IMAGENET-RIB BENCHMARK: LARGE PRE-TRAINING DATASETS DON'T GUARANTEE ROBUSTNESS AFTER FINE-TUNING

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ABSTRACT

Highly performant large-scale pre-trained models promise to also provide a valuable foundation for learning specialized tasks, by fine-tuning the model to the desired task. By starting from a good general-purpose model, the goal is to achieve both specialization in the target task and maintain robustness. To assess the robustness of models to out-of-distribution samples after fine-tuning on downstream datasets, we introduce a new robust fine-tuning benchmark, ImageNet-RIB (Robustness Inheritance Benchmark). The benchmark consists of a set of related but distinct specialized (downstream) tasks; pre-trained models are fine-tuned on one task in the set and their robustness is assessed on the rest, iterating across all tasks for fine-tuning and assessment. We find that the continual learning methods, EWC and LwF maintain robustness after fine-tuning though fine-tuning generally does reduce performance on generalization to related downstream tasks across models. Not surprisingly, models pre-trained on large and rich datasets exhibit higher initial robustness across datasets and suffer more pronounced degradation during fine-tuning. The distance between the pre-training and downstream datasets, measured by optimal transport, predicts this performance degradation on the pre-training dataset. However, counterintuitively, model robustness after fine-tuning on related downstream tasks is the worst when the pre-training dataset is the richest and the most diverse. This suggests that starting with the strongest foundation model is not necessarily the best approach for performance on specialist tasks. The benchmark thus offers key insights for developing more resilient fine-tuning strategies and building robust machine learning models[1].

1 INTRODUCTION

Deep learning has progressed towards utilizing larger datasets (Lin et al., 2014; Russakovsky et al., 2015; Schuhmann et al., 2022) and deeper architectures (Dosovitskiy et al., 2021; He et al., 2016; Jiang et al., 2023). Consequently, starting with a model pre-trained on a large-scale dataset and fine-tuning it for specific downstream tasks has become standard in machine learning to achieve better performance than training from scratch. While this approach capitalizes on the extensive knowledge embedded in pre-trained models, it often results in a significant loss of that knowledge due to catastrophic forgetting (French, 1999; Robins, 1995). To mitigate this issue, methods only training a part of the pre-trained model such as linear probing, low-rank adaptation (Hu et al., 2021), and visual prompt (Bahng et al., 2022) have been proposed. However, these methods typically underperform compared to fine-tuning the entire model on the downstream task.

Fine-tuning on the downstream task also negatively impacts a model's robustness to out-of-distribution (OOD) samples as the model is optimized for a narrower distribution (Figure 1). This issue has been extensively studied using various OOD datasets, typically beginning with an ImageNet pre-trained model and evaluating it on OOD datasets that exhibit natural distribution shifts, such as changes in viewpoints (Barbu et al., 2019), time (Recht et al., 2019), styles (Hendrycks et al., 2021a; Wang et al., 2019), or synthetic data based on the original dataset (Hendrycks & Dietterich, 2019; Salvador & Oberman, 2022).

[1] https://jd730.github.io/projects/ImageNet-RIB

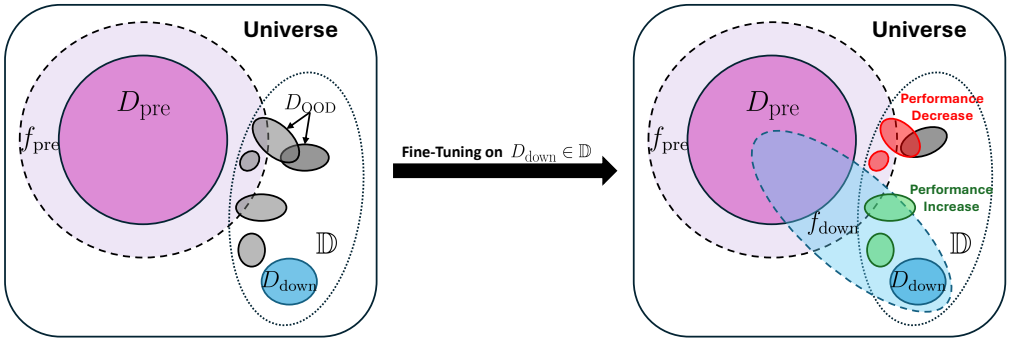

Figure 1: **Conceptual diagram of the impact of fine-tuning on pre-trained models on out-of-distribution (OOD) generalization.** A model f_{pre} pre-trained on the dataset D_{pre} (purple solid circle) can generalize to certain out-of-distribution data (purple dashed circle). The dashed gray line represents a volume ($\mathbb{D}$) containing inter-related OOD datasets (dark gray ellipsoids). Fine-tuning on one of these datasets, referred to as the downstream dataset (D_{down}, blue) shifts f_{pre} to f_{down}, making it more specialized to D_{down} (blue dashed ellipsoid). This specialization improves performance on D_{down} and possibly others within the inter-related OOD set (green solid ellipsoids), but may also lead to degradation on some OOD datasets (red solid ellipsoids).

Taori et al. (2020) proposed a benchmark that evaluates pre-trained models fine-tuned on ImageNet-1K across multiple realistic ImageNet-based OOD datasets. It is widely used to measure model robustness changes after fine-tuning (Kumar et al., 2022; Wortsman et al., 2022a;b) However, this benchmark only uses one downstream task (ImageNet-1K), and certain pre-training datasets may include parts of ImageNet as they are often uncurated (Schuhmann et al., 2022). This limitation motivates the need for a broader and more comprehensive evaluation of robustness across multiple OOD datasets.

In this paper, we introduce ImageNet-RIB (Robustness Inheritance Benchmark), a new benchmark designed to assess the robustness of fine-tuned models across diverse downstream and evaluation OOD dataset pairs related to ImageNet. For each experiment, we fine-tune a pre-trained model on one OOD dataset (as a downstream dataset) and evaluate its performance on the remaining OOD datasets. This process is repeated across all available datasets to thoroughly assess how well the model retains robustness after fine-tuning. To achieve this, we employ a variety of fine-tuning strategies, including vanilla fine-tuning, linear probing (fine-tuning the last layer only), LoRA (Hu et al., 2021), regularization-based continual learning methods (Li & Hoiem, 2017; Zenke et al., 2017), and robust fine-tuning methods (Kumar et al., 2022; Wortsman et al., 2022a;b). We also investigate the relationship between dataset distance metrics and robust fine-tuning outcomes, allowing us to estimate the robustness changes prior to training.

Our experimental results show that models pre-trained on larger and more diverse datasets demonstrate superior robustness on the OOD datasets and accuracy on ImageNet-1K. However, fine-tuning causes performance drops on ImageNet-1K, which we find is aligned with the distance between the pre-training dataset and the downstream dataset, as measured by Optimal Transport Dataset Distance (OTDD) (Alvarez-Melis & Fusi, 2020). The combination of Model Soup (Wortsman et al., 2022a) with regularization-based continual learning methods achieves the best performance in the benchmark, while linear probing performs the best when using LAION-2B pre-trained models. Furthermore, our findings indicate that continual learning methods not only mitigate catastrophic forgetting related to the pre-training dataset but also enhance robustness when compared to standard fine-tuning. This improvement is attributed to leveraging the distributional properties of both pre-training and downstream datasets. Interestingly, pre-training on LAION-2B, despite its size and diversity, does not always yield the best results when fine-tuned on downstream tasks, suggesting that starting with large, rich datasets may not always be the optimal approach for preserving robustness.

In summary, the contributions of this paper are four-fold:

- We propose ImageNet-RIB, a new benchmark leveraging multiple ImageNet-based OOD datasets to quantify the robustness of fine-tuned models in comparison to pre-trained models.
- We find that the performance drop on the pre-training dataset during fine-tuning can be predicted by the distance between pre-training and downstream datasets.

- We empirically demonstrate that regularization-based continual learning methods improve robustness by leveraging both the pre-training and downstream dataset distributions and this improvement is amplified when combined with robust fine-tuning methods.

- The absolute performance of the models pre-trained on richer datasets is worse on the downstream tasks, suggesting that starting with rich foundation models may not always be the best approach.

2 Related Work

2.1 Robustness in Machine Learning

Robustness in machine learning refers to a models ability to maintain performance under various perturbations, such as noise, corruption, and domain shifts. Robustness is typically evaluated on synthetic datasets derived from original data (Hendrycks & Dietterich, 2019; Salvador & Oberman, 2022) or real-world datasets featuring distribution shifts, such as different viewpoints (Barbu et al., 2019), styles (Hendrycks et al., 2021a; Wang et al., 2019), or temporal changes (Recht et al., 2019). To develop more robust models, data augmentation techniques have been widely explored including style transfer (Geirhos et al., 2019), perturbation-based image-to-image networks (Hendrycks et al., 2021a), and adversarial logit pairing (Kannan et al., 2018). Robust-fine-tuning usually aims to maintain the robustness of the pre-trained model to OOD datasets during fine-tuning. Taori et al. (2020) address the limitations of previous robustness evaluations that used synthetic datasets by proposing a new evaluation protocol that utilizes realistic datasets; ImageNet-V2, ImageNet-A, ImageNet-R, ImageNet-Sketch, and ObjectNet after fine-tuning on ImageNet. This benchmark is widely used with vision and language models such as CLIP (Radford et al., 2021). Shi et al. (2023) extend this to joint training on two dataset; ImageNet-1K with CIFAR-10 (Krizhevsky et al., 2009) or YFCC (Thomee et al., 2016). To solve this problem, Wortsman et al. (2022a) demonstrate that averaging the parameters of multiple trained models improves both in-distribution and OOD performance. WiSE-FT (Wortsman et al., 2022b) further shows that linearly interpolating the weights of pre-trained CLIP and ImageNet fine-tuned CLIP improves robustness, although it requires tuning the interpolation ratio for optimal performance. Goyal et al. (2023) show that contrastive learning using text encoder in fine-tuning improves robustness. Kumar et al. (2022) propose a two-stage method (LP-FT) that first applies linear probing followed by fine-tuning the entire network. Recently concurrent work (Ramanujan et al., 2024) analyzes the effect of pre-training datasets on robust fine-tuning in the WILDS (Koh et al., 2021) dataset, showing that having more data is beneficial, while greater diversity per class is not. Unlike existing benchmarks (Shi et al., 2023; Taori et al., 2020), which only fine-tune on ImageNet or two datasets simultaneously from unknown or uncurated pre-training datasets, our benchmark provides diverse downstream datasets for a comprehensive understanding of robust fine-tuning.

2.2 Single Domain Generalization

Single-domain generalization refers to the task where only one source domain is available during training, and the model is evaluated on multiple unseen target domains (Qiao et al., 2020). While the high-level concept is similar to the existing robust fine-tuning benchmark (Taori et al., 2020), the objectives differ. Robust fine-tuning focuses on maintaining or improving a model's robustness to OOD datasets during fine-tuning, whereas single-domain generalization aims to achieve generalization to unseen OOD datasets, often through meta-learning-based data augmentation (Chen et al., 2023; Qiao et al., 2020) or adaptive batch normalization (Fan et al., 2021). Recently, Fan et al. (2021) applied single-domain generalization to the PACS dataset (Li et al., 2017), using one domain as the training set and the remaining domains as test sets. This setup resembles our ImageNet-RIB benchmark in that each dataset is used for training while the others are used for testing. However, the goals of the two benchmarks differ: our robust fine-tuning benchmark aims to mitigate robustness degradation during fine-tuning, while single-domain generalization benchmarks focus on improving generalizability from a single source domain.

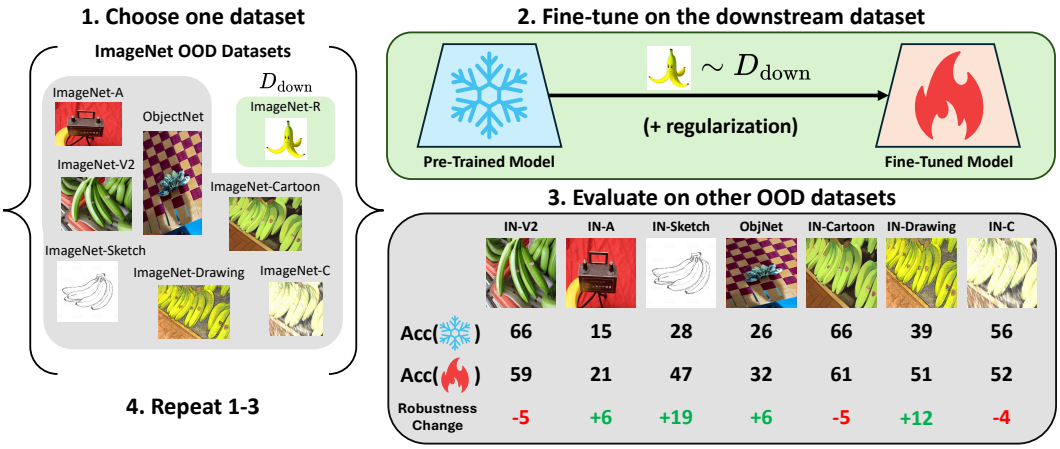

Figure 2: **Illustration of the ImageNet-RIB benchmark.** (1) The process begins by selecting one dataset from the set of ImageNet OOD datasets as the downstream dataset D_{down} (2) The pre-trained model is fine-tuned on D_{down}, then (3) evaluated on the remaining OOD datasets to assess robustness changes compared to the pre-trained model. (4) This process is repeated across all OOD datasets as downstream tasks, ensuring a detailed evaluation of fine-tuning's impact on robustness.

2.3 Continual Learning

Continual learning aims to enable models to learn new tasks without forgetting previously learned knowledge. Existing approaches can be broadly categorized into three types: regularization-based methods, replay-based methods, and architecture-based methods. Regularization-based methods (Cheung et al., 2019; Kirkpatrick et al., 2017; Li & Hoiem, 2017; Zenke et al., 2017) use additional loss terms to limit changes to the model's parameters, ensuring that previously learned knowledge is retained. For instance, Kirkpatrick et al. (2017) employ the Fisher information matrix to determine the importance of each parameter, helping to preserve critical weights from earlier tasks. Li & Hoiem (2017) use knowledge distillation to transfer outputs from a model trained on past tasks to guide learning new tasks. Replay-based methods (Robins, 1995) mitigate catastrophic forgetting by creating a replay buffer that contains a small subset of previous task data or synthetic data (Van de Ven et al., 2020) and a model is trained on the buffer along with a new task. Techniques such as reservoir sampling, reinforcement learning (Rebuffi et al., 2017), and gradient-based selection (Aljundi et al., 2019) help efficiently manage memory and select important data. Architecture-based methods modify the models structure to accommodate new tasks. These methods dynamically grow the network as needed. For example, Rusu et al. (2016), Yan et al. (2021), and Wang et al. (2022) introduce new model components for each task and use distillation to integrate them with the previous model. In our work, we focus on regularization-based continual learning methods to ensure a fair comparison with other fine-tuning approaches.

3 ImageNet Robustness Inheritance Benchmark (ImageNet-RIB)

We propose the ImageNet-RIB (Robustness Inheritance Benchmark), a novel benchmark designed to measure robustness using existing ImageNet-related out-of-distribution (OOD) datasets as both downstream and evaluation datasets. ImageNet-RIB fine-tunes pre-trained models on a variety of downstream datasets, then evaluates robustness to other OOD datasets in the benchmark (Figure 2), offering a more comprehensive understanding of robustness fine-tuning.

3.1 Benchmark Protocol and Robustness Metric

Protocol Figure 2 and Algorithm 1 in Appendix illustrate the protocol of our benchmark. Given a set of out-of-distribution (OOD) datasets $\mathbb{D} = \{D_1, D_2, ..., D_n\}$, a model pre-trained on the dataset D_{pre} is fine-tuned on the downstream dataset $D_{\text{down}} \sim \mathbb{D}$. After fine-tuning, both the pre-trained

model and the fine-tuned model are evaluated on the remaining datasets in $\mathbb{D} \setminus D_{\text{down}}$. This process is repeated by selecting each dataset in $\mathbb{D}$ as the downstream dataset.

Metric We define the robustness improvement score (RI) as the average relative robustness (Taori et al., 2020). Specifically, RI measures the accuracy difference between fine-tuned and pre-trained models on OOD datasets. Formally, robustness improvement (RI) after fine-tuning on $D_i (= D_{\text{down}})$ is defined as:

$$RI_i = \frac{1}{n-1} \sum_{j=1, j \neq i}^{n} A_i^{(j)} - A_{\text{pre}}^{(j)}, \tag{1}$$

where $A_{\text{pre}}^{(j)}$ and $A_i^{(j)}$ denote the average accuracies of pre-trained and fine-tuned models on D_j, respectively. In addition to relative robustness, effective robustness (Taori et al., 2020) is an alternative metric commonly used to evaluate OOD performance. Effective robustness measures how much the accuracy of a model deviates from an expected baseline, typically using a reference in-distribution dataset (*e.g.*, ImageNet-1K). While effective robustness is insightful, we use relative robustness in this benchmark to facilitate direct comparisons between different fine-tuning methods and initial pre-training datasets. We summarize the overall robustness improvement across all datasets as the mean robustness improvement (mRI).

3.2 Dataset Suites

We leverage all existing ImageNet OOD datasets designed for measuring robustness to distribution shifts: ImageNet-V2 (Recht et al., 2019), ImageNet-A (Hendrycks et al., 2021b), ImageNet-Drawing (Salvador & Oberman, 2022), ImageNet-Cartoon (Salvador & Oberman, 2022), and ImageNet-Sketch (Wang et al., 2019), ObjectNet (Barbu et al., 2019), and ImageNet-C (Hendrycks & Dietterich, 2019). Although ObjectNet and ImageNet-C were originally designed solely for evaluating the OOD performance of ImageNet pre-trained models, with restrictions on their use for training, we extend their application in this benchmark by fine-tuning models on these datasets and evaluating their robustness on other OOD datasets. For detailed descriptions of each dataset, please refer to Appendix A.1.

4 Experiments

We use the RIB benchmark to assess the robustness of different pre-trained models to fine-tune on a set of related downstream tasks. The goal is to assess which methods of fine-tuning do best across multiple pre-training datasets.

4.1 Experimental Details

Pre-Trained Models We use several architectures of Vision Transformer (ViT) (Dosovitskiy et al., 2021) and ResNet (He et al., 2016). The models are pre-trained on ImageNet-1K (Russakovsky et al., 2015), or ImageNet-21K (Ridnik et al., 2021) and then fine-tuned on ImageNet-1K. The standard data augmentation and regularization technique for ViT, AugReg (Steiner et al., 2022) can also be used for training on ImageNet-1K or ImageNet-21K. Alternatively, some models are pre-trained on LAION-2B (Schuhmann et al., 2022) or OpenAI CLIP (Radford et al., 2021), followed by fine-tuning on ImageNet-1K. In other words, all pre-trained models are trained on ImageNet-1K to directly leverage its classifier before conducting experiments. For simplicity, we refer to them by the names of the first pre-training datasets (*e.g.*, ImageNet-21K, LAION-2B).

In the main paper, we focus on ImageNet-1K with AugReg pre-trained ViT-B/16 and experiments using other pre-trained models are reported in Appendix D along with ImageNet-1K with SAM (Chen et al., 2022) and ImageNet-21K-P (Ridnik et al., 2021). We employ the `timm` (Wightman, 2019) and `torchvision` (maintainers & contributors, 2016) for acquiring model weights and implementation. Please refer to Appendix A.2 for more details.

Methods We employ standard fine-tuning methods, regularization-based continual learning methods, and robust fine-tuning methods for measuring performance on the proposed benchmark. The fine-tuning methods we evaluate include vanilla fine-tuning (FT), Linear Probing, LoRA (Hu et al.,

Table 1: The average accuracy of various pre-trained ViT-B/16 on each OOD dataset. LAION-2B pre-trained model generally has the best performance.

D_{pre}	ImageNet-1K	Realistic OOD					Synthetic OOD		
		IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
IN-1K + AugReg	79.2	66.4	15.0	38.0	28.0	25.7	66.2	39.1	56.0
IN-21K	81.8	71.4	32.0	47.3	35.8	33.1	69.4	44.1	58.3
IN-21K + AugReg	84.5	74.0	43.2	56.8	43.2	39.1	75.1	54.9	**66.5**
OpenAI	85.3	**75.7**	**47.3**	65.9	50.9	**50.7**	76.3	55.7	62.6
LAION-2B	**85.5**	75.6	41.5	**68.8**	**55.4**	42.3	**78.2**	**58.4**	63.0

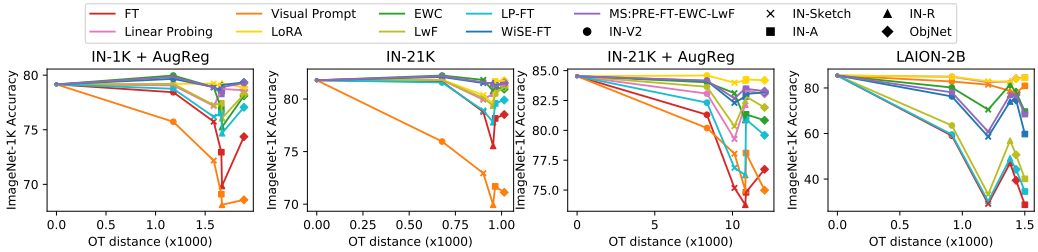

Figure 3: **Relationship between post fine-tuning ImageNet-1K accuracy and the distance between ImageNet-1K and the downstream dataset.** As the distance increases, accuracy generally decreases across fine-tuning methods. We exclude synthetic datasets since it is made from ImageNet-1K validation set that causes interference.

Table 2: Pearson correlation coefficient between the accuracy on ImageNet-1K and the dataset distance between ImageNet-1K and each downstream dataset. There is a negative correlation between accuracy and dataset distance. Notably, FT and Prompter consistently exhibit a strong negative correlation across different pre-trained models.

Method	FT	LinearProbing	Prompter	LoRA	EWC	LwF	LP-FT	WiSE-FT	MS:PRE-FT-EWC-LwF
IN-1K + AugReg	-0.64	-0.22	-0.91	-0.63	-0.57	-0.49	-0.59	-0.46	-0.54
IN-21K	-0.77	-0.36	-0.92	-0.25	-0.88	-0.56	-0.69	-0.92	-0.89
IN-21K + AugReg	-0.68	0.10	-0.86	-0.63	-0.91	-0.38	-0.39	-0.52	-0.51
LAION-2B	-0.67	-0.19	-0.74	-0.31	-0.32	-0.44	-0.56	-0.31	-0.13

2021), Visual Prompt (Bahng et al., 2022), LwF (Li & Hoiem, 2017), and EWC (Kirkpatrick et al., 2017)[2]. We do not use LoRA for ResNet as they are designed for ViT. We also employ robust fine-tuning methods; LP-FT (Kumar et al., 2022), WiSE-FT (Wortsman et al., 2022b), and uniform model soup (Wortsman et al., 2022a), which averages the parameters of pre-trained model, vanilla fine-tuned model (FT), LwF, and EWC. We denote the uniform model soup MS:PRE-FT-EWC-LwF to reveal the source of the parameters.

Training Each pre-trained model is fine-tuned on the downstream dataset for 10 epochs with a batch size of 64. We use stochastic gradient descent (SGD) with a learning rate of 0.005 and a momentum of 0.9 with cosine annealing (Loshchilov & Hutter, 2017). Visual Prompt is trained for 10 epochs with a learning rate of 40 without weight decay following Bahng et al. (2022). The experiment was conducted on NVIDIA A100. Please refer to Appendix A.3 and the code repository for detailed implementation.

Dataset Distance We measure the distance between datasets by using Optimal Transport Dataset Distance (OTDD) (Alvarez-Melis & Fusi, 2020) and Normalized Compression Distance (NCD) (Cilibrasi & Vitányi, 2005). We measure the distance in the image space and the feature space from ImageNet-1K with AugReg pre-trained ViT-16/B, class tokens before the classifier layer. For NCD, we employ concatenated images and features. We use OTDD in the feature space in the main paper and other distance metrics are discussed in Appendix B.

[2]We do not use other continual learning methods as the pre-training dataset is not accessible, and to ensure a fair comparison with other methods.

Table 3: mean Robustness Improvement (mRI) of each method with different architectures and pre-training datasets. Model Soup (MS) and WiSE-FT generally achieve the best performance while Linear Probing performs the best with LAION-2B pre-trained models.

Architecture	ViT-B/16					ViT-B/32				ViT-S/16		ViT-S/32	ViT-L/16		ResNet-18	ResNet-50
Method	IN-1K + AugReg	IN-21K	IN-21K + AugReg	OpenAI	LAION-2B	IN-1K + AugReg	IN-21K + AugReg	OpenAI	LAION-2B	IN-1K + AugReg	IN-21K + AugReg	IN-21K + AugReg	IN-1K	IN-21K + AugReg	IN-1K	IN-1K
FT	1.3	-0.1	-5.5	-38.0	-38.1	-8.2	-0.0	-0.1	-28.7	-31.6	-2.3	-2.9	1.3	-2.1	-5.2	-5.2
Linear Probing	0.7	0.4	-0.3	**-2.0**	**-2.0**	1.1	0.3	**-1.3**	**-1.4**	0.3	-0.2	-0.1	0.5	-1.3	-7.3	-11.2
Visual Prompt	-4.5	-9.4	-8.8	-8.4	-8.2	-5.4	-8.4	-8.0	-8.4	-7.4	-9.2	-9.6	-6.7	-12.9	-8.3	-6.5
LoRA	0.9	-0.3	-2.1	-3.6	-3.6	0.9	0.9	-1.8	-1.9	0.9	-1.5	0.4	0.4	1.0	-	-
EWC	2.8	1.4	0.6	-12.7	-12.5	1.3	1.6	-7.0	-10.0	1.6	1.6	1.0	1.7	1.1	-5.7	-8.9
LwF	3.1	1.6	-1.0	-33.1	-33.9	1.8	1.7	-23.9	-26.7	0.6	0.5	0.3	2.7	-0.2	-1.9	-5.8
LP-FT	2.3	0.5	-2.6	-36.9	-37.1	1.5	1.2	-27.7	-30.8	-1.2	-0.8	-1.1	2.1	-3.5	-4.8	-5.1
WiSE-FT	3.6	2.5	1.7	-18.1	-21.6	2.5	**3.0**	-9.7	-13.5	2.9	2.8	**2.3**	2.7	2.3	**0.7**	**1.2**
MS	**3.9**	**2.7**	**2.2**	-16.0	-17.9	**2.5**	2.8	-8.1	-10.9	**3.0**	**2.8**	2.3	**2.8**	**2.5**	-0.1	-0.5

Table 4: RI and mRI of ImageNet-1K with AugReg pre-trained ViT-B/16 with different fine-tuning methods and downstream datasets on each OOD dataset in ImageNet-RIB.

Method	mRI	Realistic Downstream Dataset					Synthetic Downstream Dataset		
		IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
FT	1.3	2.9	-4.0	2.8	4.4	-2.7	0.6	0.4	5.9
Linear Probing	0.7	0.1	-0.1	0.8	1.2	0.3	0.2	0.1	3.2
Visual Prompt	-4.5	-2.3	-9.1	-4.9	-1.6	-11.2	-3.9	-4.3	1.7
LoRA	0.9	0.2	0.4	1.1	2.6	0.3	-0.1	1.3	1.1
EWC	2.8	2.9	-0.2	5.2	4.4	1.4	1.6	2.8	4.3
LwF	3.1	2.8	-0.0	6.2	4.6	0.7	1.9	2.1	6.5
LP-FT	2.3	**3.0**	-0.9	5.2	4.5	-0.1	1.2	0.6	4.7
WiSE-FT	3.6	2.5	**0.7**	7.5	4.5	2.1	2.3	3.0	6.5
MS:PRE-FT-EWC-LwF	**3.9**	2.7	0.7	**7.8**	**5.0**	**2.2**	**2.4**	**3.3**	**6.7**

4.2 Optimal Transport Dataset Distance Aligns With ImageNet-1K Accuracy Drop During Fine-Tuning

First, we start with the baseline of assessing model performance on the set of OOD tasks without any fine-tuning. Not surprisingly, models pre-trained on larger and more diverse datasets have better performance on both ImageNet-1K and downstream datasets as shown in Table 1. However, the ImageNet-21K with AugReg pre-trained model achieves better performance on ImageNet-C than LAION-2B pre-trained model since AugReg includes several corruptions in ImageNet-C (*e.g.*, brightness and contrast).

We consider how the accuracy on ImageNet-1K changes after fine-tuning on each downstream dataset. We compute the Optimal Transport Dataset Distance (OTDD) (Alvarez-Melis & Fusi, 2020) between downstream datasets and ImageNet-1K in the feature space extracted from pre-trained ViT-B/16 models. Synthetic datasets are excluded from this comparison, as they are generated from the ImageNet-1K validation set. In general, ImageNet-1K accuracy decreases as the distance between the downstream dataset and ImageNet-1K (pre-training dataset) increases as shown in Figure 3. We also calculate the Pearson correlation coefficient between the accuracy and the distance in Table 2 and there is a negative correlation regardless of the method except linear probing. Especially, FT and Prompter show a strong correlation (< -0.5). However, we did not find clear evidence of a correlation between the OTDD and the accuracy on out-of-distribution (OOD) datasets after fine-tuning on downstream datasets. Please refer to Appendix B for comparison with other dataset distances.

4.3 Models That Combine Continual Learning with Robust Fine-Tuning Do Best

Table 5 presents accuracy on each OOD dataset before and after fine-tuning an ImageNet-1K with AugReg pre-trained ViT-B/16 model with each method on the downstream dataset. We also illustrate performance on each corruption in ImageNet-C in Table 35 in the Appendix. Linear probing (LP) generally changes performance on both ImageNet-1K and OOD datasets less than fine-tuning (FT) as the backbone network is fixed. However, both methods exhibit similar increase and decrease patterns. Visual Prompt reduces performance even on ImageNet-1K after fine-tuning on synthetic datasets of the ImageNet validation set. This is inconsistent with Bahng et al. (2022), which showed its robustness to OOD datasets. Continual learning methods and robust fine-tuning methods generally improve performance on most OOD datasets after fine-tuning on the downstream datasets. A strong correlation exists between ImageNet-R, ImageNet-Sketch, and ImageNet-Drawing, as they share drawing and sketch renditions, and ImageNet-R and ImageNet-Sketch share images. Fine-tuning on ImageNet-C improves performance on other synthetic datasets but the converse does not hold. This is because ImageNet-C contains 15 different corruptions with 5 different severity.

From these results, we see that the combination of a robust fine-tuning method (Wortsman et al., 2022a) with continual learning methods (MS:PRE-FT-EWC-LwF) achieves the highest mean robustness improvement (mRI) across different backbones and pre-training datasets as shown in Table 3. Moreover, end-to-end continual learning methods show comparable performance to the multi-stage method (Kumar et al., 2022) or the post-hoc robustness method (Wortsman et al., 2022b). We believe that this shows the potential of continual learning methods in the field of robust fine-tuning. The robustness of linear probing and Visual Prompt remains relatively unchanged since they do not modify the models' weights significantly but their performance on the downstream dataset tends to be worse (see Appendix D.2). Consequently, they have much better performance with LAION-2B pre-trained models compared to other methods, which show a significant robustness decrease.

Individual robustness improvement scores (RI) after fine-tuning on each downstream dataset with ImageNet-1K with AugReg pre-trained ViT-B/16 also show that MS:PRE-FT-EWC-LwF consistently performs the highest in most downstream datasets, followed by WiSE-FT as demonstrated in Table 4. This is because they directly use the weights of pre-trained models, thus taking advantage of their robustness. In contrast, Visual Prompt severely deteriorates robustness with all downstream datasets.

4.4 Paradoxically, Models Pre-Trained on the Largest Datasets Do Worst After Fine-Tuning

The extent of robustness degradation increases with the size and diversity of the pre-training dataset, as illustrated in Table 3 and Figure 4. As a result, the robustness of fine-tuned models pre-trained on larger datasets (*e.g.*, LAION-2B, OpenAI) exhibit worse robustness compared to those pre-trained on smaller datasets and their corresponding fine-tuned counterparts when using vanilla fine-tuning. One possible explanation is that models pre-trained on the larger, more diverse dataset demonstrate higher robustness to OOD datasets (see Table 1). Consequently, these models have more room for performance degradation from catastrophic forgetting. However, this does not fully explain the pronounced robustness loss observed in LAION-2B pre-trained models and OpenAI CLIPs, particularly when compared to ImageNet-21K with AugReg pre-trained models, which exhibit similar initial robustness. Moreover, Appendix C shows that these models learn downstream datasets slower than the ImageNet-21K with AugReg pre-trained model and the catastrophic robustness degradation happens in the beginning of fine-tuning.

Notably, ImageNet-21K and its variants begin to cause robustness degradation, especially when using vanilla fine-tuning. This could be an early indicator of performance decay in larger pre-trained models. Although ImageNet-21K is the second-largest dataset with 14 million images, it is much smaller than LAION-2B, which contains two billion images. We hypothesize that this discrepancy in dataset size contributes to the difference in robustness degradation. However, further investigation is required to pinpoint when severe robustness degradation begins and to identify its underlying causes.

5 Discussion

In this work, we introduced ImageNet-RIB (Robustness Inheritance Benchmark), a comprehensive benchmark designed to assess the robustness of fine-tuned models relative to pre-trained models across diverse out-of-distribution (OOD) datasets. A key distinction of ImageNet-RIB is that it fine-tunes models on multiple downstream datasets and evaluates their performance on various OOD datasets, providing a more holistic understanding of robustness compared to the prior benchmark (Taori et al., 2020), which focused on a single downstream dataset. This expanded framework allows us to better examine how downstream dataset distributions affect OOD performance.

Our results demonstrate that continual learning methods and robust fine-tuning approaches, particularly in combination, are effective in preserving or even improving robustness. Specifically, the combination of Model Soup with continual learning techniques consistently achieved superior performance. This finding underscores the potential of integrating these strategies to mitigate catastrophic forgetting and enhance the robustness to OOD datasets.

We also found that models pre-trained on larger, more diverse datasets, such as LAION-2B, experienced more severe robustness degradation during fine-tuning. While these models exhibited high initial robustness, the performance drop was more prominent compared to models pre-trained on smaller datasets like ImageNet-1K, leading to even worse performance. In these scenarios, simpler

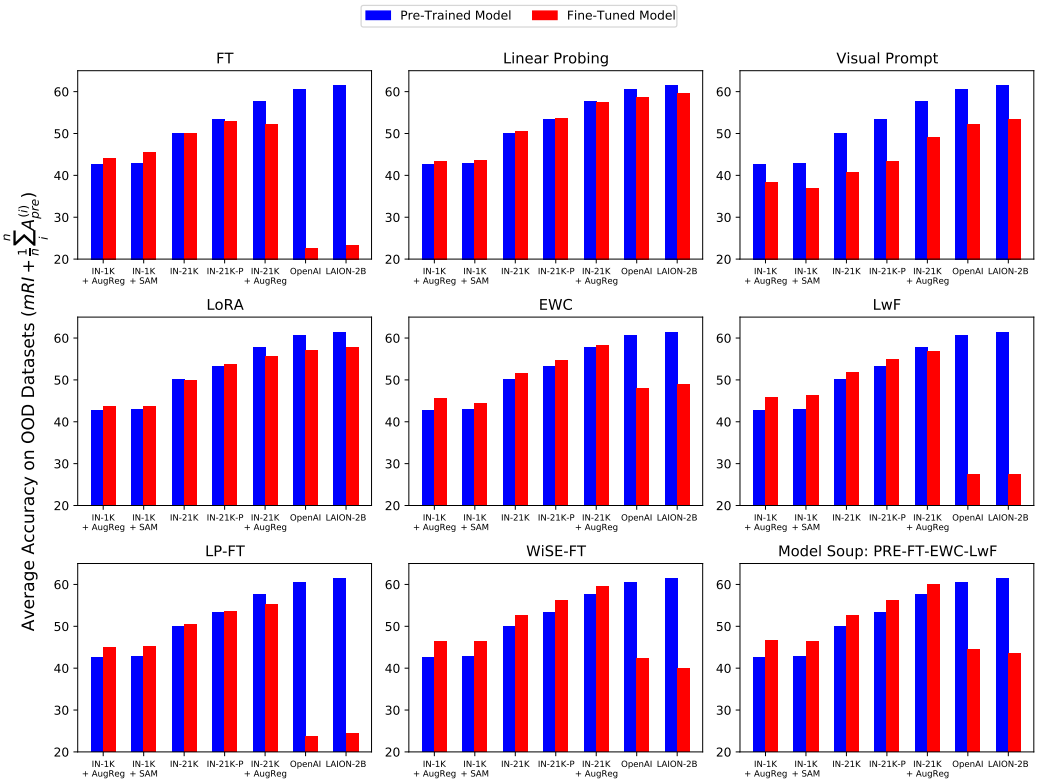

Figure 4: **Fine-tuning LAION-2B pre-trained model and OpenAI CLIP cause severe robustness loss relative to ImageNet-1K pre-trained model.** The average accuracy on OOD datasets before (blue) and after (red) fine-tuning with each method on downstream datasets. The red bar is calculated directly by evaluating pre-trained models on OOD datasets while the blue bar is calculated by adding mRI of each method to the pre-trained models' accuracy. Note that it is identical to the average accuracy on OOD datasets after fine-tuning on each downstream dataset ($mRI + \frac{1}{n}\sum_i^n A_{\text{pre}}^{(i)} = \frac{1}{n}\sum_j \frac{1}{n-1}\sum_{i,i\neq j}^n A_{\text{down}}^{(i)}$). Fine-tuning LAION-2B pre-trained model and OpenAI CLIP on the downstream OOD datasets causes severe robustness loss leading to worse performance than ImageNet-1K with AugReg pre-trained model. Conversely, ImageNet-1K with AugReg pre-trained model improves robustness after fine-tuning. Note that the difference between red and blue bars is mRI.

methods such as linear probing, which freeze most of the model's layers, were more effective in maintaining robustness, as more complex methods often led to significant performance degradation. This highlights the nuanced relationship between the size and diversity of the pre-training dataset and the model's ability to generalize after fine-tuning.

Despite these contributions, our work has certain limitations. We primarily focused on fine-tuning, continual learning, and robust fine-tuning methods. Future research could explore the role of advanced data augmentation techniques (Cubuk et al., 2019; Hendrycks et al., 2021a; Wang et al., 2023) in further improving OOD robustness. Moreover, while Optimal Transport Dataset Distance (OTDD) shows promise in predicting performance degradation on the pre-training dataset after fine-tuning, more refined metrics are needed to better capture and address robustness degradation.

Future research should focus on understanding the significant robustness degradation after fine-tuning observed in models pre-trained on larger datasets like LAION-2B. Uncovering why such extensive pre-training leads to worse robustness compared to models pre-trained on smaller datasets could inform more effective robustness fine-tuning strategies. Moreover, expanding the scope of our analysis to include a broader range of model architectures and datasets would further enhance the generalizability of our findings. We believe that ImageNet-RIB offers a valuable framework for studying the impact of fine-tuning on OOD generalization, and we hope this work encourages further research into developing more robust and generalizable machine learning models.

