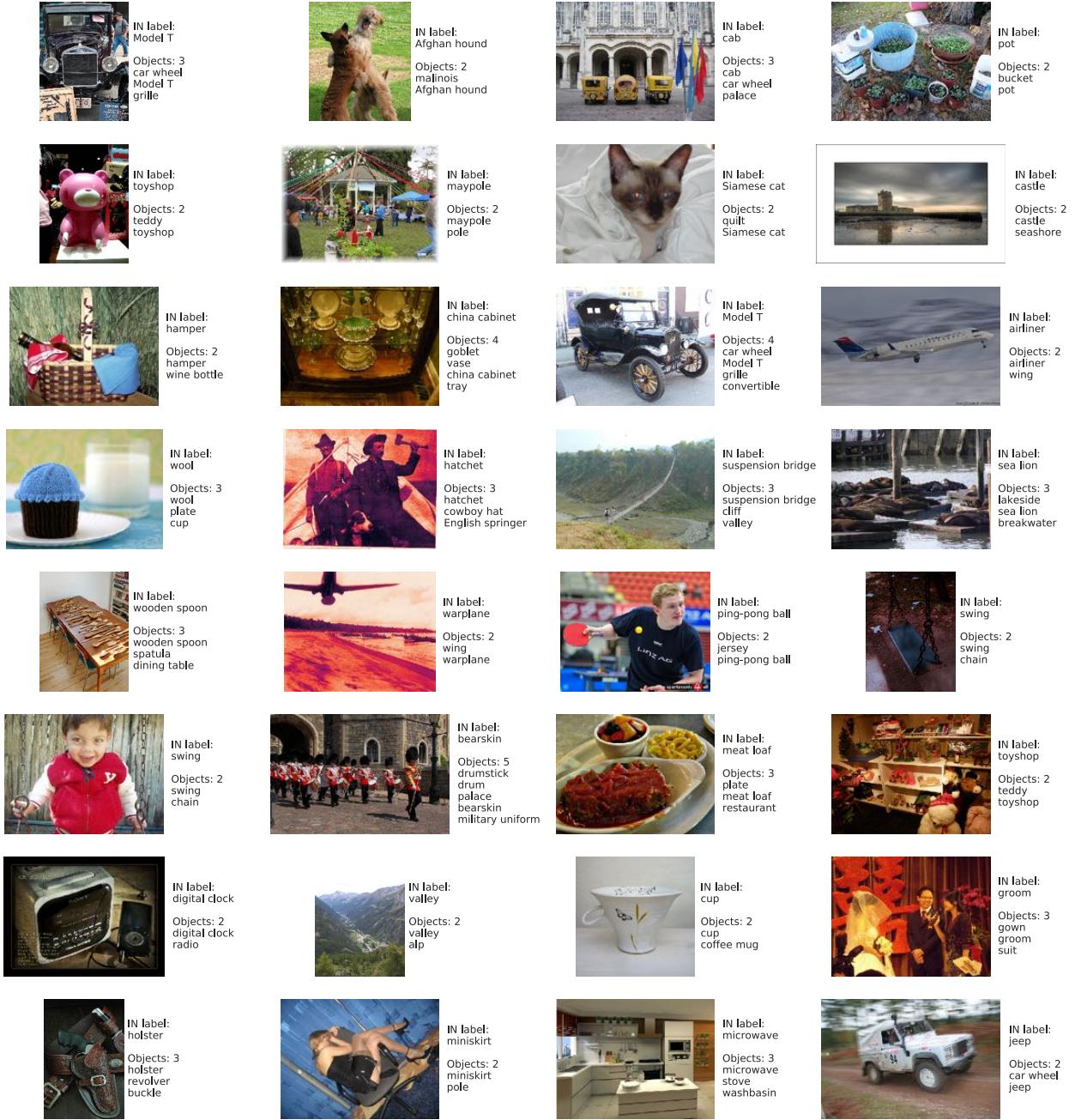


Figure 17: Sample ImageNet images with more than one valid label as per human annotators (cf. Section 3.1).

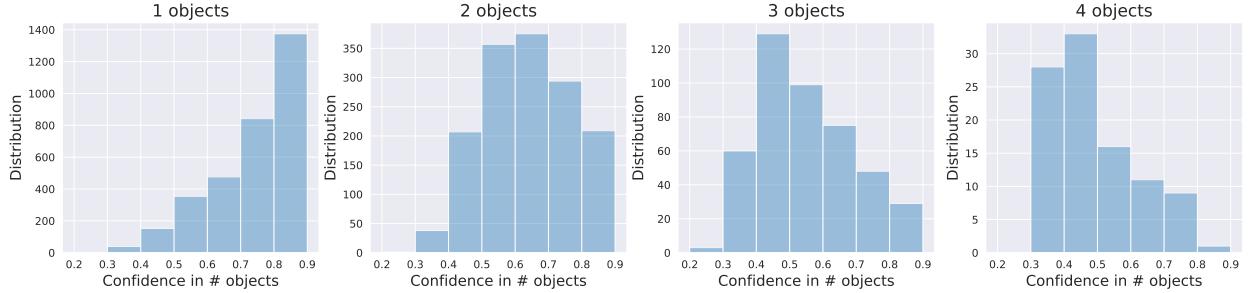


Figure 18: Annotator agreement for multi-object images. Recall that we determine the number of objects in an image based on a majority vote over annotators. Here, we define “confidence” as the fraction of annotators that make up that majority, relative to the total number of annotators shown the image (cf. Section 3.2). We visualize the distribution of annotator confidence, as a function of the number of image objects.

In Figure 19, we visualize instances where the ImageNet label does not match with what annotators deem to be the “main object”. In many of these cases, we find that models perform at predicting the ImageNet label, even though the images contain other, more salient objects according to annotators—Figure 20.

