On Robustness and Transferability of Convolutional Neural Networks

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Abstract

Modern deep convolutional networks (CNNs) are often criticized for not generalizing under distributional shifts. However, several recent breakthroughs in transfer learning suggest that these networks can cope with severe distribution shifts and successfully adapt to new tasks from a few training examples. In this work we revisit the out-of-distribution and transfer performance of modern image classification CNNs and investigate the impact of the pre-training data size, the model scale, and the data preprocessing pipeline. We find that increasing both the training set and model sizes significantly improve the distributional shift robustness. Furthermore, we show that, perhaps surprisingly, simple changes in the preprocessing such as modifying the image resolution can significantly mitigate robustness issues in some cases. Finally, we outline the shortcomings of existing robustness evaluation datasets and introduce a synthetic dataset we use for a systematic analysis across common factors of variation.

1 Introduction

Deep convolutional networks have attained impressive results across a plethora of visual classification benchmarks [34, 58] where the training and testing distributions match. In the real world, however, the conditions in which the models are deployed can often differ significantly from the conditions in which the model was trained. It is imperative to understand the impact *dataset shifts* [48] have on the performance of these models. This problem has gained a lot of traction and several systematic investigations have showed unexpectedly high sensitivity of image classifiers to various dimensions, including photometric perturbations [25], natural perturbations obtained from video data [52], as well model-specific adversarial perturbations [22].

The problem of dataset shift, or *out-of-distribution (OOD) generalization*, is closely related to a learning paradigm known as *transfer learning* [54, §13]. In transfer learning we are interested in constructing models that can improve their performance on some target task by leveraging data from different related problems. In contrast, under dataset shift one assumes that there are two environments, namely training and testing [54], with the constraint that the model cannot be adapted using data from the target environment. As a consequence, the two environments typically have to be more similar and their differences more structured than in the transfer setting (c.f. Section 2.1).

In this work we evaluate the most successful recent recipes for transfer learning—model and data scale—on the problem of OOD generalization on the most prominent recent datasets, neural architec-

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tures, and training regimes and find that increasing model and data scale are surprisingly effective to mitigate the effects of different types of *dataset shift*.

Contributions We systematically investigate the classification accuracy of image classification models on the training distribution, their generalization to OOD data (without adaptation), and their transfer learning performance with adaptation in the low-data regime. Specifically, we present: (i) A meta-analysis of existing OOD metrics and transfer learning benchmarks across a wide variety of models, ranging from self-supervised to fully supervised models with up to 900M parameters, and show that most of the variance contained in the various metrics is explained by the IMAGENET validation set accuracy. However, increasing the model and data scale disproportionately improves transfer performance, despite providing only marginal improvements performance on the IMAGENET validation set. (ii) Focusing on OOD robustness, we analyze the effects of the training set size, model scale, and the training regime and testing resolution, and conclude that the effect of scale overshadows all other dimensions. (iii) We introduce a novel dataset for a fine-grained OOD analysis to quantify the robustness to common factors of variation: object size, object location, and object orientation (rotation angle). In a systematic study we show that the models become less sensitive (and hence more robust) to each of these factors of variation as the dataset size and model size increase.

2 Background

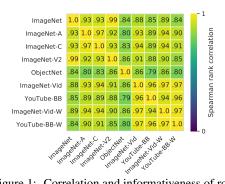
2.1 Robustness of image classification models

Understanding and correcting for dataset shifts are classical problems in statistics and machine learning, and have as such received substantial attention, see e.g. the monograph [48]. Formally, let us denote the observed variable by X and the variable we want to predict by Y. A dataset shift occurs when we train on samples from $P_{\mathrm{train}}(X,Y)$, but are at test time evaluated under a different distribution $P_{\mathrm{test}}(X,Y)$. Storkey [54] discusses and precisely defines different possibilities how P_{train} and P_{test} can differ. We are mostly interested in covariate shifts, i.e., when the conditionals $P_{\mathrm{train}}(Y|X) = P_{\mathrm{test}}(Y|X)$ agree, but the marginals $P_{\mathrm{train}}(X)$ and $P_{\mathrm{test}}(X)$ differ. Most robustness datasets proposed in the literature targeting IMAGENET models are such instances—the images X come from a source $P_{\mathrm{test}}(X)$ different from the original collection process $P_{\mathrm{train}}(X)$, but the label semantics are not supposed to change. As a robustness score one typically uses the expected accuracy, i.e., $P_{\mathrm{test}}(Y=f(X))$, where f(X) is the class predicted by the model.

Robustness datasets and dataset shift types IMAGENET-V2 is a recollected version of the IMAGENET validation set [50]. The authors attempted to replicate the data collection process, but found that all models drop significantly in accuracy. Recent work attributes this drop to statistical bias in the data collection [17]. IMAGENET-C and IMAGENET-P [25] are obtained by corrupting the IMAGENET validation set with classical corruptions, such as blur, different types of noise and compression, and further cropping the images to 224×224 . These datasets define a total of 15 noise, blur, weather, and digital corruption types, each appearing at 5 severity levels or intensities. OBJECTNET [3] presents a new test set of images collected directly using crowd-sourcing. OBJECTNET is particular as the objects are captured at unusual poses in cluttered, natural scenes, which can severely degrade recognition performance. Given this clutter, and arguably better suitability as a detection than recognition task [5], Y|X might be hard to define and the dataset goes beyond a covariate shift. In contrast, the IMAGENET-A dataset [28] consists of real-world, unmodified, and naturally occurring examples that are misclassified by ResNet models. Hence in addition to the covariate shift due to the data source, this dataset is not model-agnostic and exhibits a strong selection bias [54]. In an attempt to focus on naturally occurring invariances [52] turned to videos and annotated two datasets, namely, IMAGENET-VID-ROBUST and YOUTUBE-BB-ROBUST derived from the IMAGENET-VID [11] and YOUTUBE-BB [49] video datasets, respectively. In addition to measuring accuracy over the frames, the available temporal structure allows for more fine-grained robustness metrics. In [52] the authors suggest the following pm-k metric—given an anchor frame and up to k frames before and after it, a prediction is marked as correct only if the classifier correctly classifies all 2k+1 frames around the anchor. We present the details of each dataset in Appendix A.

2.2 Transferability of image classification models

In transfer learning [46], a model might leverage the data it has seen on a related distribution, $P_{\text{pre-train}}$, to achieve better performance on a new task P_{train} . Note that in contrast to the covariate



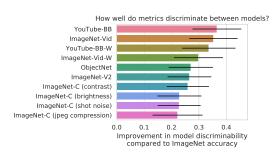


Figure 1: Correlation and informativeness of robustness metrics. Most metrics correlate strongly with IMA-GENET accuracy and provide little additional discriminability. (**Left**) Spearman's correlation between metrics. (**Right**) Difference in accuracy of a logistic classifier trained to discriminate between model types based on IMAGENET accuracy plus one additional metric, compared to a classifier trained only on IMAGENET accuracy (higher is better, top 10 metrics shown). Bars show mean±s.d. of 1000 bootstrap samples from the 39 models.

shift setting, the disparity between $P_{\rm pre-train}$ and the new task is typically larger, but one is additionally given samples from $P_{\rm train}$. While there exist many approaches in how to transfer knowledge to the new task, the most common approach in modern deep learning, which we use, is to (i) train a model on $P_{\rm pre-train}$ (using perhaps an auxiliary, self-supervised task [15, 21]), and then (ii) train a model on $P_{\rm train}$ by initializing the model weights from the model trained in the first step.