Table 5: The accuracy on each OOD dataset after fine-tuning on ImageNet-1K with AugReg pre-trained ViT-B/16 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		79.2	66.4	15.0	38.0	28.0	25.7	66.2	39.1	56.0
FT	IN-V2	78.4	-	**25.2**	41.9	29.2	37.1	64.7	40.4	57.4
	IN-A	72.9	60.6	-	36.7	24.9	35.0	55.3	32.6	53.5
	IN-R	69.8	59.2	20.9	-	46.7	32.0	61.3	51.4	52.0
	IN-Sketch	75.7	63.9	17.3	**59.1**	-	33.0	66.3	50.8	53.8
	ObjNet	74.4	62.2	24.9	36.3	25.1	-	55.6	33.6	52.3
	IN-Cartoon	85.2	63.5	19.9	40.5	29.5	33.5	-	41.2	51.3
	IN-Drawing	81.5	62.9	16.5	41.1	32.7	32.4	64.2	-	56.0
	IN-C	**99.8**	61.1	13.9	37.0	25.1	27.7	**92.2**	**70.2**	-
Linear Probing	IN-V2	79.1	-	15.6	38.2	28.1	33.1	66.2	39.0	55.9
	IN-A	78.6	65.9	-	38.5	27.4	34.1	65.6	38.6	55.8
	IN-R	78.7	66.6	17.1	-	30.2	33.4	66.1	39.8	56.2
	IN-Sketch	77.2	64.8	16.6	46.3	-	33.5	65.6	40.5	54.5
	ObjNet	78.6	65.9	18.1	38.6	27.9	-	65.1	39.3	56.1
	IN-Cartoon	80.5	65.4	15.1	39.2	28.1	32.2	-	40.9	55.6
	IN-Drawing	78.1	65.2	14.9	41.3	28.5	33.3	65.6	-	54.3
	IN-C	97.1	61.9	15.1	36.8	25.2	28.3	83.3	57.4	-
Visual Prompt (Bahng et al., 2022)	IN-V2	75.7	-	12.7	39.6	27.4	34.4	60.5	36.7	47.9
	IN-A	69.1	57.1	-	36.3	21.9	32.7	50.6	26.1	38.0
	IN-R	68.1	55.9	9.6	-	36.2	30.0	55.7	41.8	40.1
	IN-Sketch	72.2	59.5	9.4	51.6	-	32.3	60.6	44.9	44.3
	ObjNet	68.6	56.2	13.0	33.7	22.2	-	46.8	23.0	35.3
	IN-Cartoon	74.5	61.2	10.2	41.2	27.0	31.5	-	35.2	41.8
	IN-Drawing	72.1	59.4	8.4	42.2	28.8	30.6	59.3	-	44.2
	IN-C	77.9	65.2	14.8	40.1	28.3	35.7	63.5	49.8	-
LoRA (Hu et al., 2021)	IN-V2	79.2	-	15.3	38.2	28.1	33.2	66.4	39.3	56.1
	IN-A	79.0	66.4	-	38.9	27.8	35.5	65.2	39.3	56.5
	IN-R	79.2	66.8	16.7	-	29.7	34.8	66.9	40.0	56.7
	IN-Sketch	79.2	66.8	16.5	45.9	-	34.6	67.7	44.1	56.6
	ObjNet	78.9	66.3	18.3	39.3	27.8	-	65.1	39.2	55.0
	IN-Cartoon	78.7	65.8	14.8	39.3	28.3	32.1	-	39.8	54.6
	IN-Drawing	77.9	66.3	15.0	43.7	32.1	33.5	66.4	-	55.1
	IN-C	79.9	67.4	16.3	39.2	28.1	34.1	67.5	40.8	-
EWC (Kirkpatrick et al., 2017)	IN-V2	80.0	-	19.7	41.8	29.4	36.8	67.1	42.8	58.2
	IN-A	76.9	64.9	-	40.4	27.8	**38.2**	61.1	36.5	56.6
	IN-R	75.2	63.9	19.0	-	43.9	33.3	66.4	57.5	56.1
	IN-Sketch	78.9	66.6	16.6	52.2	-	34.2	68.3	49.6	57.2
	ObjNet	78.1	66.2	23.1	40.9	29.0	-	62.4	39.8	56.9
	IN-Cartoon	79.2	66.0	16.5	42.7	29.9	33.8	-	42.6	54.7
	IN-Drawing	79.3	66.7	16.3	44.5	34.0	34.7	67.9	-	58.3
	IN-C	80.1	**67.8**	20.0	42.5	31.2	37.5	66.8	50.0	-
LwF (Li & Hoiem, 2017)	IN-V2	79.2	-	22.9	41.3	29.4	36.4	65.8	41.0	57.9
	IN-A	77.4	65.5	-	39.4	27.5	36.7	61.8	38.3	57.2
	IN-R	76.1	64.7	21.7	-	**47.8**	34.1	66.8	54.9	57.2
	IN-Sketch	77.3	65.2	17.3	57.8	-	33.5	67.8	49.6	55.2
	ObjNet	78.2	66.2	24.1	38.4	27.3	-	62.3	38.8	56.3
	IN-Cartoon	87.2	65.9	19.4	41.2	29.9	34.2	-	42.7	55.6
	IN-Drawing	84.0	65.4	17.7	41.9	33.2	33.4	67.7	-	58.2
	IN-C	99.2	65.8	13.5	40.7	27.8	31.4	90.6	61.7	-
LP-FT (Kumar et al., 2022)	IN-V2	78.8	-	24.7	41.6	29.3	36.8	65.3	41.3	57.6
	IN-A	76.5	64.6	-	38.2	27.4	37.1	60.5	36.7	56.2
	IN-R	74.7	63.4	21.1	-	46.9	34.7	65.4	53.1	55.3
	IN-Sketch	76.2	64.5	18.0	58.8	-	33.9	67.0	48.9	54.4
	ObjNet	77.1	64.9	24.9	38.2	26.8	-	60.7	37.7	54.9
	IN-Cartoon	86.3	64.2	19.5	41.0	29.9	33.5	-	43.1	52.8
	IN-Drawing	82.1	63.2	16.5	41.7	32.9	32.0	64.8	-	56.0
	IN-C	98.0	61.0	13.7	37.5	25.7	27.3	87.1	66.0	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	79.7	-	21.3	40.5	29.5	36.0	66.5	40.9	58.0
	IN-A	78.6	66.4	-	39.3	28.5	37.1	64.4	38.6	57.8
	IN-R	79.1	67.1	23.0	-	44.7	37.4	69.5	54.7	59.6
	IN-Sketch	78.9	66.4	17.6	52.1	-	34.7	68.7	48.7	57.3
	ObjNet	79.3	67.3	23.5	40.0	29.0	-	65.2	40.5	57.6
	IN-Cartoon	83.8	66.5	19.3	41.0	30.4	34.9	-	43.2	56.3
	IN-Drawing	82.5	66.9	18.5	42.2	33.5	35.0	68.2	-	59.5
	IN-C	93.4	66.9	18.7	41.3	29.9	34.7	82.4	57.6	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	79.8	-	21.0	41.0	29.7	36.0	66.9	41.7	58.0
	IN-A	78.3	66.4	-	39.7	28.5	37.5	63.7	38.4	57.8
	IN-R	78.9	67.1	23.1	-	45.9	37.2	69.6	55.8	59.6
	IN-Sketch	78.9	66.6	17.5	54.0	-	34.6	69.1	49.8	57.5
	ObjNet	79.3	67.4	24.1	40.3	29.1	-	64.9	40.6	57.7
	IN-Cartoon	83.7	66.4	18.9	41.8	30.6	34.7	-	43.6	56.2
	IN-Drawing	82.6	66.9	18.4	43.0	34.0	35.2	68.7	-	**59.7**
	IN-C	92.6	67.5	18.6	42.3	30.6	35.3	81.3	57.3	-

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Algorithm 1 Protocol of ImageNet-RIB

Input: A set of out-of-distribution datasets $\mathbb{D} = \{D_1, D_2, ..., D_n\}$, pre-trained model f_{pre}, fine-tuning method $\mathsf{fine\text{-}tune}(\cdot)$.
Output: Mean robustness improvement, mRI.

```
procedure IMAGENET-RIB
    for D_down (= D_i) ∈ 𝔻 do
        f_down ← fine-tune(f_pre; D_down)        ▷ Fine-tune pre-trained model f_pre on D_down.
        for D_j ∈ 𝔻 \ D_down do
            A_i^(j) = eval(f_down; D_j)          ▷ Evaluate f_down on D_j.
            A_pre^(j) = eval(f_pre; D_j)         ▷ Evaluate f_pre on D_j.
        end for
        RI_i = 1/(n−1) Σ_{j=1, j≠i}^{n} A_i^(j) − A_pre^(j)   ▷ Calculate Robustness Improvement (RI).
    end for
    mRI = Σ_i^n RI_i                             ▷ Calculate mean RI.
end procedure
```

APPENDIX

A EXPERIMENTAL DETAILS

In this section, we describe the details of the experimental setup.

A.1 OUT-OF-DISTRIBUTION DATASETS IN IMAGENET-RIB

We leverage all existing ImageNet variants designed to measure the robustness of the trained network during distribution shifts. ImageNet-O (Hendrycks et al., 2021b) is not used since it is an out-of-distribution detection dataset.

ImageNet-V2 (Recht et al., 2019) ImageNet-V2 is designed to have a distribution as similar as possible to the original ImageNet-1K. It has 50,000 images with 1,000 classes same as the original validation set. The dataset is used under the MIT license.

ImageNet-A (Hendrycks et al., 2021b) ImageNet-A is an adversarially filtered test image that ImageNet-1K pre-trained ResNet-50 (He et al., 2016) is difficult to predict correctly. It contains 7,500 images with 200 difficult subclasses from ImageNet-1K. The dataset is used under the MIT license.

ImageNet-R (Hendrycks et al., 2021a) ImageNet-R (Renditions) contains 30,000 images from 200 ImageNet classes with various rendition styles such as painting, sculpture, embroidery, origami, cartoon, toy, and so on. The drawing rendition overlaps with ImageNet-Sketch (Wang et al., 2019). The dataset is used under the MIT license.

ImageNet-Sketch (Wang et al., 2019) ImageNet-Sketch comprises black and white sketch drawings of the ImageNet-1K classes and each class has 50 images. The dataset is used under the MIT license.

ImageNet-Cartoon and ImageNet-Drawing (Salvador & Oberman, 2022) ImageNet-Cartoon and ImageNet-Drawing are to be converted from ImageNet validation set images to cartoon, and drawing styles based on generative adversarial network (Wang & Yu, 2020) and image processing (Lu et al., 2012). These simplified representations test a model's ability to identify objects from minimalistic and abstract visual information. The dataset is used under the Creative Commons Attribution 4.0 International license.

ObjectNet (Barbu et al., 2019) ObjectNet is designed for evaluating object recognition models under more realistic conditions such as various poses, backgrounds, and viewpoints. There are 50,000

Table 6: Python libraries and the names of network weights for each pre-trained model.

Architecture	D_{pre}	Library	Weight Name
ViT-B/16	IN-1K + AugReg	timm	vit_base_patch16_224.augreg_in1k
	IN-1K + SAM	timm	vit_base_patch16_224.sam_in1k
	IN-21K	timm	vit_base_patch16_224.orig_in21k_ft_in1k
	IN-21K + AugReg	timm	vit_base_patch16_224.augreg_in21k_ft_in1k
	IN-21K-P	timm	vit_base_patch16_224_miil.in21k_ft_in1k
	LAION-2B	timm	vit_base_patch16_clip_224.laion2b_ft_in1k
	OpenAI	timm	vit_base_patch16_clip_224.openai_ft_in1k
ViT-B/32	IN-1K + AugReg	timm	vit_base_patch32_224.augreg_in1k
	IN-21K + AugReg	timm	vit_base_patch32_224.augreg_in21k_ft_in1k
	LAION-2B	timm	vit_base_patch32_clip_224.laion2b_ft_in1k
	LAION-2B	timm	vit_base_patch32_clip_224.openai_ft_in1k
ViT-S/16	IN-21K + AugReg	timm	vit_small_patch16_224.augreg_in21k_ft_in1k
ViT-S/32	IN-21K + AugReg	timm	vit_small_patch32_224.augreg_in21k_ft_in1k
ViT-L/16	IN-21K + AugReg	timm	vit_large_patch16_224.augreg_in21k_ft_in1k
ResNet-18	IN-1K	torchvision	ResNet18_Weights.DEFAULT
ResNet-50	IN-1K	torchvision	ResNet50_Weights.DEFAULT

images with 313 object classes and 113 classes are overlapped with ImageNet. We only use ImageNet class objects. The dataset is used under the MIT license.

ImageNet-C (Hendrycks & Dietterich, 2019) ImageNet-C is designed for measuring the robustness of models to common perturbations such as noise, blur, weather, and digital distortions. In the dataset, ImageNet validation set images are perturbed with various severity from 1 to 5. Unlike the original metrics, corruption error compared with AlexNet, we use average accuracy for consistency with other datasets. The dataset is used under the Apache-2.0 license.

A.2 Pre-Trained Model

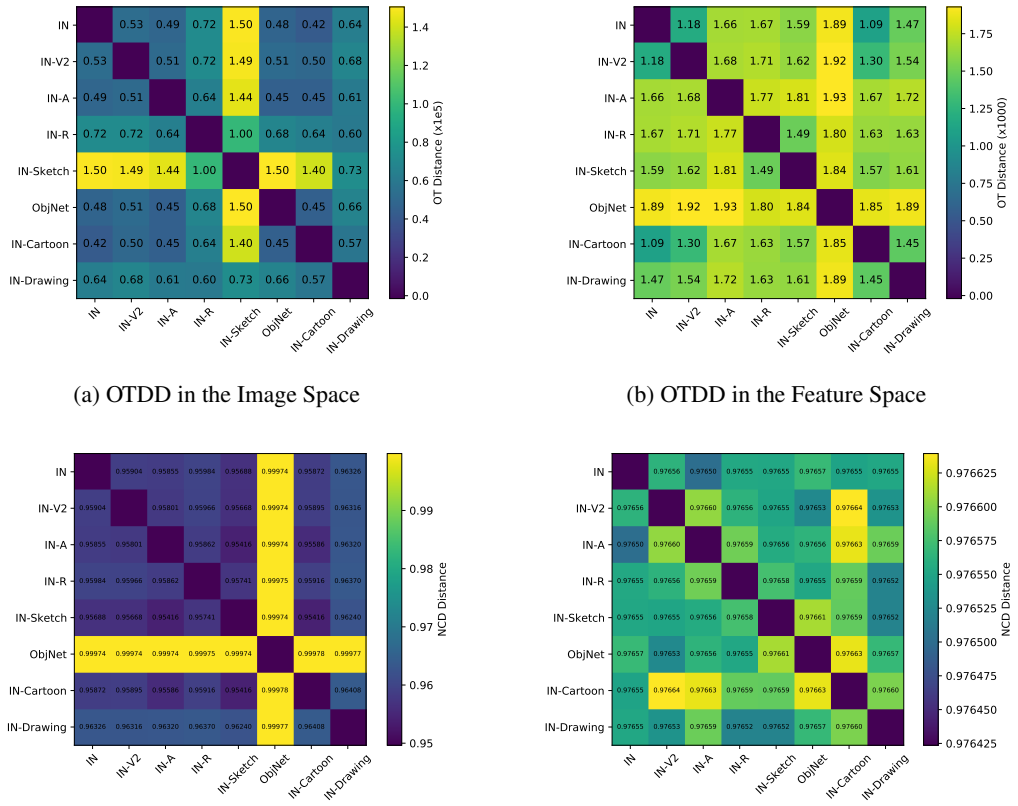
Table 6 lists the libraries and corresponding network weight names for each model. We use the entire models in timm and torchvision library, which are finally fine-tuned on ImageNet-1K, with patch sizes of 16 and 32, and input image shape of 224 among ViT small, base, and large. For ResNets, we use the default ImageNet-1K pre-trained weights from the torchvision library.

A.3 Training and Hyperparameters

Each pre-trained model is fine-tuned on the downstream dataset for 10 epochs where the average accuracy on downstream datasets for each pre-trained ViT-B/16 model achieves more than 90% with vanilla fine-tuning. We applied LoRA on query and value projection layers with rank 8 following the original implementation (Hu et al., 2021). We use 2 as a temperature for calculating KL divergence for LwF following Li & Hoiem (2017). For WiSE-FT, we use the interpolation ratio between pre-trained and fine-tuned models as 0.5 following the recommendation by Wortsman et al. (2022b) instead of finding the best hyperparameters evaluated on the benchmark for the fair comparison.

B Dataset Distance

We measure the Optimal Transport dataset distance(OTDD) (Alvarez-Melis & Fusi, 2020) between each dataset using both images and the pre-trained model features from ImageNet-1K with AugReg pre-trained ViT-B/16, as shown in Figures 5a and 5b, respectively. Since ImageNet-C comprises multiple corruptions with different severities, we do not measure the distance to ImageNet-C. As shown in Figure 5a, in the image space, ImageNet-Sketch is the farthest from other datasets as it is black and white sketch images. ImageNet-Drawing is the closest to the dataset and the ImageNet-R is the second closest as they share the same styles and images, respectively.



(a) OTDD in the Image Space

(b) OTDD in the Feature Space

(c) NCD in the Image Space

(d) NCD in the Feature Space

Figure 5: **Optimal Transport Dataset Distances (OTDD) in the feature space aligns with each dataset design.** Pairwise OTDD (up) and Normalized Compression Distance (NCD) (down) between datasets using images (left) and features extracted by ImageNet-1K with AugReg pre-trained ViT-B/16 on each dataset (right), respectively.

OTDD in the feature space (Figure 5b) demonstrates a better alignment with the dataset design principles. For example, ImageNet-V2 is designed to replicate the distribution of the ImageNet validation set. It leads ImageNet-V2 the closest to ImageNet-1K among realistic datasets. Moreover, the distances between ImageNet-1K and ImageNet-V2 to other datasets are consistent across both image and feature spaces. This is not true with ImageNet-Cartoon since it is a synthetic dataset based on the ImageNet validation set. As shown in Table 5, ImageNet-Cartoon improves ImageNet-1K accuracy more than ImageNet-Drawing, suggesting that the distribution shift in cartoon-style images is less severe than that of drawing-style images. Similarly, ObjectNet is intentionally collected with different viewpoints and backgrounds and it is the most distant from all other datasets in the feature space.

We also measure Normalized Compression Distance (NCD) using both images and the features from ImageNet-1K with AugReg pre-trained ViT-B/16. However, the distance between each dataset pair is too insignificant to compare with each dataset as shown in Figures 5c and 5d.

C Overfitting Does Not Drive Robustness Collapse of LAION-2B Pre-Trained Model and OpenAI CLIP

A potential explanation for the significant robustness decline observed in LAION-2B and OpenAI pre-trained ViT-B/16 during fine-tuning as shown in Section 4.4, is that these models may overfit earlier compared to other models. To investigate this, we analyze the robustness performance change

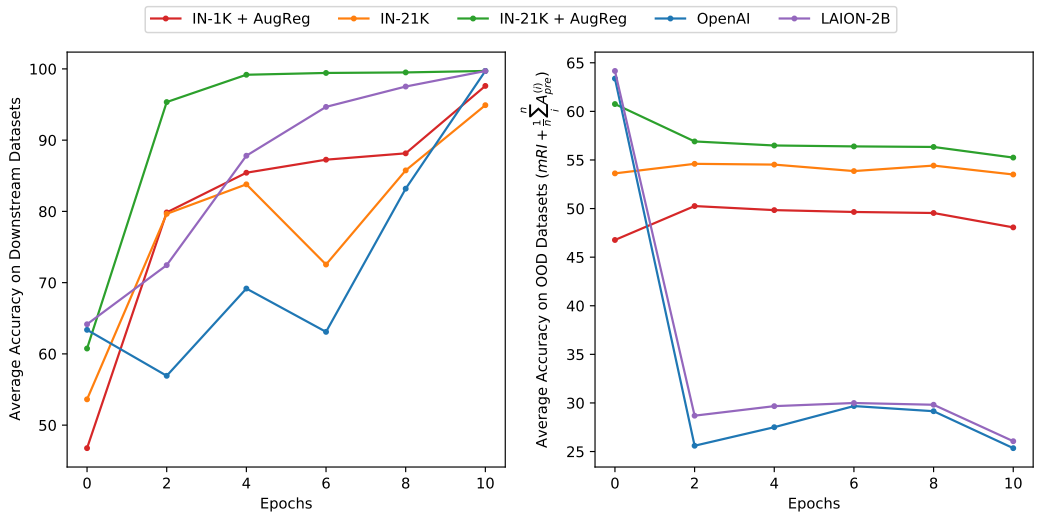


Figure 6: **Fine-tuning LAION-2B and OpenAI pre-trained model cause severe robustness loss while learning slower than ImageNet-21K with AugReg pre-trained model.** The average accuracy on Downstream Datasets (left) and the average accuracy on OOD datasets (right) while fine-tuning on the downstream dataset using vanilla fine-tuning method (FT) with ViT-B/16. Although LAION-2B pre-trained model and OpenAI CLIP learn slower than other methods, they suffer from a huge robustness drop even in the early period of fine-tuning.

throughout the fine-tuning process on the downstream dataset using a standard fine-tuning (FT) approach along with the average accuracy on downstream datasets.

Figure 6 illustrates that the ImageNet-21K model pre-trained with AugReg learns downstream datasets more rapidly than other methods, while the OpenAI CLIP models exhibit the slowest learning pace. However, only the LAION-2B and OpenAI CLIP pre-trained models experience a severe degradation in robustness to out-of-distribution datasets. This suggests that overfitting is not the primary cause of the dramatic performance decline.

D Additional Experiments with Various Pre-Trained Models

In this section, we also use ViT-B/16 pre-trained on ImageNet-1K with Sharpness Aware Minimization (SAM) (Chen et al., 2022)), ImageNet-21K-P (Ridnik et al., 2021), ViT-B/32 pre-trained on ImageNet-1K with SAM and OpenAI CLIP ViT-B/16 and ViT-B/32 models.

D.1 Robustness of Pre-Trained Models

We evaluate pre-trained models mentioned in Appendix A.2 on OOD datasets as shown in Table 7. Larger networks with smaller patch sizes achieve higher accuracy on both ImageNet-1K and OOD datasets. Similarly, models pre-trained on larger, more diverse datasets demonstrate better performance.

D.2 Performance on Downstream Dataset

Table 8 9, and 10 demonstrate the accuracy on downstream datasets (*i.e.*, training accuracy) with ViT base, ViT large and ViT small, and ResNet, respectively. FT, LwF, and LP-FT can overfit to the downstream dataset but WiSE-FT and Model Soup (PRE-FT-LwF-EWC) have worse performance which might be due to using pre-trained model weights. Visual Prompt and LoRA rarely learn a downstream dataset.

Table 7: The average accuracy of various pre-trained models on ImageNet-1K and OOD datasets.

Arch	D_{pre}	ImageNet	Realistic OOD (Taori et al., 2020)					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	IN-1K + AugReg	79.2	66.4	15.0	38.0	28.0	33.0	66.2	39.1	56.0
	IN-1K + SAM	80.2	68.2	9.0	40.1	27.7	34.2	66.9	42.3	54.6
	IN-21K	81.8	71.4	32.0	47.3	35.8	42.5	69.4	44.1	58.3
	IN-21K-P	84.3	74.0	34.1	51.5	40.2	46.7	73.5	45.1	61.4
	IN-21K + AugReg	84.5	74.0	43.2	56.8	43.2	48.4	75.1	54.9	66.5
	OpenAI	85.3	75.7	47.3	65.9	50.9	50.7	76.3	55.7	62.6
	LAION-2B	85.5	75.6	41.5	**68.8**	**55.4**	51.1	78.2	58.4	63.0
ViT-B/32	IN-1K + SAM	73.7	59.9	4.3	36.6	23.0	25.2	63.2	40.6	48.8
	IN-21K + AugReg	80.7	69.0	22.4	49.3	37.1	40.7	70.6	42.5	60.5
	OpenAI	82.0	70.9	22.6	55.8	45.0	41.5	71.1	42.5	57.9
	LAION-2B	82.6	71.6	22.8	59.2	49.1	43.5	73.0	42.3	57.5
ViT-S/16	IN-21K + AugReg	81.4	70.3	27.0	46.0	32.9	32.2	67.8	37.7	58.0
ViT-S/32	IN-21K + AugReg	76.0	63.9	11.5	39.7	26.2	24.8	62.9	34.3	52.0
ViT-L/16	IN-21K + AugReg	**85.8**	**76.2**	**55.5**	64.4	51.8	**52.8**	**79.5**	**64.6**	**72.2**
ResNet-18	IN-1K	69.8	57.3	1.1	33.1	20.2	18.1	48.2	20.4	31.7
ResNet-50	IN-1K	80.3	69.5	16.7	41.6	28.4	33.0	61.1	31.1	46.6

D.3 Robustness Improvement Results of Different Models

Across the ImageNet pre-trained models, WiSE-FT and Model Soup consistently have better robustness improvement compared to other methods fine-tuning on realistic OOD datasets (Tables 12, 14, and 15). Linear Probing consistently achieves the best robustness improvement using LAION-2B pre-trained models (Table 17) and OpenAI CLIP models (Table 18).

D.4 Accuracy of Using Various Pre-Trained Models on Each OOD Datasets

The following tables present the accuracy on each OOD (out-of-distribution) dataset after fine-tuning on various datasets. Specifically:

- Tables 19, 20, 21, 22, and 23 show results for the ViT-B/16 pre-trained on ImageNet-1K with SAM, ImageNet-21K, ImageNet-21K with AugReg, ImageNet-21K-P, OpenAI and LAION-2B, respectively. Table 24 uses OpenAI CLIP ViT-B/16 as a pre-trained model.
- Tables 25, 26, 28, and 27 provide the corresponding accuracy for ViT-B/32 pre-trained on ImageNet-1K with AugReg, ImageNet-21K with AugReg, LAION-2B, respectively. Table 28 uses OpenAI CLIP ViT-B/32 as a pre-trained model.
- Table 32 report the accuracy for ViT-L/16 pre-trained on ImageNet-21K with AugReg.
- Finally, Tables 33 and 34 present results for ResNet-18 and ResNet-50 pre-trained on ImageNet-1K.

D.5 Accuracy of Using Various Pre-Trained Models on Each Corruption in ImageNet-C

Each pre-trained and fine-tuned model is evaluated on ImageNet-C with 15 corruptions at severity levels ranging from 1 to 5. Following the original benchmark (Hendrycks & Dietterich, 2019), we average the performance over the different severity levels. However, for consistency with other datasets, we report the results as accuracy rather than error.

Specifically:

- Table 35 shows the results for ViT-B/16 pre-trained on ImageNet-1K with AugReg, repspectively. Table 36 denotes the results for ViT-B/16 pre-trained on ImageNet-1K with SAM, while Tables 37, 38, 39 and 40 present the performance of ViT-B/16 pre-trained on ImageNet-21K, ImageNet-21K with AugReg, ImageNet-21K-P and LAION-2B, respectively. Table 41 uses OpenAI CLIP ViT-B/16 as a pre-trained model.

Table 8: Accuracy on downstream datasets after fine-tuning with each method using ViT-B/16. FT and LP-FT generally achieve the highest performance, while Visual Prompt and LoRA show the lowest.

Arch	*Dpre*	Method	Realistic Downstream Dataset					Synthetic Downstream Dataset		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	IN-1K + AugReg	FT	96.3	**97.5**	98.4	96.0	97.7	97.5	97.6	**100.0**
		Linear Probing	71.5	42.4	60.4	58.8	57.8	76.1	61.2	89.7
		Visual Prompt	66.6	28.8	58.9	45.8	46.3	72.7	64.8	64.4
		LoRA	66.5	18.7	41.8	39.0	36.7	69.7	62.4	58.6
		EWC	72.0	54.3	65.3	50.3	50.8	76.2	70.3	67.7
		LwF	95.8	95.5	97.3	95.1	95.1	96.7	96.5	100.0
		LP-FT	**96.7**	97.2	**98.5**	**96.1**	**97.9**	**97.5**	**97.6**	94.6
		WiSE-FT	81.2	56.6	71.2	61.4	63.7	84.0	74.0	88.8
		MS:PRE-FT-EWC-LwF	82.4	67.4	75.5	66.8	66.8	85.5	78.7	88.0
	IN-1K + SAM	FT	77.9	**67.2**	**87.2**	**84.3**	**75.1**	87.1	85.7	**100.0**
		Linear Probing	68.7	14.3	50.5	38.8	41.4	71.3	53.6	80.7
		Visual Prompt	64.4	17.0	50.6	37.2	40.1	69.7	56.2	57.7
		LoRA	68.2	10.0	44.9	32.7	36.7	69.6	49.6	67.5
		EWC	69.0	23.9	50.4	43.8	41.3	72.6	62.3	59.6
		LwF	77.6	62.5	84.2	81.7	69.7	85.9	84.0	99.9
		LP-FT	**78.3**	64.9	86.6	83.5	74.6	**87.2**	**86.1**	84.4
		WiSE-FT	72.7	31.4	64.7	52.6	52.4	78.9	68.1	78.8
		MS:PRE-FT-EWC-LwF	72.8	36.5	66.7	55.6	53.0	79.3	70.7	80.3
	IN-21K	FT	92.2	94.9	**96.3**	92.8	94.3	94.7	94.1	**100.0**
		Linear Probing	75.0	51.8	66.4	59.0	63.2	77.7	59.6	86.4
		Visual Prompt	66.8	37.4	58.2	43.9	51.0	68.9	57.9	58.6
		LoRA	71.5	38.2	52.9	39.8	47.1	73.5	53.8	49.4
		EWC	74.5	59.7	65.6	50.1	56.1	77.3	67.6	66.5
		LwF	91.9	92.8	94.3	90.9	91.2	93.7	92.1	99.9
		LP-FT	**93.4**	**95.1**	96.2	**93.1**	**94.7**	**95.1**	**94.3**	97.3
		WiSE-FT	81.8	67.7	75.1	63.5	68.7	83.2	72.8	84.7
		MS:PRE-FT-EWC-LwF	82.6	73.7	78.3	67.0	70.6	84.5	76.0	88.7
	IN-21K-P	FT	95.4	98.7	99.3	96.7	99.2	97.3	97.6	**100.0**
		Linear Probing	78.0	57.0	70.5	67.3	68.5	81.0	64.5	88.8
		Visual Prompt	70.2	43.1	63.3	49.9	56.1	74.6	63.6	63.2
		LoRA	74.2	37.5	53.1	47.4	48.9	75.6	67.4	63.1
		EWC	76.8	66.7	73.0	57.8	61.0	80.7	73.9	69.7
		LwF	94.2	97.2	98.5	95.7	97.0	96.1	96.2	100.0
		LP-FT	**96.2**	**98.8**	**99.4**	**96.9**	**99.3**	**97.7**	**98.1**	100.0
		WiSE-FT	84.2	74.3	80.1	70.2	73.4	87.0	78.0	88.7
		MS:PRE-FT-EWC-LwF	84.7	80.8	82.8	73.5	75.9	87.8	80.9	89.0
	IN-21K + AugReg	FT	100.0	**100.0**	**99.8**	98.0	**100.0**	99.9	99.9	**100.0**
		Linear Probing	98.3	97.3	91.7	93.2	92.0	96.5	91.1	98.6
		Visual Prompt	74.2	52.0	71.7	56.6	61.1	78.7	73.2	70.2
		LoRA	75.1	53.1	66.5	56.5	56.4	78.6	74.4	19.2
		EWC	91.1	97.8	91.2	73.4	93.8	86.2	84.1	76.8
		LwF	100.0	**100.0**	99.8	98.0	**100.0**	99.9	99.9	100.0
		LP-FT	**100.0**	**100.0**	**99.8**	**98.1**	**100.0**	**99.9**	**99.9**	100.0
		WiSE-FT	95.9	97.0	94.7	88.1	91.0	95.3	92.7	96.2
		MS:PRE-FT-EWC-LwF	96.8	98.6	96.5	89.9	95.9	95.3	93.9	96.8
	OpenAI	FT	**100.0**	**100.0**	99.8	**98.0**	**100.0**	**99.9**	99.9	**100.0**
		Linear Probing	82.3	78.0	86.1	74.1	79.3	86.0	79.5	92.2
		Visual Prompt	77.7	54.4	76.9	58.1	60.4	80.3	71.2	66.5
		LoRA	79.1	65.1	79.2	60.1	62.0	83.0	76.9	41.7
		EWC	88.7	90.0	90.9	73.8	86.2	87.0	85.4	77.8
		LwF	**100.0**	100.0	99.8	98.0	99.9	99.9	99.9	**100.0**
		LP-FT	100.0	**100.0**	**99.8**	98.0	**100.0**	99.9	**99.9**	100.0
		WiSE-FT	88.0	76.8	89.9	78.6	81.5	91.5	91.0	94.7
		MS:PRE-FT-EWC-LwF	88.9	81.7	91.3	79.4	83.3	91.0	91.1	93.0
	LAION-2B	FT	100.0	100.0	**99.8**	98.0	100.0	99.9	**99.9**	**100.0**
		Linear Probing	82.8	77.2	88.4	79.3	80.9	87.6	80.0	93.3
		Visual Prompt	77.2	49.9	79.6	62.1	63.6	81.3	72.4	68.1
		LoRA	78.1	58.6	79.8	62.3	61.5	83.9	76.4	39.8
		EWC	83.8	68.7	89.3	71.8	79.9	86.3	83.5	74.2
		LwF	100.0	99.9	99.8	98.0	99.9	99.9	99.9	100.0
		LP-FT	**100.0**	**100.0**	99.8	**98.0**	**100.0**	**99.9**	**99.9**	100.0
		WiSE-FT	85.8	46.5	87.6	77.9	77.6	91.0	89.9	93.3
		MS:PRE-FT-EWC-LwF	87.3	64.6	89.5	79.2	80.3	90.6	90.1	94.3

- Tables 42, 43, 44, and 45 report the corresponding results for ViT-B/32 pre-trained on ImageNet-1K with AugReg, ImageNet-1K with SAM, ImageNet-21K with AugReg, and LAION-2B.

  Table 46 uses OpenAI CLIP ViT-B/32 as a pre-trained model.
- Tables 47, 48, and 49 show the results for ViT-S/16 pre-trained on ImageNet-1K and ImageNet-21K, and ViT-S/32 pre-trained on ImageNet-21, respectively. All models are pre-trained with AugReg.
- Table 50 provides the results for ViT-L/16 pre-trained on ImageNet-21K with AugReg.
- Finally, Tables 51 and 52 present the accuracy for ResNet-18 and ResNet-50 models, both pre-trained on ImageNet-1K.

Table 9: Accuracy on downstream datasets after fine-tuning with each method using various ViTs. FT and LP-FT generally achieve the highest performance, while Visual Prompt and LoRA show the lowest.

Arch	*Dpre*	Method	Realistic Downstream Dataset					Synthetic Downstream Dataset		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/32	IN-1K	FT	99.1	**99.4**	99.5	**97.0**	99.4	99.1	99.3	100.0
		Linear Probing	65.2	17.8	54.5	43.5	42.0	69.1	54.3	75.8
		Visual Prompt	62.8	15.5	55.9	42.6	37.5	69.4	61.0	58.5
		LoRA	63.0	9.4	42.3	41.9	29.5	66.6	59.7	66.3
		EWC	74.8	56.5	68.9	52.9	54.1	74.9	68.8	62.8
		LwF	98.8	99.1	99.2	4.3	98.9	98.8	99.1	100.0
		LP-FT	**99.2**	99.3	**99.6**	10.0	**99.5**	**99.2**	**99.4**	**100.0**
		WiSE-FT	84.4	57.9	77.3	67.1	63.7	86.3	80.4	91.8
		MS:PRE-FT-EWC-LwF	86.8	72.2	83.1	0.2	70.2	87.5	84.9	90.3
	IN-1K + AugReg	FT	94.6	94.0	97.3	95.3	95.9	96.3	96.3	100.0
		Linear Probing	68.7	34.9	63.4	62.1	54.7	75.1	62.6	90.9
		Visual Prompt	59.6	15.1	54.0	41.4	38.3	68.3	60.1	59.3
		LoRA	61.1	10.1	42.1	31.9	31.0	67.3	53.1	66.3
		EWC	65.9	33.4	59.3	45.6	42.1	71.3	64.3	62.7
		LwF	94.0	91.2	95.7	94.2	92.6	95.5	95.0	99.9
		LP-FT	**96.1**	**94.5**	**97.7**	**95.7**	**96.7**	**96.9**	**96.9**	**100.0**
		WiSE-FT	77.7	39.3	67.4	58.7	56.4	81.6	71.7	87.7
		MS:PRE-FT-EWC-LwF	79.0	49.1	71.0	63.0	60.6	82.7	75.4	86.8
	IN-1K + SAM	FT	73.5	**46.8**	**82.5**	**83.8**	**66.4**	84.3	82.5	**100.0**
		Linear Probing	60.7	8.9	48.3	35.5	33.4	67.2	51.2	83.4
		Visual Prompt	57.2	8.5	44.6	31.8	29.9	63.9	50.1	52.8
		LoRA	59.9	5.2	41.6	28.1	28.6	65.3	46.9	62.2
		EWC	60.9	10.2	45.1	37.7	31.1	67.0	52.3	53.7
		LwF	73.2	43.1	79.2	81.3	61.2	83.0	80.4	99.9
		LP-FT	**74.2**	44.8	81.8	82.4	66.1	**84.8**	**82.7**	100.0
		WiSE-FT	66.0	17.6	59.3	46.9	42.6	74.5	64.0	76.0
		MS:PRE-FT-EWC-LwF	66.1	20.1	60.8	51.1	43.3	74.8	65.5	76.5
	IN-21K + AugReg	FT	99.5	100.0	99.8	97.7	99.9	99.5	99.6	100.0
		Linear Probing	83.5	65.6	77.5	78.2	73.5	86.0	72.9	94.4
		Visual Prompt	68.2	32.0	66.3	51.4	52.4	74.0	67.3	65.2
		LoRA	69.1	25.0	51.5	43.0	43.4	71.9	63.2	66.1
		EWC	76.3	69.5	72.1	56.3	70.0	78.0	72.5	68.0
		LwF	99.2	99.8	99.5	97.3	99.7	99.2	99.1	100.0
		LP-FT	**99.8**	**100.0**	**99.8**	**97.9**	**100.0**	**99.8**	**99.8**	**100.0**
		WiSE-FT	87.9	72.0	80.4	72.3	73.8	88.9	79.1	92.5
		MS:PRE-FT-EWC-LwF	89.0	82.8	85.0	76.8	82.1	89.6	83.2	90.6
	OpenAI	FT	100.0	**100.0**	99.8	98.0	100.0	99.9	**99.9**	**100.0**
		Linear Probing	74.8	47.1	75.9	64.3	63.6	80.1	71.2	89.0
		Visual Prompt	71.6	29.3	65.6	50.7	47.5	75.5	64.9	62.3
		LoRA	72.5	34.7	67.7	53.3	48.4	77.9	69.6	71.5
		EWC	88.4	86.9	88.4	70.8	79.8	85.1	83.4	72.6
		LwF	99.9	99.8	99.8	97.9	99.8	99.8	99.9	100.0
		LP-FT	**100.0**	**100.0**	**99.8**	**98.0**	**100.0**	**99.9**	99.9	100.0
		WiSE-FT	85.9	71.4	88.6	78.1	75.5	89.3	89.9	93.4
		MS:PRE-FT-EWC-LwF	87.0	76.0	89.1	77.7	76.6	88.1	89.5	91.1
	LAION-2B	FT	**100.0**	**100.0**	99.8	**98.0**	**100.0**	99.9	**99.9**	**100.0**
		Linear Probing	75.5	47.8	78.7	67.3	66.7	81.4	71.5	88.7
		Visual Prompt	72.2	30.0	69.2	54.6	51.2	76.1	65.1	62.1
		LoRA	72.9	35.7	70.4	56.4	51.4	79.3	69.5	73.4
		EWC	85.6	80.7	87.3	71.6	77.2	84.8	83.4	69.7
		LwF	99.9	99.8	99.8	97.9	99.8	99.8	99.8	100.0
		LP-FT	**100.0**	**100.0**	**99.8**	98.0	100.0	**99.9**	99.9	100.0
		WiSE-FT	85.3	68.0	87.9	77.8	76.1	87.5	88.6	92.9
		MS:PRE-FT-EWC-LwF	85.9	73.9	88.8	77.8	77.1	86.4	88.5	91.9
ViT-S/16	IN-1K	FT	**99.8**	100.0	99.8	97.8	100.0	99.7	99.7	**100.0**
		Linear Probing	75.3	46.2	63.2	64.0	62.4	77.7	63.8	83.5
		Visual Prompt	66.2	30.7	58.6	43.6	49.2	71.8	63.9	60.0
		LoRA	67.0	17.4	42.4	41.1	38.6	70.1	64.2	55.4
		EWC	78.1	75.5	69.8	53.1	62.6	77.6	72.0	66.3
		LwF	99.6	99.8	99.6	97.6	99.8	99.3	99.4	100.0
		LP-FT	**99.8**	**100.0**	**99.8**	**97.9**	**100.0**	**99.8**	**99.8**	100.0
		WiSE-FT	88.6	72.2	78.1	70.3	73.4	88.2	80.6	91.7
		MS:PRE-FT-EWC-LwF	90.4	86.6	84.6	76.6	79.7	89.8	85.9	90.5
	IN-21K + AugReg	FT	99.9	**100.0**	99.8	97.9	100.0	99.7	99.7	100.0
		Linear Probing	84.0	67.6	73.9	75.0	73.2	84.0	69.5	88.8
		Visual Prompt	69.3	40.6	63.8	49.4	56.5	74.5	65.3	62.8
		LoRA	70.7	29.4	49.8	45.9	45.1	71.5	65.6	16.2
		EWC	79.5	84.9	75.2	57.1	68.8	79.4	73.6	68.9
		LwF	99.7	99.9	99.7	97.6	99.9	99.4	99.3	100.0
		LP-FT	**99.9**	**100.0**	**99.8**	**98.0**	**100.0**	**99.9**	**99.9**	**100.0**
		WiSE-FT	90.2	82.7	82.9	74.9	78.3	89.6	81.2	90.4
		MS:PRE-FT-EWC-LwF	91.0	91.8	87.4	79.1	85.3	90.7	85.6	92.7
ViT-S/32	IN-21K + AugReg	FT	99.9	**100.0**	99.8	97.8	100.0	99.6	99.7	100.0
		Linear Probing	78.3	50.0	68.0	68.0	63.9	79.7	64.1	83.4
		Visual Prompt	60.7	21.4	54.1	40.4	43.8	66.6	57.0	54.7
		LoRA	64.0	12.5	42.4	39.9	35.6	65.5	57.3	36.2
		EWC	73.7	67.9	67.1	50.4	57.3	73.5	66.7	61.5
		LwF	99.6	99.9	99.6	97.5	99.9	99.3	99.4	100.0
		LP-FT	**100.0**	**100.0**	**99.8**	**97.9**	**100.0**	**99.8**	**99.9**	**100.0**
		WiSE-FT	87.4	67.1	77.9	69.7	71.2	87.8	77.0	90.9
		MS:PRE-FT-EWC-LwF	88.7	81.7	83.1	75.8	78.6	88.7	82.4	88.6
ViT-L/16	IN-1K	FT	98.7	**99.5**	99.6	98.0	**99.9**	99.6	**99.7**	**100.0**
		Linear Probing	68.9	26.7	56.1	45.6	48.2	71.6	56.2	81.4
		Visual Prompt	68.4	24.6	54.6	40.6	44.9	72.1	64.4	65.0
		LoRA	67.5	16.7	41.0	30.6	34.6	67.7	50.6	71.0
		EWC	73.8	57.1	61.6	51.5	52.6	75.7	69.7	64.9
		LwF	98.2	98.9	99.4	97.8	99.3	99.0	99.3	100.0
		LP-FT	**98.8**	99.4	**99.7**	**98.0**	**99.9**	**99.6**	99.7	-1.0
		WiSE-FT	85.0	64.3	74.9	63.6	65.5	86.0	77.4	88.5
		MS:PRE-FT-EWC-LwF	86.1	75.8	79.8	68.0	69.6	87.0	81.8	86.6
	IN-21K + AugReg	FT	99.9	**100.0**	**99.8**	98.0	**100.0**	99.9	99.9	**100.0**
		Linear Probing	98.3	98.1	94.0	93.1	92.9	96.9	91.7	99.1
		Visual Prompt	71.3	48.0	69.4	50.8	59.6	76.0	66.7	67.1
		LoRA	76.5	59.9	66.4	54.7	56.8	80.0	68.6	72.7
		EWC	82.9	91.2	87.9	70.9	87.0	85.1	82.8	80.5
		LwF	99.9	**100.0**	99.8	97.8	100.0	99.8	99.8	100.0
		LP-FT	**100.0**	**100.0**	99.8	**98.1**	**100.0**	**99.9**	**99.9**	99.8
		WiSE-FT	93.1	77.7	93.5	85.7	88.3	93.8	90.3	96.1
		MS:PRE-FT-EWC-LwF	93.3	90.5	92.9	87.8	93.0	93.9	90.9	97.1

Table 10: Accuracy on downstream datasets after fine-tuning with each method. FT and LP-FT generally achieve the highest performance, while EWC shows the lowest.

Arch	$Dpre$	Method	Realistic Downstream Dataset					Synthetic Downstream Dataset		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ResNet-18	IN-1K	FT	98.3	**98.7**	**99.1**	95.7	**97.6**	97.4	97.1	100.0
		Linear Probing	59.9	6.5	47.0	33.3	34.2	65.1	48.3	50.8
		Visual Prompt	52.4	5.8	35.9	22.9	29.1	46.8	28.2	28.1
		EWC	63.0	17.5	50.8	37.9	38.0	66.0	54.0	42.6
		LwF	97.0	97.6	98.3	94.7	96.7	96.2	95.8	99.9
		LP-FT	**98.5**	98.5	98.9	**95.8**	97.4	**97.7**	**97.3**	**100.0**
		WiSE-FT	80.2	30.7	69.4	53.5	58.7	75.9	58.6	75.6
		MS:PRE-FT-EWC-LwF	80.8	41.8	72.9	59.9	62.4	80.3	70.3	74.9
ResNet-50	IN-1K	FT	95.3	94.5	**98.6**	96.2	96.9	97.4	97.8	100.0
		Linear Probing	69.8	19.8	52.3	32.9	46.2	75.0	57.0	55.5
		Visual Prompt	66.0	22.4	47.3	33.3	45.6	59.3	39.3	42.1
		EWC	72.0	43.1	58.4	44.5	49.5	76.3	63.6	52.4
		LwF	94.6	94.0	97.9	95.4	95.6	96.4	96.8	100.0
		LP-FT	**95.7**	**94.8**	98.6	**96.2**	**97.0**	**97.5**	**97.9**	**100.0**
		WiSE-FT	82.7	56.6	73.7	56.7	68.6	82.5	65.9	83.8
		MS:PRE-FT-EWC-LwF	84.1	66.7	78.9	62.4	71.6	86.4	76.0	84.8

Table 11: RI and mRI of ImageNet-1K pre-trained models with different fine-tuning methods and downstream datasets on each dataset in ImageNet-RIB.