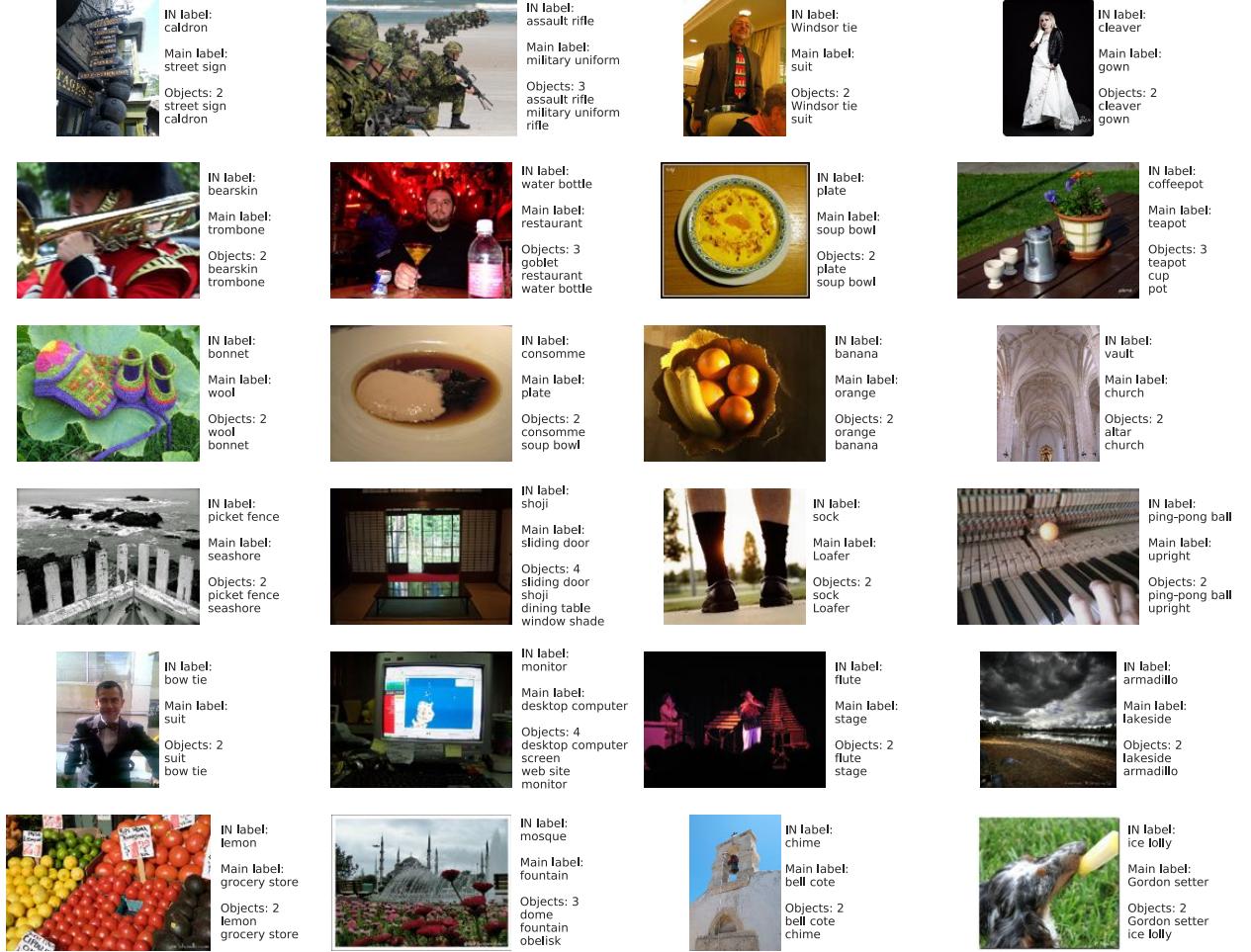


Figure 19: Sample images for which the main label as per annotators differs from the ImageNet label.

In Figure 3b, we visualize pairs of ImageNet classes that frequently co-occur in images—e.g., suit and tie, space bar and keyboard. For some of these co-occurring class pairs, model performance as a whole, seems to

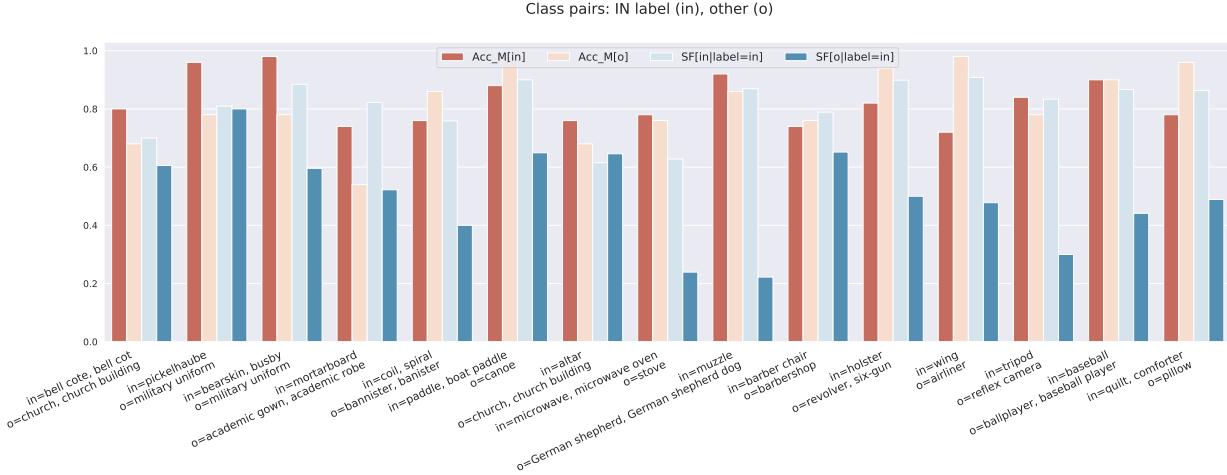


Figure 20: Classes for which human main label frequently differs from the ImageNet label. Here, although annotator selection frequency for the ImageNet label is high, the selection frequency for *another* class—which humans consider to be the main label—is also consistently high. Models still predict the ImageNet label, possibly by picking up on distinctive features of the objects.

be poor (cf. Figures 21)—possibly because of an inherent significant overlap in the image distributions of the two classes.