Recently, a suite of datasets has been collected to benchmark modern image classification transfer techniques [69]. The Visual Task Adaptation Benchmark (VTAB) defines 19 datasets with 1000 labeled samples each, categorized in into three groups of *natural*, *specialized* and *structured* datasets: *natural* (most similar to IMAGENET) consists of standard natural classification tasks (e.g. CIFAR, VGG Flowers); *specialized*, contains medical and satellite images; and *structured* (least similar to IMAGENET), consists mostly synthetic tasks that require understanding of the geometric layout of scenes. We compute an overall transfer score as the mean across all 19 datasets, as well as scores for each subgroup of tasks. We provide details for all of the tasks in Appendix A.

3 Analysis of existing robustness and transfer metrics

While many robustness metrics have been proposed to capture a different sources of brittleness, it is not well understood how these metrics relate to each other. We investigate (i) the amount of complementary information in these metrics, and (ii) their usefulness in guiding design choices. Further, despite the close relationship between the notions of robustness and transferability, there has been no analysis of how predictive of each other their corresponding metrics are. To analyze these questions, we evaluated 39 different models over 23 robustness metrics and the 19 transfer tasks.

Metrics We consider metrics that quantify both robustness and transfer performance. For robustness, we measure the model accuracy on the IMAGENET, IMAGENET-V2 (the *matched frequency* variant) and OBJECTNET datasets. We also consider video datasets, IMAGENET-V1D and YOUTUBE-BB; we use both the accuracy metric and the *pm*-10 metric (suffix -W). On IMAGENET-C we report the AlexNet-accuracy-weighted [37] accuracy over all corruption times (called *mean corruption error* in [25]). To evaluate the transferability of the models, we use the VTAB-1K benchmark that we introduced in Section 2.2. We evaluate average transfer performance across all 19 datasets, with 1000 examples each, as well as per-group performance. To transfer a model we performed a sweep over two learning rates and schedules. We report the median testing accuracy over three fine-tuning runs with parameters selected using a 800-200 example train-validation split.

Models We consider several model families, some of which make use of additional data besides IMAGENET. We evaluate ResNet-50 [23] and six EfficientNet (B0 through B5) models [58] including variants using AutoAugment [10] and AdvProp [66], which have been trained on IMAGENET. We include self-supervised SimCLR [6] (three variants: linear classifier on top of representation (lin), fine-tuned on 10% (ft-10), and 100% (ft-100) of the IMAGENET data), as well as self-supervised-semi-supervised (S4L) [68] models that have been fine-tuned to 10% and 100% of the IMAGENET data. We also consider a set of models that incorporate other data sources. Specifically, we test three NoisyStudent [67] variants which use IMAGENET and unlabelled data from the JFT dataset, BiT (BigTransfer) [34] models that have been first trained on IMAGENET, IMAGENET-21K, or JFT

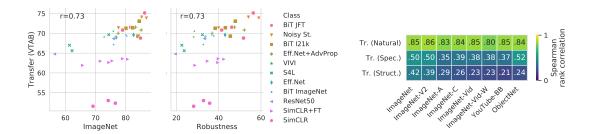


Figure 2: The relationship between transfer learning, IMAGENET, and robustness performance. (**Left**) Average score on all transfer benchmarks versus IMAGENET performance. (**Center**) Average score on all robustness benchmarks versus average transfer performance. (**Right**) Correlation between different groups of transfer datasets (natural, specialized, structured), and robustness metrics.

and then transferred to IMAGENET by fine-tuning, and the Video-Induced Visual Invariance (VIVI) model [63], which uses IMAGENET and unlabelled videos from the YT8M dataset [1]. Finally, we consider the BigBiGAN [14] model which has been first trained as a class-conditional generative model and then fine-tuned to an IMAGENET classifier. All model details can be found in Appendix E.

How well does IMAGENET accuracy predict performance on OOD data? We start with an analysis of mutual dependence of the robustness metrics by measuring the Spearman's ρ rank correlation coefficient. Figure 1 (left) shows the rank correlation between the metrics. We observe that all metrics are highly correlated with each other, with a median Spearman's ρ of 0.9. The metrics also strongly correlate with the accuracy on the IMAGENET validation set with a median Spearman's ρ of 0.89 and a 0.84 minimum. To understand the benefit of these metrics beyond IMAGENET accuracy, we fit linear regression models for each metric with IMAGENET accuracy as the single covariate. Consistent with the rank correlation analysis, we find that 75.2% of the variance in the metric values is explained by IMAGENET accuracy. A principal component analysis shows that the space of robustness metric residuals spans approximately one statistically significant dimension (Appendix A). This raises the question to what degree the robustness metrics provide useful information beyond standard IMAGENET accuracy, which we investigate next.

Can robustness metrics discriminate between models? The goal of a metric is to discriminate between different models and thus guide design choices. We therefore quantify the usefulness of each metric in terms of how much it improves the discriminability between the various models beyond the information provided by IMAGENET accuracy. Specifically, we train logistic regression classifiers to discriminate between the 12 model groups outlined above. We compared the performance of a classifier using only IMAGENET accuracy as input feature, to a classifier using IMAGENET and up to two of the other metrics, see Fig. 1 (right) and Appendix A. We found that most of the tested metrics provide little increase in model discriminability over IMAGENET accuracy. Of course, this result is conditioned on the size and composition of our dataset, and may differ for a different set of models. However, based on our dataset of 39 models in 12 groups, the most informative metrics are those based on different datasets and/or video, rather than IMAGENET-derived datasets.