Architecture	Method	mRI	Realistic OOD					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	FT	-6.9	-4.1	-13.0	-3.2	-8.0	-13.2	-5.6	-9.2	1.3
	Linear Probing	0.4	0.0	-0.0	0.2	0.8	-0.1	0.2	0.4	1.6
	Visual Prompt	-7.5	-5.5	-10.8	-6.2	-5.9	-17.3	-7.0	-6.0	-1.5
	LoRA	0.5	0.0	**0.0**	0.1	2.1	**0.0**	0.1	**1.0**	0.7
	EWC	0.1	**1.2**	-2.8	1.4	**2.8**	-2.6	-0.5	-0.5	2.0
	LwF	-3.6	-3.6	-6.2	0.6	-7.6	-6.2	-3.1	-6.1	3.4
	LP-FT	-5.8	-4.6	-10.0	-2.3	-6.4	-11.2	-5.6	-8.5	2.5
	WiSE-FT	**1.5**	0.7	-0.8	4.8	2.2	-0.9	**0.8**	0.8	**4.5**
	MS:PRE-FT-EWC-LwF	1.4	0.8	-1.3	**4.9**	2.3	-1.3	0.6	0.6	4.5
ViT-B/32	FT	-8.2	-5.8	-18.7	-5.6	-6.2	-17.6	-5.6	-9.4	2.9
	Linear Probing	0.4	0.0	-0.1	0.1	0.6	-0.1	0.2	0.3	1.9
	Visual Prompt	-8.5	-3.4	-20.2	-4.5	-3.9	-27.9	-3.3	-4.0	-0.5
	LoRA	0.7	0.0	**0.0**	0.2	2.6	**0.0**	0.3	**1.1**	1.4
	EWC	-0.9	**0.8**	-6.6	2.6	**3.0**	-6.2	-0.5	-1.7	1.5
	LwF	-8.2	-3.2	-9.0	0.1	-43.3	-8.0	-2.5	-5.2	5.7
	LP-FT	-11.4	-4.9	-15.2	-4.1	-42.9	-14.9	-5.1	-8.5	4.2
	WiSE-FT	**1.4**	0.4	-1.2	4.2	2.3	-1.4	**0.8**	0.4	5.6
	MS:PRE-FT-EWC-LwF	-4.6	0.5	-2.5	**4.4**	-43.6	-2.1	0.7	-0.0	**5.9**
ViT-L/16	FT	1.3	1.6	-3.9	3.8	**4.1**	-2.4	0.3	2.2	4.8
	Linear Probing	0.5	0.0	-0.0	0.2	0.9	-0.1	0.2	0.4	2.1
	Visual Prompt	-6.7	-3.8	-7.9	-6.6	-3.4	-23.3	-3.9	-4.5	0.3
	LoRA	0.4	0.0	0.0	0.0	0.6	0.0	0.0	0.3	2.0
	EWC	1.7	1.2	**0.7**	4.4	2.6	0.1	1.4	2.0	1.5
	LwF	2.7	**1.8**	-0.3	5.8	3.9	0.6	1.7	2.7	5.5
	LP-FT	2.1	1.6	-2.3	5.0	4.0	-0.8	0.8	2.3	**6.0**
	WiSE-FT	2.7	1.4	0.7	5.7	3.5	**1.1**	1.9	2.6	5.0
	MS:PRE-FT-EWC-LwF	**2.8**	1.6	0.7	**6.0**	3.7	1.0	**2.0**	**2.8**	4.7

Table 12: RI and mRI of ImageNet-1K with AugReg pre-trained models with different fine-tuning methods and downstream datasets on each dataset in ImageNet-RIB.

Architecture	Method	mRI	Realistic OOD					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	FT	1.3	2.9	-4.0	2.8	4.4	-2.7	0.6	0.4	5.9
	Linear Probing	0.7	0.1	-0.1	0.8	1.2	0.3	0.2	0.1	3.2
	Visual Prompt	-4.5	-2.3	-9.1	-4.9	-1.6	-11.2	-3.9	-4.3	1.7
	LoRA	0.9	0.2	0.4	1.1	2.6	0.3	-0.1	1.3	1.1
	EWC	2.8	2.9	-0.2	5.2	4.4	1.4	1.6	2.8	4.3
	LwF	3.1	2.8	-0.0	6.2	4.6	0.7	1.9	2.1	6.5
	LP-FT	2.3	**3.0**	-0.9	5.2	4.5	-0.1	1.2	0.6	4.7
	WiSE-FT	3.6	2.5	**0.7**	7.5	4.5	2.1	2.3	3.0	6.5
	MS:PRE-FT-EWC-LwF	**3.9**	2.7	0.7	**7.8**	**5.0**	**2.2**	**2.4**	**3.3**	**6.7**
ViT-B/32	FT	-0.0	1.6	-5.5	0.2	2.6	-5.4	0.3	-0.3	6.4
	Linear Probing	1.1	0.1	-0.1	0.9	1.3	0.4	1.0	1.1	3.8
	Visual Prompt	-5.4	-2.7	-13.3	-4.7	-2.0	-12.7	-2.4	-5.0	-0.1
	LoRA	0.9	0.3	**0.3**	0.5	1.0	**0.7**	0.7	0.5	3.1
	EWC	1.3	**1.9**	-2.9	3.2	2.6	0.1	1.2	2.0	2.6
	LwF	1.8	1.5	-2.0	3.9	3.2	-1.9	1.4	1.2	**6.9**
	LP-FT	1.5	1.5	-1.7	3.4	2.9	-1.9	1.0	0.3	6.4
	WiSE-FT	2.5	1.5	0.2	5.0	3.3	0.3	1.6	2.2	6.1
	MS:PRE-FT-EWC-LwF	**2.5**	1.7	-0.5	**5.1**	**3.5**	0.2	**1.8**	**2.4**	6.0
ViT-S/16	FT	-3.2	-0.0	-8.2	-2.9	0.3	-9.7	-2.4	-5.3	2.9
	Linear Probing	0.3	0.1	-0.5	0.9	1.4	-0.2	-0.1	0.6	-0.1
	Visual Prompt	-7.4	-4.6	-13.3	-6.1	-3.5	-18.1	-6.3	-6.0	-1.4
	LoRA	0.9	0.2	0.1	1.6	3.6	-0.1	-0.3	**1.5**	0.8
	EWC	1.6	**2.6**	-2.2	4.2	**5.5**	-1.9	0.6	0.9	2.7
	LwF	0.6	0.9	-1.5	3.5	1.5	-2.7	0.3	-2.4	5.4
	LP-FT	-1.2	0.9	-4.0	0.1	1.8	-5.8	-1.2	-4.2	2.8
	WiSE-FT	2.9	2.2	**0.7**	6.5	4.7	0.1	1.9	1.4	5.8
	MS:PRE-FT-EWC-LwF	**3.0**	2.2	0.3	**6.7**	5.3	**0.1**	**1.9**	1.3	**6.0**
ResNet-18	FT	-5.2	-2.1	-11.7	-0.6	-5.0	-8.8	-5.7	-13.6	5.7
	Linear Probing	-7.3	-1.4	-2.5	-1.2	-26.9	-3.9	-4.7	-15.5	-2.1
	Visual Prompt	-8.3	-4.3	-18.3	-7.5	-6.9	-12.9	-6.1	-7.8	-2.8
	EWC	-5.7	-0.6	-9.6	2.0	-11.7	-4.3	-4.6	-15.1	-1.5
	LwF	-1.9	-0.9	-5.5	2.6	-2.7	-4.7	-1.4	-9.0	**6.7**
	LP-FT	-4.8	-2.2	-10.0	1.0	-6.2	-7.1	-5.7	-13.9	6.1
	WiSE-FT	**0.7**	**-0.1**	**-1.5**	**4.3**	**2.4**	**-1.5**	**-0.7**	**-2.8**	5.3
	MS:PRE-FT-EWC-LwF	-0.1	-0.2	-2.7	4.2	1.9	-1.9	-1.2	-5.7	4.9
ResNet-50	FT	-5.2	-0.1	-2.9	2.8	-10.7	-4.3	-6.5	-22.4	2.4
	Linear Probing	-11.2	-1.5	-1.2	-1.2	-37.0	-4.2	-5.6	-35.2	-3.9
	Visual Prompt	-6.5	-5.9	-7.8	-6.0	-5.9	-9.1	-6.2	-6.0	-5.1
	EWC	-8.9	-1.1	-0.5	2.2	-21.7	-3.2	-7.2	-36.2	-3.3
	LwF	-5.8	0.5	-2.2	3.6	-12.3	-3.0	-4.9	-31.5	3.2
	LP-FT	-5.1	-0.2	-2.6	3.2	-10.3	-4.1	-6.4	-22.1	1.9
	WiSE-FT	**1.2**	**0.7**	**0.9**	6.1	**1.2**	**-0.0**	**-0.6**	**-3.0**	4.3
	MS:PRE-FT-EWC-LwF	-0.5	0.5	0.6	**6.1**	0.2	-0.6	-2.1	-13.1	**4.6**

Table 13: RI and mRI of ImageNet-1K with SAM pre-trained models with different fine-tuning methods and downstream datasets on each dataset in ImageNet-RIB.

Architecture	Method	mRI	Realistic OOD					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	FT	2.5	**3.4**	-3.2	5.8	5.7	-2.3	1.7	1.8	7.3
	Linear Probing	0.8	0.1	0.3	0.5	1.1	0.0	0.0	0.4	4.0
	Visual Prompt	-6.1	-4.1	-12.4	-6.4	-6.3	-10.6	-3.4	-4.9	-0.2
	LoRA	0.9	0.1	0.4	0.8	1.1	0.3	0.1	0.5	3.6
	EWC	1.6	0.7	0.3	3.7	2.4	1.2	1.0	2.0	1.3
	LwF	3.5	3.2	-1.3	6.9	**5.7**	0.2	2.3	2.2	**8.7**
	LP-FT	2.4	3.3	-2.3	6.4	5.6	-1.5	1.7	1.5	4.8
	WiSE-FT	3.6	2.0	**1.9**	7.1	4.3	1.5	**2.4**	2.8	6.5
	MS:PRE-FT-EWC-LwF	**3.7**	2.0	1.7	**7.3**	4.6	**1.6**	2.4	**3.0**	6.7
ViT-B/32	FT	1.4	**2.4**	-4.6	4.2	3.8	-4.0	0.9	0.8	7.6
	Linear Probing	0.9	0.1	0.4	0.8	1.1	0.2	0.3	0.2	4.2
	Visual Prompt	-5.9	-2.5	-17.1	-5.3	-5.0	-12.6	-1.9	-2.6	-0.1
	LoRA	0.8	0.1	0.6	1.0	1.0	0.5	0.3	0.3	2.9
	EWC	1.0	0.6	-0.3	2.5	2.1	0.6	0.6	1.1	1.0
	LwF	2.4	2.3	-2.3	**5.5**	**4.0**	-1.3	1.5	1.4	8.3
	LP-FT	1.9	2.3	-3.0	5.1	3.7	-2.8	1.0	0.4	**8.3**
	WiSE-FT	2.6	1.5	**1.1**	5.2	3.1	**0.7**	**1.7**	2.0	5.6
	MS:PRE-FT-EWC-LwF	**2.6**	1.5	0.8	5.4	3.4	0.7	1.7	**2.1**	5.5

Table 14: RI and mRI of ImageNet-21K pre-trained models with different fine-tuning methods and downstream datasets on each dataset in ImageNet-RIB.

Architecture	Method	mRI	Realistic OOD					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	FT	-0.1	1.5	-2.8	0.3	2.7	-4.0	-1.2	-1.8	4.2
	Linear Probing	0.4	0.3	0.4	0.2	0.0	0.8	-0.0	1.0	0.5
	Visual Prompt	-9.4	-7.7	-12.7	-11.1	-7.7	-14.8	-8.4	-10.0	-3.3
	LoRA	-0.3	0.2	0.5	-1.6	-0.5	**0.9**	-0.4	0.6	-1.9
	EWC	1.4	1.5	0.2	2.4	2.9	0.1	0.5	1.2	2.6
	LwF	1.6	1.5	-0.5	2.9	3.5	-0.8	0.9	0.0	5.3
	LP-FT	0.5	1.6	-1.2	2.2	2.7	-1.8	-0.5	-1.3	2.1
	WiSE-FT	2.5	1.7	**0.8**	**4.9**	3.8	0.6	1.3	1.7	5.5
	MS:PRE-FT-EWC-LwF	**2.7**	**1.7**	0.7	4.7	**4.2**	0.6	**1.4**	**1.8**	**6.0**

Table 15: RI and mRI of ImageNet-21K with AugReg pre-trained models with different fine-tuning methods and downstream datasets on each dataset in ImageNet-RIB.

Architecture	Method	mRI	Realistic OOD					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	FT	-5.5	-1.4	-9.1	-5.4	-5.3	-11.1	-3.6	-5.7	-2.5
	Linear Probing	-0.3	-0.4	-0.4	-0.9	-1.3	-0.5	0.4	0.6	0.2
	Visual Prompt	-8.0	-6.1	-9.2	-9.3	-6.1	-16.6	-7.1	-7.0	-3.0
	LoRA	-2.1	0.7	**0.8**	2.6	2.9	**0.8**	0.8	1.6	-27.4
	EWC	0.6	**2.0**	-2.0	2.3	**3.5**	-3.5	0.4	0.5	1.7
	LwF	-1.0	-1.0	-2.3	0.5	-1.5	-4.2	0.3	-1.3	1.7
	LP-FT	-2.6	0.3	-3.5	-4.7	-3.0	-6.2	-0.6	-2.5	-0.5
	WiSE-FT	1.7	1.8	-0.2	4.0	2.4	-0.9	2.0	1.5	3.2
	MS:PRE-FT-EWC-LwF	**2.2**	1.9	0.3	**4.6**	2.8	-0.7	**2.1**	**1.7**	**5.0**
ViT-B/32	FT	-0.1	0.7	-3.9	0.8	2.7	-4.9	-0.1	-0.6	4.4
	Linear Probing	0.3	-0.1	-0.8	0.1	0.7	-0.0	0.7	1.2	0.7
	Visual Prompt	-8.4	-4.9	-13.1	-7.8	-5.0	-20.7	-6.2	-7.3	-2.4
	LoRA	0.9	0.0	0.5	1.0	1.2	0.7	0.1	1.5	2.0
	EWC	1.6	**1.9**	-0.7	4.0	3.9	-1.0	1.0	1.7	2.3
	LwF	1.7	1.0	-0.5	3.9	2.8	-1.3	1.7	1.2	5.0
	LP-FT	1.2	1.1	-1.3	3.3	2.1	-0.9	1.5	0.8	3.0
	WiSE-FT	**3.0**	1.7	**0.9**	**5.6**	4.0	**1.0**	**2.0**	**2.5**	**6.0**
	MS:PRE-FT-EWC-LwF	2.8	1.7	0.6	5.6	**4.1**	0.6	2.0	2.4	5.6
ViT-S/16	FT	-2.3	-0.2	-5.4	-0.8	0.4	-8.5	-1.8	-4.1	1.8
	Linear Probing	-0.2	-0.1	-0.8	-0.1	0.3	-0.3	0.3	0.6	-1.2
	Visual Prompt	-9.2	-5.7	-12.1	-8.9	-5.0	-21.3	-8.3	-9.6	-2.8
	LoRA	-1.5	0.1	0.4	1.5	2.8	**0.5**	0.3	1.6	-19.5
	EWC	1.6	**2.0**	-0.8	4.2	**4.8**	-1.7	0.8	1.0	2.7
	LwF	0.5	0.5	-0.8	3.2	1.4	-3.1	0.9	-1.3	3.4
	LP-FT	-0.8	0.5	-2.9	1.6	1.1	-4.6	-0.5	-2.3	0.7
	WiSE-FT	2.8	1.8	**0.8**	6.1	4.4	-0.1	1.9	**2.0**	5.1
	MS:PRE-FT-EWC-LwF	**2.8**	1.7	0.6	**6.3**	4.6	-0.2	**2.0**	1.8	**5.9**
ViT-S/32	FT	-2.9	-1.2	-8.1	-1.3	0.1	-9.3	-2.5	-4.9	4.2
	Linear Probing	-0.1	-0.1	-1.5	0.1	0.6	-0.2	0.5	0.1	-0.2
	Visual Prompt	-9.6	-4.7	-21.6	-8.5	-5.6	-19.1	-5.7	-8.6	-2.7
	LoRA	0.4	0.1	**0.5**	1.1	2.7	**0.5**	0.3	1.1	-3.0
	EWC	1.0	**1.5**	-3.1	3.6	**4.2**	-1.5	0.2	0.7	2.2
	LwF	0.3	-0.1	-2.1	3.2	1.6	-4.0	0.5	-1.5	4.8
	LP-FT	-1.1	-0.5	-4.5	1.5	0.8	-5.1	-0.9	-3.0	3.0
	WiSE-FT	**2.3**	1.1	0.1	5.5	3.8	-0.6	1.2	**1.2**	**6.2**
	MS:PRE-FT-EWC-LwF	2.3	1.1	-0.5	**5.6**	4.1	-0.6	**1.2**	1.2	6.0
ViT-L/16	FT	-2.1	0.3	-8.7	-3.5	-0.6	-3.1	-0.8	-0.9	0.1
	Linear Probing	-1.3	-0.5	-4.1	-6.1	-1.2	-0.5	0.7	0.7	0.7
	Visual Prompt	-12.9	-10.7	-13.6	-13.5	-15.0	-17.0	-10.4	-14.2	-9.0
	LoRA	1.0	0.2	0.7	1.1	1.2	0.9	0.7	1.1	1.7
	EWC	1.1	-0.6	0.3	2.5	2.3	-0.7	1.2	1.5	1.9
	LwF	-0.2	-0.6	0.4	-1.9	0.5	-0.2	-0.6	-1.8	2.6
	LP-FT	-3.5	0.5	-14.0	-16.4	-0.5	-0.8	1.3	0.8	0.8
	WiSE-FT	2.3	**2.1**	0.1	3.3	**2.6**	1.1	**2.4**	2.7	4.4
	MS:PRE-FT-EWC-LwF	**2.5**	1.8	**1.1**	**3.4**	2.5	**1.1**	2.0	**2.7**	**5.1**

Table 16: RI and mRI of ImageNet-21K-P pre-trained models with different fine-tuning methods and downstream datasets on each dataset in ImageNet-RIB.

Architecture	Method	mRI	Realistic OOD					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	FT	-0.5	0.7	-3.5	1.6	3.0	-4.4	-1.4	-2.2	2.3
	Linear Probing	0.2	0.2	0.4	0.5	1.1	0.3	0.2	0.3	-1.0
	Visual Prompt	-10.1	-8.0	-11.5	-9.9	-7.8	-19.9	-8.8	-11.1	-3.6
	LoRA	0.4	0.1	0.3	0.5	1.2	0.5	-0.2	0.9	-0.1
	EWC	1.3	1.3	0.6	1.1	3.0	0.8	0.6	0.6	2.1
	LwF	1.7	1.6	-0.1	4.5	3.5	-0.3	1.0	-0.2	3.7
	LP-FT	0.4	0.8	-1.1	3.8	3.3	-1.2	-0.4	-1.8	0.1
	WiSE-FT	**3.0**	2.0	**1.3**	6.3	4.1	**1.3**	**1.8**	2.0	**5.3**
	MS:PRE-FT-EWC-LwF	3.0	**2.0**	1.1	**6.3**	**4.3**	1.3	1.7	**2.0**	5.3

Table 17: RI and mRI of LAION-2B pre-trained models with different fine-tuning methods and downstream datasets on each dataset in ImageNet-RIB.

Architecture	Method	mRI	Realistic OOD					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	FT	-38.1	-39.4	-53.7	-36.9	-46.9	-49.2	-29.0	-36.6	-12.9
	Linear Probing	**-2.0**	**-0.6**	**-0.9**	**-1.5**	**-0.8**	**-1.9**	**-2.4**	**-5.5**	-2.0
	Visual Prompt	-8.2	-6.4	-8.1	-8.1	-6.7	-16.7	-8.3	-8.0	-2.9
	LoRA	-3.6	-0.8	-1.3	-1.6	-1.2	-3.0	-2.8	-5.8	-12.3
	EWC	-12.5	-16.1	-27.2	-2.4	-17.3	-19.0	-6.4	-9.9	**-1.7**
	LwF	-33.9	-37.3	-49.3	-31.7	-45.2	-44.7	-22.3	-31.0	-9.9
	LP-FT	-37.1	-39.3	-51.0	-35.9	-46.1	-47.7	-28.3	-33.7	-14.6
	WiSE-FT	-21.6	-25.3	-39.1	-17.6	-31.9	-25.4	-11.3	-16.3	-5.5
	MS:PRE-FT-EWC-LwF	-17.9	-21.1	-31.3	-12.9	-29.7	-22.1	-8.6	-14.6	-2.7
ViT-B/32	FT	-31.6	-31.1	-47.0	-28.9	-37.5	-41.3	-24.5	-32.8	-9.6
	Linear Probing	**-1.4**	**-0.1**	**-1.5**	**0.2**	**0.5**	**-2.1**	**-2.3**	**-6.0**	0.5
	Visual Prompt	-8.4	-6.4	-12.1	-6.9	-6.0	-21.9	-6.1	-6.7	-1.5
	LoRA	-1.9	-0.2	-2.0	-0.4	-0.9	-4.0	-2.6	-6.1	**1.1**
	EWC	-10.0	-10.6	-25.6	-1.2	-11.5	-15.1	-3.5	-11.0	-1.1
	LwF	-26.7	-28.5	-40.5	-22.8	-33.7	-34.4	-18.5	-26.8	-8.6
	LP-FT	-30.8	-31.3	-45.7	-27.9	-35.9	-39.7	-24.4	-30.8	-10.3
	WiSE-FT	-13.5	-15.5	-22.8	-8.6	-17.8	-17.9	-8.4	-14.4	-2.2
	MS:PRE-FT-EWC-LwF	-10.9	-12.4	-19.0	-5.7	-16.4	-14.3	-5.7	-12.5	-1.3

Table 18: RI and mRI of OpenAI CLIP models with different fine-tuning methods and downstream datasets on each dataset in ImageNet-RIB.

Architecture	Method	mRI	Realistic OOD					Synthetic OOD		
			IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
ViT-B/16	FT	-38.0	-38.3	-51.6	-35.4	-48.5	-50.3	-28.9	-35.8	-15.3
	Linear Probing	**-2.0**	**-0.5**	**-0.8**	**-1.3**	-1.3	**-1.2**	**-3.4**	**-5.6**	-1.8
	Visual Prompt	-8.4	-7.4	-8.1	-7.6	-6.3	-16.3	-9.4	-9.9	-2.7
	LoRA	-3.6	-0.6	-1.0	-1.9	**-1.0**	-2.8	-4.0	-6.4	-11.3
	EWC	-12.7	-14.4	-20.9	-2.4	-24.8	-19.9	-7.5	-10.8	**-0.8**
	LwF	-33.1	-35.5	-46.4	-30.6	-47.1	-44.3	-22.7	-30.2	-7.9
	LP-FT	-36.9	-38.3	-50.0	-34.4	-48.5	-49.0	-29.8	-31.7	-13.3
	WiSE-FT	-18.1	-19.5	-26.7	-11.7	-31.0	-23.7	-11.1	-15.8	-5.5
	MS:PRE-FT-EWC-LwF	-16.0	-17.1	-24.3	-9.4	-30.3	-20.9	-9.1	-14.4	-2.7
ViT-B/32	FT	-28.7	-28.1	-43.8	-26.4	-35.0	-39.1	-20.8	-28.2	-8.4
	Linear Probing	**-1.3**	**0.2**	**-0.9**	-0.8	**-0.1**	**-1.8**	**-2.1**	-5.6	0.9
	Visual Prompt	-8.0	-5.4	-12.5	-6.2	-4.6	-20.8	-5.9	-7.0	-1.4
	LoRA	-1.8	0.1	-1.6	**-0.8**	-0.6	-3.7	-2.3	**-5.4**	-0.2
	EWC	-7.0	-5.6	-17.0	-1.1	-11.4	-13.0	-3.1	-6.5	**1.7**
	LwF	-23.9	-24.8	-37.0	-21.1	-31.3	-31.7	-16.5	-24.3	-4.4
	LP-FT	-27.7	-27.4	-42.2	-24.3	-33.7	-37.7	-20.2	-26.9	-9.0
	WiSE-FT	-9.7	-10.3	-16.5	-5.3	-14.2	-12.5	-5.7	-11.3	-1.5
	MS:PRE-FT-EWC-LwF	-8.1	-8.5	-14.7	-3.2	-13.4	-10.6	-4.4	-9.9	0.5

Table 19: The accuracy on each OOD dataset after fine-tuning on ImageNet-1K with SAM pre-trained ViT-B/16 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		79.2	66.4	15.0	38.0	28.0	25.7	66.2	39.1	56.0
Pre-Trained		80.2	68.2	9.0	40.1	27.7	34.2	66.9	42.3	54.6
FT	IN-V2	81.1	-	17.1	42.9	29.7	38.7	69.5	44.1	56.8
	IN-A	77.1	65.7	-	37.9	25.7	39.8	60.4	30.9	51.3
	IN-R	75.0	64.1	19.1	-	49.5	36.1	66.9	53.6	53.9
	IN-Sketch	79.2	67.3	14.2	59.5	-	35.8	71.0	52.0	55.7
	ObjNet	77.6	66.1	**21.9**	37.1	25.9	-	57.3	32.2	52.2
	IN-Cartoon	82.6	67.1	15.4	44.2	32.2	35.2	-	42.8	51.3
	IN-Drawing	79.9	65.1	12.9	45.1	34.0	33.5	67.2	-	55.4
	IN-C	**99.7**	63.0	15.5	39.3	27.1	30.4	92.5	71.4	-
HeadOnly	IN-V2	80.3	-	9.0	40.2	27.6	34.1	67.5	42.3	54.7
	IN-A	80.2	68.0	-	41.0	27.8	34.9	67.4	42.4	54.5
	IN-R	80.1	68.1	9.6	-	28.6	34.1	67.9	43.5	54.6
	IN-Sketch	79.5	67.3	9.3	45.2	-	34.2	67.7	44.9	54.1
	ObjNet	80.1	67.9	9.2	40.0	27.9	-	67.3	42.3	54.6
	IN-Cartoon	80.3	68.1	8.4	41.6	28.2	32.8	-	43.5	53.8
	IN-Drawing	79.9	67.5	8.9	42.7	29.3	32.7	67.9	-	54.6
	IN-C	93.4	65.6	11.4	40.6	28.1	32.1	80.6	58.1	-
Visual Prompt (Bahng et al., 2022)	IN-V2	75.5	-	8.1	39.9	24.1	35.5	58.5	35.0	44.7
	IN-A	67.5	55.6	-	35.8	19.1	34.0	45.6	26.4	30.4
	IN-R	69.9	57.4	6.3	-	32.0	29.2	56.5	39.7	36.8
	IN-Sketch	71.2	58.2	5.6	47.2	-	28.3	56.4	39.5	36.3
	ObjNet	70.7	58.7	9.0	36.2	20.1	-	48.2	27.2	35.3
	IN-Cartoon	75.8	62.3	6.5	42.5	27.0	31.8	-	39.8	42.3
	IN-Drawing	72.8	59.8	5.4	43.0	28.1	28.6	59.0	-	42.2
	IN-C	77.7	65.7	8.8	41.3	28.0	36.7	62.1	44.1	-
LoRA (Hu et al., 2021)	IN-V2	80.2	-	8.9	40.1	27.7	34.2	67.4	42.3	54.7
	IN-A	80.2	68.2	-	41.1	27.8	34.6	67.7	42.7	54.8
	IN-R	80.2	68.2	9.7	-	29.0	34.8	68.2	43.9	54.7
	IN-Sketch	79.9	67.7	9.4	44.0	-	34.7	68.1	44.8	54.6
	ObjNet	80.1	68.0	9.2	40.9	28.2	-	67.5	42.5	54.7
	IN-Cartoon	80.1	68.2	8.7	41.5	28.2	33.3	-	43.5	53.7
	IN-Drawing	80.0	67.8	9.1	42.6	29.0	33.1	68.1	-	54.5
	IN-C	80.2	68.6	13.7	42.4	30.7	36.9	68.6	52.4	-
EWC (Kirkpatrick et al., 2017)	IN-V2	80.4	-	9.7	40.8	28.2	35.0	67.8	43.0	55.1
	IN-A	79.5	68.2	-	41.3	27.4	39.0	64.3	41.5	54.7
	IN-R	80.3	68.6	11.5	-	36.2	36.5	70.2	49.6	56.3
	IN-Sketch	80.1	68.1	9.7	47.9	-	34.2	69.3	47.7	55.6
	ObjNet	80.4	68.6	12.5	41.4	28.3	-	66.7	43.0	56.5
	IN-Cartoon	80.4	68.2	9.3	42.8	29.3	34.4	-	44.6	54.3
	IN-Drawing	80.1	67.9	10.0	44.5	31.2	35.3	68.7	-	56.9
	IN-C	80.4	68.6	11.0	41.2	28.8	36.7	66.8	44.7	-
LwF (Li & Hoiem, 2017)	IN-V2	81.1	-	16.1	42.8	29.7	38.3	69.5	44.3	56.8
	IN-A	78.6	67.1	-	39.4	26.7	40.2	63.4	34.3	53.9
	IN-R	77.2	66.1	17.9	-	49.6	37.1	69.2	55.3	56.0
	IN-Sketch	79.6	67.8	13.8	59.0	-	35.7	71.3	51.6	56.3
	ObjNet	79.4	67.7	20.2	39.7	27.5	-	62.5	37.3	55.0
	IN-Cartoon	82.9	68.0	14.7	44.3	32.0	35.7	-	44.3	53.1
	IN-Drawing	80.6	65.9	12.3	45.2	34.4	34.2	68.1	-	56.2
	IN-C	99.4	65.5	14.7	42.4	28.9	33.0	**93.0**	**71.8**	-
LP-FT (Kumar et al., 2022)	IN-V2	81.1	-	16.9	42.8	29.7	38.6	69.4	44.0	56.8
	IN-A	77.8	66.3	-	38.5	26.1	40.2	61.7	32.7	52.3
	IN-R	76.2	65.2	18.4	-	**49.7**	37.1	67.9	54.9	54.5
	IN-Sketch	78.9	67.1	13.9	**60.0**	-	35.9	70.7	51.4	55.6
	ObjNet	78.1	66.7	21.7	37.8	26.3	-	59.0	33.7	53.0
	IN-Cartoon	82.6	66.9	15.4	44.5	32.2	34.8	-	43.3	51.1
	IN-Drawing	79.6	64.6	12.9	46.1	34.4	32.5	66.9	-	53.8
	IN-C	93.9	65.1	11.6	41.2	28.9	31.4	82.5	61.4	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	80.9	-	12.2	41.8	29.1	36.6	68.8	43.9	56.1
	IN-A	80.7	69.0	-	42.0	29.0	39.7	68.2	42.6	57.0
	IN-R	80.5	69.0	15.2	-	43.8	38.1	72.3	55.5	58.7
	IN-Sketch	80.5	68.5	11.9	51.4	-	36.2	70.9	49.9	56.8
	ObjNet	80.6	69.0	15.4	41.1	28.9	-	67.1	41.8	56.4
	IN-Cartoon	82.3	69.0	12.2	43.5	30.9	36.1	-	46.0	55.2
	IN-Drawing	81.4	68.5	11.7	44.1	32.6	35.7	69.9	-	57.9
	IN-C	89.1	69.2	16.6	43.5	31.5	37.1	79.5	56.3	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	80.8	-	12.2	41.9	29.1	36.6	68.9	44.0	56.1
	IN-A	80.5	68.9	-	41.9	28.6	**40.4**	67.5	41.6	57.0
	IN-R	80.3	69.1	15.5	-	44.8	38.2	72.4	55.7	**58.7**
	IN-Sketch	80.5	68.5	12.0	52.6	-	36.3	71.1	50.4	57.0
	ObjNet	80.6	69.0	15.7	41.3	28.9	-	66.7	41.9	56.7
	IN-Cartoon	82.2	68.9	12.1	43.9	31.1	35.9	-	46.1	55.0
	IN-Drawing	81.2	68.4	11.7	44.8	33.2	35.7	70.0	-	58.0
	IN-C	89.3	**69.3**	16.2	43.9	31.7	37.3	79.5	57.2	-

Table 20: The accuracy on each OOD dataset after fine-tuning ImageNet-21K pre-trained ViT-B/16 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		81.8	71.4	32.0	47.3	35.8	42.5	69.4	44.1	58.3
FT	IN-V2	81.7	-	**40.4**	49.6	36.2	45.4	68.5	41.6	58.5
	IN-A	78.2	68.1	-	47.4	33.4	45.7	62.7	37.2	55.0
	IN-R	75.5	65.2	34.2	-	50.2	39.8	64.6	48.9	52.9
	IN-Sketch	78.8	68.3	32.6	**64.7**	-	41.7	69.7	51.3	55.5
	ObjNet	78.5	67.8	39.3	44.3	32.5	-	60.6	33.3	52.8
	IN-Cartoon	85.2	68.0	33.0	49.5	36.4	41.9	-	41.4	52.9
	IN-Drawing	81.5	66.6	27.0	50.3	38.4	39.4	67.0	-	55.3
	IN-C	**99.7**	65.6	25.4	45.4	32.9	36.7	93.2	**72.9**	-
Linear Probing	IN-V2	81.8	-	32.8	47.6	35.9	42.9	69.7	44.2	58.5
	IN-A	81.4	71.0	-	48.6	35.9	45.9	67.8	43.9	58.7
	IN-R	80.5	70.1	33.5	-	38.3	42.0	69.8	44.3	56.7
	IN-Sketch	79.9	69.2	30.1	53.9	-	41.1	69.9	44.5	56.4
	ObjNet	81.3	71.1	37.6	48.3	36.1	-	67.9	44.2	58.9
	IN-Cartoon	82.5	70.3	31.7	49.3	36.4	41.5	-	45.2	56.9
	IN-Drawing	82.0	70.2	32.8	50.0	38.1	42.5	71.0	-	59.0
	IN-C	96.7	65.3	27.6	42.8	31.7	36.2	85.5	57.0	-
Visual Prompt (Bahng et al., 2022)	IN-V2	76.0	-	25.2	43.8	29.4	41.7	58.2	32.1	45.5
	IN-A	71.7	60.6	-	41.0	24.1	39.2	50.9	25.8	38.3
	IN-R	69.9	59.1	18.1	-	35.0	35.0	54.9	35.8	38.3
	IN-Sketch	72.9	61.7	18.1	53.3	-	38.7	58.3	40.3	41.1
	ObjNet	71.1	59.6	25.1	38.0	23.8	-	49.0	22.6	36.9
	IN-Cartoon	75.6	63.4	20.9	44.9	29.9	37.9	-	33.9	41.9
	IN-Drawing	73.3	61.8	17.1	45.4	30.0	35.1	55.5	-	41.8
	IN-C	78.9	67.2	25.3	45.5	31.5	42.7	63.6	43.5	-
LoRA (Hu et al., 2021)	IN-V2	81.8	-	32.4	47.4	35.8	42.8	69.6	44.1	58.4
	IN-A	81.7	71.2	-	48.5	35.9	45.9	67.9	43.8	58.9
	IN-R	79.6	68.3	30.2	-	37.4	40.2	69.7	43.3	53.6
	IN-Sketch	80.4	69.4	30.1	51.2	-	40.6	70.7	43.0	56.3
	ObjNet	81.8	71.5	37.4	48.7	36.1	-	67.7	43.9	59.2
	IN-Cartoon	81.1	70.1	30.9	49.4	36.4	41.3	-	44.1	56.1
	IN-Drawing	81.6	71.0	32.1	49.9	37.3	42.7	70.2	-	58.0
	IN-C	81.5	70.7	29.8	45.8	33.4	42.3	69.6	37.8	-
EWC (Kirkpatrick et al., 2017)	IN-V2	82.2	-	35.5	49.0	36.3	44.8	70.2	44.7	59.4
	IN-A	81.1	70.9	-	49.1	35.4	**48.4**	66.7	41.0	58.8
	IN-R	80.8	69.8	34.5	-	44.3	42.6	70.3	51.0	57.6
	IN-Sketch	81.8	71.2	31.9	57.1	-	42.5	71.8	51.6	59.3
	ObjNet	80.9	69.8	39.0	47.8	35.3	-	66.5	42.3	58.2
	IN-Cartoon	81.8	70.5	32.6	50.6	36.8	42.4	-	45.2	56.7
	IN-Drawing	81.0	70.6	31.7	52.1	38.0	44.0	69.1	-	59.4
	IN-C	82.2	**71.6**	35.2	50.3	37.7	45.4	69.1	51.1	-
LwF (Li & Hoiem, 2017)	IN-V2	81.8	-	38.3	49.2	36.6	44.8	69.3	42.6	59.3
	IN-A	80.5	70.3	-	48.5	34.9	45.6	66.4	41.7	58.1
	IN-R	79.4	68.6	35.7	-	49.6	41.6	69.1	52.0	57.3
	IN-Sketch	80.1	70.0	33.2	64.0	-	42.7	71.0	51.6	57.3
	ObjNet	81.1	70.3	38.3	46.8	35.0	-	66.0	39.6	57.0
	IN-Cartoon	86.7	70.5	34.7	50.4	37.3	43.3	-	43.8	57.9
	IN-Drawing	83.3	68.9	29.6	51.2	39.0	40.9	69.3	-	58.1
	IN-C	99.7	67.4	25.3	48.1	35.2	38.2	**93.3**	72.3	-
LP-FT (Kumar et al., 2022)	IN-V2	81.6	-	39.8	49.3	36.3	45.2	69.0	42.2	58.7
	IN-A	79.6	69.2	-	48.3	35.0	46.6	64.7	39.9	56.7
	IN-R	77.8	67.4	35.0	-	**50.2**	41.8	68.1	51.2	55.4
	IN-Sketch	78.9	68.5	32.6	64.4	-	41.7	70.4	50.5	55.8
	ObjNet	79.9	69.2	40.2	46.2	33.9	-	63.8	37.2	55.5
	IN-Cartoon	86.0	68.2	33.1	49.8	36.7	42.0	-	43.4	54.4
	IN-Drawing	82.2	67.1	27.8	50.9	39.1	39.3	67.7	-	56.0
	IN-C	99.1	63.5	21.4	43.7	31.3	33.6	92.2	71.7	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	82.1	-	37.6	49.0	36.6	45.2	69.7	43.9	59.3
	IN-A	81.3	71.2	-	49.1	36.3	47.0	68.4	43.4	59.0
	IN-R	81.5	71.3	38.2	-	47.6	45.6	71.7	53.7	60.0
	IN-Sketch	81.5	71.4	34.2	59.4	-	43.9	72.1	51.7	59.2
	ObjNet	81.5	71.1	39.0	48.0	36.3	-	68.1	42.0	58.2
	IN-Cartoon	84.8	71.3	34.8	49.8	37.2	44.0	-	45.6	58.1
	IN-Drawing	83.1	71.0	32.9	51.0	39.6	43.3	70.6	-	59.8
	IN-C	92.0	71.3	33.7	50.4	38.4	43.8	82.4	60.8	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	82.2	-	37.4	49.1	36.6	45.1	69.8	44.0	59.5
	IN-A	81.2	71.2	-	49.3	36.0	47.1	67.9	42.9	59.1
	IN-R	81.4	71.2	37.6	-	48.0	44.7	71.8	53.6	59.8
	IN-Sketch	81.6	71.4	34.3	60.8	-	43.8	72.4	52.5	59.4
	ObjNet	81.5	70.9	39.2	48.1	36.2	-	67.9	42.2	58.3
	IN-Cartoon	84.7	71.1	34.9	50.3	37.5	44.0	-	45.6	58.2
	IN-Drawing	83.1	71.1	32.8	51.7	39.8	43.5	70.6	-	**60.1**
	IN-C	93.5	71.2	33.1	50.9	38.9	43.6	84.1	62.9	-