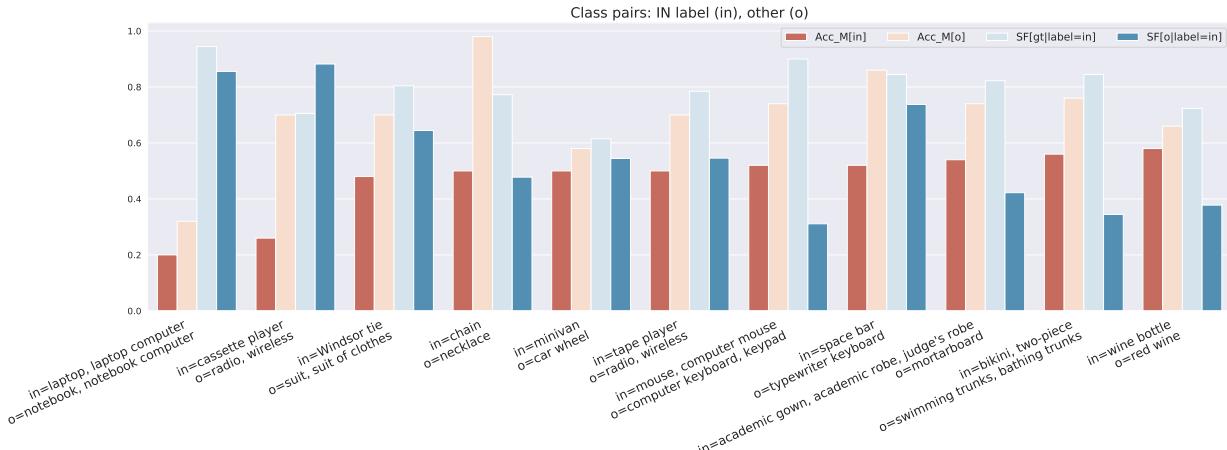


Figure 21: Classes where model accuracy is consistently low due to frequent object co-occurrences: in these cases, an object from the ImageNet class frequently co-occurs with (or is a sub-part of) objects from another class. Here, models seem to be unable to disambiguate the two classes completely, and thus perform poorly on one/both classes. Note that human selection frequency for the ImageNet class is high, indicating that an object from that class is present in the image.

Top-5 accuracy in the multi-label context. The issue of label ambiguity that can arise in multi-object images was noted by the creators of the ILSVRC challenge [Rus+15]. To tackle this issue, they proposed evaluating models based on top-5 accuracy. Essentially, a model is deemed correct if any of the top 5 predicted labels match the ImageNet label. We find that model top-5 accuracy is much higher than top-1 (or even our notion of multi-label) accuracy on multi-object images—see Figure 22. However, a priori, it is not obvious whether this increase is actually because of adjusting for model confusion between distinct objects.

In fact, one would expect that properly accounting for such multi-object confusions should yield numbers similar to (and not markedly higher than) top-1 accuracy on single-object images.

To get a better understanding of this, we visualize the fraction of *top-5 corrections*—images for which the ImageNet label was not the top prediction of the model, but was in the top 5—that correspond to *different objects* in the image. Specifically, we only consider images where the top model prediction and ImageNet label were selected by annotators as: (a) present in the image and (b) corresponding to different objects. We observe that the fraction of top-5 corrections that correspond to multi-object images is relatively small—about 20% for more recent models. This suggests that top-5 accuracy may be overestimating model performance and, in a sense, masking model errors on single objects. Overall, these findings highlight the need for designing better performance metrics that reflect the underlying dataset structure.

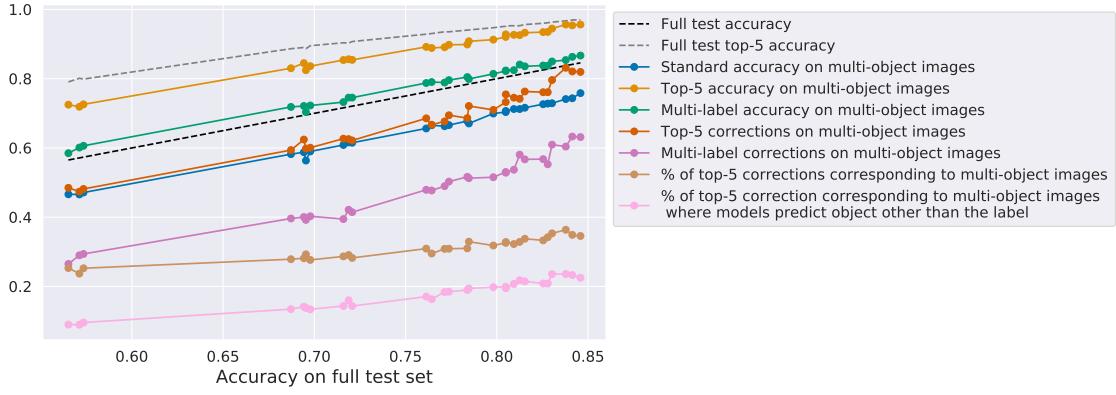


Figure 22: A closer look at top-5 accuracy: we visualize top-1, top-5 and multi-label (cf. Section 4.1) on multi-object images in ImageNet. We also measure the fraction of top-5 corrections (ImageNet label is not top model prediction, but is among top 5) that correspond to multi-object confusions—wherein the ImageNet label and top prediction belong to distinct image objects as per human annotators. We see that although top-5 accuracy is much higher than top-1, even for multi-object images, it may be overestimating model performance. In particular, a relatively small fraction of top-5 corrections actually correspond to the aforementioned multi-object images.

C.2 Bias in label validation

Potential biases in selection frequency estimates. In the course of obtaining fine-grained image annotations, we collect selection frequencies for several potential image labels (including the ImageNet label) using the CONTAINS task (cf. Section 3.1). Recall however, that during the ImageNet creation process, every image was already validated w.r.t. the ImageNet label (also via the CONTAINS task) by a different pool of annotators, and only images with high selection frequency actually made it into the dataset. This fact will result in a *bias* for our new selection frequency measurements [Eng+20]. At a high level, if we measure a low selection frequency for the ImageNet label of an image, it is more likely that we are observing an underestimate, rather than the actual selection frequency being low. In order to understand whether this bias significantly affects our findings, we reproduce the relevant plots in Figure 23 using only a subset of workers (this should exacerbate the bias allowing us to detect it). We find however, that the difference is quite small, not changing any of the conclusions. Moreover, since most of our analysis is based on the per-image annotation task for which this specific bias does not apply, we can effectively ignore it in our study.