How related are OOD robustness and transfer metrics? Next, we turn to transfer learning. It has been observed that better IMAGENET models transfer better [35, 69]. Since robustness is correlated with IMAGENET (Figure 1), we might expect a similar relationship. To get an overall view, we compute the mean of all robustness metrics, and compare it to transfer performance. Figure 2 (center) shows this average robustness plotted against transfer performance, while Figure 2 (left) shows transfer versus IMAGENET accuracy. Indeed, we observe a large correlation $\rho = 0.73$ between robustness metrics and transfer; however, the correlation is not stronger than between transfer and IMAGENET. Further, we compute the correlation of the residual robustness score (mean robustness minus IMAGENET accuracy) against transfer score, and find only a weak relationship of $\rho = 0.12$. This indicates that robustness metrics, on aggregate, do not provide additional signal that predicts model transferability beyond that of the base IMAGENET performance. We do, however, see some interesting differences in the relative performances of different model groups. Certain model groups, while attaining reasonable IMAGENET/robustness scores, transfer less well to VTAB. Therefore, there are factors that influence transferability unrelated to robust inference. One example is batch normalization which is outperformed by group normalization with weight standardization in transfer [34]. Next, we break down the correlation by robustness metrics and transfer datasets in Fig. 2 (right). We

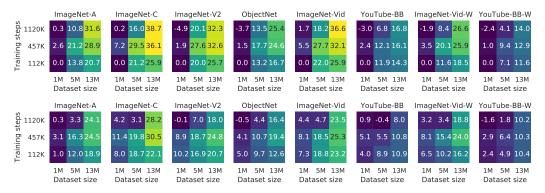


Figure 3: (**Top**) Reduction (in %) in classification error relative to the classification error of the model trained for 112k steps on 1M examples (bottom left corner) as a function of training iterations and training set size. The results are for ResNet-101x3 trained on IMAGENET-21K subsets. (**Bottom**) Relative reduction (in %) in classification error going from ResNet-50 to ResNet-101x3 as a function of training steps and training set size (IMAGENET-21K subsets). The reduction generally increases with the training set size and longer training.

see that each metric correlates similarly with the task groups. However, for the groups that require more distant transfer (Specialized, Structured), no metric predicts transferability well. Curiously, raw IMAGENET accuracy is the best predictor of transfer to *structured* tasks, indicating that robustness metrics do not relate to challenging transfer tasks, at least not more than raw IMAGENET accuracy.

Summary We have seen that many popular robustness metrics are highly correlated. Some metrics, particularly those not based on IMAGENET, have only a little additional discriminative power to distinguish models over IMAGENET accuracy. Transferability is also related to IMAGENET accuracy, and hence robustness. We observe that while there is correlation, transfer highlights failures that are somewhat independent of robustness. Further, no particular robustness metric appears to correlate better with any particular group of transfer tasks than IMAGENET does. Since all of these metrics seem closely linked, we investigate strategies known to be effective for IMAGENET and transfer learning on the newer robustness benchmarks.

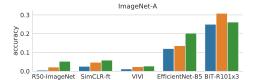
4 The effectiveness of scale for OOD generalization

Increasing the scale of pre-training data, model architecture, and training steps have recently led to diminishing improvements in terms of IMAGENET accuracy. By contrast, it has been recently established that scaling along these axes can lead to substantial improvements in transfer learning performance [34, 58]. In the context of robustness, this type of scaling has been explored less. While there are some results suggesting that scale improves robustness [25, 50, 67, 61], no principled study decoupling the different scale axes has been performed. Given the strong correlation between transfer performance and robustness, this motivates the systematic investigation of the effects of the pre-training data size, model architecture size, training steps, and input resolution.

4.1 Effect of model size, training set size, and training schedule

We consider the standard IMAGENET training setup [23] as a baseline, and scale up the training accordingly. To study the impact of dataset size, we consider the IMAGENET-21K [11] and JFT [55] datasets for the experiments, as pre-training on either of them has shown great performance in transfer learning [34]. We scale from the IMAGENET training set size (1.28M images) to the IMAGENET-21K training set size (13M images, about 10 times larger than IMAGENET). To explore the effect of the model size, we use a ResNet-50 as well as the deeper and $3 \times$ wider ResNet-101x3 model. We further investigate the impact of the training schedule as larger datasets are known to benefit from longer training for transfer learning [34]. To disentangle the impact of dataset size and training schedules, we train the models for every pair of dataset size and schedule.

We fine-tune the trained models to IMAGENET using the BiT HyperRule [34], and assess their OOD generalization performance in the next section. Throughout, we report the reduction in classification error relative to the model which was trained on the smallest number of examples, for the fewest iterations, and hence achieves the lowest accuracy. Other details are presented in Appendix B.



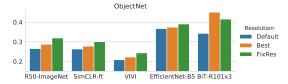


Figure 4: Comparison of different types of evaluation preprocessing and resolutions. Default: Accuracy obtained for the preprocessing and resolution proposed by the authors of the respective models. Best: The accuracy when selecting the best resolution from $\{64, 128, 224, 288, 320, 384, 512, 768\}$. FixRes: Applying FixRes for the same set of resolutions and selecting the best resolution. Increasing the evaluation resolution and additionally using FixRes helps across a large range of models and pretraining datasets on IMAGENET-A and OBJECTNET.

Dataset size impact The results for the ResNet-101x3 model are presented in Fig. 3. When trained on IMAGENET-21K, the OOD classification error significantly decreases with increasing dataset size and training duration: We observe relative error reductions of 20–30% when going from 112k steps on 1M data points to 1.12M steps on 13M data points. The reductions are least pronounced for YOUTUBE-BB/YOUTUBE-BB-W. Also note that training for 1.12M steps leads to a lower accuracy than training for only 457k steps unless the full IMAGENET-21K dataset is used. For models trained on JFT we observe a similar behavior except that training for 1.12M steps leads to a higher accuracy than training for 257k steps even when only 112k or 457k data points are used. The JFT results are presented in Appendix B. These results suggest that, if the models have enough capacity, increasing the amount of training data, with no additional changes, leads to massive gains in all datasets *simultaneously* which is in line with recent results in transfer learning [34].

Model size impact Figure 3 shows the relative reduction in classification error when using ResNet-101x3 instead of ResNet-50 as a function of the number of training steps and the dataset size. It can be seen that increasing the model size can lead to substantial reductions of 5-20%. For a fixed training duration, using more data always helps. However, on IMAGENET-21K, training too long can lead to increases in the classification error when the model size is increased, unless the full IMAGENET-21K is used. This is likely due to overfitting. This effect is much less pronounced when JFT is used for training. JFT results are presented in Appendix B. Again, reductions in classification error are least pronounced for YOUTUBE-BB/YOUTUBE-BB-W.

4.2 Effect of the testing resolution

During training, images are typically cropped randomly, with many crop sizes and aspect ratios, to prevent overfitting. In contrast, during testing, the images are usually rescaled such that the shorter side has a pre-specified length, and a fixed-size center crop is taken and then fed to the classifier. This leads to a mismatch in object sizes between training and testing. Increasing the resolution at which images are tested leads to an improvement in accuracy across different architectures [60, 61]. Furthermore, additional benefits can be obtained by applying FixRes – fine-tuning the network on the training set with the test-time preprocessing (i.e. omitting random cropping with aspect ratio changes), and at higher resolution. We explore the effect of this discrepancy on the robustness of different architectures. As some of the robustness datasets were collected in a different way from IMAGENET, discrepancies in the cropping are likely. We investigate both adjusting test-time resolution and applying FixRes. For FixRes, we use a simple setup with a single schedule and learning rate for all models (except using a 10× smaller learning rate for the BiT models), and without heavy color augmentation as in [60] or label smoothing as in [61]. Furthermore we did not extensively tune hyperparameters, but chose a setup that works reasonably well across architectures and datasets.