Table 21: The accuracy on each OOD dataset after fine-tuning ImageNet-21K with AugReg pre-trained ViT-B/16 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		84.5	74.0	43.2	56.8	43.2	48.4	75.1	54.9	66.5
FT	IN-V2	81.3	-	47.5	56.8	40.0	49.7	70.6	49.3	64.4
	IN-A	74.8	64.8	-	50.6	35.6	46.3	60.7	40.7	56.3
	IN-R	73.8	63.7	33.9	-	52.4	42.5	65.1	54.4	55.7
	IN-Sketch	75.2	65.2	28.4	70.6	-	43.7	65.3	54.2	54.8
	ObjNet	76.7	65.6	37.1	47.6	32.5	-	62.2	36.0	54.9
	IN-Cartoon	95.3	67.2	35.1	54.9	39.8	44.8	-	58.9	61.5
	IN-Drawing	91.1	65.2	27.6	54.2	41.1	41.1	78.4	-	59.9
	IN-C	**99.9**	62.7	20.2	46.5	31.8	35.0	**98.1**	**84.1**	-
Linear Probing	IN-V2	83.1	-	45.1	56.3	42.8	48.3	73.7	53.3	65.7
	IN-A	83.3	73.6	-	56.7	42.5	51.0	73.6	52.8	65.8
	IN-R	82.2	72.1	44.6	-	45.3	49.2	71.6	52.2	64.0
	IN-Sketch	79.3	69.2	42.3	64.6	-	49.0	70.0	53.0	62.1
	ObjNet	83.1	73.2	47.8	56.3	41.4	-	73.3	52.6	65.9
	IN-Cartoon	91.1	71.9	43.3	56.5	42.2	47.5	-	58.5	69.9
	IN-Drawing	87.6	71.9	42.0	57.5	43.5	47.0	79.7	-	**70.0**
	IN-C	99.2	65.0	35.2	50.3	37.0	39.5	93.8	76.1	-
Visual Prompt (Bahng et al., 2022)	IN-V2	81.3	-	37.2	53.6	38.8	48.8	67.8	42.8	56.9
	IN-A	78.5	67.3	-	52.3	35.0	51.5	63.1	34.6	51.1
	IN-R	74.9	64.1	27.4	-	47.4	43.3	62.2	49.2	46.4
	IN-Sketch	78.3	67.4	28.0	64.2	-	45.0	67.2	52.7	51.7
	ObjNet	75.0	64.2	34.8	43.9	30.4	-	54.1	27.8	42.5
	IN-Cartoon	80.8	68.6	31.8	54.3	39.3	45.2	-	45.4	53.1
	IN-Drawing	79.3	68.3	27.9	55.1	40.1	44.6	67.8	-	54.5
	IN-C	82.3	71.3	38.8	53.3	38.9	48.1	70.6	53.7	-
LoRA (Hu et al., 2021)	IN-V2	84.6	-	44.9	57.1	43.4	49.9	75.2	55.0	67.2
	IN-A	84.3	**74.5**	-	57.9	42.8	**52.8**	74.7	54.2	67.8
	IN-R	84.2	74.1	47.6	-	48.5	52.4	75.4	58.8	67.0
	IN-Sketch	84.0	73.7	44.9	66.5	-	51.3	75.6	60.7	66.9
	ObjNet	84.2	74.3	49.5	58.0	42.4	-	74.5	53.6	67.2
	IN-Cartoon	84.5	73.8	44.9	58.3	43.7	50.0	-	55.5	66.4
	IN-Drawing	84.0	73.8	43.9	61.2	47.3	49.7	75.3	-	67.1
	IN-C	64.8	52.2	7.9	36.4	24.9	24.6	39.4	18.9	-
EWC (Kirkpatrick et al., 2017)	IN-V2	84.0	-	**52.3**	59.4	43.6	52.1	73.2	54.0	67.7
	IN-A	81.3	71.3	-	56.8	41.8	52.4	69.8	46.8	65.8
	IN-R	80.9	70.5	47.1	-	56.2	48.4	72.3	63.0	63.9
	IN-Sketch	83.1	72.9	44.8	70.3	-	50.1	75.4	63.9	66.2
	ObjNet	80.8	70.6	49.9	53.3	40.1	-	67.4	44.5	63.5
	IN-Cartoon	84.6	72.2	45.0	58.5	43.6	49.2	-	57.4	63.9
	IN-Drawing	84.2	73.1	42.2	59.3	45.8	49.0	75.4	-	65.9
	IN-C	85.4	74.2	46.5	56.4	42.8	49.6	75.9	62.5	-
LwF (Li & Hoiem, 2017)	IN-V2	83.6	-	42.9	56.3	40.7	48.2	73.8	53.5	66.0
	IN-A	82.8	72.1	-	55.5	39.4	48.4	72.2	51.6	64.1
	IN-R	82.5	71.9	39.3	-	54.3	46.5	74.1	58.7	64.1
	IN-Sketch	80.3	70.1	33.2	69.2	-	46.6	71.7	56.5	61.5
	ObjNet	81.9	71.4	42.2	53.6	38.4	-	70.7	45.9	62.2
	IN-Cartoon	96.6	71.8	37.9	57.1	41.7	47.0	-	62.0	71.7
	IN-Drawing	94.3	69.9	31.1	57.5	43.6	44.1	83.6	-	68.5
	IN-C	99.9	69.2	27.8	53.9	38.5	41.8	97.5	79.4	-
LP-FT (Kumar et al., 2022)	IN-V2	82.3	-	50.8	56.9	41.9	50.3	72.4	52.5	65.6
	IN-A	80.9	70.9	-	54.5	40.2	51.0	69.3	45.7	63.2
	IN-R	76.3	66.2	35.3	-	49.0	45.3	66.5	52.8	57.0
	IN-Sketch	76.9	66.7	35.1	69.7	-	46.8	68.0	53.6	58.5
	ObjNet	79.6	68.9	42.2	52.5	36.1	-	67.4	43.4	59.9
	IN-Cartoon	96.0	69.6	40.0	55.6	40.9	47.2	-	60.9	68.6
	IN-Drawing	92.8	67.5	31.0	56.4	42.5	43.7	81.7	-	66.9
	IN-C	99.9	63.3	27.6	49.3	34.8	37.1	97.2	83.0	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	84.1	-	50.0	58.5	43.5	51.4	74.6	54.9	68.0
	IN-A	83.0	73.1	-	57.2	42.2	52.5	72.6	53.3	66.5
	IN-R	82.8	72.8	47.7	-	56.8	50.4	75.4	63.7	66.9
	IN-Sketch	82.3	72.9	40.5	70.7	-	49.8	74.5	62.5	65.1
	ObjNet	83.2	72.9	48.0	56.1	41.9	-	73.2	50.0	65.6
	IN-Cartoon	92.0	72.8	45.5	58.4	44.2	50.1	-	61.8	68.6
	IN-Drawing	90.2	73.0	41.1	59.0	46.4	49.1	80.3	-	69.2
	IN-C	96.5	71.7	36.9	55.8	41.2	46.4	92.3	73.9	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	84.2	-	49.9	58.6	43.7	51.1	74.7	55.3	68.0
	IN-A	83.5	73.7	-	57.7	42.9	52.3	73.4	53.9	66.9
	IN-R	83.5	73.6	48.4	-	**57.2**	50.5	76.1	64.4	67.4
	IN-Sketch	82.7	72.8	41.6	**71.0**	-	49.8	75.0	62.6	65.6
	ObjNet	83.3	73.1	49.4	56.0	42.1	-	72.8	49.7	65.6
	IN-Cartoon	91.7	73.0	44.9	58.8	44.3	49.8	-	61.9	69.2
	IN-Drawing	90.2	73.0	40.9	59.7	46.8	48.6	80.7	-	69.6
	IN-C	96.5	72.9	41.0	58.0	43.6	47.7	92.1	75.5	-

Table 22: The accuracy on each OOD dataset after fine-tuning ImageNet-21K-P pre-trained ViT-B/16 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		84.3	74.0	34.1	51.5	40.2	46.7	73.5	45.1	61.4
FT	IN-V2	83.5	-	44.6	52.9	40.4	47.1	71.4	39.2	62.1
	IN-A	80.8	70.7	-	50.3	38.6	47.2	65.5	35.5	60.5
	IN-R	78.9	68.8	38.7	-	54.6	42.8	69.9	54.2	57.5
	IN-Sketch	81.9	71.8	35.4	**67.0**	-	44.5	74.8	54.4	59.3
	ObjNet	81.1	70.6	43.8	47.5	36.8	-	63.1	29.6	57.7
	IN-Cartoon	89.0	71.0	38.0	51.9	40.2	43.4	-	42.5	56.1
	IN-Drawing	85.8	69.5	31.4	52.7	42.7	41.8	70.3	-	57.9
	IN-C	99.8	67.9	25.6	47.1	34.7	37.4	95.0	73.7	-
HeadOnly	IN-V2	84.3	-	34.8	51.6	40.0	46.4	74.1	45.6	61.4
	IN-A	84.0	73.9	-	51.9	40.1	48.5	73.9	45.2	61.8
	IN-R	83.8	73.9	35.6	-	42.0	46.5	73.3	46.1	61.0
	IN-Sketch	83.2	73.4	34.8	57.2	-	46.9	73.4	47.7	60.8
	ObjNet	83.9	73.7	36.6	51.3	39.8	-	73.7	45.1	61.9
	IN-Cartoon	85.6	73.8	34.5	52.3	40.3	45.7	-	46.5	61.3
	IN-Drawing	84.5	73.5	33.2	53.0	41.7	45.5	74.5	-	62.0
	IN-C	97.3	68.4	30.0	44.6	33.4	39.2	86.4	56.2	-
Visual Prompt (Bahng et al., 2022)	IN-V2	79.7	-	27.1	46.9	32.7	45.2	62.1	32.9	49.6
	IN-A	76.7	66.0	-	44.0	27.5	46.4	55.6	27.6	44.6
	IN-R	74.1	62.8	20.3	-	41.0	39.4	59.3	42.1	40.5
	IN-Sketch	77.0	65.5	18.3	56.6	-	40.9	62.6	43.8	44.1
	ObjNet	72.4	61.1	22.1	34.8	23.1	-	46.4	18.4	34.8
	IN-Cartoon	79.0	67.2	21.6	48.5	33.4	41.7	-	34.8	44.2
	IN-Drawing	75.9	63.9	17.1	48.0	33.2	38.4	58.5	-	44.3
	IN-C	80.9	70.2	28.5	48.5	35.4	45.1	65.6	46.9	-
LoRA (Hu et al., 2021)	IN-V2	84.2	-	34.5	51.3	40.3	46.6	73.9	45.5	61.3
	IN-A	84.1	74.1	-	51.4	40.1	47.9	73.7	45.4	62.1
	IN-R	84.1	73.9	35.5	-	41.0	46.7	74.1	46.1	61.2
	IN-Sketch	84.1	73.8	34.1	55.0	-	46.4	74.5	49.4	61.4
	ObjNet	84.2	74.1	36.8	51.3	40.0	-	73.6	45.6	62.1
	IN-Cartoon	84.0	73.6	33.9	52.1	40.7	45.4	-	45.6	60.3
	IN-Drawing	84.0	73.6	33.5	54.9	43.9	45.9	73.9	-	61.6
	IN-C	84.5	74.3	35.3	50.6	38.6	46.7	73.9	45.1	-
EWC (Kirkpatrick et al., 2017)	IN-V2	84.4	-	37.9	52.6	40.9	47.8	74.1	45.8	62.4
	IN-A	83.8	**74.4**	-	53.2	40.3	**50.8**	72.0	42.0	63.7
	IN-R	81.4	71.4	30.2	-	52.1	43.3	72.7	57.7	55.3
	IN-Sketch	83.9	73.6	34.2	62.0	-	46.2	76.0	54.4	61.4
	ObjNet	84.0	74.1	42.0	51.9	40.5	-	71.7	42.6	62.5
	IN-Cartoon	84.3	73.7	35.3	54.2	41.5	46.0	-	47.0	59.9
	IN-Drawing	83.4	73.0	33.3	56.1	44.0	45.0	73.3	-	60.9
	IN-C	84.2	74.2	38.8	52.7	41.5	48.5	73.0	50.9	-
LwF (Li & Hoiem, 2017)	IN-V2	83.9	-	44.0	53.5	41.1	47.2	72.9	42.0	62.9
	IN-A	83.3	73.7	-	52.4	40.2	48.4	71.2	42.5	63.5
	IN-R	82.3	72.2	40.9	-	**55.0**	45.1	74.3	57.2	62.0
	IN-Sketch	82.9	72.7	36.7	65.9	-	45.4	75.7	53.7	61.1
	ObjNet	83.5	73.3	44.5	50.4	39.8	-	69.7	38.5	61.8
	IN-Cartoon	89.8	73.1	39.6	53.3	41.7	45.4	-	45.6	61.3
	IN-Drawing	87.0	71.5	32.8	53.7	43.6	44.0	73.4	-	61.2
	IN-C	99.7	70.5	25.6	50.3	37.6	40.6	94.7	71.9	-
LP-FT (Kumar et al., 2022)	IN-V2	83.6	-	44.2	52.4	39.8	47.1	72.0	39.9	62.5
	IN-A	82.5	72.8	-	51.6	39.3	48.7	69.5	40.0	62.6
	IN-R	81.3	71.5	40.6	-	54.3	45.3	73.1	56.2	60.5
	IN-Sketch	82.2	71.9	37.2	66.7	-	45.6	75.0	53.0	60.2
	ObjNet	82.6	72.3	**44.7**	49.8	39.1	-	67.9	36.9	60.6
	IN-Cartoon	89.8	71.4	38.4	52.5	40.5	43.9	-	44.6	58.8
	IN-Drawing	86.5	69.9	30.3	53.1	43.2	41.9	71.4	-	58.7
	IN-C	**99.9**	64.7	19.8	43.5	30.7	33.1	**96.1**	**78.2**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	84.4	-	42.1	53.0	41.4	48.3	73.9	44.7	63.3
	IN-A	84.0	74.3	-	53.1	41.8	50.2	73.0	44.9	64.1
	IN-R	84.0	74.3	43.1	-	53.6	48.2	76.8	59.0	**64.3**
	IN-Sketch	84.0	74.1	37.4	62.9	-	47.3	76.6	54.4	62.7
	ObjNet	84.1	74.2	43.8	51.9	41.8	-	72.3	42.3	62.9
	IN-Cartoon	87.4	74.0	40.1	53.5	42.1	46.9	-	47.8	61.4
	IN-Drawing	86.4	73.5	37.1	54.6	44.5	46.5	75.6	-	63.5
	IN-C	94.1	73.3	36.9	53.4	41.6	46.1	87.3	63.8	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	84.4	-	41.7	53.2	41.5	48.1	74.0	44.9	63.3
	IN-A	83.9	74.3	-	53.2	41.6	50.2	72.5	44.1	64.1
	IN-R	83.9	74.1	42.7	-	54.2	47.9	76.8	59.4	64.1
	IN-Sketch	84.0	74.0	37.3	64.0	-	47.1	76.7	55.0	62.7
	ObjNet	84.1	74.2	44.4	51.9	41.4	-	71.9	42.1	62.9
	IN-Cartoon	87.2	74.0	39.5	53.8	42.1	46.6	-	47.6	61.4
	IN-Drawing	86.2	73.5	37.0	55.0	44.6	46.6	75.4	-	63.4
	IN-C	93.8	73.9	36.3	53.8	42.1	46.2	86.4	63.4	-

Table 23: The accuracy on each OOD dataset after fine-tuning LAION-2B pre-trained ViT-B/16 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre}	Realistic OOD					Synthetic OOD		
		IN	IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		85.5	**75.6**	41.5	68.8	55.4	51.1	78.2	58.4	**63.0**
FT	IN-V2	59.0	-	8.1	25.6	12.2	21.1	36.6	12.2	24.5
	IN-A	28.7	20.4	-	11.9	4.5	10.3	14.9	4.0	8.5
	IN-R	47.1	36.4	7.2	-	29.5	19.4	33.7	17.0	21.4
	IN-Sketch	29.1	20.3	2.6	37.8	-	9.2	20.4	8.0	9.7
	ObjNet	39.4	30.5	4.8	16.4	6.7	-	20.2	4.7	13.5
	IN-Cartoon	90.2	52.8	9.9	36.4	22.0	27.6	-	29.1	32.6
	IN-Drawing	62.0	37.0	5.0	29.7	19.1	15.4	48.6	-	22.5
	IN-C	99.9	54.4	8.2	40.8	27.0	24.3	98.6	85.1	-
Linear Probing	IN-V2	84.9	-	42.0	68.7	54.0	50.2	77.4	57.5	62.3
	IN-A	84.5	74.9	-	68.9	53.6	**53.2**	76.3	54.2	62.7
	IN-R	82.8	72.6	37.4	-	57.6	47.9	75.7	60.5	61.2
	IN-Sketch	82.5	72.8	37.9	**74.8**	-	49.1	76.0	59.6	60.7
	ObjNet	84.2	74.5	**44.3**	66.9	52.5	-	74.6	53.7	61.2
	IN-Cartoon	85.7	72.6	36.7	69.8	52.9	47.5	-	57.8	59.7
	IN-Drawing	83.8	71.1	27.7	67.0	51.7	43.9	76.0	-	57.7
	IN-C	97.6	67.8	25.9	61.4	47.5	40.2	93.2	78.8	-
Visual Prompt (Bahng et al., 2022)	IN-V2	82.8	-	32.3	64.4	51.4	49.5	72.3	47.0	54.4
	IN-A	80.9	70.9	-	64.1	49.0	53.0	69.5	36.8	50.7
	IN-R	78.7	68.0	30.1	-	54.7	45.9	68.5	49.5	49.4
	IN-Sketch	81.4	70.6	28.6	69.5	-	48.9	71.6	49.8	50.9
	ObjNet	77.9	66.8	30.1	55.2	41.1	-	61.5	26.8	42.4
	IN-Cartoon	82.4	71.0	30.9	64.0	49.3	47.8	-	43.7	48.7
	IN-Drawing	81.6	70.8	26.6	63.3	49.3	47.4	69.9	-	50.2
	IN-C	83.8	73.3	34.1	66.6	52.2	49.2	74.5	58.9	-
LoRA (Hu et al., 2021)	IN-V2	85.0	-	40.8	68.6	53.9	50.6	77.3	57.8	62.0
	IN-A	84.5	75.0	-	68.6	53.6	52.8	76.2	53.1	62.2
	IN-R	82.7	72.2	36.9	-	58.2	47.6	75.8	60.2	61.2
	IN-Sketch	82.9	72.5	35.2	74.6	-	48.4	76.3	60.2	60.9
	ObjNet	84.1	74.0	42.5	67.3	52.2	-	72.8	51.6	59.7
	IN-Cartoon	83.7	72.6	35.9	69.5	53.3	47.0	-	57.3	58.4
	IN-Drawing	81.7	70.9	28.2	67.1	52.1	44.8	74.4	-	55.8
	IN-C	78.9	67.8	20.3	61.4	47.3	38.7	68.8	38.3	-
EWC (Kirkpatrick et al., 2017)	IN-V2	80.2	-	26.4	49.4	31.9	41.2	65.2	38.0	51.4
	IN-A	69.6	60.3	-	34.8	19.7	38.1	47.6	19.7	39.9
	IN-R	81.5	71.2	38.3	-	**58.4**	47.8	73.6	58.3	58.7
	IN-Sketch	70.5	57.0	18.4	60.6	-	28.0	64.0	45.8	41.7
	ObjNet	78.1	67.0	28.5	45.5	30.7	-	59.6	28.5	48.0
	IN-Cartoon	84.0	71.4	34.1	64.5	47.2	46.9	-	52.3	52.6
	IN-Drawing	80.9	67.7	24.8	62.8	46.8	39.5	72.1	-	50.4
	IN-C	85.5	74.3	34.3	66.8	51.1	48.2	77.6	64.5	-
LwF (Li & Hoiem, 2017)	IN-V2	63.5	-	8.7	28.0	14.7	22.7	41.0	12.2	28.0
	IN-A	40.1	30.0	-	15.1	5.7	14.5	20.6	6.1	13.6
	IN-R	56.9	46.1	7.8	-	33.5	23.1	41.6	22.2	26.9
	IN-Sketch	33.3	24.7	2.6	39.0	-	11.0	22.5	8.9	11.5
	ObjNet	50.6	39.2	6.3	19.8	9.1	-	28.4	6.3	19.2
	IN-Cartoon	93.8	60.8	12.3	43.9	28.6	32.2	-	37.7	42.0
	IN-Drawing	70.8	42.2	5.6	37.8	26.9	17.1	58.5	-	28.8
	IN-C	99.9	60.4	8.9	47.8	32.8	29.1	98.2	82.6	-
LP-FT (Kumar et al., 2022)	IN-V2	59.5	-	8.0	26.4	12.7	21.2	37.6	11.3	24.3
	IN-A	34.5	27.2	-	13.6	5.2	13.6	17.6	4.7	11.4
	IN-R	49.1	38.6	7.1	-	30.2	20.3	34.5	18.5	22.5
	IN-Sketch	30.2	22.9	2.3	38.7	-	10.6	21.1	8.0	10.5
	ObjNet	44.2	33.6	5.7	17.5	7.0	-	23.4	4.8	15.4
	IN-Cartoon	90.9	53.5	10.7	37.6	23.0	27.7	-	31.2	32.3
	IN-Drawing	67.8	39.0	5.2	34.2	22.5	16.2	55.9	-	24.4
	IN-C	**99.9**	51.1	6.8	38.2	23.5	20.9	**98.9**	**87.4**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	76.3	-	17.9	38.9	22.2	34.7	58.1	23.5	43.7
	IN-A	59.8	48.0	-	24.2	10.8	22.8	34.4	10.0	26.7
	IN-R	74.1	62.1	18.2	-	41.1	36.2	60.9	38.1	43.3
	IN-Sketch	58.6	47.0	7.2	48.0	-	21.4	43.7	20.6	25.4
	ObjNet	74.7	62.2	18.3	40.0	23.3	-	55.4	21.4	42.3
	IN-Cartoon	88.5	69.5	26.3	54.7	39.0	42.6	-	49.8	53.0
	IN-Drawing	81.1	61.7	15.6	53.6	41.0	30.8	70.5	-	45.9
	IN-C	94.2	67.1	19.2	58.2	42.2	39.3	90.0	74.6	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	78.1	-	20.5	44.2	27.8	37.3	61.3	31.2	46.2
	IN-A	68.5	56.6	-	31.3	16.0	30.6	45.7	15.9	35.0
	IN-R	77.0	65.3	22.5	-	46.9	39.7	65.4	45.6	47.8
	IN-Sketch	60.8	49.0	8.0	50.9	-	23.4	46.6	23.5	27.5
	ObjNet	77.0	65.2	21.6	43.0	27.1	-	58.5	25.4	45.0
	IN-Cartoon	88.7	71.1	27.9	58.4	43.2	43.9	-	54.5	54.5
	IN-Drawing	81.3	62.3	16.2	57.3	44.9	31.4	72.2	-	47.0
	IN-C	94.3	69.5	22.2	62.1	47.2	40.6	90.8	77.5	-

Table 24: The accuracy on each OOD dataset after fine-tuning OpenAI CLIP ViT-B/16 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		85.3	**75.7**	47.3	65.9	50.9	50.7	76.3	55.7	**62.6**
FT	IN-V2	60.8	-	9.7	24.2	10.1	22.0	36.4	13.0	25.7
	IN-A	29.8	23.3	-	10.5	4.1	11.4	14.3	4.1	8.9
	IN-R	47.9	37.9	7.9	-	29.4	19.3	34.4	20.1	22.2
	IN-Sketch	24.4	18.0	1.9	34.6	-	8.2	17.3	7.5	7.2
	ObjNet	36.0	26.7	4.9	12.5	5.4	-	18.3	3.7	10.6
	IN-Cartoon	92.3	52.7	10.5	34.0	18.1	24.5	-	33.9	32.8
	IN-Drawing	67.3	36.1	5.0	29.5	17.7	14.2	53.0	-	23.0
	IN-C	**99.9**	51.0	7.0	35.4	19.0	20.8	98.2	84.0	-
HeadOnly	IN-V2	84.7	-	48.0	65.6	50.3	50.9	75.3	53.9	61.6
	IN-A	84.1	74.5	-	66.5	49.1	**53.6**	74.1	51.9	62.3
	IN-R	82.3	72.9	42.0	-	54.7	48.5	73.8	58.5	59.9
	IN-Sketch	82.0	72.6	41.5	72.4	-	48.8	74.3	57.6	58.0
	ObjNet	83.9	74.5	**52.0**	65.5	49.0	-	73.7	51.2	60.1
	IN-Cartoon	85.0	73.1	40.7	65.6	48.9	46.5	-	53.9	56.3
	IN-Drawing	83.1	71.4	32.2	64.6	47.9	43.9	75.3	-	54.7
	IN-C	97.0	68.7	32.3	59.1	44.4	40.3	90.6	74.2	-
Visual Prompt (Bahng et al., 2022)	IN-V2	82.4	-	38.2	60.5	46.4	48.3	68.2	42.5	53.6
	IN-A	80.4	70.5	-	62.1	45.1	51.9	66.2	35.1	50.5
	IN-R	79.3	68.8	38.2	-	51.2	46.5	66.9	46.6	47.9
	IN-Sketch	81.2	70.5	35.6	67.3	-	47.9	69.0	48.9	50.8
	ObjNet	77.6	67.0	37.7	53.0	38.9	-	57.8	25.2	41.1
	IN-Cartoon	81.8	70.1	35.7	60.7	44.4	45.5	-	40.2	46.2
	IN-Drawing	80.5	69.5	27.2	60.6	45.9	43.2	66.9	-	46.8
	IN-C	83.1	73.1	41.5	64.4	49.3	49.5	71.2	54.6	-
LoRA (Hu et al., 2021)	IN-V2	84.7	-	47.4	65.7	50.3	51.4	75.3	53.7	61.5
	IN-A	84.0	74.6	-	66.4	48.9	53.5	73.8	51.7	62.0
	IN-R	81.9	71.9	40.9	-	54.4	47.9	73.3	58.1	59.5
	IN-Sketch	82.7	73.1	40.2	**72.7**	-	48.4	74.9	59.1	58.6
	ObjNet	83.3	74.0	49.5	65.6	48.2	-	71.3	48.6	57.9
	IN-Cartoon	83.4	72.8	39.6	65.4	48.7	46.7	-	53.0	54.6
	IN-Drawing	81.4	71.3	31.8	64.0	48.1	43.9	73.1	-	52.5
	IN-C	79.5	69.6	26.9	59.6	42.7	41.5	69.3	33.6	-
EWC (Kirkpatrick et al., 2017)	IN-V2	80.6	-	33.0	48.4	29.3	40.3	64.2	40.7	52.9
	IN-A	73.8	62.9	-	40.9	23.5	39.3	52.2	27.0	45.3
	IN-R	80.5	71.2	43.5	-	**55.4**	46.7	71.5	56.3	58.0
	IN-Sketch	58.5	48.2	17.7	49.3	-	25.4	53.7	33.6	32.8
	ObjNet	77.8	67.1	33.1	43.6	24.8	-	57.0	23.2	46.6
	IN-Cartoon	84.1	71.4	37.4	61.2	42.7	45.0	-	49.5	49.4
	IN-Drawing	80.5	67.7	27.7	59.2	41.7	37.6	70.6	-	49.0
	IN-C	86.7	74.2	41.5	65.1	47.8	47.0	77.3	64.1	-
LwF (Li & Hoiem, 2017)	IN-V2	65.3	-	10.2	28.0	12.6	24.4	42.3	14.3	28.8
	IN-A	42.3	33.6	-	14.8	5.1	16.1	21.4	7.0	14.7
	IN-R	57.9	46.6	8.0	-	33.2	22.3	41.9	25.4	27.7
	IN-Sketch	26.8	20.1	2.0	35.8	-	9.2	19.2	9.1	8.8
	ObjNet	52.4	40.1	6.1	18.2	7.6	-	27.4	6.4	18.6
	IN-Cartoon	95.0	60.1	13.1	40.3	23.5	28.6	-	42.5	41.4
	IN-Drawing	75.6	43.7	5.9	36.0	23.5	17.3	61.5	-	30.3
	IN-C	99.5	65.7	12.4	51.0	34.9	33.5	96.1	73.7	-
LP-FT (Kumar et al., 2022)	IN-V2	60.9	-	9.6	24.9	9.7	22.3	36.8	12.4	25.8
	IN-A	33.6	25.8	-	11.7	4.4	13.8	17.3	4.4	10.4
	IN-R	50.2	39.9	8.3	-	29.9	21.4	35.5	20.1	23.3
	IN-Sketch	23.8	17.6	2.2	34.8	-	7.6	17.2	7.8	7.3
	ObjNet	40.3	30.6	5.0	13.9	6.0	-	18.9	4.4	12.7
	IN-Cartoon	91.6	51.8	10.4	33.6	18.2	24.1	-	31.7	30.6
	IN-Drawing	77.5	43.4	5.8	32.4	18.2	17.9	62.2	-	27.7
	IN-C	99.9	53.2	7.2	38.6	22.3	21.7	**98.6**	**87.6**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	79.1	-	26.3	43.1	23.9	38.0	62.9	30.9	47.9
	IN-A	72.2	60.0	-	32.5	15.9	34.1	49.0	20.3	39.1
	IN-R	77.1	65.6	25.8	-	45.0	39.5	65.8	47.2	48.5
	IN-Sketch	55.4	44.4	8.6	47.0	-	21.6	45.1	24.7	25.5
	ObjNet	76.2	64.2	23.2	38.6	21.8	-	57.3	21.8	41.7
	IN-Cartoon	89.1	69.9	28.4	52.6	35.1	40.7	-	52.0	52.4
	IN-Drawing	82.0	61.9	18.0	51.5	37.5	30.5	71.9	-	47.4
	IN-C	94.1	67.4	21.0	54.9	37.6	36.7	90.2	76.0	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	79.7	-	27.8	46.7	28.1	39.2	64.5	34.7	48.7
	IN-A	73.1	61.6	-	36.0	19.0	35.7	52.3	23.1	39.8
	IN-R	78.3	67.4	28.5	-	48.2	41.2	67.6	49.9	50.4
	IN-Sketch	55.1	44.8	9.0	48.2	-	21.9	45.7	26.0	26.3
	ObjNet	77.8	66.1	25.6	42.2	26.3	-	59.5	24.5	44.2
	IN-Cartoon	89.0	71.3	29.7	55.5	38.7	41.2	-	55.1	53.8
	IN-Drawing	82.7	63.3	18.9	54.1	39.9	31.2	72.8	-	48.6
	IN-C	93.2	70.9	26.2	59.4	42.6	40.3	89.1	74.9	-

Table 25: The accuracy on each OOD dataset after fine-tuning ImageNet-1K with AugReg pre-trained ViT-B/32 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from images in the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		74.9	61.0	8.0	37.5	27.1	28.0	65.2	40.5	53.5
FT	IN-V2	73.6	-	**12.8**	41.0	28.4	**31.4**	63.1	40.9	53.4
	IN-A	66.5	54.1	-	35.4	24.0	28.0	53.5	31.9	47.5
	IN-R	64.7	52.8	11.0	-	43.4	26.5	57.2	47.0	47.0
	IN-Sketch	70.8	57.9	8.9	55.8	-	28.2	63.1	47.2	51.1
	ObjNet	68.5	55.9	12.7	33.7	23.3	-	52.4	29.1	47.8
	IN-Cartoon	82.7	58.0	11.2	39.8	28.3	28.6	-	41.8	50.1
	IN-Drawing	77.1	56.9	9.0	40.8	29.1	26.5	63.2	-	52.8
	IN-C	99.6	54.8	8.1	35.3	23.5	24.1	93.5	72.7	-
Linear Probing	IN-V2	74.8	-	8.3	37.8	27.1	28.1	65.1	40.5	53.5
	IN-A	73.8	60.3	-	38.0	26.7	29.6	64.1	40.2	53.2
	IN-R	74.0	60.4	8.9	-	29.7	29.1	65.6	43.4	52.8
	IN-Sketch	72.3	58.9	8.5	47.6	-	28.8	64.8	43.4	51.0
	ObjNet	74.3	60.4	9.9	38.7	27.4	-	64.8	41.3	53.3
	IN-Cartoon	77.7	60.5	8.2	39.6	27.2	28.6	-	44.5	54.2
	IN-Drawing	75.7	59.8	8.5	41.7	28.3	28.3	67.1	-	54.4
	IN-C	97.9	54.3	7.9	35.2	23.2	21.5	88.5	63.6	-
Visual Prompt (Bahng et al., 2022)	IN-V2	69.8	-	7.0	38.4	25.1	28.8	58.3	38.1	45.5
	IN-A	58.2	46.7	-	32.9	18.2	24.5	44.4	23.4	29.9
	IN-R	62.1	50.5	6.5	-	33.7	25.2	52.9	42.1	39.4
	IN-Sketch	66.1	53.4	5.8	48.8	-	26.5	57.1	45.0	43.1
	ObjNet	60.5	49.0	7.1	29.8	17.6	-	44.0	23.7	33.1
	IN-Cartoon	70.6	56.7	6.5	40.1	26.3	27.0	-	39.6	42.4
	IN-Drawing	66.2	53.2	4.8	39.5	26.0	23.9	55.6	-	42.3
	IN-C	72.1	58.8	8.0	37.6	25.8	29.1	61.1	46.3	-
LoRA (Hu et al., 2021)	IN-V2	75.0	-	8.1	37.9	27.3	28.5	65.4	40.9	53.9
	IN-A	74.8	61.0	-	38.7	27.1	30.0	64.5	40.6	53.4
	IN-R	73.8	60.1	8.7	-	28.6	29.1	65.9	43.5	50.6
	IN-Sketch	73.9	60.1	8.1	42.2	-	28.9	66.3	43.7	51.6
	ObjNet	74.8	61.2	9.9	39.2	27.5	-	65.1	41.6	53.4
	IN-Cartoon	74.7	60.8	7.9	39.6	27.7	29.0	-	43.1	52.6
	IN-Drawing	73.6	60.6	8.5	41.7	28.0	28.5	64.4	-	52.1
	IN-C	75.6	61.9	9.9	41.1	28.7	31.2	66.0	50.6	-
EWC (Kirkpatrick et al., 2017)	IN-V2	75.4	-	9.8	40.2	28.1	30.8	65.7	43.0	55.3
	IN-A	69.7	56.9	-	38.8	25.9	28.8	58.1	34.4	49.9
	IN-R	71.2	58.4	10.9	-	39.7	29.4	63.9	51.2	52.5
	IN-Sketch	73.7	60.2	8.7	48.8	-	28.5	65.2	46.6	53.8
	ObjNet	74.1	61.0	11.2	38.1	26.9	-	62.4	39.7	54.0
	IN-Cartoon	75.0	60.9	8.6	41.2	28.5	28.8	-	43.2	52.8
	IN-Drawing	74.3	60.6	9.0	43.9	31.0	29.5	65.5	-	55.1
	IN-C	75.5	**62.0**	9.7	40.5	28.4	31.3	65.4	48.3	-
LwF (Li & Hoiem, 2017)	IN-V2	74.3	-	11.9	40.6	28.2	30.7	64.1	41.0	54.0
	IN-A	71.1	58.5	-	37.2	25.5	29.8	59.3	36.8	52.0
	IN-R	71.2	58.5	11.2	-	**44.7**	28.8	63.4	51.1	53.0
	IN-Sketch	72.3	59.1	8.7	55.3	-	28.6	64.7	47.2	52.5
	ObjNet	73.1	59.5	12.2	36.5	25.2	-	59.8	34.6	52.1
	IN-Cartoon	84.6	59.9	10.7	39.9	28.3	29.2	-	43.0	54.1
	IN-Drawing	79.3	58.9	9.3	41.3	29.6	27.5	66.6	-	55.2
	IN-C	99.0	59.2	7.6	38.7	26.7	26.4	92.3	64.7	-
LP-FT (Kumar et al., 2022)	IN-V2	73.8	-	12.7	40.7	28.1	31.1	63.7	40.6	53.7
	IN-A	71.7	58.9	-	36.8	25.9	30.1	60.5	36.7	52.2
	IN-R	70.4	57.9	11.6	-	43.6	29.8	62.4	50.1	51.4
	IN-Sketch	71.1	58.2	9.0	**56.3**	-	28.5	63.8	47.3	51.1
	ObjNet	72.3	58.9	12.7	36.8	25.7	-	59.4	34.9	51.3
	IN-Cartoon	84.7	58.7	11.0	40.3	28.2	28.5	-	43.7	52.6
	IN-Drawing	78.1	57.1	8.6	41.9	30.1	26.1	64.8	-	53.6
	IN-C	**99.9**	51.8	7.2	35.1	22.7	20.0	**96.7**	**78.4**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	75.1	-	10.9	39.7	28.1	30.5	65.2	41.6	54.7
	IN-A	74.0	60.9	-	38.6	27.3	31.2	63.3	38.7	54.3
	IN-R	74.2	61.2	10.9	-	41.0	30.9	66.7	52.0	55.4
	IN-Sketch	74.3	61.0	9.0	49.7	-	29.6	66.5	46.9	54.4
	ObjNet	74.7	61.4	11.6	38.3	27.2	-	63.3	38.8	54.3
	IN-Cartoon	80.3	61.1	10.4	40.0	28.5	29.8	-	42.9	54.2
	IN-Drawing	78.4	61.0	9.7	41.3	30.3	29.5	67.2	-	56.9
	IN-C	92.0	60.8	10.2	39.7	28.1	29.4	83.0	58.8	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	75.2	-	10.8	40.0	28.2	30.6	65.3	42.0	54.9
	IN-A	73.1	60.0	-	38.4	26.8	31.1	62.0	37.2	53.6
	IN-R	74.1	61.1	11.2	-	41.8	30.7	66.6	52.5	55.3
	IN-Sketch	74.4	60.9	8.9	51.0	-	29.5	66.4	47.2	54.4
	ObjNet	74.6	61.4	11.9	38.0	27.0	-	62.9	38.5	54.3
	IN-Cartoon	80.2	61.2	10.1	40.6	28.8	29.8	-	43.4	54.3
	IN-Drawing	78.2	61.0	9.6	42.2	30.9	29.5	67.3	-	**56.9**
	IN-C	91.0	61.6	9.9	40.4	28.6	29.7	81.6	58.0	-

Table 26: The accuracy on each OOD dataset after fine-tuning ImageNet-21K pre-trained ViT-B/32 with AugReg on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		80.7	69.0	22.4	49.3	37.1	40.7	70.6	42.5	60.5
FT	IN-V2	78.8	-	**31.5**	50.5	36.1	42.9	67.0	39.5	60.2
	IN-A	75.0	64.1	-	47.6	34.4	42.5	60.8	36.1	56.9
	IN-R	72.2	62.0	25.0	-	**51.3**	38.3	63.7	52.8	55.3
	IN-Sketch	76.0	65.2	23.6	**65.3**	-	40.1	68.1	54.4	57.0
	ObjNet	74.9	63.5	29.1	44.3	32.1	-	57.4	35.5	55.3
	IN-Cartoon	88.0	65.3	25.1	50.4	36.5	39.5	-	47.4	56.7
	IN-Drawing	84.3	64.1	21.7	51.5	39.3	38.2	71.1	-	59.5
	IN-C	99.8	62.2	18.7	45.5	32.0	34.1	94.3	75.5	-
Linear Probing	IN-V2	80.3	-	23.7	49.5	36.7	40.3	70.1	41.9	60.1
	IN-A	79.3	67.7	-	49.1	36.4	40.9	69.2	41.5	59.4
	IN-R	79.7	68.6	23.9	-	39.4	39.9	69.4	42.7	59.7
	IN-Sketch	77.9	66.6	23.8	57.0	-	40.6	68.3	45.1	58.4
	ObjNet	79.7	68.3	24.4	49.5	36.9	-	69.5	42.3	60.3
	IN-Cartoon	85.6	67.8	22.0	50.1	36.7	40.2	-	46.8	62.6
	IN-Drawing	82.6	68.1	23.3	51.1	38.4	40.4	73.5	-	63.0
	IN-C	98.3	59.2	20.1	43.4	30.7	31.7	89.5	62.0	-
Visual Prompt (Bahng et al., 2022)	IN-V2	76.1	-	18.9	46.6	33.2	40.5	62.6	35.7	51.1
	IN-A	67.6	55.5	-	40.6	25.7	38.7	50.2	27.3	39.7
	IN-R	67.2	56.8	13.9	-	42.5	33.4	56.2	42.5	42.6
	IN-Sketch	72.2	60.3	14.0	57.2	-	37.0	61.3	44.2	46.2
	ObjNet	62.6	51.1	13.1	32.0	20.7	-	40.8	18.0	30.9
	IN-Cartoon	75.4	62.8	15.4	46.7	32.4	37.9	-	37.5	45.5
	IN-Drawing	73.1	61.0	12.6	48.3	34.6	34.1	61.3	-	46.7
	IN-C	77.3	65.2	20.7	45.9	31.8	41.1	64.3	45.6	-
LoRA (Hu et al., 2021)	IN-V2	80.7	-	22.5	49.2	37.1	40.7	70.6	42.5	60.5
	IN-A	80.7	69.4	-	49.9	37.2	42.4	70.3	43.0	61.2
	IN-R	80.7	69.3	24.9	-	37.6	42.3	70.6	43.9	60.9
	IN-Sketch	80.6	69.1	22.9	52.7	-	41.2	70.9	46.0	60.8
	ObjNet	80.7	69.3	25.4	50.1	37.1	-	70.0	43.2	61.3
	IN-Cartoon	80.7	69.1	22.3	49.8	37.0	40.8	-	42.9	60.2
	IN-Drawing	80.3	69.3	23.8	53.2	40.4	41.5	70.7	-	61.0
	IN-C	80.0	68.8	24.7	51.5	37.9	41.5	68.3	53.1	-
EWC (Kirkpatrick et al., 2017)	IN-V2	81.0	-	28.0	51.2	37.6	44.0	70.2	43.4	62.1
	IN-A	78.8	67.7	-	50.7	36.4	**45.2**	66.2	37.8	60.9
	IN-R	78.7	67.6	26.5	-	49.2	40.8	69.9	56.8	60.0
	IN-Sketch	80.2	68.8	24.1	60.8	-	41.7	71.9	54.0	61.1
	ObjNet	77.9	67.3	30.7	48.0	36.2	-	62.2	39.9	60.1
	IN-Cartoon	80.4	68.1	23.5	52.1	37.9	41.1	-	46.6	59.0
	IN-Drawing	80.3	68.8	23.1	53.5	41.6	41.5	71.9	-	61.2
	IN-C	81.0	**69.5**	26.6	51.0	38.3	43.4	69.6	49.1	-
LwF (Li & Hoiem, 2017)	IN-V2	80.1	-	28.0	50.6	36.9	42.3	69.4	41.4	61.1
	IN-A	79.3	68.2	-	49.7	36.2	42.5	67.7	41.4	60.6
	IN-R	79.2	67.8	25.9	-	50.3	39.8	70.9	54.6	60.9
	IN-Sketch	78.1	67.1	23.4	63.2	-	40.6	70.1	51.1	59.1
	ObjNet	78.5	67.2	30.8	47.5	34.7	-	64.8	38.4	59.1
	IN-Cartoon	89.8	68.3	25.2	51.1	37.3	40.9	-	47.3	63.0
	IN-Drawing	86.3	67.0	22.7	51.9	39.9	39.4	73.8	-	63.1
	IN-C	99.4	66.5	20.0	49.4	35.9	38.2	93.1	63.7	-
LP-FT (Kumar et al., 2022)	IN-V2	79.4	-	30.3	50.9	36.7	42.6	68.3	41.2	60.7
	IN-A	77.8	67.0	-	48.7	36.0	43.3	65.8	40.0	59.5
	IN-R	77.3	66.5	26.4	-	50.5	40.4	68.0	54.7	59.0
	IN-Sketch	76.3	65.3	23.2	64.2	-	40.4	68.3	50.5	57.5
	ObjNet	78.0	67.2	30.2	48.3	34.8	-	65.4	39.9	58.9
	IN-Cartoon	90.5	66.5	26.0	51.2	37.1	40.2	-	49.6	61.3
	IN-Drawing	86.3	65.4	22.9	51.9	39.8	38.8	73.8	-	62.6
	IN-C	**99.9**	57.5	15.0	43.1	29.8	29.7	**96.7**	**80.4**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	80.7	-	28.7	51.0	37.8	43.3	70.1	42.6	61.7
	IN-A	80.1	69.0	-	50.9	37.7	45.1	69.0	42.5	61.9
	IN-R	80.0	69.1	28.7	-	49.8	43.4	71.9	56.8	62.4
	IN-Sketch	79.9	69.0	24.5	61.4	-	42.1	71.9	53.1	61.0
	ObjNet	80.1	69.0	29.8	49.8	37.3	-	68.2	43.1	61.2
	IN-Cartoon	86.0	69.0	25.9	51.5	38.2	41.7	-	48.2	60.9
	IN-Drawing	84.4	68.8	25.1	52.6	41.3	41.7	73.6	-	**63.6**
	IN-C	95.3	68.6	24.9	51.0	37.8	41.3	87.5	62.2	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	80.7	-	28.3	51.1	37.7	43.3	70.1	42.8	61.7
	IN-A	79.9	68.9	-	50.7	37.3	44.8	68.5	41.8	61.6
	IN-R	79.9	69.1	28.6	-	50.4	42.6	71.9	57.3	62.2
	IN-Sketch	79.8	68.9	24.1	62.5	-	41.9	71.9	53.6	61.0
	ObjNet	79.7	68.6	30.7	49.2	36.9	-	67.2	42.1	60.9
	IN-Cartoon	85.7	68.8	25.4	51.9	38.2	41.5	-	48.1	61.1
	IN-Drawing	84.3	68.5	24.7	52.9	41.5	41.4	73.7	-	63.3
	IN-C	94.1	69.0	24.9	51.5	38.3	41.5	85.7	60.0	-