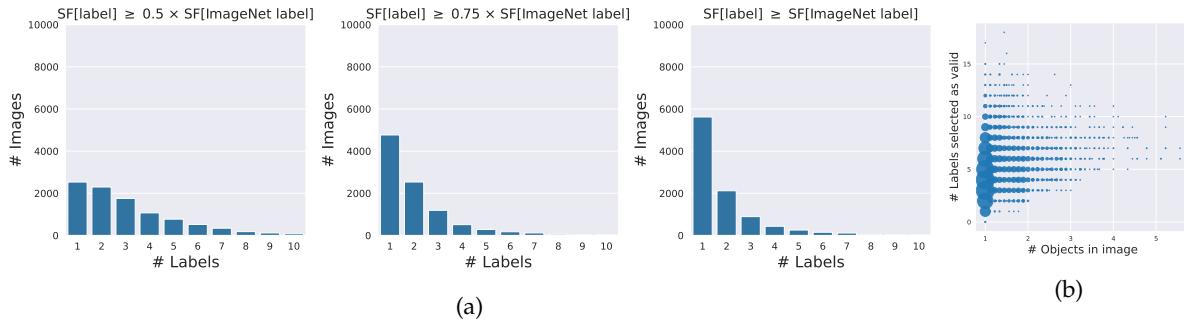


Figure 23: Effect of subsampling annotator population (5 instead of 9 annotators): (a) Number of labels annotators consider valid determined based on the selection frequency of a label relative to that of the ImageNet label. Even in this annotator subpopulation, for >70% of images, another label is still selected at least half as often as they select the ImageNet label (*leftmost*). (b) Number of labels that at least one (of five) annotators selected as valid for an image (cf. Section 3.1) versus the number of objects in the image (cf. Section 3.2). (Dot size is proportional to the number of images in each 2D bin.) Even when annotators consider the image as containing only a single object, they often select multiple labels as valid.

Selection frequency and model accuracy. In typical dataset creation pipelines, selection frequency (and other similar metrics) is often used to filter out images that are not easily recognizable by humans. We now consider how the selection frequency of a class relates to model accuracy on that class—see Figure 24. While we see that, in general, classes with high human selection frequency are also easier for models to classify, this is not uniformly true—in particular, there seem to be classes that significantly deviate from this trend. Given our observations about the nuances in ImageNet data, this may be justified—for instance, multi-object images would have high human selection frequency for the ImageNet label, but may not be easy to learn.

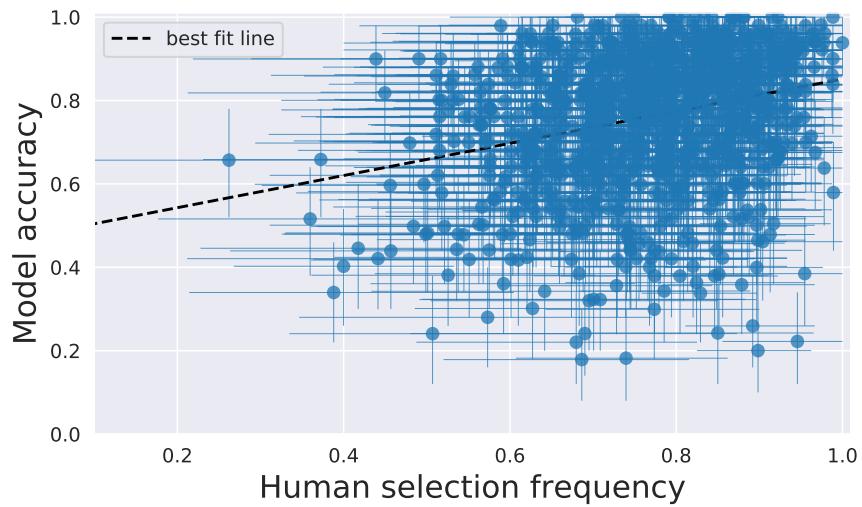


Figure 24: Relationship between per-class selection frequency and model (ResNet-50) accuracy. We observe that while in general higher selection frequency does correlate with better accuracy, this is not uniformly true. This suggests that using selection frequency as a proxy for how easy an image is in terms of object recognition may not be perfect—especially if the dataset contains fine-grained classes or multi-object images.

C.3 Mislabeled examples

In the course of our human studies in Section 3.1, we also identify a set of possibly mislabeled ImageNet images. Specifically, we find images for which:

- Selection frequency for the ImageNet label is 0, i.e., no annotator selected the label to be contained in the image (cf. Section 3.1). We identify 150 (of 10k) such images— cf. Appendix Figure 25 for examples.
- The ImageNet label was not selected at all (for any object) during the detailed image annotation phase in Section 3.2. We identify 119 (of 10k) such images— cf. Appendix Figure 26 for examples.