Results and discussion Figure 4 shows the accuracy for IMAGENET-A and OBJECTNET at the testing resolution proposed by the authors of the respective architecture along with the highest accuracy obtained by selecting the best testing resolution in $\{64, 128, 224, 288, 320, 384, 512, 768\}$, and after applying FixRes. The results for other datasets are deferred to Appendix C.

We start by discussing observations that apply to most of the models, excluding the BiT models which will be discussed below. While FixRes only leads to marginal benefits on IMAGENET, it can lead to substantial improvements on the robustness metrics. Choosing the optimal testing resolution leads to a significant increase in accuracy on IMAGENET-A and OBJECTNET in most cases, and applying FixRes often leads to additional substantial gains. For OBJECTNET, fine-tuning with testing



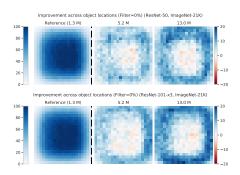


Figure 5: (**Left**) Sample images from our synthetic dataset. We consider 614 foreground objects from 62 classes and 867 backgrounds and vary the object location, rotation angle, and object size for a total of 611 608 images. (**Right**) In the first column, for each location on the grid, we compute the average accuracy. Then, we normalize each location by the 95th percentile across all locations, which quantifies the gap between the locations where the model performs well, and the ones where it under-performs (first column, dark blue versus white). Then, we consider models trained with more data, compute the same normalized score, and plot the *difference* with respect to the first column. We observe that, as dataset size increases, sensitivity to object location decreases – the outer regions improve in relative accuracy more than the inner ones (e.g. dark blue vs white on the second and third columns). The effect is more pronounced for the larger model. The full set of results is presented in Figure 15.

preprocessing (i.e. fine-tuning with central cropping instead of random cropping as used during training) even helps without increasing resolution in some cases.

Increasing the resolution and/or applying FixRes often slightly helps on IMAGENET-V2. For IMAGENET-C, the optimal testing resolution often corresponds to the resolution used for training, and applying FixRes rarely changes this picture. This is not surprising as the IMAGENET-C images are cropped to 224 pixels by default, and increasing the resolution does not add any new information to the image. For the video-derived robustness datasets IMAGENET-VID-ROBUST and YOUTUBE-BB-ROBUST, evaluating at a larger testing resolution and/or applying FixRes at a higher resolution can substantially improve the accuracy on the anchor frame and the robustness accuracy for small EfficientNet and ResNet models, but does not help the larger ones. For the BiT models, the resolution suggested by the authors is almost always optimal, except on OBJECTNET and IMAGENET-A, where changing the preprocessing considerably helps. FixRes arguably does not lead to improvements as it was already applied in BiT as a part of the BiT HyperRule. Based on these results we strongly suggest the application of these adjustments to address the shift caused by resolution mismatch.

4.3 A systematic study on the effect of scale on common factors of variation

There are several factors of variation, such as object location, size, and rotation, that we want our models to be robust to. For a solid diagnostic of the failure modes, one should ideally be able to vary testing data according to these axes. However, the combinatorial nature of the number of possible combinations of such factors of variation precludes any large-scale systematic data collection scheme.

In this work we present a scalable alternative and construct a novel synthetic dataset for fine-grained evaluation. We paste objects extracted from OpenImages [38] using segmentation masks onto uncluttered backgrounds sourced from the web (Figure 5, details in Appendix D). We can thus conduct controlled studies by systematically varying the object class, size, location, and orientation (rotation angle). We study one factor of variation at a time (e.g. location of the object center), and look at the average performance for each location over a uniform grid.

We investigate the effect of model and dataset size on these three factors of variation by evaluating the ResNet-50 and ResNet-101x3 models. We observe that the models become more invariant to location (Figure 5), size (Figure 6), and rotation of the objects (Figure 6) as the model or training set size increases. The improvements are more pronounced for the larger ResNet-101x3 model. The analogous results on the JFT dataset are presented in Appendix D.

5 Related work

There has been a growing literature exploring the robustness of image classification networks. Early investigations in face and natural image recognition found that performance degrades by introducing

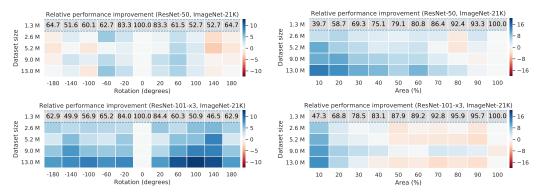


Figure 6: (**Left**) In the first row of both plots we show the ratio of the accuracy and the best accuracy (across all rotations). For the second row (model trained on 2.6M instances) and other rows, we compute the same normalized score and visualize the difference with the first row. Larger differences imply a more uniform behavior across object rotations. We observe that, as the dataset size increases, the average prediction accuracy across various rotation angles becomes more uniform. The effect is more pronounced for the larger model. (**Right**) Similarly, the average accuracy across various object sizes becomes more uniform for both models. As expected, the improvement is most pronounced for small object sizes covering 10–20% of the pixels. The full set of results is presented in Figures 13 and 14.

blur, Gaussian noise, occlusion, and compression artifacts, but less by color distortions [12, 33]. Subsequent studies have investigated brittleness to similar corruptions [51, 73], as well as to impulse noise [29], photometric perturbations [59], and small shifts and other transformations [2, 17, 71]. CNNs have also been shown to over-rely upon texture rather than shape to make predictions, in contrast to human behavior [20]. Robustness to adversarial attacks [22] is a related, but distinct problem, where performance under worst-case perturbations are studied. In this paper we did not study such adversarial robustness, but have focused on average-case robustness to natural perturbations.

Several techniques have been shown to improve model robustness on these datasets. Using better data augmentation can improve performance on data with synthetic noise [27, 41]. Auxiliary self-supervision [7, 68] can improve robustness to label noise and common corruptions [26]. Transductive fine-tuning using self-supervision on the test data improves performance under distribution shift [56]. Training with adversarial perturbations improves many robustness benchmarks if one uses separate Batch-Norm parameters for clean and adversarial data [66]. Finally, additional pre-training using very large auxiliary datasets has recently shown significant improvements in Robustness. Noisy Student [67] reports good performance on several robustness datasets, while Big Transfer (BiT) [34] reports strong performance on the recently introduced OBJECTNET dataset [3].

Deep networks are often trained by pre-training the network on a different problem and then fine-tuning on the target task. This pre-training is often referred to as representation learning; representations can be trained using supervised [30, 34], weakly-supervised [42], or unsupervised data [13, 14, 63, 67]. Recent benchmarks have been proposed to evaluate transfer to several datasets, to assess generalization to tasks with different characteristics, or those disjoint from the pre-training data [62, 69]. While state-of-the-art performance on many competitive datasets is attained via transfer learning [67, 34], the implication for final robustness metrics remain unclear.

Creating synthetic datasets by inserting objects onto backgrounds has been used for training [72, 16] and evaluating models [34], but previous works do not systematically vary object size, location or orientation, or analyze translation and rotation robustness only at the image level [18].