Table 27: The accuracy on each OOD datasets after fine-tuning LAION-2B pre-trained ViT-B/32 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		82.6	**71.6**	22.8	59.2	49.1	43.5	73.0	42.3	57.5
FT	IN-V2	50.6	-	5.1	24.7	11.4	16.9	34.5	15.1	21.7
	IN-A	21.2	18.6	-	10.2	4.1	10.1	12.8	4.1	7.0
	IN-R	42.0	32.5	4.5	-	31.9	16.7	31.6	19.4	20.9
	IN-Sketch	24.7	20.2	1.6	37.5	-	8.8	19.3	10.3	9.7
	ObjNet	31.9	23.7	3.6	15.0	6.9	-	18.6	6.2	12.2
	IN-Cartoon	85.0	42.6	5.8	30.6	17.1	18.6	-	32.0	27.3
	IN-Drawing	52.2	29.3	3.0	25.6	15.3	10.6	41.8	-	21.6
	IN-C	99.8	44.1	4.7	31.7	18.4	16.8	97.3	81.2	-
Linear Probing	IN-V2	82.4	-	24.2	58.7	46.8	44.3	72.1	42.5	58.1
	IN-A	81.2	70.6	-	59.0	45.7	**46.5**	70.6	35.2	**58.2**
	IN-R	79.3	68.0	21.2	-	52.6	40.8	71.1	51.1	56.1
	IN-Sketch	79.5	68.0	21.2	**66.8**	-	42.0	70.8	49.1	55.6
	ObjNet	81.0	69.7	**26.7**	56.9	43.7	-	67.8	38.8	56.6
	IN-Cartoon	81.3	68.2	19.5	59.7	45.7	39.7	-	45.6	51.2
	IN-Drawing	78.0	64.5	13.4	58.0	44.4	35.5	68.7	-	49.8
	IN-C	96.0	64.2	15.7	53.3	41.0	33.9	88.4	68.5	-
Visual Prompt (Bahng et al., 2022)	IN-V2	78.7	-	16.4	54.2	44.3	41.5	65.1	33.2	47.9
	IN-A	73.9	62.1	-	52.1	36.7	42.2	57.7	23.7	36.9
	IN-R	74.3	62.5	15.0	-	48.7	38.4	62.1	41.0	43.9
	IN-Sketch	76.2	63.9	13.5	60.7	-	39.0	64.5	41.3	45.1
	ObjNet	68.3	55.9	14.6	34.1	28.6	-	47.4	13.9	27.7
	IN-Cartoon	78.4	65.5	14.6	55.9	43.9	38.9	-	39.2	44.9
	IN-Drawing	77.6	65.3	13.3	56.5	44.8	38.1	64.7	-	47.2
	IN-C	80.0	68.2	18.6	57.9	46.0	41.7	68.8	50.0	-
LoRA (Hu et al., 2021)	IN-V2	82.3	-	23.7	58.6	46.5	44.4	72.2	42.8	58.1
	IN-A	81.0	70.2	-	58.8	45.2	46.1	70.3	33.8	57.9
	IN-R	78.8	67.2	20.3	-	52.2	40.2	71.1	50.9	54.8
	IN-Sketch	78.6	66.8	17.6	64.9	-	39.4	70.1	51.1	53.4
	ObjNet	80.3	68.9	24.0	55.6	42.2	-	65.4	36.4	54.9
	IN-Cartoon	79.9	67.8	19.2	59.4	45.6	39.7	-	45.4	50.3
	IN-Drawing	76.7	64.3	13.6	57.9	44.4	35.9	67.7	-	49.8
	IN-C	83.1	70.4	23.8	58.9	46.7	41.9	73.1	53.9	-
EWC (Kirkpatrick et al., 2017)	IN-V2	76.5	-	16.1	46.3	31.0	35.6	61.4	34.0	48.4
	IN-A	60.0	48.3	-	31.6	18.8	28.5	40.6	18.0	30.7
	IN-R	76.1	65.1	21.5	-	**53.9**	39.1	67.5	51.0	53.0
	IN-Sketch	66.6	54.9	12.8	55.4	-	26.8	60.0	40.1	39.7
	ObjNet	72.9	60.1	18.5	41.8	29.0	-	50.5	26.3	43.0
	IN-Cartoon	81.0	67.1	19.6	57.7	43.7	39.1	-	46.1	48.1
	IN-Drawing	72.6	59.0	12.2	53.4	41.0	28.8	62.0	-	43.6
	IN-C	81.2	68.3	18.6	56.9	43.2	40.3	70.5	55.9	-
LwF (Li & Hoiem, 2017)	IN-V2	56.9	-	5.4	26.5	13.2	19.6	40.2	16.8	26.1
	IN-A	37.9	29.4	-	16.6	7.2	13.2	23.7	8.3	14.5
	IN-R	54.5	42.8	5.2	-	36.0	20.0	41.9	25.5	28.9
	IN-Sketch	33.3	26.0	2.4	40.9	-	11.3	26.4	13.4	13.7
	ObjNet	49.0	37.4	3.8	20.3	10.1	-	30.0	12.3	20.7
	IN-Cartoon	89.8	51.9	6.9	36.2	22.2	23.5	-	39.0	36.6
	IN-Drawing	63.9	37.5	3.7	32.1	20.4	14.9	52.0	-	28.2
	IN-C	99.6	49.5	4.6	35.3	21.0	19.8	96.1	75.1	-
LP-FT (Kumar et al., 2022)	IN-V2	50.4	-	5.7	24.1	11.3	16.2	34.6	14.2	22.0
	IN-A	25.0	19.7	-	11.5	5.2	10.4	15.0	5.1	9.0
	IN-R	44.2	34.3	4.5	-	32.8	17.6	33.5	19.9	22.2
	IN-Sketch	28.5	22.4	2.1	39.3	-	9.9	21.9	11.3	11.5
	ObjNet	35.7	27.3	4.0	16.1	7.7	-	20.6	7.6	14.4
	IN-Cartoon	85.9	43.5	5.4	30.8	17.1	18.3	-	31.1	28.6
	IN-Drawing	57.3	31.6	3.1	27.2	17.0	12.2	46.9	-	22.7
	IN-C	**99.9**	42.0	4.2	29.8	17.1	14.1	**98.2**	**83.4**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	72.8	-	12.8	40.0	25.0	31.1	54.9	31.4	43.5
	IN-A	65.3	53.5	-	32.9	19.7	28.0	44.5	20.8	37.0
	IN-R	72.3	60.4	12.9	-	44.1	33.1	59.5	42.8	46.5
	IN-Sketch	60.9	49.6	7.4	52.0	-	23.4	49.3	30.3	33.3
	ObjNet	70.7	57.0	13.5	37.2	22.7	-	49.7	28.0	41.6
	IN-Cartoon	84.8	63.5	14.4	47.4	32.0	33.4	-	47.6	48.8
	IN-Drawing	75.5	55.3	9.5	45.7	32.6	25.1	63.2	-	44.7
	IN-C	91.7	61.2	10.5	51.0	36.6	30.6	86.4	69.8	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	74.7	-	14.1	43.6	28.6	33.2	57.5	37.0	46.5
	IN-A	68.8	56.3	-	36.5	22.9	31.2	48.6	26.8	40.5
	IN-R	74.5	63.0	14.9	-	47.9	35.1	62.2	47.3	49.8
	IN-Sketch	61.6	50.4	7.8	53.6	-	23.7	51.1	34.0	34.7
	ObjNet	73.8	61.2	14.6	41.1	26.8	-	53.5	33.0	45.1
	IN-Cartoon	85.3	65.5	15.3	50.9	36.3	35.1	-	51.9	50.9
	IN-Drawing	76.0	56.6	9.7	49.1	37.0	26.4	63.9	-	46.2
	IN-C	91.1	62.8	11.1	53.0	38.3	31.6	85.4	69.9	-

Table 28: The accuracy on each OOD dataset after fine-tuning OpenAI CLIP ViT-B/32 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		82.0	**70.9**	22.6	55.8	45.0	41.5	71.1	42.5	57.9
FT	IN-V2	54.8	-	6.5	24.5	10.4	18.4	38.3	16.2	25.9
	IN-A	26.3	21.0	-	11.0	3.9	12.3	14.8	5.1	10.1
	IN-R	44.0	33.9	5.7	-	32.1	16.4	34.0	21.9	23.1
	IN-Sketch	28.0	21.1	2.2	39.9	-	9.1	21.8	12.6	11.1
	ObjNet	33.8	25.0	3.9	15.0	8.6	-	19.6	6.8	13.4
	IN-Cartoon	88.7	47.2	6.7	31.9	17.6	19.3	-	36.8	31.4
	IN-Drawing	60.3	32.9	3.5	28.0	16.7	12.4	49.4	-	24.6
	IN-C	99.8	44.5	4.5	30.2	17.2	16.2	97.1	80.7	-
HeadOnly	IN-V2	81.6	-	23.5	56.1	43.4	42.4	71.1	42.4	**59.0**
	IN-A	80.6	69.9	-	55.9	42.2	**44.5**	69.8	37.8	58.5
	IN-R	77.7	66.3	18.2	-	48.1	37.5	69.8	50.8	55.5
	IN-Sketch	78.0	66.3	19.1	**63.5**	-	39.2	69.7	48.6	55.4
	ObjNet	80.3	69.4	**26.6**	54.6	41.2	-	68.2	36.9	56.7
	IN-Cartoon	80.8	67.5	20.0	57.1	42.4	37.9	-	43.8	53.1
	IN-Drawing	77.4	64.0	14.9	55.6	41.7	34.1	66.8	-	48.6
	IN-C	95.8	62.9	16.4	50.8	38.7	31.7	87.7	67.6	-
Visual Prompt (Bahng et al., 2022)	IN-V2	78.5	-	16.3	52.1	41.2	40.0	64.3	35.1	50.1
	IN-A	72.9	61.3	-	47.3	31.3	40.9	55.7	21.4	39.6
	IN-R	73.9	62.7	15.5	-	44.8	37.3	61.8	41.7	44.2
	IN-Sketch	76.4	64.3	14.5	58.0	-	38.7	64.5	43.0	47.2
	ObjNet	65.9	53.5	14.8	41.9	24.9	-	41.4	14.5	29.5
	IN-Cartoon	77.7	65.3	16.2	53.3	39.7	37.7	-	37.5	45.4
	IN-Drawing	77.0	64.6	12.8	53.1	39.7	36.2	63.2	-	46.1
	IN-C	79.2	67.8	20.6	55.5	41.9	41.0	66.8	46.3	-
LoRA (Hu et al., 2021)	IN-V2	81.5	-	23.2	56.1	43.5	42.3	71.1	42.4	58.9
	IN-A	80.3	69.6	-	55.5	42.1	43.8	69.0	35.9	58.1
	IN-R	77.5	66.0	18.4	-	48.0	37.5	69.5	51.8	55.1
	IN-Sketch	77.8	65.7	18.5	61.9	-	38.4	68.9	51.4	53.5
	ObjNet	79.3	67.8	23.3	54.1	39.9	-	66.8	34.6	53.4
	IN-Cartoon	79.5	67.4	19.6	56.8	42.4	38.1	-	43.7	52.0
	IN-Drawing	76.3	64.6	15.5	55.6	42.1	34.7	66.1	-	48.4
	IN-C	81.1	69.5	21.8	57.7	44.5	38.6	73.4	43.0	-
EWC (Kirkpatrick et al., 2017)	IN-V2	78.2	-	20.3	49.0	33.0	37.2	65.5	38.8	53.9
	IN-A	67.1	55.4	-	38.3	24.5	31.9	49.3	25.7	40.9
	IN-R	75.2	63.8	21.7	-	**51.2**	36.7	66.9	51.2	52.5
	IN-Sketch	64.9	53.1	13.4	52.7	-	24.9	59.3	40.3	38.8
	ObjNet	73.1	61.2	20.9	43.0	29.5	-	52.9	23.3	44.7
	IN-Cartoon	80.8	67.2	20.3	55.4	41.0	37.9	-	44.7	48.1
	IN-Drawing	76.8	63.3	14.9	53.8	40.6	31.6	66.6	-	48.7
	IN-C	82.9	70.0	23.6	56.0	42.4	40.5	72.3	56.6	-
LwF (Li & Hoiem, 2017)	IN-V2	60.5	-	6.8	27.8	13.9	20.0	44.4	20.2	30.2
	IN-A	42.3	33.0	-	16.9	7.1	14.8	26.4	10.1	17.6
	IN-R	55.1	43.5	5.4	-	34.5	19.0	43.3	28.2	30.1
	IN-Sketch	36.1	27.6	2.4	43.3	-	10.8	27.8	16.0	15.3
	ObjNet	52.1	40.1	4.9	20.0	10.7	-	32.3	12.9	23.1
	IN-Cartoon	91.7	53.0	6.8	35.3	21.1	22.0	-	43.0	39.6
	IN-Drawing	67.6	38.8	3.7	32.6	19.5	14.8	56.0	-	29.6
	IN-C	98.7	59.1	5.9	42.7	29.3	25.4	93.3	62.8	-
LP-FT (Kumar et al., 2022)	IN-V2	55.4	-	6.3	26.2	11.7	17.6	39.0	17.8	26.0
	IN-A	30.7	23.6	-	13.0	4.9	12.4	17.9	6.2	11.6
	IN-R	47.6	37.3	5.6	-	33.1	17.9	37.1	25.1	25.7
	IN-Sketch	30.1	23.4	2.6	41.4	-	10.0	23.1	13.9	12.3
	ObjNet	38.6	28.8	4.5	15.1	7.4	-	21.5	8.3	16.3
	IN-Cartoon	89.2	47.1	6.5	32.6	18.8	19.2	-	39.2	31.3
	IN-Drawing	63.1	34.8	4.2	29.0	17.3	12.8	52.8	-	25.7
	IN-C	**99.9**	42.1	4.7	29.1	16.0	14.5	**98.0**	**82.5**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	75.6	-	15.2	42.9	26.9	32.7	60.7	37.0	49.1
	IN-A	69.8	57.5	-	37.0	21.5	31.3	51.7	27.2	43.3
	IN-R	73.4	61.5	14.6	-	45.8	32.7	62.7	47.4	49.5
	IN-Sketch	64.2	52.2	8.2	54.6	-	23.4	52.8	35.8	36.3
	ObjNet	73.5	61.3	15.0	40.9	28.5	-	55.7	30.1	46.7
	IN-Cartoon	85.8	64.7	15.6	48.4	33.0	33.4	-	50.2	50.8
	IN-Drawing	77.3	56.8	10.0	47.0	34.6	23.8	66.8	-	46.9
	IN-C	91.9	61.4	11.1	47.9	32.7	29.6	86.6	69.7	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	76.5	-	15.6	45.7	29.6	33.5	62.1	40.1	50.2
	IN-A	71.2	59.3	-	38.8	24.3	31.9	53.4	29.8	44.3
	IN-R	74.9	63.6	16.2	-	48.4	34.1	64.5	50.6	51.8
	IN-Sketch	64.8	52.8	8.1	55.7	-	23.4	54.0	37.2	37.2
	ObjNet	75.2	63.1	16.5	42.7	30.3	-	57.7	32.8	48.7
	IN-Cartoon	85.8	65.6	15.9	50.1	35.1	33.9	-	53.0	51.7
	IN-Drawing	77.9	58.3	10.3	49.4	36.9	25.0	67.7	-	47.9
	IN-C	90.8	65.2	13.2	51.7	37.1	32.5	85.1	68.1	-

Table 29: The accuracy on each OOD dataset after fine-tuning ImageNet-1K with AugReg pre-trained ViT-S/16 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		78.8	66.7	13.4	37.1	25.9	33.6	63.3	37.2	53.2
FT	IN-V2	75.5	-	19.8	38.1	25.0	35.3	58.2	35.9	51.2
	IN-A	66.5	55.9	-	33.5	22.0	31.0	46.5	26.6	44.1
	IN-R	62.8	52.6	14.5	-	41.2	28.8	53.0	40.4	42.7
	IN-Sketch	70.6	59.2	11.5	56.6	-	31.4	58.9	43.7	45.5
	ObjNet	67.3	55.8	15.7	30.1	18.5	-	43.9	23.0	41.9
	IN-Cartoon	86.8	59.3	15.1	37.0	23.9	31.7	-	38.7	44.4
	IN-Drawing	77.6	55.9	10.2	35.8	24.8	26.7	56.5	-	46.0
	IN-C	99.9	55.0	8.3	31.1	18.3	24.0	91.8	68.8	-
Linear Probing	IN-V2	78.6	-	14.3	37.4	25.8	33.9	63.0	36.8	53.1
	IN-A	77.7	65.5	-	37.1	25.4	35.1	61.4	36.3	53.0
	IN-R	78.2	66.2	15.3	-	29.0	34.3	63.3	38.5	53.0
	IN-Sketch	76.1	64.0	15.0	47.2	-	34.6	62.6	39.5	50.9
	ObjNet	78.1	66.1	16.2	37.0	25.2	-	61.1	36.6	53.4
	IN-Cartoon	80.4	64.9	13.0	38.5	25.8	32.9	-	38.8	52.6
	IN-Drawing	78.6	65.2	13.8	39.7	27.2	33.3	63.6	-	54.3
	IN-C	93.5	58.7	10.9	32.6	21.5	27.5	75.4	50.0	-
Visual Prompt (Bahng et al., 2022)	IN-V2	74.7	-	10.8	36.3	22.3	34.1	54.9	29.2	43.9
	IN-A	65.4	53.7	-	29.7	15.9	33.0	41.7	18.0	32.1
	IN-R	65.4	53.9	8.9	-	33.9	28.7	52.8	37.5	35.0
	IN-Sketch	70.5	58.0	8.3	48.3	-	31.4	55.7	39.0	39.2
	ObjNet	62.6	51.0	8.6	24.2	13.3	-	34.7	11.1	26.8
	IN-Cartoon	73.3	59.6	8.4	37.2	22.0	31.1	-	28.4	36.0
	IN-Drawing	71.0	58.5	5.9	38.3	24.3	28.0	55.8	-	40.7
	IN-C	76.1	63.5	11.9	36.3	23.2	35.0	57.0	40.1	-
LoRA (Hu et al., 2021)	IN-V2	78.9	-	13.8	37.3	26.0	34.0	63.3	37.4	53.5
	IN-A	78.6	66.6	-	37.7	25.6	36.2	61.4	36.9	53.5
	IN-R	78.6	66.5	16.2	-	28.9	36.0	64.2	40.1	52.8
	IN-Sketch	78.7	66.5	14.8	47.7	-	34.9	65.9	46.7	53.5
	ObjNet	78.6	66.5	16.8	37.5	24.8	-	61.0	36.5	53.0
	IN-Cartoon	77.8	65.1	12.5	39.3	26.3	32.8	-	37.4	51.3
	IN-Drawing	78.1	66.2	13.4	42.0	29.4	34.1	63.7	-	54.6
	IN-C	79.2	66.8	13.9	38.1	25.9	34.6	64.5	38.6	-
EWC (Kirkpatrick et al., 2017)	IN-V2	79.1	-	19.8	40.1	26.8	**37.6**	62.7	39.5	55.4
	IN-A	74.3	62.8	-	38.3	25.2	37.2	54.5	32.2	51.4
	IN-R	74.0	62.6	16.4	-	42.3	33.6	64.4	51.6	51.8
	IN-Sketch	77.7	65.7	14.9	54.0	-	35.7	66.9	52.1	54.0
	ObjNet	74.8	63.8	**22.0**	37.1	24.3	-	52.3	32.4	51.7
	IN-Cartoon	77.9	64.7	14.0	41.6	27.7	34.0	-	39.8	49.1
	IN-Drawing	77.4	65.3	12.5	41.7	29.8	33.3	63.8	-	53.2
	IN-C	79.4	**67.0**	17.2	39.4	26.6	37.1	62.2	46.6	-
LwF (Li & Hoiem, 2017)	IN-V2	77.8	-	17.5	38.6	26.0	35.2	61.5	37.5	53.5
	IN-A	76.0	64.5	-	37.7	25.0	33.7	58.5	35.0	51.7
	IN-R	75.1	63.2	16.0	-	42.9	32.3	63.7	48.1	51.8
	IN-Sketch	74.5	62.3	11.6	55.3	-	31.9	62.1	43.5	48.6
	ObjNet	76.1	64.2	17.1	35.2	22.6	-	56.8	31.9	50.4
	IN-Cartoon	89.9	64.3	15.8	38.4	24.8	34.0	-	39.4	52.6
	IN-Drawing	83.1	60.6	11.4	36.9	26.1	29.5	60.8	-	50.8
	IN-C	99.5	63.0	10.4	37.0	23.7	29.9	90.1	60.9	-
LP-FT (Kumar et al., 2022)	IN-V2	76.4	-	20.4	38.6	25.6	36.1	59.3	37.5	52.3
	IN-A	72.5	61.4	-	35.2	23.9	34.2	53.4	32.3	48.6
	IN-R	69.4	57.7	15.2	-	41.0	31.7	57.9	43.6	46.6
	IN-Sketch	72.7	60.9	13.5	**57.3**	-	32.6	61.3	43.3	47.9
	ObjNet	72.5	60.4	17.1	33.6	20.7	-	51.3	26.4	46.6
	IN-Cartoon	88.3	60.9	15.1	37.7	24.3	32.6	-	40.9	47.2
	IN-Drawing	79.7	57.5	10.4	36.7	25.6	27.1	58.5	-	48.2
	IN-C	**99.9**	52.8	7.1	30.5	17.7	21.5	**93.5**	**73.3**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	78.8	-	18.9	39.5	27.2	36.2	63.0	39.4	55.0
	IN-A	77.6	65.8	-	39.2	26.9	37.4	61.2	36.9	54.2
	IN-R	77.3	65.7	18.8	-	43.1	36.6	67.2	52.0	55.3
	IN-Sketch	77.6	66.1	14.3	53.7	-	35.3	65.9	48.8	53.6
	ObjNet	77.8	65.7	19.2	37.7	25.5	-	60.3	35.3	53.5
	IN-Cartoon	85.2	65.7	16.6	39.7	27.2	35.0	-	43.1	52.9
	IN-Drawing	82.5	65.0	14.0	40.2	29.9	33.5	64.7	-	**55.4**
	IN-C	94.2	64.9	13.9	38.7	26.0	33.1	82.7	58.0	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	78.9	-	19.1	39.5	27.2	36.4	62.8	39.4	55.1
	IN-A	77.1	65.4	-	39.2	26.7	37.1	60.1	36.4	53.9
	IN-R	77.2	65.5	19.0	-	**44.4**	36.0	67.5	52.7	55.2
	IN-Sketch	77.6	66.1	14.6	55.6	-	35.4	66.4	49.7	53.6
	ObjNet	77.7	65.9	20.1	37.9	25.5	-	59.5	35.1	53.5
	IN-Cartoon	84.9	65.9	16.2	40.4	27.4	34.9	-	42.7	52.7
	IN-Drawing	82.3	64.8	13.7	40.6	30.1	33.3	64.9	-	55.1
	IN-C	93.0	66.2	14.4	39.8	27.1	34.3	80.8	56.8	-

Table 30: The accuracy on each OOD dataset after fine-tuning ImageNet-21K pre-trained ViT-S/16 with AugReg on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		81.4	70.3	27.0	46.0	32.9	41.3	67.8	37.7	58.0
FT	IN-V2	78.9	-	34.3	46.1	30.5	43.2	63.9	34.4	56.8
	IN-A	73.2	62.8	-	43.7	30.4	41.5	55.4	29.7	52.7
	IN-R	70.5	60.5	26.4	-	48.0	37.0	60.5	46.2	50.6
	IN-Sketch	74.4	63.1	25.2	**63.3**	-	39.1	62.5	47.2	50.7
	ObjNet	73.3	61.6	28.9	38.3	26.3	-	52.7	24.0	48.5
	IN-Cartoon	87.6	64.4	26.5	45.1	31.1	40.0	-	41.2	52.2
	IN-Drawing	83.1	62.2	20.3	45.1	33.1	36.3	64.9	-	52.8
	IN-C	99.8	59.8	15.9	39.4	25.2	32.0	91.7	71.3	-
Linear Probing	IN-V2	80.9	-	28.2	46.1	32.5	41.0	67.1	37.1	57.7
	IN-A	80.0	69.1	-	45.6	32.2	41.6	66.2	36.4	57.2
	IN-R	80.1	69.5	27.9	-	35.5	40.5	66.3	38.2	56.8
	IN-Sketch	77.5	67.0	27.7	54.5	-	40.8	64.6	40.4	55.1
	ObjNet	80.2	69.5	28.9	45.6	32.0	-	66.5	37.1	57.9
	IN-Cartoon	85.1	68.8	26.4	46.5	32.5	40.7	-	41.0	59.3
	IN-Drawing	82.5	68.8	26.9	47.4	34.1	40.0	70.4	-	60.0
	IN-C	95.6	60.4	21.4	39.8	25.9	32.8	81.7	52.3	-
Visual Prompt (Bahng et al., 2022)	IN-V2	77.0	-	22.2	42.7	28.1	41.8	58.4	29.9	47.9
	IN-A	69.3	58.7	-	38.5	22.2	40.2	48.1	21.8	39.6
	IN-R	66.9	56.4	15.7	-	38.4	32.3	53.0	38.8	38.1
	IN-Sketch	73.0	61.3	15.3	55.7	-	38.3	58.3	42.1	42.1
	ObjNet	64.1	52.7	15.1	27.2	16.5	-	35.4	14.4	29.1
	IN-Cartoon	75.2	62.2	17.8	41.6	26.8	37.7	-	29.3	39.7
	IN-Drawing	72.9	60.9	13.2	42.2	27.5	35.7	55.8	-	41.0
	IN-C	78.1	66.6	23.1	42.7	28.1	41.1	60.9	41.0	-
LoRA (Hu et al., 2021)	IN-V2	81.5	-	27.2	45.9	32.8	41.6	67.8	37.7	58.2
	IN-A	81.5	70.7	-	46.2	32.8	43.0	67.8	37.7	58.9
	IN-R	81.4	70.6	29.1	-	34.9	43.3	68.5	40.7	58.2
	IN-Sketch	81.3	70.3	28.1	54.0	-	42.1	68.6	46.0	58.3
	ObjNet	81.5	70.8	29.2	46.3	32.3	-	67.6	38.0	58.8
	IN-Cartoon	81.4	70.2	27.3	47.0	33.1	41.6	-	38.6	57.7
	IN-Drawing	81.4	70.5	27.7	49.7	36.7	42.4	68.5	-	59.0
	IN-C	68.9	56.6	8.0	26.4	15.9	27.3	42.4	9.4	-
EWC (Kirkpatrick et al., 2017)	IN-V2	81.6	-	33.2	48.2	33.3	44.6	67.1	38.4	59.7
	IN-A	78.9	68.3	-	47.2	33.0	45.4	62.7	33.9	58.0
	IN-R	78.1	67.3	30.3	-	47.5	41.1	68.1	53.4	56.4
	IN-Sketch	80.6	69.7	29.1	60.0	-	42.9	69.8	52.4	58.0
	ObjNet	78.8	68.0	**34.5**	44.5	30.9	-	59.2	34.3	56.7
	IN-Cartoon	81.0	68.9	28.4	48.6	32.9	42.0	-	42.6	55.2
	IN-Drawing	80.7	69.0	26.7	50.0	37.1	41.3	68.3	-	58.1
	IN-C	81.8	**71.0**	31.2	47.5	33.2	43.2	67.4	48.6	-
LwF (Li & Hoiem, 2017)	IN-V2	80.7	-	31.4	46.3	31.8	42.6	67.1	36.7	58.3
	IN-A	80.0	69.3	-	46.2	31.6	42.1	64.5	37.0	57.8
	IN-R	79.5	68.3	28.4	-	47.5	39.4	68.4	48.3	57.2
	IN-Sketch	77.8	66.2	25.4	60.9	-	40.9	66.1	43.8	54.5
	ObjNet	79.1	67.3	30.7	42.2	29.6	-	61.7	31.1	55.1
	IN-Cartoon	90.4	68.8	26.9	46.9	33.2	41.7	-	42.2	60.0
	IN-Drawing	86.7	66.5	21.9	46.0	34.7	38.6	68.5	-	57.8
	IN-C	99.8	64.7	17.1	43.4	29.0	36.0	91.6	65.1	-
LP-FT (Kumar et al., 2022)	IN-V2	79.4	-	34.2	46.6	31.3	43.1	65.2	36.3	57.6
	IN-A	77.0	67.0	-	44.3	31.5	42.7	60.3	32.2	56.0
	IN-R	75.4	65.0	27.6	-	47.4	39.5	64.3	49.1	53.5
	IN-Sketch	75.0	63.9	27.5	62.8	-	40.6	64.1	44.9	52.3
	ObjNet	77.4	66.1	31.5	41.4	27.9	-	59.2	28.0	53.4
	IN-Cartoon	89.3	65.3	27.2	45.8	31.8	40.9	-	42.8	56.0
	IN-Drawing	85.3	63.4	21.5	46.7	34.9	37.5	67.9	-	55.5
	IN-C	**99.9**	56.4	12.0	38.3	23.3	27.6	**94.5**	**75.6**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	81.3	-	33.4	47.6	33.4	44.0	67.6	38.1	59.3
	IN-A	80.6	69.8	-	47.7	33.9	**45.4**	66.1	38.0	58.9
	IN-R	79.9	69.8	32.6	-	48.5	43.8	70.4	53.2	59.6
	IN-Sketch	80.0	69.2	29.3	60.7	-	42.6	69.6	49.8	58.0
	ObjNet	80.5	69.3	33.1	45.6	32.5	-	65.7	35.0	57.6
	IN-Cartoon	86.7	69.5	30.2	47.7	34.0	43.1	-	43.9	58.4
	IN-Drawing	85.1	69.0	27.7	49.4	37.8	42.5	70.8	-	**60.4**
	IN-C	93.8	68.7	26.5	47.1	32.5	41.5	83.6	58.7	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	81.4	-	33.3	47.6	33.3	43.8	67.6	38.0	59.3
	IN-A	80.4	69.8	-	47.7	33.6	45.1	65.6	37.6	58.9
	IN-R	80.3	69.9	32.6	-	**49.1**	43.2	70.7	53.8	59.4
	IN-Sketch	80.0	69.2	29.2	61.5	-	42.6	69.7	49.9	57.9
	ObjNet	80.4	69.2	33.8	45.3	32.3	-	64.6	35.3	57.6
	IN-Cartoon	86.4	69.6	29.7	48.2	34.1	42.9	-	43.9	58.6
	IN-Drawing	85.0	69.2	27.0	49.2	37.8	41.9	70.6	-	60.2
	IN-C	94.2	69.3	27.2	48.0	34.0	41.9	84.1	59.7	-

Table 31: The accuracy on each OOD dataset after fine-tuning ImageNet-21K pre-trained ViT-S/32 with AugReg on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		76.0	63.9	11.5	39.7	26.2	33.1	62.9	34.3	52.0
FT	IN-V2	72.2	-	17.3	38.2	23.4	34.0	56.9	31.2	50.1
	IN-A	64.3	53.7	-	33.3	20.9	31.9	46.9	24.7	44.0
	IN-R	62.4	51.6	14.1	-	42.7	29.1	53.2	40.5	43.4
	IN-Sketch	67.2	55.1	12.0	56.9	-	30.4	56.7	41.7	45.5
	ObjNet	64.9	53.4	14.2	31.7	18.3	-	44.7	21.5	41.7
	IN-Cartoon	84.6	56.2	12.8	38.7	24.6	30.3	-	35.6	45.2
	IN-Drawing	75.4	53.0	9.6	38.0	26.1	25.8	55.9	-	46.9
	IN-C	99.7	52.1	8.1	32.9	19.8	24.2	92.9	71.0	-
Linear Probing	IN-V2	75.3	-	12.7	39.4	26.0	32.7	62.3	34.1	51.5
	IN-A	73.5	61.6	-	38.5	25.2	32.3	60.7	32.6	50.4
	IN-R	74.6	62.5	13.0	-	28.8	32.4	62.1	34.5	51.5
	IN-Sketch	71.5	60.1	13.3	49.2	-	33.1	59.6	36.6	49.6
	ObjNet	74.5	62.9	12.7	40.1	26.3	-	61.6	33.1	52.1
	IN-Cartoon	80.6	61.6	11.4	40.8	26.1	32.4	-	38.2	53.5
	IN-Drawing	77.3	61.1	11.3	40.8	27.4	30.3	65.5	-	53.6
	IN-C	93.6	52.2	10.7	33.5	20.6	25.3	79.2	49.0	-
Visual Prompt (Bahng et al., 2022)	IN-V2	69.9	-	9.6	36.9	22.5	33.1	53.6	28.5	42.6
	IN-A	48.5	38.5	-	24.9	8.8	22.0	31.2	12.4	23.2
	IN-R	58.5	48.0	6.7	-	31.1	25.5	46.2	34.4	32.3
	IN-Sketch	64.5	52.5	6.3	48.1	-	28.2	51.0	37.0	35.1
	ObjNet	53.5	42.9	7.2	23.9	12.2	-	31.8	14.1	24.5
	IN-Cartoon	69.0	56.1	7.4	38.0	22.3	30.0	-	30.6	36.0
	IN-Drawing	63.6	51.3	5.5	37.8	22.9	25.3	49.5	-	36.6
	IN-C	71.2	59.4	9.8	36.9	22.5	33.5	55.2	35.6	-
LoRA (Hu et al., 2021)	IN-V2	76.0	-	11.6	39.7	26.2	33.2	62.9	34.3	52.1
	IN-A	76.1	64.0	-	40.3	26.5	34.1	63.0	34.1	53.1
	IN-R	76.1	**64.1**	12.4	-	27.8	34.7	63.8	35.8	52.8
	IN-Sketch	75.7	63.5	12.7	48.1	-	34.1	63.8	41.5	52.9
	ObjNet	76.1	64.0	12.5	40.6	26.6	-	63.1	33.9	53.3
	IN-Cartoon	75.9	63.7	11.7	40.7	26.6	33.7	-	35.0	51.4
	IN-Drawing	75.5	63.5	10.9	43.7	30.2	32.8	63.4	-	52.3
	IN-C	74.1	62.0	9.3	36.9	23.5	30.2	58.4	30.5	-
EWC (Kirkpatrick et al., 2017)	IN-V2	76.0	-	15.8	41.0	26.1	36.0	62.1	35.4	53.6
	IN-A	70.9	59.1	-	38.3	24.0	35.8	54.9	28.1	50.2
	IN-R	71.8	60.4	14.5	-	41.4	32.6	61.9	47.4	50.7
	IN-Sketch	74.9	62.9	13.2	53.4	-	34.6	64.7	45.5	52.6
	ObjNet	72.5	60.9	**17.9**	38.7	24.8	-	55.2	31.6	50.7
	IN-Cartoon	75.0	61.8	11.7	42.4	26.9	33.1	-	37.3	48.8
	IN-Drawing	74.2	61.9	11.6	43.7	29.8	33.0	61.8	-	52.3
	IN-C	76.2	64.0	14.3	41.4	27.0	35.8	62.3	42.6	-
LwF (Li & Hoiem, 2017)	IN-V2	75.0	-	14.9	39.4	25.3	33.6	60.8	32.9	51.8
	IN-A	73.1	61.1	-	38.2	24.4	33.6	57.7	31.5	50.8
	IN-R	72.9	60.7	14.1	-	42.6	31.6	62.4	44.2	50.9
	IN-Sketch	71.2	59.1	11.9	55.3	-	32.6	60.0	40.5	48.9
	ObjNet	71.1	59.7	15.5	36.2	21.6	-	54.3	27.2	48.2
	IN-Cartoon	88.0	61.5	12.6	40.3	26.4	32.1	-	37.8	53.7
	IN-Drawing	81.4	58.2	10.6	39.1	27.4	28.8	62.2	-	52.1
	IN-C	98.7	60.0	8.9	38.2	24.1	29.1	89.2	55.7	-
LP-FT (Kumar et al., 2022)	IN-V2	73.2	-	17.4	39.0	24.5	33.9	58.4	32.1	50.7
	IN-A	69.2	58.2	-	35.0	22.9	33.4	53.9	28.6	48.2
	IN-R	68.5	56.8	14.2	-	42.5	32.3	58.0	43.2	47.5
	IN-Sketch	67.8	56.5	13.0	**57.3**	-	32.0	57.6	39.9	46.9
	ObjNet	70.2	58.2	14.8	35.8	21.4	-	53.1	24.6	47.0
	IN-Cartoon	87.3	57.7	13.2	39.2	25.2	31.2	-	37.8	50.1
	IN-Drawing	79.1	55.2	10.7	38.5	26.9	26.3	60.0	-	50.3
	IN-C	**99.8**	48.0	6.9	30.8	18.0	20.7	**94.6**	**73.5**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	75.7	-	15.7	40.3	26.3	35.3	62.0	35.0	53.1
	IN-A	74.5	62.9	-	40.0	26.1	**36.6**	60.2	34.2	52.8
	IN-R	74.0	62.8	16.2	-	42.2	35.3	64.7	47.5	53.3
	IN-Sketch	74.2	62.2	13.1	54.4	-	34.1	63.9	44.2	52.1
	ObjNet	74.5	62.6	15.9	39.1	25.4	-	59.5	32.2	51.8
	IN-Cartoon	83.0	62.6	13.6	41.0	27.1	33.7	-	39.0	51.8
	IN-Drawing	79.8	61.8	12.2	42.4	30.0	32.4	64.5	-	**54.3**
	IN-C	93.0	61.8	12.8	40.4	26.7	32.4	83.5	56.9	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	75.7	-	15.6	40.4	26.3	35.3	61.9	35.0	53.1
	IN-A	74.2	62.4	-	39.6	25.7	36.3	59.2	33.0	52.5
	IN-R	74.3	62.8	16.0	-	**43.4**	34.8	64.9	48.0	53.2
	IN-Sketch	74.2	62.3	13.0	55.5	-	34.4	64.0	44.6	52.2
	ObjNet	74.1	62.6	17.2	39.1	25.3	-	58.4	32.0	51.7
	IN-Cartoon	82.5	62.6	13.1	41.6	27.3	33.4	-	39.0	52.0
	IN-Drawing	79.6	61.7	12.3	42.5	30.1	32.1	64.4	-	54.2
	IN-C	91.5	63.1	13.2	41.2	27.3	33.3	81.0	54.5	-

Table 32: The accuracy on each OOD dataset after fine-tuning ImageNet-21K pre-trained ViT-L/16 with AugReg on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		85.8	76.2	55.5	64.4	51.8	52.8	79.5	64.6	72.2
FT	IN-V2	83.8	-	59.7	66.2	51.0	54.1	77.0	63.9	71.0
	IN-A	81.9	24.4	-	66.1	51.0	52.3	75.1	61.4	70.4
	IN-R	79.4	69.8	48.8	-	58.8	48.9	72.6	63.8	65.4
	IN-Sketch	81.6	72.8	52.0	**76.3**	-	52.5	75.6	64.7	67.6
	ObjNet	82.3	73.2	58.2	62.0	50.4	-	74.5	56.2	68.4
	IN-Cartoon	96.1	72.7	52.1	63.2	50.8	50.5	-	70.4	72.6
	IN-Drawing	93.8	72.2	46.4	65.4	52.5	49.9	85.1	-	74.7
	IN-C	99.9	70.1	37.9	58.7	45.8	44.0	98.8	**89.9**	-
Linear Probing	IN-V2	85.0	-	57.1	64.1	51.2	51.9	78.4	63.5	71.4
	IN-A	84.9	49.8	-	64.8	51.3	53.4	78.5	63.5	71.4
	IN-R	83.9	43.5	56.3	-	50.7	51.1	76.5	61.7	69.8
	IN-Sketch	82.1	72.9	55.3	70.0	-	53.2	75.6	61.3	68.4
	ObjNet	84.8	75.0	58.2	63.3	50.9	-	78.3	63.6	71.5
	IN-Cartoon	92.6	74.8	56.0	63.8	50.6	52.7	-	68.5	76.5
	IN-Drawing	89.1	75.1	55.0	64.3	51.2	51.7	84.1	-	76.0
	IN-C	99.6	69.6	49.3	59.2	45.6	45.6	96.7	84.1	-
Visual Prompt (Bahng et al., 2022)	IN-V2	80.3	-	39.4	56.9	42.1	49.8	70.2	50.1	57.4
	IN-A	77.2	66.8	-	52.6	37.2	51.1	64.8	43.4	50.5
	IN-R	75.3	64.8	34.8	-	47.4	45.2	64.9	50.7	50.3
	IN-Sketch	73.3	62.8	25.7	63.5	-	43.8	64.5	51.2	48.6
	ObjNet	77.4	66.9	40.8	52.1	36.1	-	62.8	38.8	47.7
	IN-Cartoon	80.2	69.3	37.9	58.9	43.1	47.5	-	52.2	55.8
	IN-Drawing	76.0	65.2	28.3	57.0	40.5	44.0	65.8	-	52.2
	IN-C	81.1	70.5	42.8	54.3	41.5	51.3	69.9	51.8	-
LoRA (Hu et al., 2021)	IN-V2	85.9	-	56.2	64.5	51.9	53.3	79.5	64.8	72.3
	IN-A	85.9	**76.6**	-	65.1	52.0	55.4	79.5	65.0	72.9
	IN-R	85.9	**76.6**	58.8	-	52.5	55.2	79.5	65.3	72.6
	IN-Sketch	85.9	76.4	58.0	67.0	-	54.7	79.6	65.6	72.5
	ObjNet	85.8	76.3	59.9	65.3	52.0	-	79.3	64.9	72.9
	IN-Cartoon	85.9	76.3	57.7	65.0	51.6	54.4	-	64.8	72.5
	IN-Drawing	85.8	76.4	58.1	65.8	52.4	54.8	79.7	-	73.0
	IN-C	86.7	76.5	58.0	65.3	52.3	55.0	80.6	69.2	-
EWC (Kirkpatrick et al., 2017)	IN-V2	84.3	-	52.7	66.7	51.3	51.9	77.6	65.1	71.0
	IN-A	84.2	75.8	-	67.9	51.8	**57.0**	77.0	62.4	72.0
	IN-R	84.6	75.3	62.7	-	60.0	55.0	77.9	67.7	72.0
	IN-Sketch	85.2	76.0	57.0	74.3	-	54.8	79.3	67.8	72.4
	ObjNet	83.6	74.4	61.4	64.3	51.6	-	75.3	61.4	71.2
	IN-Cartoon	86.2	76.1	58.7	66.0	52.1	54.2	-	66.9	71.8
	IN-Drawing	86.2	76.5	57.4	67.1	53.2	55.1	80.2	-	73.5
	IN-C	87.4	76.4	57.5	65.8	52.5	53.1	81.7	71.2	-
LwF (Li & Hoiem, 2017)	IN-V2	84.9	-	55.8	65.1	50.6	52.6	78.2	63.1	71.3
	IN-A	85.2	76.0	-	66.8	51.5	54.9	78.8	64.5	72.0
	IN-R	85.1	56.9	57.0	-	59.8	48.0	78.9	67.5	71.4
	IN-Sketch	83.6	74.2	53.4	74.5	-	53.1	77.9	65.4	70.2
	ObjNet	85.0	75.4	60.5	64.6	51.2	-	77.8	61.7	71.5
	IN-Cartoon	97.2	74.0	47.3	65.0	50.4	49.9	-	71.2	75.5
	IN-Drawing	94.5	70.0	43.2	66.6	53.1	42.7	87.6	-	76.6
	IN-C	**99.9**	72.4	41.5	63.1	50.0	47.4	**98.9**	89.4	-
LP-FT (Kumar et al., 2022)	IN-V2	84.6	-	59.9	65.8	52.1	53.6	78.0	63.6	71.4
	IN-A	67.4	58.1	-	57.0	40.5	50.8	59.2	44.5	53.7
	IN-R	63.1	55.1	43.9	-	40.6	46.5	55.3	47.2	49.4
	IN-Sketch	81.5	72.5	54.4	74.6	-	53.7	75.6	62.7	67.8
	ObjNet	83.9	74.1	61.1	64.2	50.7	-	76.9	60.8	70.6
	IN-Cartoon	96.2	74.2	55.7	64.4	51.5	52.6	-	71.4	77.0
	IN-Drawing	93.4	73.7	51.2	65.2	52.5	51.2	87.1	-	**77.5**
	IN-C	99.9	69.6	44.5	59.0	45.0	44.6	98.3	89.7	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	85.7	-	61.9	66.3	52.2	55.9	79.3	66.0	73.5
	IN-A	84.7	75.3	-	66.2	51.6	55.4	78.6	63.7	71.5
	IN-R	85.1	76.1	61.5	-	60.9	55.7	79.2	69.4	73.0
	IN-Sketch	85.0	76.2	57.9	74.4	-	55.2	79.5	67.8	72.1
	ObjNet	85.3	76.2	62.5	65.4	52.8	-	78.7	63.9	72.6
	IN-Cartoon	92.3	76.1	59.3	65.3	52.7	54.9	-	70.5	75.6
	IN-Drawing	91.2	76.0	57.1	67.0	54.4	55.1	84.8	-	76.8
	IN-C	97.0	75.5	54.7	65.7	51.8	53.2	93.4	81.3	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	85.7	-	60.8	66.5	52.2	55.2	79.4	66.1	73.4
	IN-A	85.4	76.3	-	67.6	52.6	56.0	79.1	65.3	72.7
	IN-R	85.3	76.4	61.7	-	**61.1**	55.1	79.4	69.4	73.3
	IN-Sketch	85.0	76.0	57.2	75.0	-	55.0	79.5	68.0	72.3
	ObjNet	85.4	76.3	**63.0**	65.5	52.7	-	78.4	63.6	72.7
	IN-Cartoon	92.3	76.0	57.2	65.8	52.3	53.8	-	70.7	75.8
	IN-Drawing	91.2	76.4	56.5	67.3	54.4	54.5	84.9	-	77.4
	IN-C	97.2	76.0	55.7	65.9	53.0	53.3	94.0	82.5	-