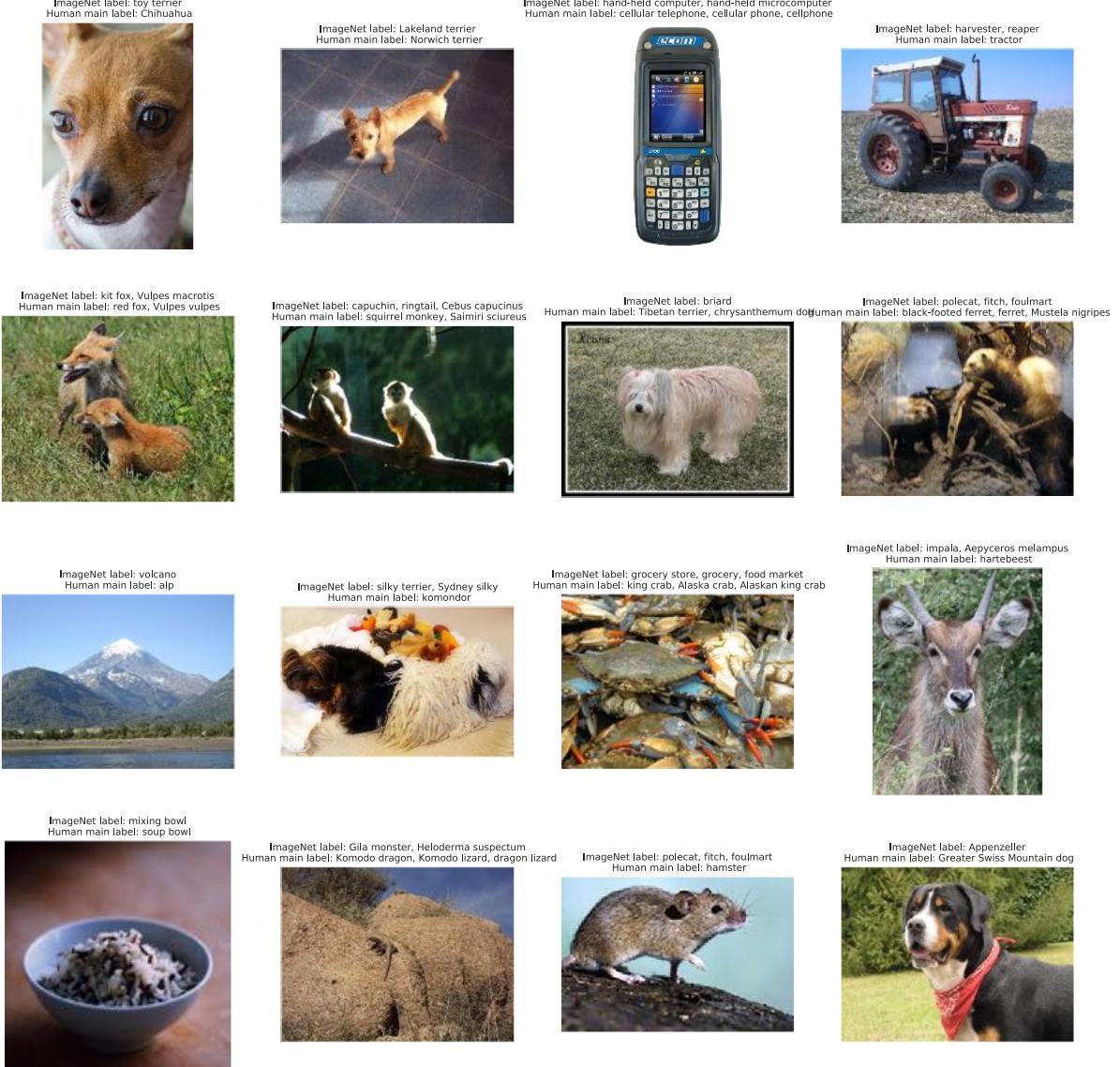


Figure 25: Possibly mislabeled images: human selection frequency for the ImageNet label is 0 (cf. Section 3.1). Also depicted is the label most frequently selected by the annotators as contained in the image (*sel*).

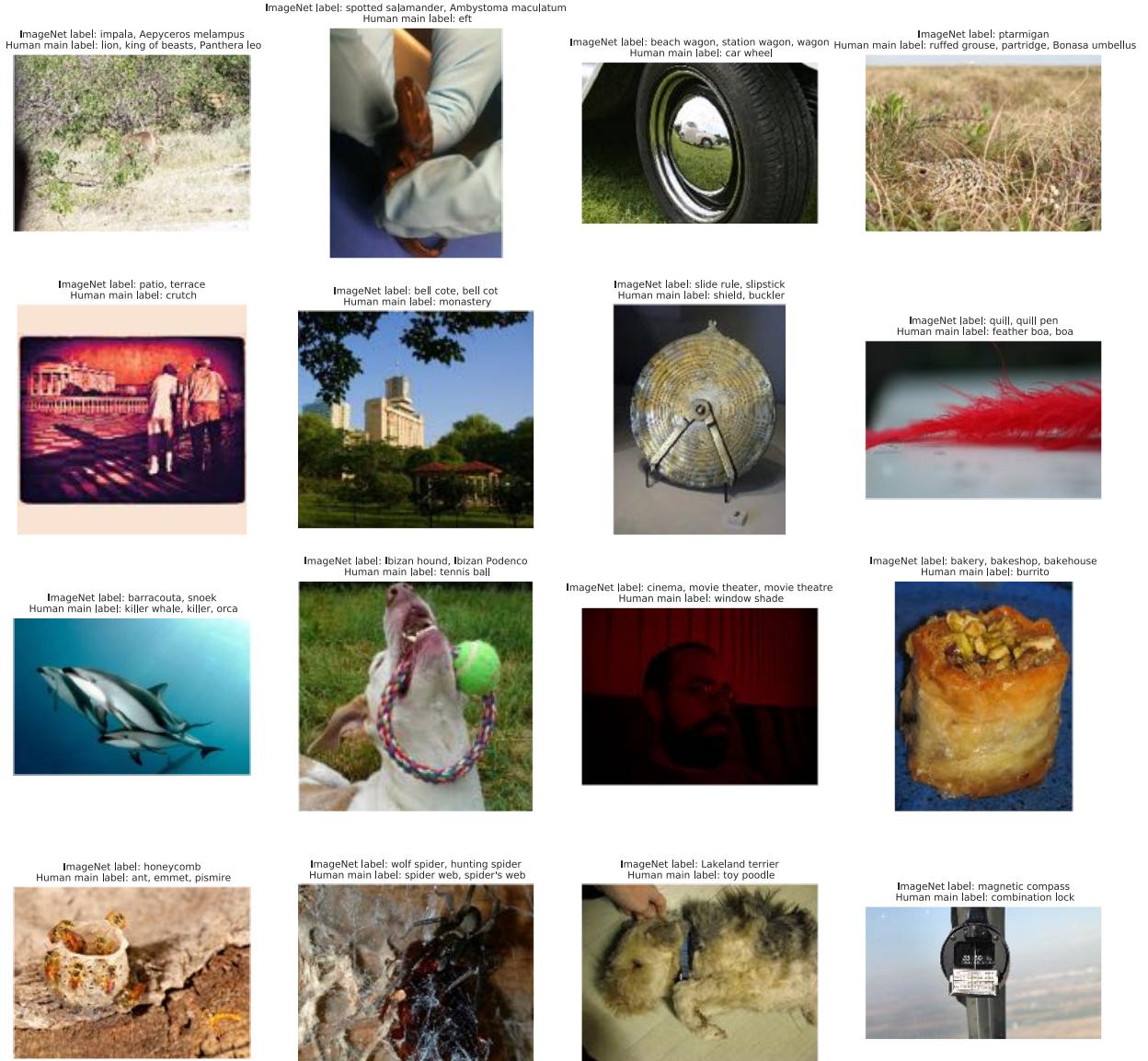


Figure 26: Possibly mislabeled images: ImageNet label is not selected by any of the annotators during fine-grained image annotation process described in Section 3.2. Also shown in the title is label that was most frequently selected by the annotators as denoting the main object in the image (*sel*).

C.4 Confusion Matrices

The (i, j) th entry of the human/model confusion matrix denotes how often an image with ImageNet label i is predicted as class j . We consider the model prediction to simply be the top-1 label. We determine the “human prediction” in two ways, as the class: (1) with highest annotator selection frequency in the CONTAINS task, and (2) which is the most likely choice for the main label in the CLASSIFY task. In Appendix Figure 27 we compare model and human confusion matrices (for both notions of human prediction). Unless otherwise specified, all other confusion matrices in the paper are based on the main label (using method (2)).