6 Limitations and future work

We analyzed OOD generalization and transferability of image classifiers, and demonstrated that model and data scale together with a simple training recipe lead to large improvements. However, the models do exhibit a substantial gap in performance when tested on OOD data, and scale is unlikely to be the only approach to close this gap. Secondly, this approach hinges on the availability of curated datasets and significant computing capabilities which is not always practical. Hence, we believe that transfer learning, i.e. train once, apply many times, is the most promising paradigm for OOD

robustness in the short term. One limitation of this study is that we consider image classification models fine-tuned to the IMAGENET label space which were developed with the goal of optimizing the accuracy on the IMAGENET test set. While existing work shows that we didn't overfit to IMAGENET, it is possible that these models have correlated failure modes on datasets which share the biases with IMAGENET [50]. This highlights the need for datasets which enable fine-grained analysis for all important factors of variation and we hope that our dataset will be useful for researchers.

Instead of requiring the model to work under various dataset shifts, one can ask an alternative question: assuming that the model will be deployed in an environment significantly different from the training one, can we at least quantify the model uncertainty for each prediction? This important property remains elusive for moderate-scale neural networks [53], but could potentially be improved by considering larger models and larger pretraining datasets which we leave for future work.

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A Analysis of existing robustness and transfer metrics

Here, we provide additional details related to the analyses presented in Figure 1.

A.1 Dimensionality of the space of robustness metrics

To estimate how many different dimensions are measured by the robustness metrics beyond what is already explained by IMAGENET accuracy, we proceeded as follows. For each of the robustness metrics shown in Figure 1 and 8, a linear regression was fit to predict that metric's value for the 39 models, using IMAGENET accuracy as the sole predictor variable. Then, the residuals were computed for each metric by subtracting the linear regression prediction. The plot shows the fraction of variance explained for the first 4 principal components of the space of residuals of the robustness metrics. As a null hypothesis, we assumed that there is no correlation structure in the metric residuals. To construct corresponding null datasets, we randomly permuted the values for each metric independently, which destroys the correlation structure between metrics. Figure 7a shows that only the first principal component is significantly above the value expected under the null hypothesis.

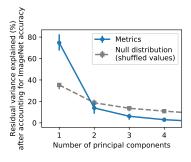


Figure 7: (**Left**) The space of robustness metrics spans approximately one statistically significant dimension after accounting for IMAGENET accuracy. Errorbars show 95% confidence intervals based on 1000 bootstrap samples (for the true data) or 1000 random permutations (for the null distribution). See Section A.1 for details. (**Right**) Details for the datasets used in this study. The datasets were used only for evaluation.

A.2 Informativeness of robustness metrics

To estimate how useful different combinations of robustness metrics are for discriminating between model types, we trained logistic regression classifiers to discriminate between the 12 model groups outlined in the main paper. We consider IMAGENET accuracy as a baseline metric and therefore compare the performance of a classifier using only IMAGENET accuracy as input feature, to a classifier using IMAGENET either one (Figure 8, left) or two (Figure 8, right) additional metrics as input features. Figure 8 shows difference in accuracy to the baseline (IMAGENET) classifier. These results can serve practitioners with a limited budget as a rough guideline for which metric combinations are the most informative. In our experiments, the most informative combination of metrics in addition to IMAGENET accuracy was OBJECTNET and YOUTUBE-BB, although other combinations performed similarly within the statistical uncertainty.

A.3 Visual Task Adaptation Benchmark

The Visual Task Adaptation Benchmark (VTAB) [69] contains 19 tasks. Either the full dataset or 1000-example training sets may be used, we use the version with 1000-example training sets (VTAB-1k).

The tasks are divided into three groups: Natural, standard natural image classification problems. Specialized, domain-specific images captured with specialist equipment (e.g. medical images). Structured, classification tasks that require geometric understanding of a scene. The Natural group contains the following datasets: Caltech101 [40], CIFAR-100 [36], DTD [9], Flowers102 [45], Pets [47], Sun397 [65], SVHN [44]. The Specialized group contains remote sensing datasets, EuroSAT

DATASET INSTANCES CLS. 50 000 IMAGENET [37] 1000 IMAGENET-A [28] IMAGENET-C [25] 7500 200 $15\times4\!\times\!50\,000$ 1000 18 574 OBJECTNET [3] 113 IMAGENET-V2 [50] 10,000 1000 IMAGENET-VID [52] 22 179 293 YTBB-ROBUST [52] 51 826 229

⁽a) The space of robustness metrics.

⁽b) The name and reference, number of instances, and the number of classes overlapping with ImageNet for each dataset.

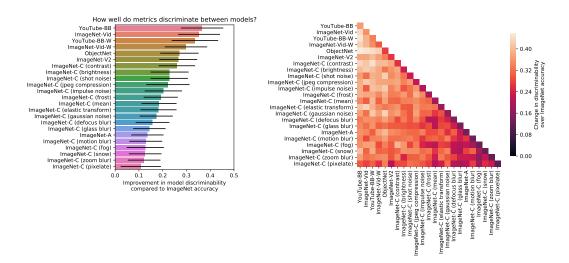


Figure 8: Informativeness of robustness metrics (related to Figure 1). (**Left**) Similar to Figure 1 (left), but showing all 23 robustness metrics. Difference in accuracy of a logistic classifier trained to discriminate between model types based on IMAGENET accuracy plus one additional metric, compared to a classifier trained only on IMAGENET accuracy (higher is better, top 10 metrics shown). Bars show mean±s.d. of 1000 bootstrap samples from the 39 models. (**Right**) Increase in classifier accuracy over IMAGENET accuracy when including up to two robustness metrics as explanatory variables. The diagonal shows the single-feature values from (left).

[24] and Resisc45 [8], and medical images, Patch Camelyon [64] and Diabetic Retinopathy [32]. The Structured group contains the following tasks: Counting and distance prediction on CLEVR [31]. Pixel-location and orientation prediction on dSprites [43]. Camera elevation and object orientation on SmallNORB [39]. Object distance on DMLab [4]. Vehicle distance on KITTI [19].

B Scale and OOD generalization

Training Details The models are firstly pre-trained on IMAGENET-21K and JFT, followed by fine-tuning on IMAGENET to match the label space for evaluation. We follow the pre-training and BiT-HyperRule fine-tuning setup proposed in [34].

Specifically, for pre-training, we use SGD with momentum with initial learning rate of 0.1, and momentum 0.9. We use linear learning rate warm-up for 5000 optimization steps and multiply the learning rate by $\frac{\text{batch size}}{256}$. We use a weight decay of 0.0001. We use the random image cropping technique from [57], and random horizontal mirroring followed by 224×224 image resize. We use a global batch size of 1024 and train on a Cloud TPUv3-128. We pre-train models for the cross product of the following combinations:

- **Dataset Size**: {1.28M (1× ImageNet train set), 2.6M (2× ImageNet train set), 5.2M (4× ImageNet train set), 9M (7× ImageNet train set), 13M (10× ImageNet train set)}.
- Train Schedule (steps): {113K (90 ImageNet epochs), 229K (180 ImageNet epochs), 457K (360 ImageNet epochs), 791K (630 ImageNet epochs), 1.1M (900 ImageNet epochs)}.