Table 33: The accuracy on each OOD dataset after fine-tuning ImageNet-1K pre-trained ResNet-18 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		69.8	**57.3**	1.1	33.1	20.2	26.0	48.2	20.4	31.7
FT	IN-V2	67.1	-	2.2	31.0	17.7	25.1	42.7	17.2	29.9
	IN-A	50.4	40.6	-	22.8	12.1	19.7	30.0	10.1	19.9
	IN-R	53.1	42.6	3.4	-	37.1	21.3	43.4	27.6	25.6
	IN-Sketch	48.1	37.4	2.1	47.4	-	16.5	36.9	22.9	19.2
	ObjNet	55.2	44.3	**3.7**	25.3	13.7	-	32.8	9.9	20.8
	IN-Cartoon	75.7	45.2	2.2	28.8	17.3	20.3	-	16.3	20.0
	IN-Drawing	46.4	32.3	2.1	24.0	15.2	10.8	23.1	-	15.1
	IN-C	99.2	38.3	2.5	26.6	13.4	14.3	85.8	65.3	-
Linear Probing	IN-V2	69.0	-	1.1	31.6	18.8	24.6	45.4	19.7	29.8
	IN-A	66.1	53.5	-	30.8	18.7	23.6	43.5	20.5	28.7
	IN-R	64.3	51.7	1.2	-	23.9	21.6	48.6	23.7	25.9
	IN-Sketch	5.9	4.4	1.0	12.5	-	3.4	4.7	1.9	1.7
	ObjNet	64.7	51.8	1.7	30.0	16.6	-	44.5	15.4	25.0
	IN-Cartoon	63.7	48.1	1.3	30.7	18.5	20.4	-	16.0	21.8
	IN-Drawing	38.2	29.0	1.5	22.8	13.5	9.7	21.2	-	11.4
	IN-C	77.2	48.6	2.5	28.1	16.1	20.5	50.3	25.2	-
Visual Prompt (Bahng et al., 2022)	IN-V2	60.6	-	2.2	30.7	16.7	24.5	37.8	17.1	21.4
	IN-A	39.5	30.1	-	19.6	8.8	18.2	19.2	5.6	7.3
	IN-R	53.4	42.6	2.3	-	18.3	22.6	33.8	16.3	16.6
	IN-Sketch	54.6	42.9	2.3	32.4	-	22.6	34.5	17.2	17.1
	ObjNet	47.3	36.0	2.9	23.6	11.6	-	25.6	9.1	12.9
	IN-Cartoon	58.2	45.4	2.2	29.8	15.7	22.8	-	13.6	17.8
	IN-Drawing	54.0	43.0	1.9	29.7	17.1	20.6	33.1	-	17.3
	IN-C	61.8	50.5	2.2	31.1	18.2	25.4	38.7	20.5	-
EWC (Kirkpatrick et al., 2017)	IN-V2	69.7	-	1.1	32.2	19.2	25.7	45.8	20.7	31.5
	IN-A	56.0	45.5	-	23.5	8.5	22.1	35.4	12.6	22.0
	IN-R	64.5	52.2	1.7	-	31.3	24.2	53.0	28.0	29.0
	IN-Sketch	39.5	29.5	2.0	28.2	-	13.3	31.5	17.9	13.3
	ObjNet	63.9	51.6	2.7	29.5	15.5	-	42.4	15.0	24.9
	IN-Cartoon	62.0	47.6	1.3	31.9	19.5	20.2	-	16.3	20.7
	IN-Drawing	36.7	29.2	1.5	24.5	15.4	9.9	19.2	-	12.0
	IN-C	66.2	54.4	2.3	31.2	18.5	**26.8**	40.4	22.0	-
LwF (Li & Hoiem, 2017)	IN-V2	68.7	-	1.9	32.3	19.1	25.8	45.4	18.8	31.0
	IN-A	61.4	50.3	-	28.0	16.0	23.0	38.9	15.7	26.7
	IN-R	62.3	50.6	2.6	-	36.2	23.8	50.0	29.6	30.3
	IN-Sketch	54.7	43.1	1.7	**47.8**	-	19.1	42.0	23.6	21.8
	ObjNet	61.9	50.0	3.3	29.8	16.9	-	39.3	14.1	25.6
	IN-Cartoon	81.6	52.5	1.8	32.2	19.5	23.7	-	21.5	29.0
	IN-Drawing	60.3	41.0	2.0	27.0	16.8	15.5	31.3	-	20.8
	IN-C	97.2	47.2	1.6	31.0	18.1	18.4	83.2	53.4	-
LP-FT (Kumar et al., 2022)	IN-V2	67.0	-	2.3	31.0	17.7	25.1	42.8	17.0	29.8
	IN-A	54.4	44.2	-	23.4	12.6	20.8	30.9	12.2	22.6
	IN-R	56.2	45.5	3.3	-	**37.9**	21.9	46.2	29.5	27.5
	IN-Sketch	45.8	36.1	2.2	45.2	-	15.5	35.9	21.6	17.5
	ObjNet	58.1	46.8	3.6	27.0	14.8	-	36.4	11.5	22.2
	IN-Cartoon	76.3	45.2	2.2	28.8	17.2	20.2	-	16.6	19.7
	IN-Drawing	46.4	31.5	2.1	24.0	14.8	10.8	22.6	-	14.5
	IN-C	**99.4**	37.4	2.5	26.6	13.0	13.5	**88.3**	**67.6**	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	69.6	-	1.6	32.9	19.9	26.3	47.0	19.8	32.3
	IN-A	66.5	54.7	-	31.5	18.9	26.5	45.5	18.4	30.7
	IN-R	66.2	54.2	1.9	-	33.9	25.7	54.0	31.6	**33.6**
	IN-Sketch	64.9	52.3	1.5	46.6	-	24.1	50.3	30.2	29.8
	ObjNet	67.2	54.9	2.3	32.6	19.3	-	44.9	17.6	30.4
	IN-Cartoon	76.5	54.4	1.5	33.5	20.5	25.0	-	21.2	28.8
	IN-Drawing	68.6	51.4	1.6	32.8	20.8	21.1	41.9	-	28.8
	IN-C	86.0	52.9	1.9	35.4	20.9	24.2	68.0	40.0	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	69.6	-	1.6	32.8	19.7	26.2	46.7	20.1	32.2
	IN-A	65.1	53.5	-	30.7	17.6	25.8	44.3	16.7	29.2
	IN-R	65.9	54.0	2.1	-	34.7	25.4	53.8	31.6	32.9
	IN-Sketch	63.2	50.9	1.5	47.4	-	23.0	49.7	30.6	28.2
	ObjNet	66.3	54.2	2.6	32.3	18.6	-	44.4	17.0	29.3
	IN-Cartoon	74.8	53.1	1.5	33.6	20.6	24.3	-	20.9	27.5
	IN-Drawing	62.6	46.8	1.7	31.1	19.8	18.0	35.7	-	24.2
	IN-C	84.3	53.9	1.7	35.5	21.2	25.0	64.9	38.5	-

Table 34: The accuracy on each OOD dataset after fine-tuning ImageNet-1K pre-trained ResNet-50 on the downstream datasets with various methods. Note that ImageNet-Drawing, ImageNet-Cartoon, and ImageNet-C are generated from the ImageNet validation set. Green and red indicate relative performance increases and decreases, respectively, compared to the pre-trained model. Bold indicates the best performance on each evaluation dataset.

Method	Downstream Dataset	D_{pre} IN	Realistic OOD IN-V2	IN-A	IN-R	IN-Sketch	ObjNet	Synthetic OOD IN-Cartoon	IN-Drawing	IN-C
Pre-Trained		80.3	**69.5**	16.7	41.6	28.4	42.7	61.1	31.1	46.6
FT	IN-V2	79.6	-	18.2	42.4	28.7	41.8	58.1	31.0	47.0
	IN-A	75.7	65.2	-	40.6	28.0	42.6	52.4	25.8	46.3
	IN-R	72.5	61.7	16.5	-	49.1	37.2	61.7	46.0	43.7
	IN-Sketch	57.3	45.7	5.5	55.0	-	25.6	48.9	30.3	23.3
	ObjNet	75.3	63.5	**22.0**	38.5	23.3	-	53.0	22.7	41.8
	IN-Cartoon	81.4	58.8	12.9	39.6	28.0	34.6	-	25.1	31.9
	IN-Drawing	42.9	32.6	4.9	30.3	24.2	11.9	30.0	-	16.3
	IN-C	**99.7**	56.5	6.6	38.2	23.1	28.3	89.3	66.0	-
Linear Probing	IN-V2	79.6	-	12.4	41.0	27.5	40.1	56.5	34.4	45.6
	IN-A	78.2	66.8	-	40.8	28.0	41.1	55.0	35.2	45.4
	IN-R	76.2	64.5	16.7	-	31.5	39.2	60.0	35.2	40.6
	IN-Sketch	10.5	8.3	1.7	15.9	-	7.1	9.5	4.9	2.8
	ObjNet	76.1	63.9	17.0	39.4	25.3	-	55.2	25.7	39.4
	IN-Cartoon	73.7	60.3	11.5	39.9	26.0	32.4	-	31.6	35.6
	IN-Drawing	10.4	7.9	1.8	15.5	17.7	2.9	5.3	-	8.8
	IN-C	82.5	62.5	16.3	35.3	23.6	38.1	56.1	31.6	-
Visual Prompt (Bahng et al., 2022)	IN-V2	75.4	-	11.9	37.5	24.2	39.9	51.8	24.9	36.4
	IN-A	73.1	61.3	-	37.0	23.4	41.3	48.8	21.9	32.8
	IN-R	73.2	61.1	13.1	-	28.9	38.5	51.5	28.0	32.8
	IN-Sketch	73.8	61.5	12.3	43.4	-	39.0	50.9	28.1	33.0
	ObjNet	72.7	60.5	13.5	34.6	22.9	-	47.2	19.9	33.1
	IN-Cartoon	74.5	62.3	11.3	38.1	24.3	38.1	-	24.7	34.5
	IN-Drawing	74.2	62.3	11.3	39.6	26.4	37.9	52.3	-	35.1
	IN-C	75.0	63.4	11.9	37.0	23.7	39.8	51.8	28.1	-
EWC (Kirkpatrick et al., 2017)	IN-V2	80.2	-	13.6	41.5	28.3	41.3	58.0	31.6	46.0
	IN-A	78.3	67.5	-	42.9	28.8	43.1	56.7	31.9	46.8
	IN-R	77.0	65.4	17.4	-	40.3	40.2	64.8	40.3	42.9
	IN-Sketch	40.9	32.1	4.0	32.7	-	17.8	36.0	21.4	13.2
	ObjNet	77.1	65.5	18.7	40.7	25.7	-	56.8	24.0	41.3
	IN-Cartoon	72.1	58.8	11.4	39.1	25.5	33.2	-	25.4	33.1
	IN-Drawing	8.1	6.8	1.5	14.4	17.2	2.8	3.1	-	7.5
	IN-C	76.1	64.9	18.0	38.0	25.3	40.6	51.1	30.2	-
LwF (Li & Hoiem, 2017)	IN-V2	79.7	-	19.4	43.1	29.0	42.3	58.7	31.8	47.5
	IN-A	76.4	65.8	-	41.3	28.6	42.8	53.5	26.6	46.8
	IN-R	73.7	63.0	17.0	-	**49.3**	38.0	62.8	46.6	44.9
	IN-Sketch	54.3	43.1	5.5	51.8	-	24.5	47.5	29.7	21.4
	ObjNet	76.7	65.3	21.9	39.7	24.6	-	55.3	24.1	43.1
	IN-Cartoon	82.4	60.4	14.5	41.0	29.1	35.8	-	26.9	34.6
	IN-Drawing	17.5	13.8	2.7	21.2	22.4	5.7	8.2	-	12.3
	IN-C	99.7	58.4	5.9	38.9	23.5	29.7	**90.9**	**66.5**	-
LP-FT (Kumar et al., 2022)	IN-V2	79.6	-	17.7	42.3	28.5	41.4	58.3	31.6	47.1
	IN-A	76.3	65.8	-	40.2	28.1	43.0	52.6	26.8	46.4
	IN-R	73.4	62.3	16.3	-	48.9	37.9	62.5	46.6	44.2
	IN-Sketch	57.6	46.0	5.1	55.5	-	25.9	49.1	31.6	24.2
	ObjNet	75.5	63.6	21.5	39.1	23.7	-	54.0	22.9	41.8
	IN-Cartoon	81.7	59.0	12.8	39.6	28.1	34.5	-	25.8	32.2
	IN-Drawing	46.4	35.2	5.1	29.9	22.9	13.4	28.4	-	16.7
	IN-C	99.6	56.9	6.3	37.8	22.9	28.4	88.7	63.7	-
WiSE-FT (Wortsman et al., 2022b)	IN-V2	80.7	-	17.3	42.5	29.2	42.6	60.9	32.3	48.1
	IN-A	80.1	69.5	-	43.0	30.1	**44.5**	60.1	31.6	48.9
	IN-R	79.2	68.5	18.6	-	45.2	42.5	67.7	47.1	**49.3**
	IN-Sketch	76.6	65.3	9.9	56.7	-	38.3	63.4	42.6	41.5
	ObjNet	79.7	68.4	20.5	42.0	27.4	-	60.1	29.5	46.8
	IN-Cartoon	83.8	67.5	16.4	43.3	29.7	40.9	-	31.8	42.8
	IN-Drawing	78.8	64.6	12.4	42.6	30.5	35.0	58.6	-	41.8
	IN-C	91.4	67.4	11.3	44.2	29.4	39.0	79.1	50.8	-
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	80.6	-	16.8	42.7	29.4	42.3	60.1	32.2	48.0
	IN-A	79.5	68.6	-	43.1	30.0	44.2	58.8	31.2	48.9
	IN-R	78.4	67.7	18.9	-	47.2	41.8	67.3	47.6	48.4
	IN-Sketch	74.0	62.7	8.9	**58.4**	-	36.0	60.9	45.0	38.7
	ObjNet	79.1	67.7	21.1	41.8	27.1	-	59.3	27.9	45.7
	IN-Cartoon	82.1	65.2	15.0	42.9	29.5	39.6	-	30.0	39.5
	IN-Drawing	62.2	49.5	8.9	36.8	28.6	20.5	41.7	-	28.9
	IN-C	91.2	67.3	12.1	44.3	29.6	39.5	78.4	52.1	-

Table 35: Accuracy of ImageNet-1K with AugReg pre-trained ViT-B/16 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		56.0	57	54	54	49	42	53	46	48	55	61	74	56	59	67	66
FT	IN-V2	57.4	56	54	53	51	40	55	46	53	59	65	74	59	58	68	67
	IN-A	53.5	53	51	50	50	38	52	39	50	56	57	70	56	51	65	64
	IN-R	52.0	52	50	49	46	44	49	37	49	55	57	66	53	51	62	61
	IN-Sketch	53.8	55	53	52	46	39	49	43	51	56	58	70	55	55	63	62
	ObjNet	52.3	52	48	48	46	37	51	38	50	55	58	70	51	52	64	63
	IN-Cartoon	51.3	53	50	50	44	35	48	35	48	50	54	74	53	53	65	58
	IN-Drawing	56.0	58	56	55	46	43	52	40	55	62	61	74	53	57	66	62
Linear Probing	IN-V2	55.9	56	54	54	49	42	53	46	48	55	61	73	56	59	66	65
	IN-A	55.8	56	53	53	49	42	54	46	48	55	61	73	57	59	66	65
	IN-R	56.2	56	54	54	49	44	54	47	49	55	61	73	56	60	66	66
	IN-Sketch	54.5	54	52	52	48	41	51	45	48	54	59	72	55	58	65	64
	ObjNet	56.1	56	54	54	49	43	54	48	48	56	62	73	53	60	66	65
	IN-Cartoon	55.6	56	54	53	48	42	52	46	48	55	59	75	54	59	67	67
	IN-Drawing	54.3	57	55	55	43	43	50	44	51	61	49	74	39	59	66	67
Visual Prompt (Bahng et al., 2022)	IN-V2	47.9	44	42	41	41	35	46	42	42	46	51	69	48	55	59	57
	IN-A	38.0	33	31	29	31	24	36	31	35	38	43	60	37	46	48	49
	IN-R	40.1	39	38	36	33	28	36	30	36	41	41	61	38	45	50	50
	IN-Sketch	44.3	43	41	40	37	29	40	36	39	45	46	65	47	49	54	55
	ObjNet	35.3	28	26	24	28	22	33	29	32	35	41	61	37	44	45	44
	IN-Cartoon	41.8	39	37	36	34	27	38	33	36	38	42	66	43	50	55	53
	IN-Drawing	44.2	45	43	43	33	32	38	32	41	51	42	65	39	50	56	52
LoRA (Hu et al., 2021)	IN-V2	56.1	57	54	54	49	43	53	46	48	55	61	74	57	59	67	66
	IN-A	56.5	57	54	54	49	44	55	48	49	57	61	74	52	60	67	66
	IN-R	56.7	57	54	54	50	44	54	48	49	56	62	74	56	60	67	66
	IN-Sketch	56.6	56	54	54	51	43	53	47	50	56	62	74	57	59	67	66
	ObjNet	55.0	57	54	54	48	43	54	47	48	55	55	74	44	60	67	66
	IN-Cartoon	54.6	56	53	53	48	43	50	45	48	54	56	73	50	58	66	65
	IN-Drawing	55.1	58	56	56	44	45	51	43	51	63	54	74	43	59	66	66
EWC (Kirkpatrick et al., 2017)	IN-V2	58.2	58	55	55	52	44	56	49	52	58	64	75	59	61	68	67
	IN-A	56.6	55	53	52	52	42	56	46	52	58	62	73	59	57	67	66
	IN-R	56.1	55	54	53	50	44	53	43	53	59	62	72	58	56	64	65
	IN-Sketch	57.2	57	56	55	50	44	54	47	52	57	61	74	57	59	67	67
	ObjNet	56.9	56	53	53	51	43	56	47	52	58	62	74	58	59	67	66
	IN-Cartoon	54.7	55	52	52	48	40	52	43	48	54	60	73	56	58	66	64
	IN-Drawing	58.3	59	57	57	50	44	55	45	54	63	65	74	59	60	68	66
LwF (Li & Hoiem, 2017)	IN-V2	57.9	57	55	54	51	42	55	47	53	59	65	75	60	59	69	68
	IN-A	57.2	56	54	54	52	42	55	45	53	60	62	73	59	57	68	66
	IN-R	57.2	57	56	55	50	48	54	43	54	59	62	72	57	57	67	66
	IN-Sketch	55.2	56	54	53	48	40	51	45	52	57	60	72	56	57	65	64
	ObjNet	56.3	56	53	53	51	41	55	44	52	57	63	73	57	57	67	66
	IN-Cartoon	55.6	56	53	53	49	40	52	41	51	55	59	77	57	58	68	65
	IN-Drawing	58.2	59	56	56	50	45	55	43	55	63	64	77	56	59	69	65
LP-FT (Kumar et al., 2022)	IN-V2	57.6	57	54	54	51	41	55	46	53	59	65	74	60	59	68	67
	IN-A	56.2	55	52	52	51	41	55	43	53	59	62	73	59	56	67	65
	IN-R	55.3	55	54	52	48	47	52	41	52	58	60	70	56	56	65	64
	IN-Sketch	54.4	54	53	52	48	40	50	44	51	55	59	70	56	56	64	63
	ObjNet	54.9	54	51	51	48	40	54	43	51	57	61	72	54	56	66	64
	IN-Cartoon	52.8	53	50	50	46	37	49	38	49	52	55	75	54	55	66	61
	IN-Drawing	56.0	59	56	56	44	44	52	40	56	63	57	76	49	58	67	64
WiSE-FT (Wortsman et al., 2022b)	IN-V2	58.0	58	55	55	51	42	55	47	52	58	65	75	60	60	69	68
	IN-A	57.8	57	55	55	52	43	56	46	53	59	64	74	60	59	68	66
	IN-R	59.6	59	58	57	53	49	57	48	55	61	65	75	60	61	69	68
	IN-Sketch	57.3	58	56	56	50	42	53	47	53	59	63	74	59	59	67	66
	ObjNet	57.6	57	54	54	51	43	56	46	53	58	64	74	59	59	68	67
	IN-Cartoon	56.3	57	54	55	50	41	53	43	51	55	61	76	58	59	68	65
	IN-Drawing	59.5	61	59	59	51	45	56	46	55	63	65	77	59	61	69	67
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	58.0	58	55	55	51	43	55	47	52	59	64	75	60	60	69	68
	IN-A	57.8	57	55	54	52	43	56	46	53	59	64	74	60	58	68	67
	IN-R	59.6	59	58	57	53	49	57	47	55	61	65	74	60	61	69	68
	IN-Sketch	57.5	58	56	56	50	42	53	47	53	59	63	74	59	59	67	66
	ObjNet	57.7	57	54	54	52	43	56	47	53	58	64	74	59	59	68	67
	IN-Cartoon	56.2	57	54	54	50	41	53	43	51	55	61	76	58	59	68	65
	IN-Drawing	59.7	61	59	59	51	45	56	46	55	63	66	77	59	61	69	67

Table 36: Accuracy of ImageNet-1K with SAM pre-trained ViT-B/16 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		54.6	53	50	51	50	48	55	47	47	51	51	73	46	64	68	67
FT	IN-V2	56.8	51	49	48	54	49	59	50	51	53	59	75	52	65	69	68
	IN-A	51.3	42	39	36	56	45	56	43	46	46	56	71	52	58	61	61
	IN-R	53.9	49	48	47	53	51	54	42	50	54	55	70	52	58	62	64
	IN-Sketch	55.7	53	52	51	52	46	55	49	50	52	59	72	52	60	66	66
	ObjNet	52.2	43	41	38	56	46	55	47	47	48	54	71	49	60	64	64
	IN-Cartoon	51.3	44	42	39	50	40	53	42	46	45	54	74	52	59	66	65
	IN-Drawing	55.4	54	53	52	47	48	54	43	51	59	55	74	47	61	67	66
HeadOnly	IN-V2	54.7	52	50	50	50	49	55	47	47	51	52	73	47	64	68	67
	IN-A	54.5	52	50	49	49	48	55	47	47	51	51	73	47	64	68	67
	IN-R	54.6	52	50	49	49	49	54	47	47	51	51	73	46	64	68	67
	IN-Sketch	54.1	52	50	50	49	48	53	47	48	51	50	72	46	63	67	66
	ObjNet	54.6	52	50	50	50	48	54	47	47	51	52	73	47	64	68	67
	IN-Cartoon	53.8	52	50	49	49	48	54	46	46	50	46	73	43	64	69	67
	IN-Drawing	54.6	53	51	51	48	49	53	46	48	53	50	73	46	64	68	67
Visual Prompt (Bahng et al., 2022)	IN-V2	44.7	42	41	40	39	37	42	39	36	40	38	66	34	57	58	61
	IN-A	30.4	26	25	22	22	24	27	25	26	29	26	53	22	43	41	44
	IN-R	36.8	38	37	36	27	28	31	28	31	35	26	60	22	48	51	56
	IN-Sketch	36.3	36	35	34	27	27	30	27	33	36	24	61	21	48	49	57
	ObjNet	35.3	31	30	27	29	29	32	31	28	32	30	59	25	49	46	50
	IN-Cartoon	42.3	43	41	40	34	36	39	38	35	39	25	67	23	54	62	62
	IN-Drawing	42.2	46	45	44	31	37	36	34	39	46	18	64	16	55	61	62
LoRA (Hu et al., 2021)	IN-V2	54.7	52	50	50	50	49	55	47	47	51	52	73	47	64	68	67
	IN-A	54.8	52	50	50	50	49	55	47	47	51	52	73	47	64	68	67
	IN-R	54.7	52	50	50	50	49	55	47	47	51	51	73	46	64	68	67
	IN-Sketch	54.6	52	50	50	50	48	54	47	48	51	51	73	47	64	68	67
	ObjNet	54.7	52	50	50	50	48	55	47	47	51	52	73	47	64	68	67
	IN-Cartoon	53.7	52	50	50	49	49	54	47	46	51	44	73	42	64	69	67
	IN-Drawing	54.5	53	51	50	49	49	53	47	48	53	48	73	45	64	68	67
EWC (Kirkpatrick et al., 2017)	IN-V2	55.1	52	50	50	50	49	55	48	48	51	53	74	47	64	68	67
	IN-A	54.7	48	46	44	55	50	57	48	49	52	54	73	48	64	66	67
	IN-R	56.3	53	51	50	53	50	57	48	49	53	55	74	50	65	68	69
	IN-Sketch	55.6	53	52	51	51	50	55	47	48	52	52	73	48	64	69	68
	ObjNet	56.5	51	49	48	55	51	58	51	49	52	57	74	50	65	68	69
	IN-Cartoon	54.3	51	49	48	50	47	54	46	47	50	51	74	48	63	69	67
	IN-Drawing	56.9	55	54	54	51	50	56	47	50	56	55	74	50	65	69	68
LwF (Li & Hoiem, 2017)	IN-V2	56.8	52	50	49	54	49	58	50	51	53	58	75	52	65	69	68
	IN-A	53.9	45	42	40	57	48	58	47	49	49	58	73	54	61	64	65
	IN-R	56.0	51	51	49	54	52	56	45	52	55	58	72	53	61	65	66
	IN-Sketch	56.3	53	52	51	52	47	56	49	51	53	59	73	53	61	67	67
	ObjNet	55.0	47	45	43	57	48	58	50	49	50	57	73	52	63	67	66
	IN-Cartoon	53.1	46	44	42	51	43	54	44	47	47	55	75	53	61	67	66
	IN-Drawing	56.2	55	53	53	48	48	55	44	52	60	56	74	48	62	68	67
LP-FT (Kumar et al., 2022)	IN-V2	56.8	51	49	48	54	49	59	50	51	53	58	75	52	65	69	68
	IN-A	52.3	43	40	37	57	46	57	45	47	47	57	71	53	59	62	63
	IN-R	54.5	50	50	48	53	52	55	43	51	55	55	71	48	60	63	65
	IN-Sketch	55.6	53	52	51	52	47	55	48	50	52	58	72	52	60	66	66
	ObjNet	53.0	44	42	39	56	47	56	47	48	49	54	72	49	61	64	65
	IN-Cartoon	51.1	44	42	40	49	40	52	41	46	46	52	74	51	59	66	65
	IN-Drawing	53.8	54	52	51	44	48	52	43	51	59	48	73	38	61	67	65
WiSE-FT (Wortsman et al., 2022b)	IN-V2	56.1	52	50	50	52	49	57	49	50	52	56	75	50	65	69	68
	IN-A	57.0	51	49	47	54	50	59	50	52	53	59	75	53	65	69	68
	IN-R	58.7	56	55	54	54	52	58	49	53	56	60	75	54	65	70	69
	IN-Sketch	56.8	55	53	53	52	48	56	49	52	54	57	74	51	64	68	68
	ObjNet	56.4	51	49	48	54	49	58	50	51	52	58	74	51	65	69	68
	IN-Cartoon	55.2	50	48	47	51	46	56	47	49	50	56	75	52	64	69	68
	IN-Drawing	57.9	57	55	55	51	50	57	47	53	58	57	75	51	65	70	68
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	56.1	52	50	50	52	49	57	49	50	52	56	75	50	65	69	68
	IN-A	57.0	50	47	46	56	51	60	50	52	53	60	75	54	65	68	69
	IN-R	58.7	56	55	54	55	52	58	49	53	56	60	75	54	65	69	69
	IN-Sketch	57.0	55	53	53	52	48	56	49	52	54	57	74	51	64	69	68
	ObjNet	56.7	51	48	48	55	50	59	51	51	52	58	75	52	65	68	68
	IN-Cartoon	55.0	50	48	47	51	46	55	46	49	50	55	75	52	63	69	68
	IN-Drawing	58.0	57	55	55	51	50	57	47	53	58	57	75	51	65	70	68

Table 37: Accuracy of ImageNet-21K pre-trained ViT-B/16 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		58.3	55	53	53	56	50	60	52	53	54	57	75	52	64	72	69
FT	IN-V2	58.5	51	49	48	60	49	62	53	54	53	62	76	56	63	72	70
	IN-A	55.0	47	45	43	56	45	60	50	51	50	57	73	55	58	69	66
	IN-R	52.9	48	47	46	51	49	53	44	48	52	53	70	50	56	65	63
	IN-Sketch	55.5	50	49	48	53	47	56	50	51	54	57	72	53	59	69	66
	ObjNet	52.8	45	42	40	55	41	57	48	47	47	55	72	52	57	68	66
	IN-Cartoon	52.9	44	41	39	53	41	57	46	48	46	54	76	53	58	71	67
	IN-Drawing	55.3	52	51	51	48	47	55	44	52	59	55	74	49	60	69	64
Linear Probing	IN-V2	58.5	55	53	53	56	50	61	52	53	54	58	75	53	64	72	69
	IN-A	58.7	55	53	52	56	50	61	54	54	54	59	75	53	65	71	70
	IN-R	56.7	55	53	53	52	49	56	50	52	54	52	74	48	63	70	69
	IN-Sketch	56.4	55	53	53	53	49	57	49	51	53	52	73	48	62	71	69
	ObjNet	58.9	55	53	53	57	50	61	54	53	54	59	75	53	65	71	70
	IN-Cartoon	56.9	54	53	52	52	47	58	50	52	52	54	76	50	63	72	70
	IN-Drawing	59.0	56	55	55	54	50	60	52	54	57	58	76	51	65	72	70
Visual Prompt (Bahng et al., 2022)	IN-V2	45.5	42	41	39	43	34	45	43	38	40	42	66	37	55	59	59
	IN-A	38.3	35	33	31	32	25	37	34	32	33	38	59	31	49	52	52
	IN-R	38.3	36	35	33	34	28	35	33	32	36	32	60	28	47	52	52
	IN-Sketch	41.1	39	38	36	37	29	38	36	35	38	36	63	30	50	55	57
	ObjNet	36.9	33	31	29	32	25	35	34	29	31	35	59	29	48	50	53
	IN-Cartoon	41.9	37	36	34	39	29	41	38	36	35	37	65	32	52	58	57
	IN-Drawing	41.8	40	40	38	36	32	38	36	38	43	32	63	25	52	57	57
LoRA (Hu et al., 2021)	IN-V2	58.4	55	53	53	56	50	60	52	53	54	57	75	52	64	72	69
	IN-A	58.9	55	53	52	56	50	61	54	54	54	59	76	53	65	72	70
	IN-R	53.6	54	52	52	46	46	50	46	51	53	44	73	40	61	68	68
	IN-Sketch	56.3	54	53	52	52	50	56	49	51	53	50	73	48	62	71	69
	ObjNet	59.2	55	53	53	57	50	62	55	53	54	59	76	53	65	72	71
	IN-Cartoon	56.1	54	52	52	51	47	57	49	51	52	52	75	49	61	71	69
	IN-Drawing	58.0	56	54	54	53	48	59	51	53	56	57	75	48	64	72	69
EWC (Kirkpatrick et al., 2017)	IN-V2	59.4	55	53	52	58	51	62	54	54	54	59	76	54	65	73	70
	IN-A	58.8	51	49	49	60	49	63	54	55	54	62	76	56	63	72	69
	IN-R	57.6	54	53	52	55	50	58	50	52	55	59	74	54	62	68	67
	IN-Sketch	59.3	56	55	54	57	51	61	53	54	55	59	76	55	64	72	69
	ObjNet	58.2	53	51	51	58	49	62	53	53	52	60	74	53	63	71	69
	IN-Cartoon	56.7	51	49	49	55	46	59	49	52	51	57	76	54	62	72	68
	IN-Drawing	59.4	55	54	54	57	51	62	52	53	59	61	75	55	65	71	68
LwF (Li & Hoiem, 2017)	IN-V2	59.3	53	52	51	59	51	62	54	54	54	61	76	55	64	73	70
	IN-A	58.1	51	49	48	57	48	62	53	54	54	61	75	56	62	71	68
	IN-R	57.3	53	52	51	56	53	58	49	52	55	57	73	53	61	69	67
	IN-Sketch	57.3	52	51	50	55	48	58	51	53	55	58	74	55	61	70	68
	ObjNet	57.0	50	48	47	57	47	60	52	51	52	59	74	55	62	71	68
	IN-Cartoon	57.9	51	48	47	57	47	61	51	53	52	59	78	57	64	74	70
	IN-Drawing	58.1	55	53	53	52	50	59	48	54	61	58	76	52	63	72	67
LP-FT (Kumar et al., 2022)	IN-V2	58.7	52	50	49	60	49	62	53	54	54	61	76	55	63	73	70
	IN-A	56.7	49	47	46	57	46	61	52	53	52	59	74	56	61	70	67
	IN-R	55.4	51	50	49	53	51	55	46	51	54	55	72	52	59	67	66
	IN-Sketch	55.8	52	51	50	53	46	56	48	51	54	55	72	52	59	69	67
	ObjNet	55.5	48	45	43	57	44	60	51	51	51	57	74	54	61	70	68
	IN-Cartoon	54.4	46	44	42	54	42	58	47	50	48	55	77	54	60	73	68
	IN-Drawing	56.0	53	52	52	48	48	55	45	53	60	56	75	48	61	70	66
WiSE-FT (Wortsman et al., 2022b)	IN-V2	59.3	54	52	51	58	50	62	53	55	55	60	76	55	64	73	70
	IN-A	59.0	53	51	50	58	50	62	54	55	55	61	76	56	64	72	69
	IN-R	60.0	55	54	53	58	54	61	53	55	58	61	76	56	64	72	69
	IN-Sketch	59.2	55	54	53	56	50	60	53	55	57	60	75	56	63	72	69
	ObjNet	58.2	52	50	49	58	49	61	53	53	53	60	75	55	63	72	69
	IN-Cartoon	58.1	52	49	49	57	47	61	51	54	52	59	77	56	64	74	70
	IN-Drawing	59.8	57	55	55	55	51	61	51	56	60	60	77	54	65	73	69
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	59.5	54	52	52	59	51	62	54	55	55	60	76	55	64	73	70
	IN-A	59.1	52	50	49	58	49	63	54	55	55	62	76	57	64	72	69
	IN-R	59.8	55	54	53	58	54	61	52	55	58	60	76	56	64	71	69
	IN-Sketch	59.4	55	54	53	57	50	61	53	55	57	60	76	56	64	72	69
	ObjNet	58.3	53	50	50	58	49	61	53	53	53	60	75	55	63	72	69
	IN-Cartoon	58.2	52	49	49	57	47	61	51	53	52	59	77	56	64	74	70
	IN-Drawing	60.1	57	55	55	55	51	61	51	56	61	61	77	55	65	73	69

Table 38: Accuracy of ImageNet-21K with AugReg pre-trained ViT-B/16 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		66.5	67	66	66	63	54	67	59	66	62	69	80	65	66	75	74
FT	IN-V2	64.4	64	62	63	61	56	64	55	64	61	66	77	63	63	73	73
	IN-A	56.3	57	56	56	52	48	56	46	53	51	56	70	53	55	67	68
	IN-R	55.7	54	53	53	53	51	54	43	52	56	57	69	54	56	65	65
	IN-Sketch	54.8	54	53	52	52	44	53	43	52	55	57	70	55	53	64	65
	ObjNet	54.9	55	53	52	53	43	56	41	52	50	54	72	52	56	67	67
	IN-Cartoon	61.5	61	59	58	56	46	63	48	60	57	60	84	60	63	75	72
	IN-Drawing	59.9	57	54	54	51	48	60	45	58	65	64	81	56	62	74	70
Linear Probing	IN-V2	65.7	66	65	64	62	54	66	58	65	62	68	79	65	65	74	73
	IN-A	65.8	65	64	64	62	54	66	58	65	62	68	79	65	65	74	73
	IN-R	64.0	63	62	62	62	53	64	56	63	61	66	77	63	64	72	71
	IN-Sketch	62.1	62	61	60	60	50	62	54	61	59	65	75	62	61	70	69
	ObjNet	65.9	65	64	64	64	54	67	59	65	62	69	79	64	65	74	73
	IN-Cartoon	69.9	70	69	68	67	55	71	62	69	64	72	85	69	69	79	78
	IN-Drawing	70.0	70	69	69	67	59	71	61	70	69	73	83	69	69	77	76
Visual Prompt (Bahng et al., 2022)	IN-V2	56.9	53	51	50	55	43	57	51	54	52	59	75	57	60	68	68
	IN-A	51.1	44	41	40	47	34	52	46	50	47	57	71	53	54	64	65
	IN-R	46.4	43	42	40	40	35	42	36	46	48	46	68	40	51	58	60
	IN-Sketch	51.7	48	46	44	48	37	49	44	50	52	54	72	50	55	62	64
	ObjNet	42.5	33	32	29	40	25	42	36	42	40	47	67	43	47	56	58
	IN-Cartoon	53.1	51	49	49	50	37	52	45	51	49	51	74	50	57	66	65
	IN-Drawing	54.5	55	53	53	48	43	51	45	51	58	53	73	46	57	66	64
LoRA (Hu et al., 2021)	IN-V2	67.2	67	66	66	64	55	68	60	66	63	70	80	67	67	75	74
	IN-A	67.8	67	66	66	66	56	69	61	67	64	71	80	67	67	76	75
	IN-R	67.0	67	66	66	65	56	67	58	66	65	69	79	66	66	75	74
	IN-Sketch	66.9	67	66	65	65	55	67	59	67	64	70	79	67	66	74	74
	ObjNet	67.2	67	66	65	66	54	68	60	67	63	70	80	65	66	75	74
	IN-Cartoon	66.4	66	65	65	64	54	67	59	66	62	69	80	65	65	74	74
	IN-Drawing	67.1	66	65	65	64	57	67	57	68	67	71	80	67	66	74	73
EWC (Kirkpatrick et al., 2017)	IN-V2	67.7	67	66	65	65	56	68	59	68	65	71	80	68	66	76	75
	IN-A	65.8	65	64	64	63	55	67	57	66	62	69	78	67	63	74	73
	IN-R	63.9	62	61	60	62	58	63	52	62	64	66	77	65	63	71	72
	IN-Sketch	66.2	65	65	64	64	55	66	58	65	65	70	78	67	64	74	73
	ObjNet	63.5	63	62	61	62	51	65	52	64	60	67	77	63	61	73	72
	IN-Cartoon	63.9	63	62	62	62	49	66	55	64	58	66	79	65	62	73	71
	IN-Drawing	65.9	64	63	62	61	54	66	56	66	68	70	79	66	64	75	73
LwF (Li & Hoiem, 2017)	IN-V2	66.0	66	65	65	63	55	66	57	65	62	67	79	64	66	75	75
	IN-A	64.1	64	63	64	61	55	65	55	62	59	65	78	62	64	73	73
	IN-R	64.1	63	62	62	61	55	64	55	62	63	66	78	62	64	72	72
	IN-Sketch	61.5	61	60	60	58	50	61	52	59	60	64	76	60	61	70	70
	ObjNet	62.2	63	61	61	60	50	63	50	61	57	63	77	59	63	73	72
	IN-Cartoon	71.7	71	69	69	67	59	71	60	70	68	73	90	71	73	82	82
	IN-Drawing	68.5	66	64	64	64	57	70	56	66	71	72	87	62	69	82	79
LP-FT (Kumar et al., 2022)	IN-V2	65.6	65	64	64	62	54	65	57	66	62	68	78	66	65	74	73
	IN-A	63.2	62	61	61	60	53	63	55	62	59	65	77	63	62	72	71
	IN-R	57.0	54	54	53	54	51	56	47	55	57	59	71	55	58	67	65
	IN-Sketch	58.5	57	56	56	56	48	58	50	57	57	61	72	58	57	66	66
	ObjNet	59.9	59	58	58	57	47	61	48	58	56	61	75	58	60	70	70
	IN-Cartoon	68.6	69	67	67	63	52	70	58	69	64	70	88	68	68	80	77
	IN-Drawing	66.9	65	62	63	64	55	69	54	65	68	71	84	64	67	80	75
WiSE-FT (Wortsman et al., 2022b)	IN-V2	68.0	68	67	67	65	57	68	60	68	65	70	80	67	67	76	76
	IN-A	66.5	67	66	66	62	55	67	57	66	62	68	79	65	66	75	74
	IN-R	66.9	66	65	65	64	59	66	57	66	67	69	79	67	67	74	74
	IN-Sketch	65.1	65	64	64	61	53	64	55	65	64	68	78	65	64	73	73
	ObjNet	65.6	66	64	64	63	53	67	55	65	62	68	79	65	65	74	74
	IN-Cartoon	68.6	69	67	67	64	54	69	58	69	64	70	85	68	69	78	78
	IN-Drawing	69.2	70	68	68	63	56	70	57	69	70	72	84	66	68	79	77
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	68.0	68	67	67	65	57	68	60	68	65	71	80	67	67	76	75
	IN-A	66.9	68	67	67	63	56	67	58	67	62	69	80	66	66	75	74
	IN-R	67.4	66	66	65	64	59	67	58	66	67	70	79	67	67	75	74
	IN-Sketch	65.6	66	65	65	62	53	65	56	65	64	68	78	66	64	73	73
	ObjNet	65.6	66	64	65	63	52	67	55	65	61	68	79	65	65	74	74
	IN-Cartoon	69.2	70	68	68	65	55	70	59	69	65	71	85	69	69	79	78
	IN-Drawing	69.6	70	68	69	64	57	70	58	69	71	72	84	66	69	80	78