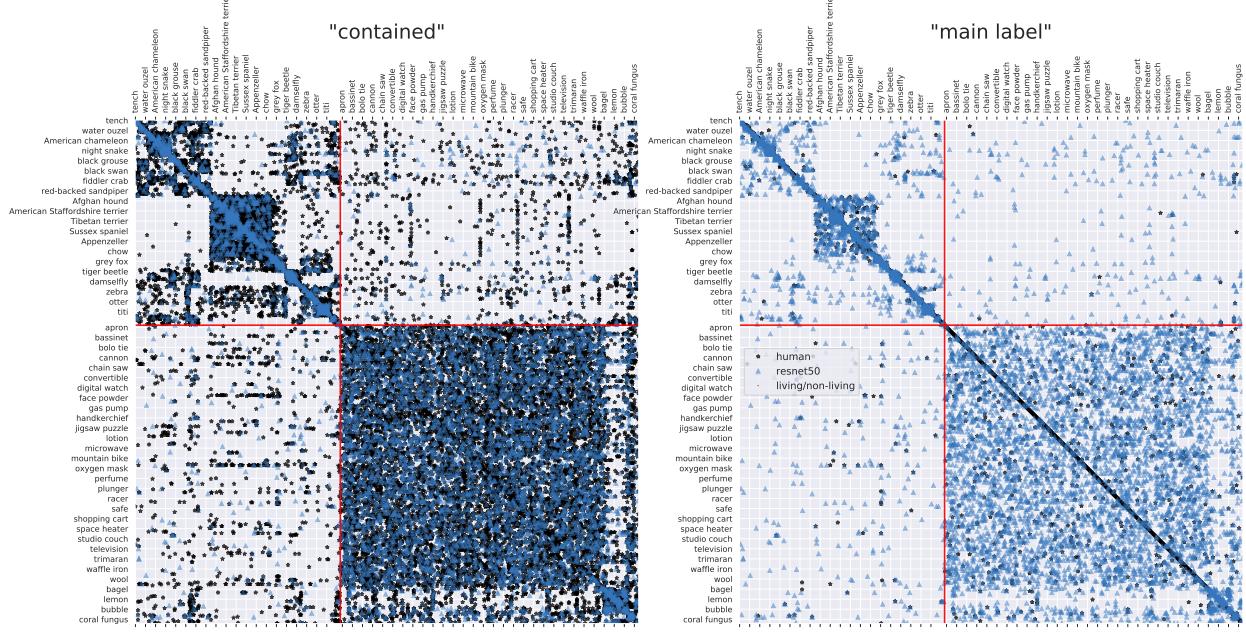


Figure 27: Comparison of model (blue; ResNet-50) and human (black) confusion matrices for all 1000 ImageNet classes. At a high-level, model and human confusion patterns seem somewhat aligned although humans seem to be particularly worse when it comes to fine-grained classes.

We compare the inter-superclass confusion matrices for humans and various models in Appendix Figure 28. We see that as models get better, their confusion patterns look similar to human annotators. Moreover, as we saw previously in Figure 27, there are blocks of superclasses where confusion seems particularly prominent—likely due to frequent object co-occurrences (cf. Figure 12b). We find that intra-superclass confusions are more prominent for humans—see Appendix Figure 29. This is in line with our findings from Section 3.1, where we observe that human annotators often select multiple labels for an image, even when they think it contains one object.