For fine-tuning, we use the BiT-Hyperrule as described in [34]: batch size 512, learning rate 0.003, no weight decay, the classification head initialized to zeros, mixup [70] with $\alpha=0.1$, fine-tuning for $20\,000$ steps with 384×384 image resolution. We present the results on the synthetic dataset in Appendix D.

Additional Results Here we highlight the results equivalent to Figure 3, with the only difference that we consider subsets of the JFT [55] dataset, instead of IMAGENET-21K (Figure 9).

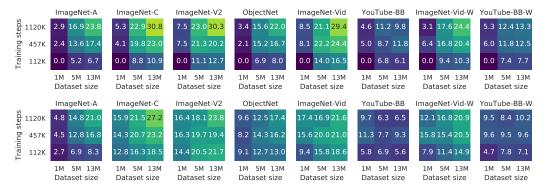


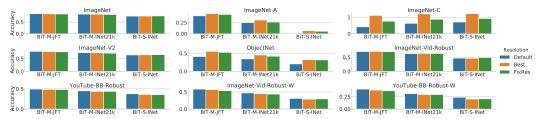
Figure 9: (**Top**) Reduction (in %) in classification error relative to the classification error of the model trained for 112k steps on 1M examples (bottom left corner) as a function of training iterations and training set size. The results are for ResNet-101x3 trained on JFT subsets. (**Bottom**) Relative reduction (in %) in classification error going from ResNet-50 to ResNet-101x3 as a function of training steps and training set size (JFT subsets). The reduction generally increases with the training set size and longer training.

C Effect of the testing resolution

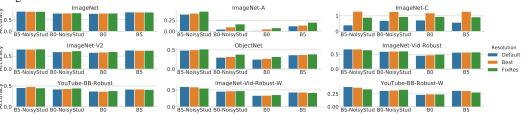
Cropping details Before applying the respective model, we first resize every image such that the shorter side has length $\lfloor 1.15 \cdot r \rfloor$ while preserving the aspect ratio and take a central crop of size $r \times r$. For the widely used 224×224 testing resolution, this leads to standard single-crop testing preprocessing, where the images are first resized such that the shorter side has length 256.

Training details for FixRes For fine-tuning to the target resolution (FixRes) we use SGD with momentum with initial learning rate of 0.004 (except for the BiT models for which we use 0.0004), and momentum 0.9, accounting for varying batch size by multiplying the learning rate with $\frac{\text{batch size}}{256}$. We train for $15\,000 \cdot \frac{\text{batch size}}{2048}$, decaying the learning rate by a factor of 10 after 1/3 and 2/3 of the iterations. The batch size is chosen based on the model size to avoid memory overflow; we use 2048 in most cases. We train on a Cloud TPUv3-64. We emphasize that we did not extensively tune the training parameters for FixRes, but chose a setting that works well across models and data sets.

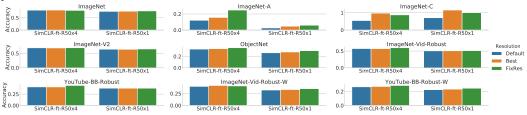
Additional results In Figure 10 we provide an extended version of Figure 4 that shows the effect of FixRes for all datasets and models. In Figure 11 we plot the performance of all models and their FixRes variants as a function of the resolution.



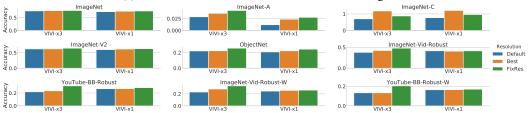
(a) Different BiT variants. -M- stands for ResNet-101x3, while -S- for ResNet-50x1. INet is a shorthand for ImageNet.



(b) Two ImageNet-trained EfficientNet variants (B0,B5) as well as those models trained using the Noisy Student protocol.



(c) SimCLR models that have been fine-tuned on ImageNet.



(d) Two VIVI variants (R50x1 and R50x3), both co-trained with ImageNet.

Figure 10: Comparison of different types of evaluation preprocessing and resolutions. Default: Accuracy obtained for the preprocessing and resolution proposed by the authors of the respective models. Best: The accuracy when selecting the best resolution from $\{64, 128, 224, 288, 320, 384, 512, 768\}$. FixRes: Applying FixRes for the same set of resolutions and selecting the best resolution. Increasing the evaluation resolution and additionally using FixRes helps across a large range of models and pretraining datasets.

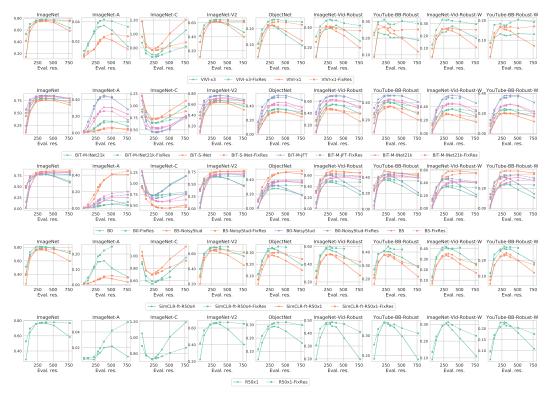


Figure 11: Comparison of different types of evaluation preprocessing and resolutions, without modifying the model and after applying FixRes. For brevity the same shorthands are used in the model names as in Figure 10.

D Synthetic dataset

In order to measure how model performance changes as object position, size and orientation change, we constructed a synthetic dataset. The dataset consists of objects pasted on relatively uncluttered backgrounds. We show a few examples in Figure 5 (left) in the main paper and here in Figure 12. The objects were extracted from OpenImages [38] using the provided segmentation masks. As we are investigating models trained or fine-tuned on ImageNet, we only used classes that could be mapped to ImageNet. We also removed all objects that are tagged as occluded or truncated, and manually remove highly incomplete or inaccurately labeled objects. We converged to 614 object instances across 62 classes. The backgrounds were images from nature taken from *pexels.com* (the license therein allows one to reuse photos with modifications). We manually filtered the backgrounds to remove ones with prominent objects, such as images focused on a single animal or person. We collected 867 such backgrounds.

F.O.V.	DATASET CONFIGURATION	IMAGES
SIZE	Objects in the center and upright, sizes ranging from 1% to 100% of the image area in 1% increments.	92 884
LOCATION	Objects upright. Sizes are 20% of the image area. We do a grid search of locations, dividing the x-coordinate dimension and y-coordinate dimensions into 20 equal parts each, for a total of 400 coordinate locations.	479 184
ROTATION	Objects in the center, sizes equal to 20%, 50%, 80% or 100% of the image size. Rotation angles ranging from 1 to 341 degrees counterclockwise in 20-degree increments.	39 540

Table 1: Synthetic dataset details. The first column shows the relevant factor of variation (F.O.V.). When there are multiple values for multiple factors of variation, we generate the full cross product of images.