Table 39: Accuracy of ViT-B/16 pre-trained on ImageNet-21K-P, using different fine-tuning methods and downstream datasets on each ImageNet-C corruption For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		61.4	60	59	58	57	46	60	53	55	55	65	79	69	64	70	71
FT	IN-V2	62.1	58	57	55	62	48	63	55	57	55	67	79	69	62	73	73
	IN-A	60.5	56	55	52	63	48	63	53	54	51	64	77	69	60	71	72
	IN-R	57.5	55	55	53	56	50	57	47	52	55	59	73	57	58	66	68
	IN-Sketch	59.3	57	57	56	54	44	58	52	54	56	61	76	65	60	70	70
	ObjNet	57.7	54	54	50	58	43	60	50	49	48	60	76	65	58	69	71
	IN-Cartoon	56.1	53	52	49	55	38	58	47	51	47	59	79	63	58	65	66
	IN-Drawing	57.9	60	58	58	46	46	57	46	54	61	57	78	57	60	66	65
HeadOnly	IN-V2	61.4	59	59	58	57	46	60	53	55	55	65	79	69	64	70	71
	IN-A	61.8	59	59	58	58	46	61	54	56	55	66	79	70	64	70	71
	IN-R	61.0	59	58	57	56	46	60	52	55	55	64	79	68	64	70	71
	IN-Sketch	60.8	58	57	56	57	45	59	52	55	55	64	78	69	64	70	71
	ObjNet	61.9	59	59	58	58	47	61	54	55	55	66	79	70	64	70	71
	IN-Cartoon	61.3	59	59	58	56	45	60	52	55	55	65	80	69	64	71	72
	IN-Drawing	62.0	60	59	58	56	47	60	52	57	59	64	80	66	66	72	73
Visual Prompt (Bahng et al., 2022)	IN-V2	49.6	45	44	43	45	34	46	45	43	44	54	72	52	56	59	61
	IN-A	44.6	38	36	35	40	29	43	40	37	39	52	68	49	51	54	58
	IN-R	40.5	35	35	33	35	26	35	33	35	41	45	65	42	48	45	53
	IN-Sketch	44.1	40	40	38	37	27	39	37	39	44	48	67	46	51	50	57
	ObjNet	34.8	27	26	25	28	22	32	30	27	30	41	62	37	43	43	49
	IN-Cartoon	44.2	37	36	34	40	28	42	39	37	38	49	70	48	52	57	57
	IN-Drawing	44.3	44	44	42	37	32	38	36	39	48	42	66	38	52	53	55
LoRA (Hu et al., 2021)	IN-V2	61.3	59	59	57	57	46	60	53	55	55	64	79	69	64	70	72
	IN-A	62.1	59	59	57	58	48	61	54	55	55	66	79	71	65	71	71
	IN-R	61.2	59	58	57	56	47	60	53	55	55	65	79	68	64	70	72
	IN-Sketch	61.4	59	59	57	58	46	60	53	55	56	64	79	68	64	71	72
	ObjNet	62.1	59	59	58	59	48	61	54	55	55	66	79	71	65	71	72
	IN-Cartoon	60.3	58	58	57	55	45	58	52	54	54	62	79	66	63	70	72
	IN-Drawing	61.6	59	59	58	56	47	59	51	57	59	64	79	67	65	71	72
EWC (Kirkpatrick et al., 2017)	IN-V2	62.4	60	59	58	58	47	62	54	57	56	66	80	70	65	72	72
	IN-A	63.7	59	59	57	63	49	65	57	58	56	69	80	72	65	73	73
	IN-R	55.3	58	58	56	41	45	52	45	51	56	50	75	50	60	63	69
	IN-Sketch	61.4	60	60	58	55	46	60	54	55	57	64	78	67	64	70	72
	ObjNet	62.5	59	59	58	60	47	62	55	56	55	67	80	70	64	72	72
	IN-Cartoon	59.9	57	56	55	56	42	59	51	54	53	64	79	70	63	70	71
	IN-Drawing	60.9	60	60	58	53	48	60	51	57	62	62	78	61	64	68	70
LwF (Li & Hoiem, 2017)	IN-V2	62.9	59	58	57	62	48	63	55	58	56	67	80	71	64	73	73
	IN-A	63.5	59	59	57	63	49	65	57	58	57	68	79	71	64	73	73
	IN-R	62.0	59	59	57	59	53	61	53	57	59	65	77	66	63	71	71
	IN-Sketch	61.1	59	59	57	57	45	60	54	56	57	64	77	68	62	71	71
	ObjNet	61.8	59	59	56	61	46	63	54	55	54	66	79	69	62	72	72
	IN-Cartoon	61.3	58	57	55	60	44	62	53	56	54	65	82	68	64	70	71
	IN-Drawing	61.2	61	60	58	51	48	61	50	58	63	62	80	64	63	70	69
LP-FT (Kumar et al., 2022)	IN-V2	62.5	58	58	56	62	47	63	55	57	55	67	79	71	63	73	73
	IN-A	62.6	58	57	55	63	50	65	56	57	55	67	79	70	63	73	72
	IN-R	60.5	57	57	55	57	52	60	51	55	58	63	76	64	62	70	70
	IN-Sketch	60.2	58	57	56	56	45	59	52	56	56	63	77	66	61	70	71
	ObjNet	60.6	57	57	54	60	46	62	52	54	53	64	78	67	61	71	72
	IN-Cartoon	58.8	56	55	53	58	40	60	50	54	51	62	80	65	61	68	69
	IN-Drawing	58.7	60	59	58	48	46	58	46	56	62	58	79	60	61	67	66
WiSE-FT (Wortsman et al., 2022b)	IN-V2	63.3	60	59	58	61	48	63	55	58	57	68	80	72	65	73	73
	IN-A	64.1	60	60	58	63	49	65	57	59	58	69	80	73	65	73	73
	IN-R	64.3	61	61	60	61	52	63	55	59	61	68	80	71	66	73	73
	IN-Sketch	62.7	61	60	59	58	46	61	55	58	58	66	79	71	64	72	73
	ObjNet	62.9	60	59	58	61	47	63	55	57	56	67	80	71	64	73	73
	IN-Cartoon	61.4	59	58	56	59	43	62	52	56	54	65	81	70	64	70	71
	IN-Drawing	63.5	63	62	61	56	48	63	53	59	63	66	81	69	65	71	71
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	63.3	60	59	58	61	47	63	55	58	57	68	80	72	65	73	73
	IN-A	64.1	60	60	58	63	49	65	57	59	57	69	80	73	65	73	73
	IN-R	64.1	61	61	59	61	51	63	55	59	61	68	79	71	66	73	73
	IN-Sketch	62.7	61	60	59	58	46	61	55	58	58	66	79	71	64	72	73
	ObjNet	62.9	60	59	58	61	47	63	55	57	56	67	80	71	64	72	73
	IN-Cartoon	61.4	58	58	56	59	43	61	53	56	54	65	81	70	64	70	71
	IN-Drawing	63.4	63	62	61	56	48	63	53	59	63	66	81	69	65	71	71

Table 40: Accuracy of LAION-2B pre-trained ViT-B/16 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		63.0	59	59	59	58	49	64	52	64	61	70	81	70	61	67	71
	IN-V2	24.5	18	17	16	15	18	19	18	19	21	35	45	33	30	31	32
	IN-A	8.5	8	7	7	5	5	6	6	6	6	12	17	11	11	11	10

Table 41: Accuracy of OpenAI CLIP ViT-B/16 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		62.6	58	58	58	57	46	63	54	63	59	69	80	70	62	71	70
FT	IN-V2	25.7	18	17	16	15	21	21	19	20	23	36	45	33	34	33	36
	IN-A	8.9	7	7	5	5	6	6	6	7	7	13	17	12	11	12	12
	IN-R	22.2	17	16	15	16	18	19	16	16	22	28	38	29	26	28	28
	IN-Sketch	7.2	7	7	6	2	3	4	4	7	9	11	14	10	7	7	12
	ObjNet	10.6	7	7	6	7	7	9	9	5	7	17	20	17	13	14	14
	IN-Cartoon	32.8	20	19	15	20	24	27	22	29	32	41	64	42	43	48	43
	IN-Drawing	23.0	18	14	15	8	13	14	13	24	39	25	56	23	27	30	26
HeadOnly	IN-V2	61.6	57	55	56	57	47	64	54	61	59	70	79	69	60	69	68
	IN-A	62.3	57	56	56	59	47	65	54	62	59	71	80	69	60	70	68
	IN-R	59.9	56	55	54	55	49	61	50	58	59	67	77	65	58	68	69
	IN-Sketch	58.0	54	53	53	53	45	58	48	56	56	66	76	63	56	67	66
	ObjNet	60.1	56	55	55	57	43	63	51	61	57	69	78	64	59	65	66
	IN-Cartoon	56.3	53	51	50	50	39	56	44	56	53	65	79	63	57	67	63
	IN-Drawing	54.7	50	50	50	47	43	53	41	53	59	62	75	58	56	64	58
Visual Prompt (Bahng et al., 2022)	IN-V2	53.6	51	51	50	47	35	53	47	52	49	59	74	58	54	61	62
	IN-A	50.5	44	43	42	44	32	51	45	50	45	59	73	58	53	59	59
	IN-R	47.9	45	44	43	41	30	46	39	47	48	53	71	48	50	55	59
	IN-Sketch	50.8	49	47	46	44	34	49	44	48	49	56	73	53	53	56	60
	ObjNet	41.1	36	34	32	36	25	41	36	41	37	47	66	45	45	46	50
	IN-Cartoon	46.2	43	42	40	39	28	45	40	43	40	50	71	48	50	57	57
	IN-Drawing	46.8	48	48	47	38	35	41	38	44	49	44	69	42	50	54	55
LoRA (Hu et al., 2021)	IN-V2	61.5	57	55	56	57	46	64	54	61	58	70	79	69	60	69	68
	IN-A	62.0	57	56	56	59	46	64	54	62	59	71	80	68	60	70	68
	IN-R	59.5	56	55	54	55	48	60	49	56	58	67	77	64	57	68	69
	IN-Sketch	58.6	54	53	53	53	45	58	48	57	58	68	77	63	57	68	67
	ObjNet	57.9	55	55	54	55	41	61	49	58	54	67	77	61	56	62	64
	IN-Cartoon	54.6	51	49	49	48	37	54	42	54	52	63	77	61	55	64	61
	IN-Drawing	52.5	48	47	48	46	40	51	39	50	56	60	73	57	53	62	56
EWC (Kirkpatrick et al., 2017)	IN-V2	52.9	43	41	42	49	41	55	41	50	50	67	74	64	53	62	62
	IN-A	45.3	33	31	32	44	36	48	35	39	41	61	65	57	46	56	56
	IN-R	58.0	53	52	52	52	49	57	46	56	57	66	75	64	57	66	67
	IN-Sketch	32.8	31	30	30	20	17	25	19	44	44	58	37	38	28	33	38
	ObjNet	46.6	37	35	35	45	36	50	38	40	40	59	69	58	48	55	56
	IN-Cartoon	49.4	43	41	41	43	33	48	36	51	45	59	73	60	50	60	58
	IN-Drawing	49.0	46	42	45	38	36	44	35	51	57	58	73	55	48	56	52
LwF (Li & Hoiem, 2017)	IN-V2	28.8	19	17	14	19	24	25	22	23	27	41	50	37	38	38	40
	IN-A	14.7	12	11	10	9	11	12	11	9	11	21	26	20	20	19	20
	IN-R	27.7	21	20	17	20	23	24	21	22	28	35	47	34	33	35	35
	IN-Sketch	8.8	8	8	7	3	3	4	4	8	12	14	16	12	8	8	14
	ObjNet	18.6	12	11	10	14	14	19	17	9	12	27	34	25	24	24	26
	IN-Cartoon	41.4	30	29	24	25	31	35	29	38	42	50	75	48	54	58	54
	IN-Drawing	30.3	23	19	19	15	20	22	20	32	45	34	66	28	35	41	36
LP-FT (Kumar et al., 2022)	IN-V2	25.8	19	17	16	15	20	21	18	21	23	37	46	33	33	33	36
	IN-A	10.4	8	7	7	7	8	8	8	7	7	15	19	14	13	14	13
	IN-R	23.3	18	17	15	17	19	20	16	18	24	30	40	30	27	29	29
	IN-Sketch	7.3	7	7	6	2	3	4	4	7	10	11	14	10	7	7	12
	ObjNet	12.7	9	8	7	9	9	11	11	7	9	19	24	19	16	17	16
	IN-Cartoon	30.6	20	19	15	17	21	24	20	25	28	39	63	40	41	45	40
	IN-Drawing	27.7	21	18	17	13	18	20	18	25	41	33	59	29	35	38	30
WiSE-FT (Wortsman et al., 2022b)	IN-V2	47.9	39	37	38	40	39	47	36	42	42	61	69	59	53	56	59
	IN-A	39.1	30	28	29	34	30	38	28	31	32	54	59	51	44	48	50
	IN-R	48.5	41	40	39	41	40	46	34	45	48	60	70	59	52	55	56
	IN-Sketch	25.5	24	23	23	13	12	17	13	28	33	44	39	33	24	22	33
	ObjNet	41.7	33	31	30	38	30	42	35	30	33	56	65	55	46	50	52
	IN-Cartoon	52.4	43	42	41	43	40	47	36	54	50	63	78	62	58	65	64
	IN-Drawing	47.4	42	37	41	30	34	39	31	54	59	58	76	49	50	56	55
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	48.7	41	39	40	38	38	46	35	46	43	61	70	59	54	58	60
	IN-A	39.8	33	30	31	33	30	38	27	31	31	55	60	52	45	48	52
	IN-R	50.4	45	43	43	42	42	48	37	48	49	60	71	59	54	57	58
	IN-Sketch	26.3	25	24	24	14	13	17	14	30	35	45	38	33	25	24	34
	ObjNet	44.2	37	35	34	39	32	44	36	35	35	57	67	56	49	53	55
	IN-Cartoon	53.8	47	45	45	42	40	48	37	57	52	64	78	62	59	66	65
	IN-Drawing	48.6	44	39	43	31	36	39	33	56	60	59	77	49	51	57	55

Table 42: Accuracy of ImageNet-1K with AugReg pre-trained ViT-B/32 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		53.5	55	54	54	46	43	49	41	43	53	54	69	52	57	67	64
FT	IN-V2	53.4	53	51	51	48	43	50	39	47	55	56	70	54	57	66	64
	IN-A	47.5	48	46	46	45	38	46	32	40	48	48	62	49	48	58	58
	IN-R	47.0	47	46	45	42	43	44	31	42	50	46	61	44	49	57	57
	IN-Sketch	51.1	53	52	51	45	41	45	39	45	52	51	65	50	53	63	61
	ObjNet	47.8	47	46	46	44	39	45	33	40	49	49	64	44	50	61	59
	IN-Cartoon	50.1	52	50	50	42	36	46	33	42	50	50	72	48	53	68	61
	IN-Drawing	52.8	57	55	55	42	44	48	37	45	58	52	70	47	56	65	63
Linear Probing	IN-V2	53.5	55	53	54	46	43	49	41	43	53	54	69	53	57	66	64
	IN-A	53.2	54	53	53	47	45	50	41	43	53	52	69	48	58	66	64
	IN-R	52.8	55	53	54	47	45	49	42	43	53	50	69	44	58	66	65
	IN-Sketch	51.0	54	52	53	44	41	46	40	41	51	48	67	47	55	64	62
	ObjNet	53.3	55	53	54	48	46	51	42	43	53	51	70	45	58	67	65
	IN-Cartoon	54.2	57	55	55	46	44	49	42	43	54	53	72	49	59	68	67
	IN-Drawing	54.4	57	55	56	47	47	50	42	46	57	52	71	45	59	67	67
Visual Prompt (Bahng et al., 2022)	IN-V2	45.5	46	44	44	39	36	41	37	37	44	43	63	41	53	58	56
	IN-A	29.9	28	26	25	22	19	26	21	23	29	32	48	31	37	40	43
	IN-R	39.4	40	39	38	33	30	35	29	33	40	36	55	38	44	50	51
	IN-Sketch	43.1	46	45	44	35	31	37	32	37	43	39	59	40	47	54	57
	ObjNet	33.1	29	27	26	26	23	28	24	25	33	37	51	37	41	44	44
	IN-Cartoon	42.4	47	46	46	34	30	36	31	32	39	34	63	36	49	57	56
	IN-Drawing	42.3	46	44	44	32	32	35	30	35	47	36	60	36	47	54	53
LoRA (Hu et al., 2021)	IN-V2	53.9	55	54	54	47	44	49	42	43	53	55	70	54	58	67	64
	IN-A	53.4	55	54	54	48	47	51	42	44	54	48	70	44	59	67	66
	IN-R	50.6	54	53	53	44	44	47	40	41	51	40	69	37	57	65	65
	IN-Sketch	51.6	55	53	54	45	43	47	41	41	51	46	69	44	56	66	64
	ObjNet	53.4	55	54	54	48	47	51	42	44	54	49	70	43	59	67	65
	IN-Cartoon	52.6	55	54	54	46	44	48	42	42	52	51	69	46	57	66	64
	IN-Drawing	52.1	56	55	55	43	45	47	40	44	56	43	70	38	58	66	65
EWC (Kirkpatrick et al., 2017)	IN-V2	55.3	55	54	54	49	45	52	43	46	55	57	71	55	60	68	66
	IN-A	49.9	50	48	49	45	41	48	35	42	50	49	65	50	52	61	61
	IN-R	52.5	54	52	52	47	46	50	39	46	54	51	68	47	55	64	64
	IN-Sketch	53.8	55	54	54	47	44	49	40	46	54	54	69	52	57	66	65
	ObjNet	54.0	55	53	53	50	45	50	40	44	54	55	70	53	57	66	65
	IN-Cartoon	52.8	55	53	53	46	42	48	40	43	52	54	70	51	56	66	64
	IN-Drawing	55.1	56	54	54	48	46	51	40	48	59	55	70	54	58	67	65
LwF (Li & Hoiem, 2017)	IN-V2	54.0	54	52	52	48	43	50	40	46	55	56	70	55	57	66	65
	IN-A	52.0	52	50	50	48	42	49	38	45	53	53	67	53	53	63	63
	IN-R	53.0	53	52	51	48	48	50	38	47	55	53	67	51	56	64	63
	IN-Sketch	52.5	54	53	53	46	42	47	40	46	54	53	67	51	55	64	62
	ObjNet	52.1	52	50	50	48	42	49	39	43	52	53	68	51	55	65	63
	IN-Cartoon	54.1	55	53	53	46	42	50	39	45	54	54	74	53	58	70	65
	IN-Drawing	55.2	58	56	56	45	46	51	40	47	59	54	73	50	58	68	65
LP-FT (Kumar et al., 2022)	IN-V2	53.7	53	51	52	48	43	50	40	46	55	56	70	55	57	66	65
	IN-A	52.2	52	51	51	48	42	50	38	45	53	52	68	52	54	64	62
	IN-R	51.4	52	51	50	46	47	49	36	45	54	50	66	47	55	63	61
	IN-Sketch	51.1	53	52	52	44	41	45	40	45	53	49	66	50	53	63	61
	ObjNet	51.3	51	49	49	47	42	49	38	43	53	51	68	48	55	64	63
	IN-Cartoon	52.6	54	52	52	44	39	48	36	44	52	53	74	51	56	70	64
	IN-Drawing	53.6	58	56	57	42	45	48	37	48	60	50	72	44	57	66	65
WiSE-FT (Wortsman et al., 2022b)	IN-V2	54.7	55	53	53	48	44	50	41	46	55	57	70	56	58	67	65
	IN-A	54.3	54	52	53	49	44	51	40	46	55	56	70	56	57	66	65
	IN-R	55.4	55	54	54	50	48	52	41	48	57	57	70	55	58	67	65
	IN-Sketch	54.4	56	55	55	48	44	49	42	47	55	55	69	55	57	66	64
	ObjNet	54.3	54	53	53	48	44	51	41	45	54	56	70	54	58	67	65
	IN-Cartoon	54.2	55	53	54	47	42	50	40	45	53	55	72	55	58	69	65
	IN-Drawing	56.9	58	57	57	48	47	53	42	49	60	58	73	55	60	69	67
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	54.9	55	53	54	49	44	51	41	46	55	57	71	55	59	67	65
	IN-A	53.6	53	52	52	49	43	51	39	45	54	55	69	55	56	65	64
	IN-R	55.3	55	54	54	50	48	52	41	48	57	56	70	55	58	67	65
	IN-Sketch	54.4	56	55	55	48	44	49	42	47	55	55	69	54	57	66	64
	ObjNet	54.3	54	53	53	49	44	51	41	45	54	56	70	54	58	67	65
	IN-Cartoon	54.3	55	53	54	47	42	50	40	45	54	55	73	54	58	69	65
	IN-Drawing	56.9	59	57	57	49	47	53	42	49	60	57	73	55	60	69	67

Table 43: Accuracy of ImageNet-1K with SAM pre-trained ViT-B/32 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		48.8	49	48	47	45	47	46	41	35	45	36	65	35	59	68	65
FT	IN-V2	51.1	48	46	45	50	48	50	42	41	47	45	68	41	61	67	67
	IN-A	43.1	36	35	33	50	42	45	32	36	38	34	59	35	53	59	59
	IN-R	49.2	49	49	48	49	47	46	34	42	48	44	62	44	55	61	62
	IN-Sketch	50.1	49	48	47	48	46	47	42	41	46	46	64	42	57	65	64
	ObjNet	44.7	38	38	35	49	43	46	36	36	40	35	61	34	56	62	61
	IN-Cartoon	47.3	44	43	40	46	41	46	38	37	41	40	67	42	55	66	65
	IN-Drawing	49.3	55	53	53	41	45	43	35	40	53	37	65	37	55	65	63
HeadOnly	IN-V2	48.8	49	47	46	45	47	46	41	35	45	36	65	36	60	68	65
	IN-A	49.0	48	47	46	46	48	47	40	36	46	37	65	35	60	68	66
	IN-R	49.2	49	48	47	47	48	47	41	36	46	36	66	35	60	67	66
	IN-Sketch	48.5	49	47	47	47	47	47	41	37	46	33	65	33	59	66	65
	ObjNet	49.2	49	47	46	48	48	47	41	36	46	36	65	34	60	67	66
	IN-Cartoon	48.2	49	47	47	44	46	46	40	35	45	33	66	33	59	68	65
	IN-Drawing	49.0	52	50	50	43	47	44	39	37	48	36	65	36	59	67	64
Visual Prompt (Bahng et al., 2022)	IN-V2	41.5	43	42	41	35	36	36	35	31	38	25	59	25	54	60	61
	IN-A	19.2	21	20	18	8	13	11	12	13	18	6	37	6	32	33	38
	IN-R	34.3	39	38	37	25	27	26	24	25	31	19	54	19	45	50	54
	IN-Sketch	34.2	36	36	35	27	28	27	26	26	32	19	54	18	45	52	54
	ObjNet	27.4	26	26	24	22	23	22	22	18	24	15	45	14	40	44	47
	IN-Cartoon	41.1	43	42	41	36	37	37	36	29	37	21	61	21	53	62	62
	IN-Drawing	41.1	46	45	45	33	35	33	31	31	40	24	59	24	52	59	60
LoRA (Hu et al., 2021)	IN-V2	48.8	49	47	47	45	47	46	41	35	46	36	65	36	60	68	65
	IN-A	49.4	49	47	46	47	48	47	41	36	46	38	66	35	60	68	66
	IN-R	49.4	49	48	47	47	48	47	41	36	46	36	66	35	60	68	66
	IN-Sketch	48.8	49	48	47	47	48	47	41	36	46	33	65	33	59	67	66
	ObjNet	49.4	49	47	46	48	49	48	41	36	46	36	66	34	61	68	67
	IN-Cartoon	48.1	49	47	46	45	46	46	41	35	45	32	65	32	59	68	65
	IN-Drawing	49.1	51	50	49	44	47	45	40	37	47	35	65	35	59	67	64
EWC (Kirkpatrick et al., 2017)	IN-V2	49.5	49	47	46	46	48	47	41	36	46	38	66	37	60	68	66
	IN-A	47.7	46	44	43	48	48	46	39	35	43	34	63	33	59	66	66
	IN-R	50.1	50	49	48	48	48	47	40	37	46	39	66	38	60	67	67
	IN-Sketch	49.8	50	48	48	48	48	47	41	38	46	39	66	37	60	67	66
	ObjNet	49.9	48	47	45	49	49	48	42	37	46	40	66	37	61	68	67
	IN-Cartoon	48.4	48	47	45	45	46	46	40	35	44	36	66	37	59	68	65
	IN-Drawing	49.9	53	51	51	44	47	45	39	38	49	37	65	38	59	67	65
LwF (Li & Hoiem, 2017)	IN-V2	51.1	48	47	45	49	48	50	43	41	47	44	67	42	61	68	67
	IN-A	46.3	40	39	37	51	45	48	36	38	41	38	62	38	57	62	62
	IN-R	51.6	52	51	50	51	49	49	38	43	50	46	65	44	58	64	64
	IN-Sketch	50.6	49	48	47	48	46	47	43	41	47	46	65	43	58	66	64
	ObjNet	48.1	43	42	40	50	47	49	40	38	43	39	64	37	59	65	64
	IN-Cartoon	48.8	45	44	42	47	43	47	40	38	43	42	68	43	58	68	66
	IN-Drawing	50.2	56	54	54	42	46	44	37	40	53	38	66	38	57	66	64
LP-FT (Kumar et al., 2022)	IN-V2	51.1	48	46	45	50	48	50	42	41	47	44	67	42	61	67	67
	IN-A	44.9	39	37	35	51	44	47	34	38	41	34	62	35	55	61	61
	IN-R	50.4	51	51	50	50	48	48	36	43	49	43	64	41	57	63	63
	IN-Sketch	49.4	49	48	46	48	46	47	41	41	46	43	64	39	56	65	63
	ObjNet	45.9	41	40	38	50	44	47	36	38	42	35	62	35	57	63	62
	IN-Cartoon	47.7	45	44	41	46	42	46	38	37	42	39	68	41	56	67	65
	IN-Drawing	48.4	55	53	53	40	44	42	34	40	53	32	65	33	55	65	63
WiSE-FT (Wortsman et al., 2022b)	IN-V2	50.4	49	47	46	47	48	48	42	39	47	41	67	39	61	68	66
	IN-A	50.4	47	45	44	49	49	50	42	40	47	42	66	40	61	67	67
	IN-R	52.8	54	53	52	49	50	49	42	43	51	45	68	43	61	68	67
	IN-Sketch	50.7	50	49	48	47	47	48	43	40	48	42	66	41	59	68	65
	ObjNet	50.1	47	45	44	49	49	49	42	39	46	42	66	39	61	68	66
	IN-Cartoon	50.0	48	47	45	47	46	48	41	38	46	41	68	41	60	69	66
	IN-Drawing	51.5	55	53	54	44	47	46	40	41	53	40	67	39	59	68	66
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	50.5	49	47	46	47	48	49	42	39	47	41	67	39	61	68	66
	IN-A	50.0	46	45	43	51	49	50	41	40	46	42	65	39	61	67	67
	IN-R	52.8	54	53	52	49	50	49	41	42	50	45	68	43	61	67	67
	IN-Sketch	50.9	50	49	48	47	48	48	43	41	48	43	66	41	60	67	65
	ObjNet	50.2	47	45	44	49	49	50	42	39	46	42	66	39	61	68	66
	IN-Cartoon	49.8	48	46	45	47	46	47	41	38	45	41	68	41	60	69	66
	IN-Drawing	51.5	56	54	54	44	47	46	39	41	53	39	67	39	59	68	66

Table 44: Accuracy of ImageNet-21K with AugReg pre-trained ViT-B/32 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		60.5	61	60	60	56	49	61	50	54	56	60	75	59	62	72	70
FT	IN-V2	60.2	59	57	58	58	48	62	50	55	57	62	75	61	60	72	70
	IN-A	56.9	54	52	53	56	46	59	46	51	53	58	71	59	56	69	68
	IN-R	55.3	54	53	53	54	50	55	43	50	55	56	68	55	55	66	65
	IN-Sketch	57.0	58	57	56	54	44	56	48	52	55	58	71	56	56	68	66
	ObjNet	55.3	54	52	52	54	46	58	44	49	52	54	71	54	56	69	67
	IN-Cartoon	56.7	57	55	56	52	41	58	45	52	51	55	76	55	57	72	67
	IN-Drawing	59.5	60	58	59	53	48	57	43	56	61	60	76	59	60	73	69
Linear Probing	IN-V2	60.1	61	59	60	56	49	61	50	54	56	60	75	58	62	72	70
	IN-A	59.4	60	59	59	55	48	60	49	53	55	60	74	58	61	71	69
	IN-R	59.7	60	59	59	55	49	60	50	53	55	60	74	57	62	72	69
	IN-Sketch	58.4	59	58	58	54	47	58	49	53	54	58	73	57	60	70	68
	ObjNet	60.3	61	59	60	57	49	62	51	54	55	61	74	58	62	72	69
	IN-Cartoon	62.6	63	62	62	58	50	64	52	55	57	62	79	61	64	76	74
	IN-Drawing	63.0	63	62	62	57	51	63	52	58	61	64	78	60	65	75	73
Visual Prompt (Bahng et al., 2022)	IN-V2	51.1	51	49	49	48	39	50	44	43	46	48	69	47	57	64	63
	IN-A	39.7	37	35	35	35	27	40	33	33	35	40	58	37	45	53	53
	IN-R	42.6	41	39	39	40	34	41	33	35	42	40	61	39	47	54	54
	IN-Sketch	46.2	46	45	45	42	33	43	37	39	44	45	65	42	50	59	59
	ObjNet	30.9	27	25	24	26	19	30	25	23	27	29	51	28	38	45	46
	IN-Cartoon	45.5	44	43	42	42	31	45	38	39	39	40	67	40	52	62	59
	IN-Drawing	46.7	48	46	45	39	37	41	35	41	51	40	66	39	52	62	59
LoRA (Hu et al., 2021)	IN-V2	60.5	61	60	60	56	49	61	50	54	56	60	75	59	62	72	70
	IN-A	61.2	61	60	60	58	50	63	52	55	56	62	76	59	63	73	70
	IN-R	60.9	61	60	60	57	50	62	51	54	56	61	75	57	63	73	70
	IN-Sketch	60.8	62	60	60	57	49	61	51	54	57	61	76	59	62	73	70
	ObjNet	61.3	61	60	60	58	50	63	52	55	56	62	76	58	63	73	71
	IN-Cartoon	60.2	61	60	60	57	49	61	50	53	55	60	75	57	62	72	70
	IN-Drawing	61.0	61	60	60	56	50	61	50	56	59	62	76	58	63	73	70
EWC (Kirkpatrick et al., 2017)	IN-V2	62.1	62	60	61	60	50	64	53	56	58	63	76	60	63	74	71
	IN-A	60.9	59	57	58	60	50	63	51	55	57	63	75	62	61	73	70
	IN-R	60.0	60	58	58	58	52	60	49	54	58	60	74	59	61	70	69
	IN-Sketch	61.1	62	61	61	57	49	61	51	55	58	62	75	60	62	72	70
	ObjNet	60.1	59	58	58	60	49	62	49	54	57	60	74	59	60	72	71
	IN-Cartoon	59.0	59	58	58	55	46	60	48	53	54	60	75	58	60	72	69
	IN-Drawing	61.2	62	61	61	55	49	61	47	58	62	62	76	60	62	73	70
LwF (Li & Hoiem, 2017)	IN-V2	61.1	61	59	60	58	49	62	51	55	57	62	75	60	62	73	71
	IN-A	60.6	60	58	58	58	49	62	51	55	56	62	75	60	61	73	70
	IN-R	60.9	61	60	60	57	53	61	50	55	59	62	74	59	62	72	69
	IN-Sketch	59.1	60	59	59	56	46	59	49	54	56	60	73	57	59	70	68
	ObjNet	59.1	59	57	57	58	48	61	49	53	54	59	74	57	60	72	70
	IN-Cartoon	63.0	63	61	61	59	50	64	53	56	58	63	80	62	65	77	74
	IN-Drawing	63.1	64	61	62	59	51	63	50	58	62	63	79	61	64	77	73
LP-FT (Kumar et al., 2022)	IN-V2	60.7	60	59	59	58	49	62	51	55	57	62	75	60	61	72	70
	IN-A	59.5	58	57	57	57	48	61	50	54	55	62	73	61	59	71	68
	IN-R	59.0	58	57	57	56	52	59	48	53	58	60	72	58	60	70	67
	IN-Sketch	57.5	58	57	57	54	45	57	48	53	54	59	71	56	58	68	66
	ObjNet	58.9	59	57	57	57	47	61	49	53	55	59	73	57	59	71	69
	IN-Cartoon	61.3	61	59	60	57	46	63	50	56	56	60	80	61	62	76	72
	IN-Drawing	62.6	63	61	62	57	51	62	48	59	63	63	78	61	63	76	72
WiSE-FT (Wortsman et al., 2022b)	IN-V2	61.7	62	60	61	58	50	63	52	56	58	63	76	61	63	73	71
	IN-A	61.9	61	59	60	59	50	64	52	56	58	64	76	62	63	74	71
	IN-R	62.4	62	61	61	59	54	63	52	56	60	64	76	61	63	73	71
	IN-Sketch	61.0	62	61	61	57	48	61	51	56	58	62	75	60	61	72	70
	ObjNet	61.2	61	60	60	58	50	63	51	55	57	62	75	60	62	73	71
	IN-Cartoon	60.9	62	60	61	56	47	62	50	56	56	61	78	60	62	74	71
	IN-Drawing	63.6	65	63	64	59	51	64	51	59	62	64	78	62	64	75	73
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	61.7	62	60	61	59	50	63	52	56	58	63	76	61	63	73	71
	IN-A	61.6	60	59	59	59	50	64	52	56	57	64	75	62	62	74	71
	IN-R	62.2	62	61	61	59	54	63	51	56	60	63	76	61	63	73	71
	IN-Sketch	61.0	62	61	61	57	48	61	51	56	58	62	75	60	61	72	70
	ObjNet	60.9	61	59	59	58	49	63	51	55	56	61	75	59	62	73	71
	IN-Cartoon	61.1	62	60	60	57	47	62	50	56	56	61	78	60	62	74	72
	IN-Drawing	63.3	65	63	64	58	51	64	51	59	62	63	78	62	64	75	73

Table 45: Accuracy of LAION-2B pre-trained ViT-B/32 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		57.5	56	55	55	53	42	57	46	52	51	61	75	64	59	68	69
FT	IN-V2	21.7	20	19	18	11	15	15	15	14	20	23	36	25	28	31	36
	IN-A	7.0	8	7	7	4	5	4	5	4	5	7	12	8	8	10	11
	IN-R	20.9	20	19	18	14	17	17	15	12	20	22	33	25	23	28	31
	IN-Sketch	9.7	10	10	9	4	5	5	6	7	11	11	17	13	9	11	17
	ObjNet	12.2	12	11	11	7	9	10	10	5	9	13	20	15	14	18	20
	IN-Cartoon	27.3	25	24	21	10	16	17	15	21	25	27	51	31	35	46	47
	IN-Drawing	21.6	20	17	19	9	13	14	13	15	32	20	46	22	24	29	30
Linear Probing	IN-V2	58.1	57	56	56	53	42	58	46	53	52	63	76	65	59	68	68
	IN-A	58.2	56	54	55	52	44	58	47	54	53	64	76	66	59	68	68
	IN-R	56.1	54	53	53	50	44	55	43	51	54	61	73	64	57	65	66
	IN-Sketch	55.6	55	54	53	50	42	54	43	51	52	60	73	61	55	65	67
	ObjNet	56.6	55	53	53	51	42	57	44	51	51	62	75	63	58	67	67
	IN-Cartoon	51.2	50	47	48	43	36	49	38	46	45	57	72	59	53	62	61
	IN-Drawing	49.8	53	52	52	37	38	45	34	45	52	54	67	53	51	57	57
Visual Prompt (Bahng et al., 2022)	IN-V2	47.9	49	48	47	39	32	45	38	41	42	49	68	50	51	58	61
	IN-A	36.9	34	33	31	28	20	33	26	31	31	42	62	42	42	46	51
	IN-R	43.9	42	42	40	39	29	41	34	38	41	46	65	44	48	52	58
	IN-Sketch	45.1	44	43	42	39	28	42	36	39	41	48	66	47	48	54	59
	ObjNet	27.7	27	26	25	21	14	23	19	21	22	31	50	30	32	37	40
	IN-Cartoon	44.9	44	43	42	39	28	41	34	39	38	44	68	46	49	57	60
	IN-Drawing	47.2	50	50	48	36	33	43	35	42	47	44	67	43	52	57	61
LoRA (Hu et al., 2021)	IN-V2	58.1	57	56	56	53	42	58	46	53	52	63	76	65	59	68	68
	IN-A	57.9	56	54	55	51	44	58	46	54	53	64	76	65	58	68	67
	IN-R	54.8	53	52	52	48	43	53	41	49	53	60	73	62	55	64	65
	IN-Sketch	53.4	53	53	52	45	40	51	41	49	50	58	70	58	52	63	64
	ObjNet	54.9	53	52	52	47	41	54	42	48	49	61	74	61	56	67	66
	IN-Cartoon	50.3	49	47	47	43	35	49	37	46	45	56	72	58	52	61	60
	IN-Drawing	49.8	52	51	51	38	38	46	34	45	52	54	67	53	51	58	56
EWC (Kirkpatrick et al., 2017)	IN-V2	48.4	47	45	46	40	34	44	35	36	45	58	69	56	50	58	62
	IN-A	30.7	28	26	27	24	19	27	21	19	23	41	46	44	31	38	44
	IN-R	53.0	51	50	50	46	44	50	38	48	52	58	70	58	53	61	65
	IN-Sketch	39.7	40	39	39	27	23	32	26	43	46	56	51	41	37	44	51
	ObjNet	43.0	38	36	37	38	33	42	32	31	39	50	65	51	45	53	56
	IN-Cartoon	48.1	46	44	44	41	32	45	33	45	43	53	71	54	50	61	59
	IN-Drawing	43.6	47	42	46	26	30	35	27	44	52	48	68	46	45	48	50
LwF (Li & Hoiem, 2017)	IN-V2	26.1	23	21	20	14	19	20	18	17	23	30	43	30	33	37	43
	IN-A	14.5	15	14	14	8	10	10	9	8	10	15	25	16	17	21	24
	IN-R	28.9	26	24	23	22	24	25	22	18	28	30	45	32	33	39	42
	IN-Sketch	13.7	15	14	13	5	7	8	8	10	16	15	24	16	14	16	24
	ObjNet	20.7	19	17	17	13	16	18	16	9	16	22	33	24	25	31	33
	IN-Cartoon	36.6	32	31	26	17	25	26	21	30	36	35	64	39	48	57	62
	IN-Drawing	28.2	25	22	22	14	20	20	17	22	38	29	55	27	32	39	40
LP-FT (Kumar et al., 2022)	IN-V2	22.0	21	19	19	12	16	16	15	13	18	23	36	24	28	32	36
	IN-A	9.0	10	10	10	5	6	6	6	5	6	9	15	10	11	13	14
	IN-R	22.2	21	20	19	15	18	18	16	13	21	22	35	26	25	30	33
	IN-Sketch	11.5	12	12	11	5	6	6	7	8	13	12	21	15	12	13	20
	ObjNet	14.4	14	13	12	9	12	12	11	7	11	15	23	17	17	21	23
	IN-Cartoon	28.6	26	25	21	12	18	19	16	22	26	26	53	32	37	47	50
	IN-Drawing	22.7	21	18	19	9	13	14	13	17	34	22	47	25	26	30	30
WiSE-FT (Wortsman et al., 2022b)	IN-V2	43.5	40	37	38	33	33	37	31	33	41	52	63	52	49	55	59
	IN-A	37.0	35	33	33	29	29	32	26	24	31	48	53	47	39	45	51
	IN-R	46.5	44	42	42	39	40	41	33	36	46	53	65	53	50	55	60
	IN-Sketch	33.3	35	33	33	20	20	23	19	28	38	45	49	40	34	35	47
	ObjNet	41.6	39	37	37	33	32	38	31	27	37	49	60	49	45	53	57
	IN-Cartoon	48.8	48	46	45	32	34	40	30	45	47	54	73	52	56	64	65
	IN-Drawing	44.7	45	40	43	28	33	35	27	42	54	49	71	47	48	54	56
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	46.5	45	43	43	35	36	39	32	38	44	54	65	53	52	57	62
	IN-A	40.5	39	36	37	33	32	35	28	28	34	50	58	49	43	50	55
	IN-R	49.8	49	48	48	42	43	45	35	41	49	54	67	54	53	58	62
	IN-Sketch	34.7	38	36	36	21	21	24	19	32	41	45	50	39	35	37	48
	ObjNet	45.1	44	42	42	36	35	42	33	32	40	51	64	50	49	56	60
	IN-Cartoon	50.9	52	50	49	34	35	41	30	50	50	56	75	53	58	64	67
	IN-Drawing	46.2	48	43	47	28	34	36	27	46	56	51	72	46	50	53	57