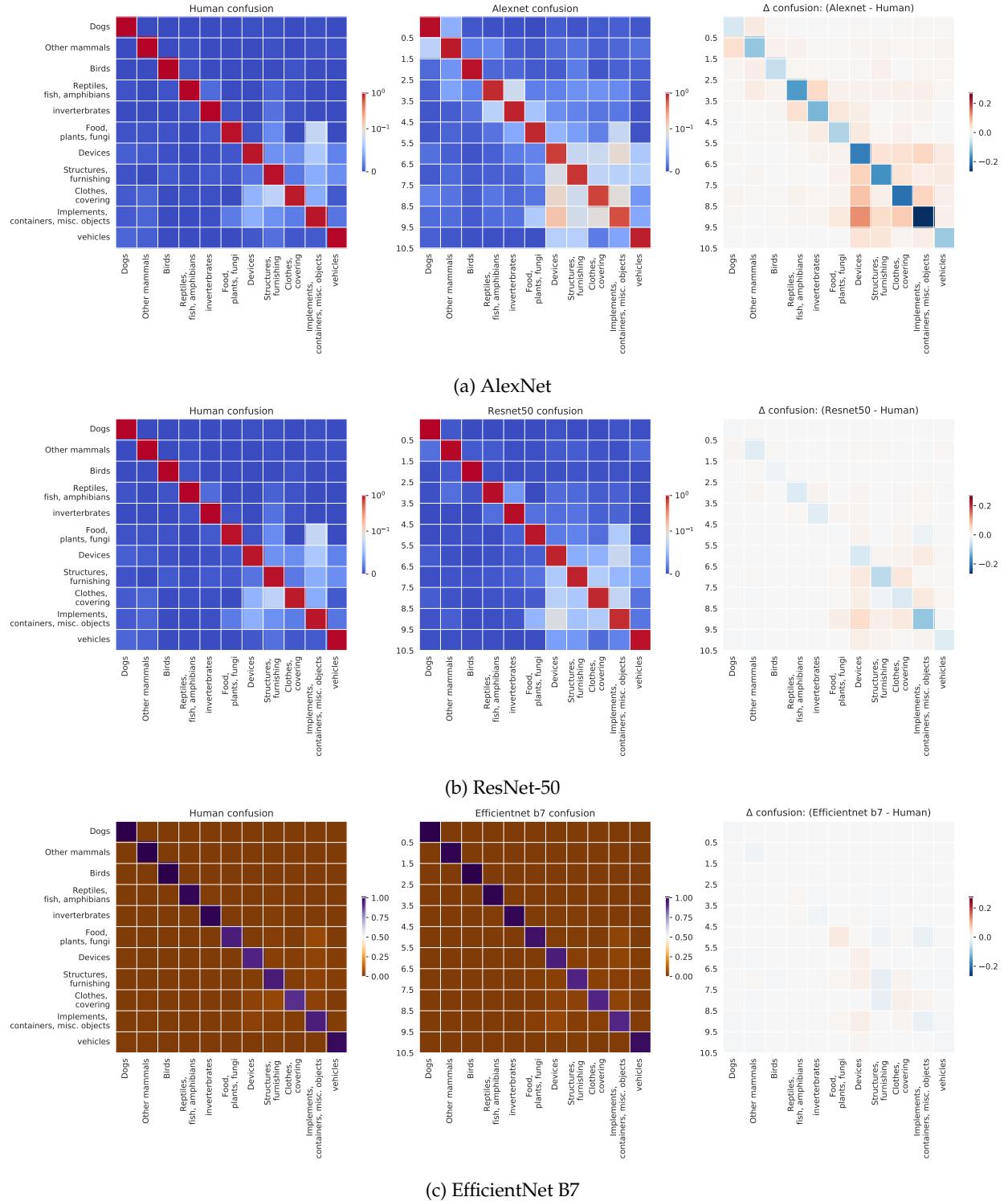
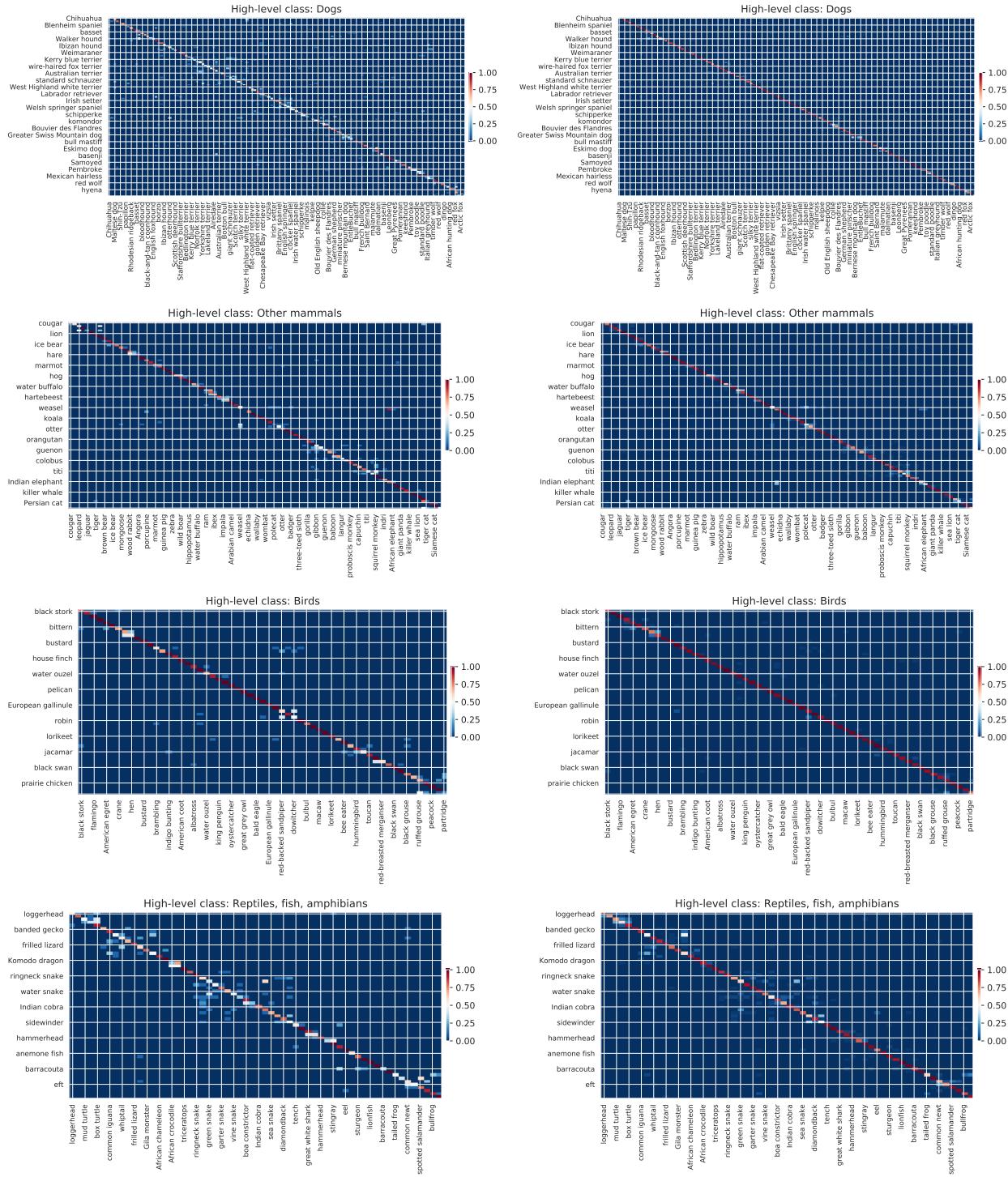
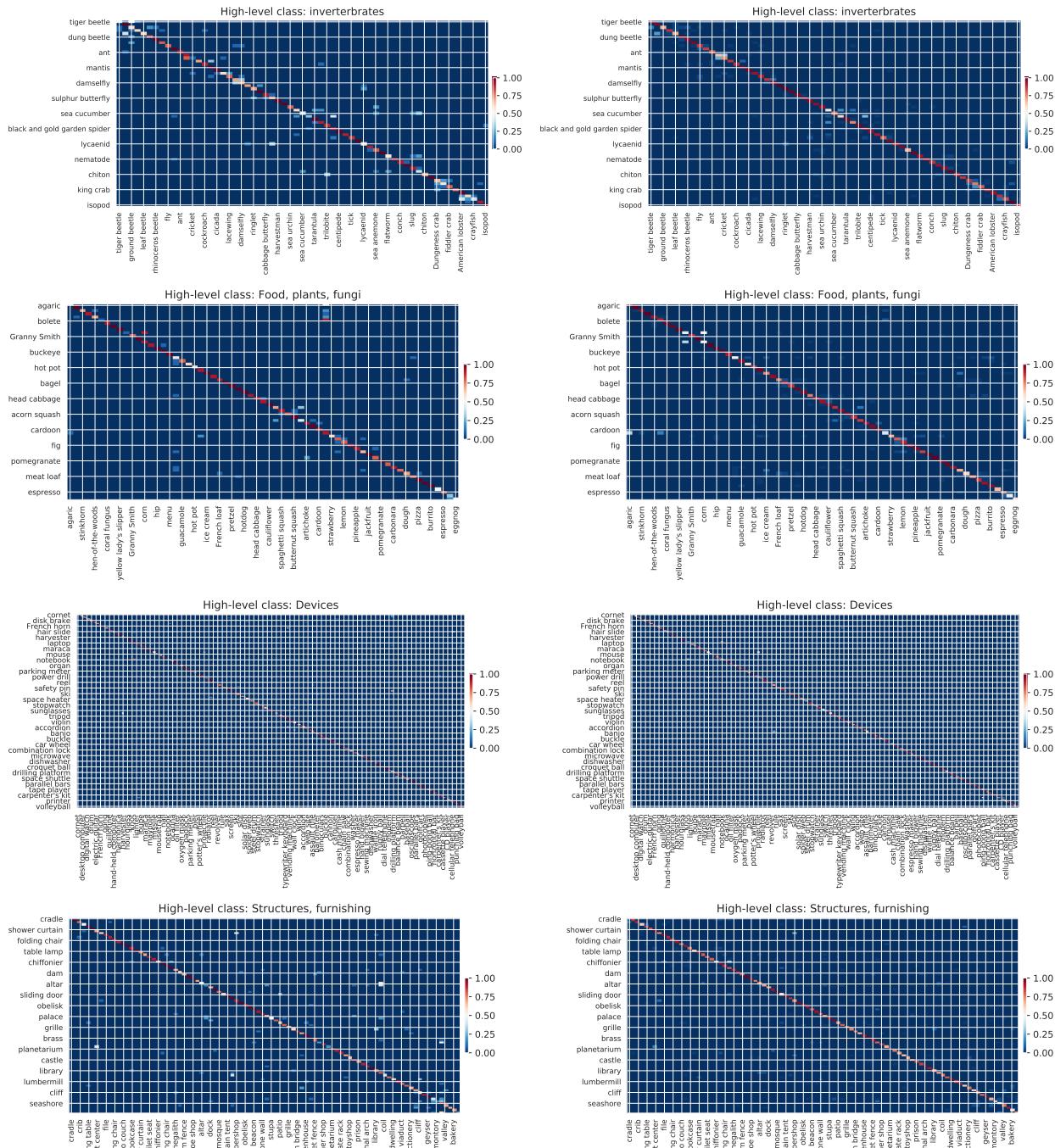