Figure 12: Sample images from our synthetic dataset. We consider 614 foreground objects from 62 classes and 867 backgrounds and vary the object location, rotation angle, and object size for a total of 611 608 images.

We constructed three subsets for evaluation, one corresponding to each factor of variation we wanted to investigate as shown in Table 1. In particular, for each object instance, we sample two backgrounds, and for each of these object-background combinations, we take a cross product over all the factors of variation. For the datasets with multiple values for more than one factor of variation, we take a cross product of all the values for each factor of variation in the set (object size, rotation, location). For example, for the rotation angle dataset, there are four object sizes and 18 rotation angles, so we do a cross product and have 72 factor of variation combinations. For the object size and rotation datasets, we only consider images where objects are at least 95% in the image. For the location dataset, such filtering removes almost all images where objects are near the edges of the image, so in the main paper we do not do such filtering. Note that since we use the central coordinates of objects as their location, at least 25% of each object is in the image even if we do not do any filtering. We present results filtering out objects that are less than 50% or 75% in the image in this section in Figures 16 and 17 respectively.

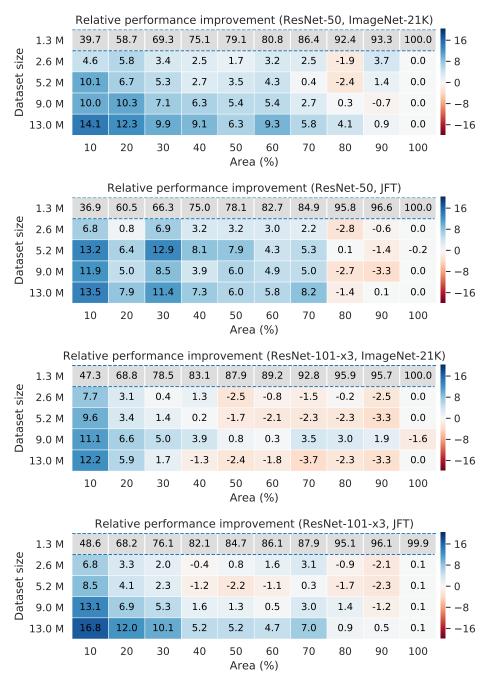


Figure 13: In the first row of both plots we show the ratio of the accuracy and the best accuracy (across all areas). For the second row (model trained on 2.6M instances), and other rows, we compute the same normalized score and visualize the difference with the first row. Larger differences imply a more uniform behavior across relative object areas. We observe that, as the dataset size increases, the average prediction accuracy across various object areas becomes more uniform. The effect is more pronounced for the larger model. As expected, the improvement is most pronounced for small object sizes covering 10-20% of the pixels.

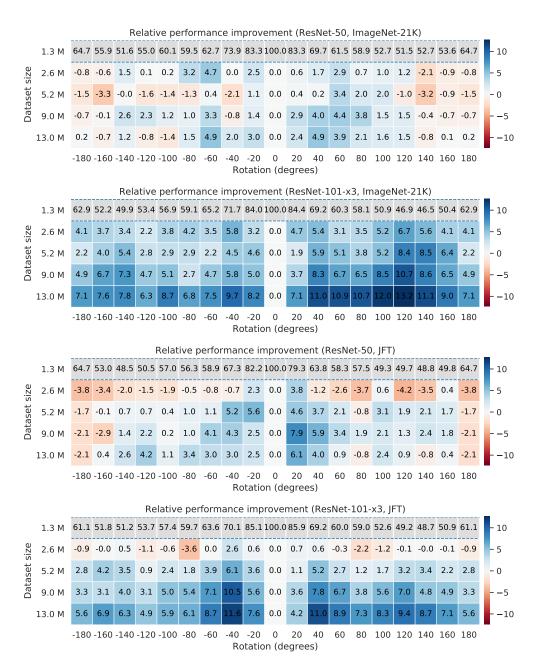


Figure 14: In the first row of both plots we show the ratio of the accuracy and the best accuracy (across all rotations). For the second row (model trained on 2.6M instances), and other rows, we compute the same normalized score and visualize the difference with the first row. Larger differences imply a more uniform behavior across object rotations. We observe that, as the dataset size increases, the average prediction accuracy across various rotation angles becomes more uniform. The effect is more pronounced for the larger model.

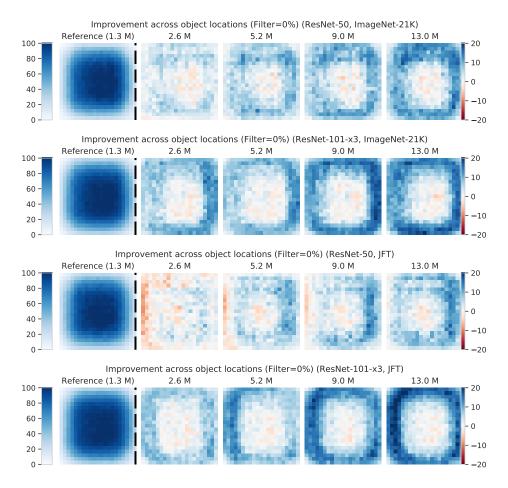


Figure 15: In the first column, for each location on the grid, we compute the average accuracy. Then, we normalize each location by the 95th percentile across all locations, which quantifies the gap between the locations where the model performs well, and the ones where it under-performs (first column, dark blue vs white). Then, we consider models trained with more data, compute the same normalized score, and plot the *difference* with respect to the first column. We observe that, as dataset size increases, sensitivity to object location decreases – the outer regions improve in relative accuracy more than the inner ones (e.g. dark blue vs white on the second and third columns). The effect is more pronounced for the larger model.

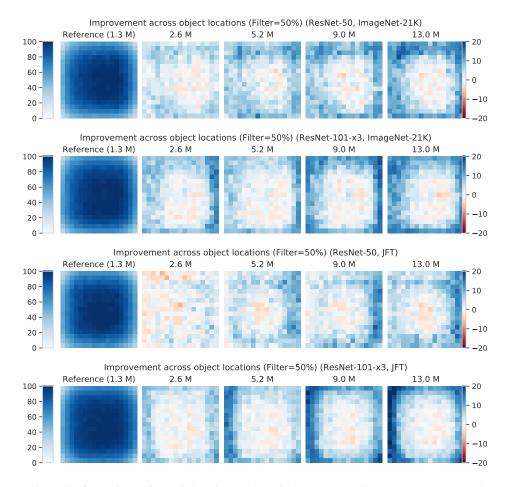


Figure 16: In the first column, for each location on the grid, we compute the average accuracy. Then, we normalize each location by the 95th percentile across all locations, which quantifies the gap between the locations where the model performs well, and the ones where it under-performs (first column, dark blue vs white). Then, we consider models trained with more data, compute the same normalized score, and plot the *difference* with respect to the first column. We observe that, as dataset size increases, sensitivity to object location decreases – the outer regions improve in relative accuracy more than the inner ones (e.g. dark blue vs white on the second and third columns). The effect is more pronounced for the larger model. We filter out all test images for which the foreground object is not at least 50% within the image.

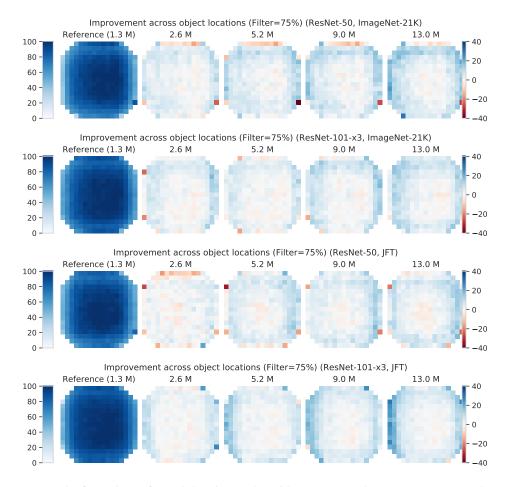


Figure 17: In the first column, for each location on the grid, we compute the average accuracy. Then, we normalize each location by the 95th percentile across all locations, which quantifies the gap between the locations where the model performs well, and the ones where it under-performs (first column, dark blue vs white). Then, we consider models trained with more data, compute the same normalized score, and plot the *difference* with respect to the first column. We observe that, as dataset size increases, sensitivity to object location decreases – the outer regions improve in relative accuracy more than the inner ones (e.g. dark blue vs white on the second and third columns). The effect is more pronounced for the larger model. We filter out all test images for which the foreground object is not at least 75% within the image.

E Overview of model abbreviations

MODEL NAME	Түре	TRAINING DATA	Architecture	DEPTH	Сн.
R50-IMAGENET-100	SUPERVISED	IMAGENET	RESNET	50	1
R50-IMAGENET-10	SUPERVISED	IMAGENET, 10%	RESNET	50	1
BIT-IMAGENET-R50-X1	SUPERVISED [34]	IMAGENET	RESNET	50	1
BIT-IMAGENET-R50-X3	SUPERVISED [34]	IMAGENET	RESNET	50	3
BIT-IMAGENET-R101-X1	SUPERVISED [34]	IMAGENET	RESNET	101	1
BIT-IMAGENET-R101-X3	SUPERVISED [34]	IMAGENET	RESNET	101	3
BIT-IMAGENET21K-R50-X1	SUPERVISED [34]	IMAGENET21K	RESNET	50	1
BIT-IMAGENET21K-R50-X3	SUPERVISED [34]	IMAGENET21K	RESNET	50	3
BIT-IMAGENET21K-R101-X1	SUPERVISED [34]	IMAGENET21K	RESNET	101	1
BIT-IMAGENET21K-R101-X3	SUPERVISED [34]	IMAGENET21K	RESNET	101	3
BIT-JFT-R50-X1	SUPERVISED [34]	JFT	RESNET	50	1
BIT-JFT-R50-X3	SUPERVISED [34]	JFT	RESNET	50	3
BIT-JFT-R101-X1	SUPERVISED [34]	JFT	RESNET	101	1
BIT-JFT-R101-X3	SUPERVISED [34]	JFT	RESNET	101	3
BIT-JFT-R152-X4	SUPERVISED [34]	JFT	RESNET	50	3
R50-IMAGENET-10-EXEMPLAR	SELF-SUP. & COTRAINING [68]	IMAGENET, 10%	RESNET	50	1
R50-IMAGENET-10-ROTATION	SELF-SUP. & COTRAINING [68]	IMAGENET, 10%	RESNET	50	1
R50-IMAGENET-100-EXEMPLAR	SELF-SUP. & COTRAINING [68]	IMAGENET	RESNET	50	1
R50-IMAGENET-100-ROTATION	SELF-SUP. & COTRAINING [68]	IMAGENET	RESNET	50	1
SIMCLR-1X-SELF-SUPERVISED	SELF-SUPERVISED [6], FINE TUNING	IMAGENET	RESNET	50	1
SIMCLR-2X-SELF-SUPERVISED	SELF-SUPERVISED [6], FINE TUNING	IMAGENET	RESNET	50	2
SIMCLR-4X-SELF-SUPERVISED	SELF-SUPERVISED [6], FINE TUNING	IMAGENET	RESNET	50	4
SIMCLR-1X-FINE-TUNED-10	SELF-SUPERVISED [6], FINE TUNING	IMAGENET, 10%	RESNET	50	1
SIMCLR-2X-FINE-TUNED-10	SELF-SUPERVISED [6], FINE TUNING	IMAGENET, 10%	RESNET	50	2
SIMCLR-4X-FINE-TUNED-10	SELF-SUPERVISED [6], FINE TUNING	IMAGENET, 10%	RESNET	50	3
SIMCLR-1X-FINE-TUNED-100	SELF-SUPERVISED [6], FINE TUNING	IMAGENET	RESNET	50	1
SIMCLR-2X-FINE-TUNED-100	SELF-SUPERVISED [6], FINE TUNING	IMAGENET	RESNET	50	2
SIMCLR-4X-FINE-TUNED-100	SELF-SUPERVISED [6], FINE TUNING	IMAGENET	RESNET	50	4
EFFICIENTNET-STD-B0	SUPERVISED [58]	IMAGENET	EFFICIENTNET	18	1
EFFICIENTNET-STD-B4	SUPERVISED [58]	IMAGENET	EFFICIENTNET	37	1
EFFICIENTNET-ADV-PROP-BO	SUPERVISED & ADVERSARIAL [66]	IMAGENET	EFFICIENTNET	18	1
EFFICIENTNET-ADV-PROP-B4	SUPERVISED & ADVERSARIAL [66]	IMAGENET	EFFICIENTNET	37	1
EFFICIENTNET-ADV-PROP-B7	SUPERVISED & ADVERSARIAL [66]	IMAGENET	EFFICIENTNET	64	2
EFFICIENTNET-NOISY-STUDENT-BO	SUPERVISED & DISTILLATION [67]	IMAGENET	EFFICIENTNET	18	1
EFFICIENTNET-NOISY-STUDENT-B4	SUPERVISED & DISTILLATION [67]	IMAGENET	EFFICIENTNET	37	1
EFFICIENTNET-NOISY-STUDENT-B7	SUPERVISED & DISTILLATION [67]	IMAGENET	EFFICIENTNET	64	2
VIVI-1X	SELF-SUP. & COTRAINING [63]	YT8M, IMAGENET	RESNET	50	1
VIVI-3X	SELF-SUP. & COTRAINING [63]	YT8M, IMAGENET	RESNET	50	3
BIGBIGAN-LINEAR	BIDIRECTIONAL ADVERSARIAL [14]		RESNET	50	1
BIGBIGAN-FINETUNE	BIDIRECTIONAL ADVERSARIAL [14]	IMAGENET	RESNET	50	1

Table 2: Overview of models used in this study. SUP. abbreviates for supervised pre-training. CH. refers to the width multiplier for the number of channels.