Figure 28: Inter-superclass confusion matrices for models and humans. We observe that as models get more accurate, their confusion also tends to align better with humans. In fact, more recent models seem to be better than humans, especially when it comes to fine-grained classes. Moreover, we see that for these models, the confusion patterns seem to mirror the object co-occurrences in Figure 12b. This suggests that part of errors of current models may stem from (legitimate) confusions due to multi-label images.





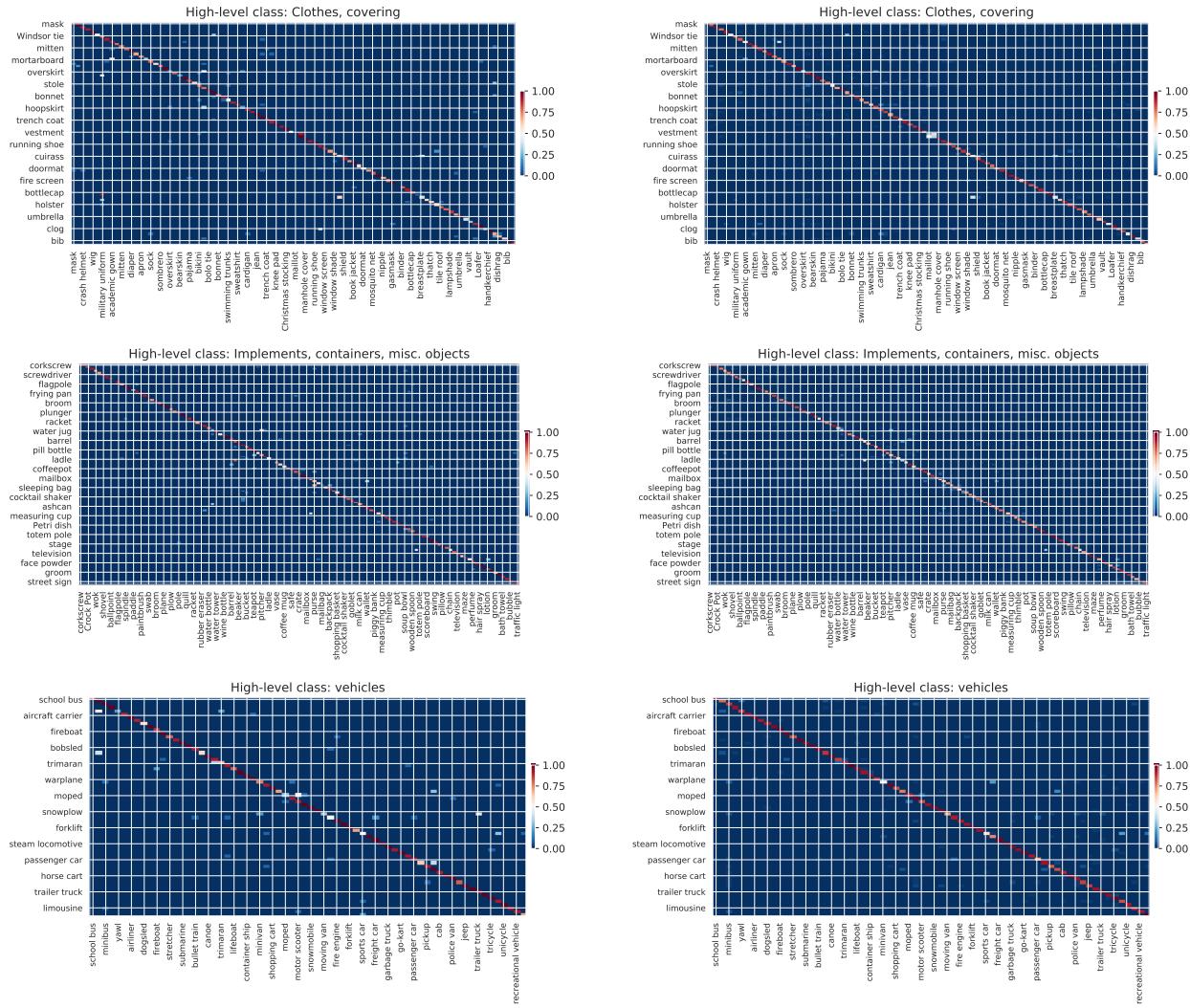


Figure 29: Intra-superclass confusion matrices for (left) humans and (right) an EfficientNet B7.