Table 46: Accuracy of OpenAI CLIP ViT-B/32 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		57.9	58	56	56	53	41	57	46	52	53	61	76	64	60	68	68
FT	IN-V2	25.9	23	22	21	16	20	20	19	17	23	29	39	30	33	37	39
	IN-A	10.1	10	9	10	7	8	8	7	6	7	10	15	12	13	15	15
	IN-R	23.1	21	20	20	17	20	19	17	15	23	23	37	26	26	30	32
	IN-Sketch	11.1	12	11	11	4	5	6	6	8	12	12	21	14	11	14	20
	ObjNet	13.4	12	11	11	9	11	11	11	6	10	15	20	16	16	20	20
	IN-Cartoon	31.4	27	26	23	13	20	22	18	25	30	29	57	34	41	52	52
	IN-Drawing	24.6	23	20	21	11	15	16	15	20	37	24	51	24	28	33	32
HeadOnly	IN-V2	59.0	58	57	57	54	43	60	48	53	54	64	76	65	60	68	68
	IN-A	58.5	57	55	55	52	43	61	48	53	53	64	76	66	60	68	67
	IN-R	55.5	56	55	55	48	44	55	43	49	54	59	72	59	56	64	65
	IN-Sketch	55.4	55	53	53	51	42	55	43	48	52	60	72	61	55	66	66
	ObjNet	56.7	56	54	54	52	41	59	45	50	50	62	75	63	59	65	66
	IN-Cartoon	53.1	52	49	50	46	38	53	39	46	46	58	74	60	55	66	64
	IN-Drawing	48.6	49	47	47	38	39	45	34	43	52	52	67	52	52	58	53
Visual Prompt (Bahng et al., 2022)	IN-V2	50.1	52	50	50	42	34	49	40	43	44	50	70	51	54	60	61
	IN-A	39.6	35	34	32	33	25	38	32	33	33	44	63	44	47	50	51
	IN-R	44.2	44	43	42	38	30	41	34	37	42	45	65	43	48	53	56
	IN-Sketch	47.2	47	46	45	42	31	45	39	39	42	49	67	49	51	57	59
	ObjNet	29.5	25	24	23	26	18	27	22	23	23	31	53	31	37	39	41
	IN-Cartoon	45.4	46	44	44	39	28	43	34	38	39	43	68	45	51	59	60
	IN-Drawing	46.1	50	50	48	37	33	41	34	40	47	40	66	40	51	56	58
LoRA (Hu et al., 2021)	IN-V2	58.9	59	57	57	54	43	60	48	52	54	63	76	65	60	68	68
	IN-A	58.1	57	55	55	52	43	61	47	52	53	64	75	65	58	67	66
	IN-R	55.1	56	54	55	48	44	55	42	48	53	58	72	57	55	64	65
	IN-Sketch	53.5	53	52	51	46	41	52	40	49	51	59	70	57	53	64	64
	ObjNet	53.4	53	51	51	46	38	55	41	46	46	60	72	59	55	63	65
	IN-Cartoon	52.0	51	48	49	45	37	51	38	45	46	57	73	59	54	64	63
	IN-Drawing	48.4	48	47	47	40	39	46	34	43	51	51	66	52	51	58	54
EWC (Kirkpatrick et al., 2017)	IN-V2	53.9	53	52	52	47	41	52	37	45	50	61	72	60	55	65	65
	IN-A	40.9	39	37	38	36	31	40	28	30	34	49	57	50	41	51	52
	IN-R	52.5	51	50	50	45	45	50	38	48	52	57	69	57	53	60	63
	IN-Sketch	38.8	41	40	40	25	22	31	23	44	45	55	47	41	36	44	49
	ObjNet	44.7	42	40	40	40	34	46	32	35	39	50	64	51	45	55	57
	IN-Cartoon	48.1	47	45	45	39	30	46	33	44	42	53	71	55	51	62	58
	IN-Drawing	48.7	51	48	49	34	36	43	33	47	55	52	70	52	51	56	53
LwF (Li & Hoiem, 2017)	IN-V2	30.2	28	26	26	19	25	23	21	19	26	32	46	33	38	44	46
	IN-A	17.6	16	15	15	11	14	13	13	10	14	19	28	21	22	26	27
	IN-R	30.1	26	25	24	22	26	26	22	21	30	30	46	33	35	41	42
	IN-Sketch	15.3	17	16	16	6	8	9	8	11	17	17	27	18	16	19	27
	ObjNet	23.1	22	20	20	16	20	21	18	11	17	24	36	26	28	34	34
	IN-Cartoon	39.6	33	32	27	19	29	30	24	34	41	38	67	41	52	63	63
	IN-Drawing	29.6	26	23	24	15	21	21	20	24	42	28	58	28	34	41	39
LP-FT (Kumar et al., 2022)	IN-V2	26.0	23	22	22	14	20	21	18	17	23	29	41	30	33	38	40
	IN-A	11.6	11	11	11	8	10	9	8	6	8	13	18	14	15	17	17
	IN-R	25.7	24	23	22	19	22	22	18	17	26	27	40	28	29	34	36
	IN-Sketch	12.3	14	13	13	5	6	7	6	8	14	13	23	15	12	15	21
	ObjNet	16.3	15	13	13	11	15	15	13	8	14	17	25	19	19	25	23
	IN-Cartoon	31.3	27	25	22	14	21	22	18	24	30	28	58	33	42	53	51
	IN-Drawing	25.7	24	21	22	11	16	17	15	20	37	26	53	27	30	36	33
WiSE-FT (Wortsman et al., 2022b)	IN-V2	49.1	48	46	46	39	41	44	35	39	45	55	66	54	54	62	63
	IN-A	43.3	43	41	42	35	36	38	30	30	36	50	60	50	47	55	57
	IN-R	49.5	48	47	47	40	43	44	34	42	50	52	67	54	54	59	61
	IN-Sketch	36.3	39	38	38	21	22	25	20	32	40	44	54	40	38	42	51
	ObjNet	46.7	45	43	44	38	39	44	34	35	42	51	64	51	51	59	60
	IN-Cartoon	50.8	48	46	45	35	38	43	33	47	49	55	74	55	60	68	67
	IN-Drawing	46.9	48	43	47	28	34	35	29	47	57	51	73	48	50	56	56
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	50.2	51	49	50	39	42	44	35	42	46	55	67	54	56	62	63
	IN-A	44.3	45	42	44	36	36	39	30	32	36	50	61	51	49	56	58
	IN-R	51.8	51	50	50	43	45	46	36	46	52	54	69	55	56	61	63
	IN-Sketch	37.2	41	40	40	22	22	26	20	34	42	46	54	39	39	42	52
	ObjNet	48.7	48	46	47	40	41	46	35	38	43	52	66	52	53	61	62
	IN-Cartoon	51.7	48	46	45	35	39	44	33	50	51	56	75	56	61	69	67
	IN-Drawing	47.9	50	45	49	29	35	36	30	49	59	52	74	49	51	57	56

Table 47: Accuracy of ImageNet-1K with AugReg pre-trained ViT-S/16 with with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		53.2	54	52	52	46	37	50	42	48	52	58	73	53	55	63	63
FT	IN-V2	51.2	49	47	46	46	36	50	38	50	52	58	70	52	52	60	62
	IN-A	44.1	43	40	40	42	31	44	31	42	43	47	62	44	44	51	57
	IN-R	42.7	40	39	37	39	37	41	31	39	44	47	58	44	44	50	52
	IN-Sketch	45.5	44	42	42	38	31	42	35	42	46	50	64	49	46	53	55
	ObjNet	41.9	40	38	38	40	30	43	30	38	38	45	61	39	43	51	54
	IN-Cartoon	44.4	44	42	41	36	28	41	28	41	40	46	71	46	47	58	54
	IN-Drawing	46.0	45	43	43	34	36	43	33	44	51	49	69	44	48	57	53
Linear Probing	IN-V2	53.1	54	52	52	46	37	50	42	49	52	58	72	53	55	63	63
	IN-A	53.0	53	51	51	46	37	51	42	49	51	59	72	53	55	62	62
	IN-R	53.0	53	51	51	47	38	52	42	49	52	57	72	52	55	62	63
	IN-Sketch	50.9	51	50	49	45	35	48	40	48	50	55	70	50	53	59	61
	ObjNet	53.4	53	52	51	47	38	52	43	49	52	59	72	51	56	62	63
	IN-Cartoon	52.6	53	51	51	45	37	49	41	47	50	56	74	52	55	63	64
	IN-Drawing	54.3	55	53	52	46	39	51	42	53	57	58	74	51	58	63	65
Visual Prompt (Bahng et al., 2022)	IN-V2	43.9	42	41	40	36	28	40	37	39	41	45	66	46	50	53	57
	IN-A	32.1	26	25	22	27	18	30	25	29	29	37	55	35	39	38	45
	IN-R	35.0	34	34	32	26	23	30	26	31	37	34	57	33	41	41	46
	IN-Sketch	39.2	38	37	36	31	24	34	31	35	39	42	61	40	43	45	50
	ObjNet	26.8	21	20	18	19	15	25	22	23	23	29	51	27	36	33	42
	IN-Cartoon	36.0	33	32	31	28	20	32	29	30	31	35	63	34	44	48	50
	IN-Drawing	40.7	41	39	39	30	28	35	31	36	45	37	62	38	46	50	51
LoRA (Hu et al., 2021)	IN-V2	53.5	54	52	52	46	37	50	42	49	52	58	73	53	55	63	64
	IN-A	53.5	54	52	52	47	38	52	43	49	52	57	73	51	56	62	63
	IN-R	52.8	54	52	51	46	38	52	42	49	52	54	73	47	56	62	64
	IN-Sketch	53.5	54	52	52	48	37	50	43	49	53	58	73	52	55	62	64
	ObjNet	53.0	54	52	52	47	38	52	43	49	52	57	73	47	56	62	64
	IN-Cartoon	51.3	52	50	50	45	37	48	40	46	50	53	72	49	53	62	62
	IN-Drawing	54.6	55	54	53	46	38	51	41	52	58	60	73	54	56	63	64
EWC (Kirkpatrick et al., 2017)	IN-V2	55.4	55	53	52	50	38	54	43	53	55	62	74	57	57	64	65
	IN-A	51.4	49	46	46	49	34	52	39	49	52	57	71	56	50	58	63
	IN-R	51.8	50	48	48	46	42	51	37	49	55	57	69	54	52	56	62
	IN-Sketch	54.0	53	52	52	47	39	51	43	51	55	59	72	56	55	61	63
	ObjNet	51.7	51	49	49	48	35	52	39	49	50	57	70	52	52	59	63
	IN-Cartoon	49.1	49	47	47	42	32	46	35	44	46	54	71	51	51	61	60
	IN-Drawing	53.2	54	52	52	44	37	50	39	51	58	58	71	55	54	62	62
LwF (Li & Hoiem, 2017)	IN-V2	53.5	52	51	50	47	38	51	41	51	53	60	72	53	55	63	64
	IN-A	51.7	50	48	48	47	37	51	39	49	51	57	71	54	53	60	62
	IN-R	51.8	50	48	47	45	42	50	40	48	53	56	69	52	54	61	61
	IN-Sketch	48.6	48	46	47	41	33	45	38	46	49	52	68	51	50	58	59
	ObjNet	50.4	50	48	48	46	36	50	39	46	48	55	70	48	51	60	61
	IN-Cartoon	52.6	53	51	50	44	36	50	38	49	49	56	77	52	56	64	63
	IN-Drawing	50.8	49	47	47	41	38	50	38	47	54	55	74	48	52	63	60
LP-FT (Kumar et al., 2022)	IN-V2	52.3	51	49	49	47	37	51	39	51	53	59	71	52	53	61	63
	IN-A	48.6	47	44	44	46	34	49	36	46	49	52	68	51	48	57	59
	IN-R	46.6	44	42	41	41	39	45	33	43	48	51	63	48	48	55	56
	IN-Sketch	47.9	47	46	46	41	32	45	37	46	48	52	66	51	48	56	57
	ObjNet	46.6	45	42	42	44	33	47	34	43	44	51	66	44	48	56	58
	IN-Cartoon	47.2	47	45	44	38	31	44	32	44	44	50	73	48	50	61	57
	IN-Drawing	48.2	47	44	45	37	37	45	34	46	53	52	71	48	50	60	55
WiSE-FT (Wortsman et al., 2022b)	IN-V2	55.0	55	53	53	48	39	52	42	53	55	61	74	56	56	64	65
	IN-A	54.2	53	52	52	49	38	53	41	52	54	60	73	57	55	62	64
	IN-R	55.3	54	52	52	49	43	52	42	53	57	61	72	57	56	63	64
	IN-Sketch	53.6	54	53	53	45	37	49	42	52	55	58	72	56	54	62	63
	ObjNet	53.5	54	52	52	48	37	52	41	50	51	59	72	53	55	63	64
	IN-Cartoon	52.9	54	52	51	45	35	49	37	50	50	57	76	55	56	64	63
	IN-Drawing	55.4	56	54	54	46	41	53	41	53	58	60	75	54	56	65	64
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	55.1	54	53	52	49	39	53	42	53	55	61	74	56	56	64	65
	IN-A	53.9	53	51	51	49	37	53	41	52	54	59	72	57	54	62	64
	IN-R	55.2	53	52	52	49	44	53	42	52	57	61	72	57	56	63	64
	IN-Sketch	53.6	54	52	52	46	37	49	42	52	54	58	72	56	54	62	63
	ObjNet	53.5	54	51	51	49	37	53	41	50	51	59	72	53	54	62	64
	IN-Cartoon	52.7	53	51	51	45	35	49	38	49	50	57	75	54	55	64	63
	IN-Drawing	55.1	55	54	54	46	40	53	41	53	58	59	75	54	56	65	63

Table 48: Accuracy of ImageNet-21K with AugReg pre-trained ViT-S/16 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		58.0	58	56	56	54	43	59	48	55	55	60	75	56	59	69	68
FT	IN-V2	56.8	54	52	53	54	44	58	46	54	55	62	74	58	56	65	67
	IN-A	52.7	49	47	48	51	39	55	43	51	50	57	69	54	51	63	64
	IN-R	50.6	48	46	46	49	45	50	39	46	51	53	66	50	51	58	60
	IN-Sketch	50.7	48	47	47	48	36	51	41	48	50	54	67	52	50	59	60
	ObjNet	48.5	45	43	43	47	34	52	37	46	45	52	67	49	49	59	61
	IN-Cartoon	52.2	51	48	49	50	34	56	40	50	45	53	74	53	53	64	63
	IN-Drawing	52.8	46	43	44	50	41	55	42	51	57	57	73	53	54	64	61
Linear Probing	IN-V2	57.7	57	55	56	53	42	59	48	55	54	60	75	56	59	69	67
	IN-A	57.2	56	54	55	53	42	59	47	55	54	60	74	57	58	68	66
	IN-R	56.8	56	54	55	52	42	58	47	54	54	59	74	55	58	68	66
	IN-Sketch	55.1	55	53	53	50	40	56	45	53	53	57	72	53	56	65	64
	ObjNet	57.9	57	55	55	55	43	60	48	55	54	61	74	58	59	68	67
	IN-Cartoon	59.3	58	56	57	54	42	61	49	56	55	63	79	59	60	71	70
	IN-Drawing	60.0	59	57	58	55	44	61	48	58	60	64	77	58	61	71	69
Visual Prompt (Bahng et al., 2022)	IN-V2	47.9	44	42	41	45	34	48	42	43	44	50	68	47	53	59	60
	IN-A	39.6	34	32	30	38	26	41	34	36	35	43	59	40	44	49	54
	IN-R	38.1	33	32	30	36	29	36	31	33	38	39	58	35	44	47	49
	IN-Sketch	42.1	39	38	37	38	28	39	35	40	43	41	63	38	47	51	55
	ObjNet	29.1	23	22	20	26	17	29	25	25	25	30	50	29	35	37	43
	IN-Cartoon	39.7	35	33	32	37	24	40	34	35	32	38	64	37	47	56	53
	IN-Drawing	41.0	40	39	38	35	29	37	32	36	44	40	62	31	46	54	52
LoRA (Hu et al., 2021)	IN-V2	58.2	58	56	56	54	43	60	48	56	55	61	76	56	59	69	68
	IN-A	58.9	58	56	56	56	44	61	49	56	55	62	76	59	60	69	68
	IN-R	58.2	58	56	56	54	43	60	48	56	55	60	75	56	59	69	68
	IN-Sketch	58.3	58	56	57	54	42	60	48	56	55	61	75	57	59	69	68
	ObjNet	58.8	58	56	56	56	43	61	49	56	55	62	76	59	60	69	68
	IN-Cartoon	57.7	57	55	56	53	42	59	47	55	54	60	75	57	59	69	68
	IN-Drawing	59.0	58	57	57	55	43	60	48	57	59	62	76	58	60	69	68
EWC (Kirkpatrick et al., 2017)	IN-V2	59.7	58	56	57	56	44	61	49	58	57	64	77	59	60	70	69
	IN-A	58.0	56	54	54	56	42	60	48	56	55	62	74	59	56	68	68
	IN-R	56.4	54	51	51	56	47	57	45	53	57	59	73	56	57	63	66
	IN-Sketch	58.0	57	55	55	55	42	59	49	56	57	62	74	58	58	67	67
	ObjNet	56.7	56	53	54	55	41	59	47	54	52	60	73	57	55	67	68
	IN-Cartoon	55.2	53	50	52	52	38	58	44	53	50	59	74	57	56	67	65
	IN-Drawing	58.1	56	55	55	53	43	59	46	56	60	63	75	58	58	67	66
LwF (Li & Hoiem, 2017)	IN-V2	58.3	57	55	56	54	44	60	47	57	55	62	75	58	58	68	68
	IN-A	57.8	56	54	55	54	44	59	47	56	55	61	75	57	58	68	67
	IN-R	57.2	56	54	54	53	47	58	46	54	56	60	73	55	58	66	66
	IN-Sketch	54.5	53	51	52	51	38	55	44	53	52	58	71	55	54	64	64
	ObjNet	55.1	53	50	50	53	40	58	44	53	51	58	73	55	56	66	66
	IN-Cartoon	60.0	59	57	57	56	44	62	48	57	55	62	81	60	62	72	70
	IN-Drawing	57.8	55	52	53	54	44	60	46	55	59	60	78	55	58	71	68
LP-FT (Kumar et al., 2022)	IN-V2	57.6	56	53	54	54	44	59	47	56	55	62	74	58	57	67	67
	IN-A	56.0	53	51	52	53	42	58	46	54	54	60	72	58	55	66	65
	IN-R	53.5	51	49	49	51	46	54	42	50	54	56	69	53	55	62	62
	IN-Sketch	52.3	51	49	50	48	37	53	42	51	51	55	69	53	52	62	62
	ObjNet	53.4	52	50	49	51	37	56	43	51	50	57	71	53	53	64	64
	IN-Cartoon	56.0	55	52	53	52	38	59	44	54	50	57	77	57	57	68	66
	IN-Drawing	55.5	50	48	49	52	43	58	43	54	58	60	75	55	56	68	63
WiSE-FT (Wortsman et al., 2022b)	IN-V2	59.3	58	56	57	55	44	61	49	58	57	63	76	59	60	69	69
	IN-A	58.9	57	55	56	55	44	61	49	57	56	63	75	59	59	69	68
	IN-R	59.6	58	56	56	56	49	60	49	57	59	63	75	59	60	68	68
	IN-Sketch	58.0	57	55	56	54	42	58	47	57	57	61	74	59	58	67	67
	ObjNet	57.6	56	54	55	54	42	60	47	56	54	61	75	57	58	68	67
	IN-Cartoon	58.4	58	55	56	55	40	61	46	57	53	61	78	58	60	70	68
	IN-Drawing	60.4	59	57	58	56	45	62	49	59	61	64	78	59	61	71	69
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	59.3	58	56	57	55	45	61	49	58	57	63	76	59	60	69	69
	IN-A	58.9	57	55	56	56	44	61	49	57	56	63	75	59	59	69	68
	IN-R	59.4	58	56	56	56	49	60	49	57	59	63	75	59	60	68	68
	IN-Sketch	57.9	57	55	56	54	41	58	48	56	56	61	74	59	58	67	67
	ObjNet	57.6	56	54	54	55	42	60	47	56	54	61	75	57	58	68	67
	IN-Cartoon	58.6	58	55	56	55	41	61	47	56	53	61	78	59	60	70	69
	IN-Drawing	60.2	59	57	58	56	44	62	49	58	61	63	78	59	60	71	69

Table 49: Accuracy of ImageNet-21K with AugReg pre-trained ViT-S/32 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption. For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		52.0	54	53	53	47	40	51	39	43	47	50	69	48	56	65	64
FT	IN-V2	50.1	49	47	47	47	40	50	40	43	47	51	66	47	52	62	62
	IN-A	44.0	43	41	41	44	37	46	34	34	39	43	59	42	44	56	56
	IN-R	43.4	42	41	40	42	40	42	31	36	43	44	57	42	45	53	54
	IN-Sketch	45.5	46	45	45	43	34	45	35	39	43	45	60	44	46	56	56
	ObjNet	41.7	40	39	38	41	33	43	31	32	37	39	58	41	44	55	55
	IN-Cartoon	45.2	46	44	43	41	30	45	31	38	38	41	68	44	48	63	57
	IN-Drawing	46.9	48	45	45	42	37	45	32	41	50	44	65	43	49	60	55
Linear Probing	IN-V2	51.5	54	52	52	47	40	51	39	42	47	49	68	48	55	65	63
	IN-A	50.4	52	51	51	46	39	50	38	41	46	48	66	48	54	63	61
	IN-R	51.5	52	51	51	48	41	52	40	42	47	51	68	49	55	64	63
	IN-Sketch	49.6	50	49	49	46	39	50	38	41	45	49	65	48	53	61	60
	ObjNet	52.1	53	52	52	49	41	53	41	42	47	51	68	50	55	64	63
	IN-Cartoon	53.5	55	54	54	49	41	53	41	43	47	52	73	51	57	68	66
	IN-Drawing	53.6	55	54	54	48	42	52	40	45	52	52	71	49	58	66	65
Visual Prompt (Bahng et al., 2022)	IN-V2	42.6	43	42	41	38	32	41	35	33	37	39	60	39	49	54	55
	IN-A	23.2	18	17	16	21	17	23	18	16	20	25	38	22	30	32	34
	IN-R	32.3	31	31	29	30	25	29	25	25	32	25	51	23	38	42	46
	IN-Sketch	35.1	36	35	34	31	23	30	25	28	34	30	54	30	40	46	49
	ObjNet	24.5	21	20	19	22	18	23	20	17	21	19	42	18	33	36	38
	IN-Cartoon	36.0	37	35	34	32	23	33	27	27	30	28	58	27	44	53	52
	IN-Drawing	36.6	40	39	39	29	28	31	26	28	39	27	55	27	42	49	48
LoRA (Hu et al., 2021)	IN-V2	52.1	54	53	53	47	41	51	39	43	47	50	69	48	56	66	64
	IN-A	53.1	54	53	53	50	42	54	41	43	48	52	70	52	56	66	64
	IN-R	52.8	54	52	53	49	42	54	41	42	48	52	70	50	56	66	64
	IN-Sketch	52.9	54	52	52	50	42	53	41	44	48	52	69	51	56	65	64
	ObjNet	53.3	54	53	53	50	42	54	42	43	48	53	70	51	57	66	64
	IN-Cartoon	51.4	53	52	52	47	41	51	39	42	47	48	69	46	55	65	64
	IN-Drawing	52.3	54	53	52	47	41	51	39	45	51	51	69	48	56	64	63
EWC (Kirkpatrick et al., 2017)	IN-V2	53.6	54	53	53	50	42	54	42	45	49	53	70	50	57	66	65
	IN-A	50.2	49	48	47	50	42	53	40	41	45	49	66	49	51	61	62
	IN-R	50.7	50	49	48	49	45	51	38	43	49	50	66	49	53	58	61
	IN-Sketch	52.6	53	52	52	49	41	52	41	45	50	53	68	51	55	64	63
	ObjNet	50.7	51	50	50	49	41	53	39	42	45	48	66	48	53	63	63
	IN-Cartoon	48.8	50	48	48	44	35	49	35	40	43	47	68	47	52	64	61
	IN-Drawing	52.3	53	52	52	46	41	52	37	46	54	52	68	50	55	64	62
LwF (Li & Hoiem, 2017)	IN-V2	51.8	53	51	51	47	41	51	40	44	48	51	68	48	55	65	64
	IN-A	50.8	51	50	50	47	40	52	40	41	46	50	67	48	53	64	63
	IN-R	50.9	51	50	49	47	43	50	38	43	49	51	66	48	54	63	62
	IN-Sketch	48.9	51	50	49	45	37	49	39	41	46	47	64	46	51	61	60
	ObjNet	48.2	48	46	46	47	37	49	37	38	43	47	65	46	50	61	61
	IN-Cartoon	53.7	55	53	53	49	41	54	39	44	48	50	74	50	58	70	67
	IN-Drawing	52.1	54	51	51	48	41	52	38	44	53	48	71	45	54	67	64
LP-FT (Kumar et al., 2022)	IN-V2	50.7	51	49	49	47	40	50	40	43	47	50	67	48	53	63	62
	IN-A	48.2	48	46	46	46	39	49	38	40	44	48	64	47	49	60	59
	IN-R	47.5	46	45	44	45	42	47	35	40	46	47	63	45	50	58	57
	IN-Sketch	46.9	48	47	46	44	36	47	37	40	44	46	61	45	48	58	57
	ObjNet	47.0	47	45	45	46	36	49	37	37	42	45	63	45	49	60	60
	IN-Cartoon	50.1	51	49	48	46	35	51	36	41	43	47	72	48	53	68	62
	IN-Drawing	50.3	52	50	50	45	40	49	35	44	52	47	68	45	52	64	60
WiSE-FT (Wortsman et al., 2022b)	IN-V2	53.1	54	52	52	49	42	53	41	45	49	53	70	50	56	66	65
	IN-A	52.8	53	52	52	50	42	54	41	44	49	53	69	50	55	65	64
	IN-R	53.3	53	52	52	50	45	53	40	46	51	54	69	51	56	64	64
	IN-Sketch	52.1	54	53	53	48	40	51	40	45	49	51	68	50	54	64	63
	ObjNet	51.8	52	51	51	48	40	52	40	43	47	51	68	49	55	65	64
	IN-Cartoon	51.8	53	52	51	47	37	52	37	43	46	50	72	50	55	68	64
	IN-Drawing	54.3	57	55	55	48	42	54	39	47	54	53	72	51	57	68	65
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	53.1	54	52	52	49	42	53	41	45	49	52	70	50	56	66	65
	IN-A	52.5	53	51	51	50	42	54	41	44	48	52	68	50	55	65	64
	IN-R	53.2	53	52	52	50	45	53	40	45	51	54	69	51	56	64	64
	IN-Sketch	52.2	54	53	53	48	40	51	40	45	49	51	68	50	54	64	63
	ObjNet	51.7	52	51	51	49	40	53	40	43	47	50	68	49	54	65	64
	IN-Cartoon	52.0	54	52	52	47	38	52	37	43	46	50	72	50	55	68	64
	IN-Drawing	54.2	57	55	55	48	42	53	39	47	54	52	72	50	57	68	65

Table 50: Accuracy of ImageNet-21K with AugReg pre-trained ViT-L/16 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		72.2	73	73	73	69	62	73	67	72	69	73	82	70	71	79	78
FT	IN-V2	71.0	72	71	72	67	62	71	64	70	70	72	81	69	69	79	78
	IN-A	70.4	72	71	71	67	61	71	64	70	69	71	80	68	68	78	77
	IN-R	65.4	68	67	67	61	61	64	55	61	64	65	76	60	64	74	74
	IN-Sketch	67.6	69	68	68	65	58	67	61	67	66	68	78	64	65	75	74
	ObjNet	68.4	70	69	69	65	60	68	59	68	67	67	79	63	67	78	77
	IN-Cartoon	72.6	74	72	73	67	59	73	63	73	70	73	89	68	72	83	81
	IN-Drawing	74.7	77	75	76	69	67	74	63	74	77	75	87	67	73	85	81
Linear Probing	IN-V2	71.4	72	72	71	68	61	72	66	72	69	72	81	69	70	78	77
	IN-A	71.4	72	72	71	68	61	72	66	71	69	72	81	70	70	78	77
	IN-R	69.8	70	70	69	67	60	70	64	70	67	71	80	68	69	77	76
	IN-Sketch	68.4	69	68	68	66	59	69	63	68	66	69	78	66	67	75	74
	ObjNet	71.5	72	71	71	69	62	72	66	71	68	73	81	70	70	78	77
	IN-Cartoon	76.5	77	76	76	73	65	77	71	76	72	77	88	75	75	85	83
	IN-Drawing	76.0	77	76	76	73	66	76	70	76	75	77	86	74	75	83	81
Visual Prompt (Bahng et al., 2022)	IN-V2	57.4	52	51	50	53	44	56	54	56	56	62	75	55	61	70	69
	IN-A	50.5	42	41	39	45	36	50	48	50	49	56	71	48	55	65	63
	IN-R	50.3	47	47	45	45	38	47	45	48	51	51	69	45	53	62	62
	IN-Sketch	48.6	46	45	43	42	38	44	43	46	49	48	67	39	52	63	62
	ObjNet	47.7	38	37	35	43	32	46	44	47	46	53	70	45	53	63	62
	IN-Cartoon	55.8	50	49	48	51	42	54	52	55	53	57	75	51	60	71	68
	IN-Drawing	52.2	50	49	48	47	43	48	45	49	55	51	70	43	56	66	64
LoRA (Hu et al., 2021)	IN-V2	72.3	73	73	73	69	62	73	67	72	70	73	82	70	71	79	78
	IN-A	72.9	73	73	73	71	63	74	68	72	70	75	82	71	72	79	78
	IN-R	72.6	73	73	73	70	63	73	67	72	69	74	82	70	72	79	78
	IN-Sketch	72.5	74	73	73	70	63	73	67	72	70	74	82	69	72	79	78
	ObjNet	72.9	73	73	73	71	64	74	68	73	70	75	82	71	72	80	78
	IN-Cartoon	72.5	73	73	72	70	63	73	67	72	69	74	82	69	71	79	78
	IN-Drawing	73.0	74	73	73	71	64	74	68	73	71	74	82	71	72	79	78
EWC (Kirkpatrick et al., 2017)	IN-V2	71.0	74	74	74	65	64	70	63	68	69	68	81	66	70	80	78
	IN-A	72.0	73	72	72	68	63	73	66	72	69	73	82	70	70	80	78
	IN-R	72.0	72	71	71	70	65	72	65	72	71	73	82	70	70	78	78
	IN-Sketch	72.4	73	73	72	70	63	72	67	72	71	73	82	70	71	79	78
	ObjNet	71.2	72	71	70	68	62	72	63	72	70	72	81	70	69	79	78
	IN-Cartoon	71.8	72	71	71	69	60	73	66	72	68	73	83	70	71	79	78
	IN-Drawing	73.5	75	74	74	70	63	74	66	74	74	75	83	72	72	80	78
LwF (Li & Hoiem, 2017)	IN-V2	71.3	74	74	74	66	63	71	65	69	68	71	81	66	71	79	78
	IN-A	72.0	74	73	73	68	63	72	66	72	69	72	82	68	71	79	78
	IN-R	71.4	73	72	72	67	64	71	64	70	70	72	81	67	71	78	78
	IN-Sketch	70.2	71	71	71	67	61	70	64	70	68	70	80	67	69	77	77
	ObjNet	71.5	73	72	72	68	62	72	65	71	69	72	82	68	70	79	78
	IN-Cartoon	75.5	79	78	78	70	66	75	65	73	72	71	91	61	78	89	86
	IN-Drawing	76.6	79	77	78	69	71	75	66	76	79	73	90	69	77	88	84
LP-FT (Kumar et al., 2022)	IN-V2	71.4	73	73	72	67	62	71	65	72	70	71	81	67	70	79	78
	IN-A	53.7	56	55	55	49	46	53	46	52	50	54	63	51	52	63	62
	IN-R	49.4	51	51	50	46	44	48	39	47	49	49	59	45	48	58	57
	IN-Sketch	67.8	68	68	68	66	58	68	62	67	66	68	77	65	66	75	74
	ObjNet	70.6	71	70	70	68	61	71	63	70	68	72	80	68	69	78	76
	IN-Cartoon	77.0	78	77	77	72	64	77	69	77	74	78	90	74	76	86	85
	IN-Drawing	77.5	80	79	79	73	68	77	69	78	78	78	88	70	76	86	83
WiSE-FT (Wortsman et al., 2022b)	IN-V2	73.5	74	74	74	71	64	74	68	74	72	75	83	72	72	80	79
	IN-A	71.5	73	72	72	67	62	72	66	72	69	72	81	69	70	78	77
	IN-R	73.0	74	74	73	70	66	73	65	72	72	74	82	70	72	80	79
	IN-Sketch	72.1	73	73	73	69	62	72	66	72	71	73	82	69	71	79	78
	ObjNet	72.6	74	73	73	70	63	73	66	73	71	73	82	70	72	80	78
	IN-Cartoon	75.6	77	76	76	72	63	76	69	76	72	77	87	73	74	83	82
	IN-Drawing	76.8	78	77	78	73	67	77	69	77	77	77	87	73	75	84	82
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	73.4	75	75	74	69	64	74	67	73	72	74	83	71	72	80	79
	IN-A	72.7	74	73	73	69	63	73	67	73	70	73	82	71	71	79	78
	IN-R	73.3	74	74	74	70	67	73	66	72	72	74	82	71	72	80	79
	IN-Sketch	72.3	73	73	73	69	63	72	66	73	71	73	82	70	71	79	78
	ObjNet	72.7	74	73	73	70	63	73	66	73	71	74	82	70	71	79	78
	IN-Cartoon	75.8	77	76	76	73	64	76	69	76	72	77	88	72	75	84	83
	IN-Drawing	77.4	79	79	79	74	68	78	69	77	77	78	87	73	76	85	83

Table 51: Accuracy of ImageNet-1K pre-trained ResNet-50 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		31.7	23	21	18	28	23	30	30	24	28	34	59	31	40	42	46
FT	IN-V2	29.9	21	20	16	26	22	27	26	25	28	31	56	27	37	41	46
	IN-A	19.9	13	13	10	16	14	17	14	16	18	23	39	20	24	30	31
	IN-R	25.6	21	21	17	20	21	22	20	21	26	26	45	22	30	35	37
	IN-Sketch	19.2	16	15	13	11	12	14	12	17	22	20	37	18	21	28	32
	ObjNet	20.8	14	14	11	17	12	21	21	15	18	27	42	20	26	27	28
	IN-Cartoon	20.0	13	12	10	13	11	16	14	14	16	21	50	23	25	34	29
	IN-Drawing	15.1	16	15	11	4	9	9	8	14	24	8	41	6	18	19	22
Linear Probing	IN-V2	29.8	23	22	18	25	23	27	26	23	27	28	56	25	39	41	45
	IN-A	28.7	23	21	18	23	21	25	23	23	28	30	53	26	36	39	42
	IN-R	25.9	19	18	15	19	19	22	22	20	24	23	53	22	36	36	39
	IN-Sketch	1.7	0	0	0	1	1	1	1	3	2	4	2	3	2	3	2
	ObjNet	25.0	16	15	13	21	16	25	25	18	21	34	49	27	33	30	33
	IN-Cartoon	21.8	13	12	10	17	15	20	19	15	17	21	49	22	31	32	34
	IN-Drawing	11.4	14	13	9	3	6	5	5	10	19	7	32	7	12	14	16
Visual Prompt (Bahng et al., 2022)	IN-V2	21.4	18	16	14	13	13	18	20	17	19	17	45	15	29	32	35
	IN-A	7.3	5	5	4	3	3	5	7	6	6	5	22	4	11	12	13
	IN-R	16.6	13	12	10	9	9	13	15	14	15	13	38	12	23	25	27
	IN-Sketch	17.1	13	12	10	9	9	13	16	15	17	15	40	14	22	25	27
	ObjNet	12.9	8	8	6	7	7	10	14	11	11	12	31	10	19	18	21
	IN-Cartoon	17.8	12	11	10	11	10	14	16	13	14	16	41	15	24	29	30
	IN-Drawing	17.3	14	13	10	8	9	12	14	16	18	14	40	13	23	26	29
EWC (Kirkpatrick et al., 2017)	IN-V2	31.5	25	23	19	27	23	29	28	25	29	31	58	26	40	43	47
	IN-A	22.0	18	17	14	16	14	18	16	17	20	24	42	18	27	33	35
	IN-R	29.0	23	22	19	23	23	26	26	22	27	27	54	24	37	38	42
	IN-Sketch	13.3	6	6	3	9	10	10	10	17	15	21	18	17	17	20	19
	ObjNet	24.9	17	17	13	21	16	25	26	19	20	32	49	23	33	30	34
	IN-Cartoon	20.7	12	11	9	16	13	19	17	14	16	20	47	22	28	33	33
	IN-Drawing	12.0	16	15	11	3	6	6	5	12	21	6	34	5	12	14	17
LwF (Li & Hoiem, 2017)	IN-V2	31.0	22	20	16	27	23	28	27	26	29	33	57	29	39	43	47
	IN-A	26.7	19	18	15	22	19	23	21	22	25	31	50	26	32	37	39
	IN-R	30.3	24	23	20	25	24	27	26	24	29	32	53	28	36	41	43
	IN-Sketch	21.8	17	16	13	14	14	17	15	18	23	24	41	21	25	32	36
	ObjNet	25.6	17	16	13	22	17	25	25	20	22	32	49	25	31	33	35
	IN-Cartoon	29.0	19	18	14	22	20	25	24	21	25	31	61	31	37	44	43
	IN-Drawing	20.8	20	18	14	9	13	15	14	19	29	14	52	10	25	28	32
LP-FT (Kumar et al., 2022)	IN-V2	29.8	21	20	16	26	22	27	26	25	28	31	56	27	37	41	46
	IN-A	22.6	15	14	12	19	17	20	17	18	21	26	44	22	28	31	34
	IN-R	27.5	23	22	18	22	23	23	22	23	28	29	48	24	32	37	39
	IN-Sketch	17.5	13	12	11	11	12	12	11	17	19	20	32	17	20	26	29
	ObjNet	22.2	15	15	11	18	14	22	23	17	19	29	44	21	28	28	30
	IN-Cartoon	19.7	13	12	10	13	10	16	14	14	16	20	49	22	25	32	28
	IN-Drawing	14.5	16	15	12	4	8	8	8	13	24	8	40	6	17	18	21
WiSE-FT (Wortsman et al., 2022b)	IN-V2	32.3	23	21	18	29	24	30	29	26	30	34	59	30	40	44	48
	IN-A	30.7	22	21	18	27	22	27	26	24	28	35	56	31	37	42	45
	IN-R	33.6	27	26	22	29	26	30	29	27	33	36	57	31	39	44	47
	IN-Sketch	29.8	24	22	19	22	21	25	23	24	30	32	55	29	35	42	46
	ObjNet	30.4	22	21	18	26	20	29	30	23	26	36	56	30	37	39	43
	IN-Cartoon	28.8	19	17	15	22	18	25	23	22	25	32	60	31	37	43	43
	IN-Drawing	28.8	25	23	19	18	20	23	23	24	32	28	59	23	35	40	42
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	32.2	23	22	18	29	24	29	29	26	29	34	59	29	40	44	48
	IN-A	29.2	22	20	17	25	20	26	23	23	26	33	54	28	35	41	43
	IN-R	32.9	27	26	22	28	26	29	28	26	32	34	57	30	39	43	47
	IN-Sketch	28.2	22	21	17	21	20	23	22	24	29	30	52	27	33	40	43
	ObjNet	29.3	21	20	17	26	19	29	29	23	25	36	54	29	36	37	40
	IN-Cartoon	27.5	18	17	14	22	18	24	22	20	23	29	58	29	36	42	41
	IN-Drawing	24.2	25	23	18	12	15	17	17	21	31	19	53	15	29	32	36

Table 52: Accuracy of ImageNet-1K pre-trained ResNet-50 with different fine-tuning methods and downstream datasets on each ImageNet-C corruption For each corruption, accuracy is averaged across 5 levels of severity.

Dataset	Method	Avg.	Noise			Blur				Weather				Digital			
			Gauss.	Shot	Im-pulse	Defo-cus	Glass	Mo-tion	Zoom	Snow	Frost	Fog	Bright	Con-trast	Elas-tic	Pixel	JPEG
Pre-Trained		46.6	41	39	36	41	27	42	43	40	45	58	71	57	47	50	59
FT	IN-V2	47.0	41	40	36	40	28	43	42	42	48	59	72	55	47	51	62
	IN-A	46.3	43	42	40	40	27	41	39	44	47	58	68	56	44	48	58
	IN-R	43.7	40	39	36	34	33	38	36	39	48	52	65	48	45	48	55
	IN-Sketch	23.3	20	19	16	13	11	17	16	26	28	33	41	23	22	29	35
	ObjNet	41.8	35	34	31	38	24	41	40	35	40	55	65	52	41	43	52
	IN-Cartoon	31.9	28	26	24	26	15	27	24	24	28	36	62	42	33	41	43
	IN-Drawing	16.3	24	18	20	2	4	5	5	24	37	8	49	7	12	11	17
Linear Probing	IN-V2	45.6	42	40	38	36	28	42	40	40	47	52	70	57	46	49	57
	IN-A	45.4	45	44	42	35	28	39	37	41	48	53	67	54	44	47	55
	IN-R	40.6	35	32	30	33	27	36	37	35	39	47	67	50	47	43	51
	IN-Sketch	2.8	1	1	0	1	1	2	2	5	4	8	3	4	2	3	4
	ObjNet	39.4	32	30	29	36	23	39	38	33	38	53	64	51	39	39	48
	IN-Cartoon	35.6	30	25	25	29	22	31	29	29	34	41	65	44	41	44	47
	IN-Drawing	8.8	17	9	15	0	0	0	0	21	32	1	29	1	1	2	3
Visual Prompt (Bahng et al., 2022)	IN-V2	36.4	31	30	26	28	20	32	36	31	34	44	63	42	40	40	49
	IN-A	32.8	27	26	23	22	16	28	31	29	31	42	59	39	37	38	46
	IN-R	32.8	26	25	22	24	17	29	32	28	31	41	59	40	37	37	45
	IN-Sketch	33.0	27	26	22	24	16	29	33	28	31	41	59	40	36	37	45
	ObjNet	33.1	27	25	22	24	17	29	34	28	31	42	59	39	37	36	45
	IN-Cartoon	34.5	29	27	23	26	18	30	34	30	32	43	61	41	39	39	47
	IN-Drawing	35.1	30	29	25	24	18	29	33	31	36	43	61	41	39	40	48
EWC (Kirkpatrick et al., 2017)	IN-V2	46.0	41	39	36	38	28	43	41	40	46	56	71	54	47	50	59
	IN-A	46.8	44	43	41	38	29	42	40	43	48	58	70	53	46	49	58
	IN-R	42.9	37	35	33	34	28	39	39	38	42	50	68	50	47	47	54
	IN-Sketch	13.2	6	5	3	7	8	10	10	24	22	21	21	12	15	17	18
	ObjNet	41.3	34	33	30	37	24	40	40	35	38	55	66	53	42	41	51
	IN-Cartoon	33.1	25	22	21	28	19	30	27	25	30	40	63	42	38	43	46
	IN-Drawing	7.5	10	7	10	0	0	0	0	21	31	0	26	0	1	1	2
LwF (Li & Hoiem, 2017)	IN-V2	47.5	42	41	37	41	28	43	42	43	48	59	72	56	47	52	63
	IN-A	46.8	43	42	40	40	28	42	40	44	47	59	69	57	44	49	58
	IN-R	44.9	41	41	37	36	34	39	37	40	48	53	66	50	46	49	56
	IN-Sketch	21.4	18	17	14	13	10	15	15	26	27	32	36	19	20	27	32
	ObjNet	43.1	37	36	32	39	25	42	41	37	41	56	67	54	42	45	54
	IN-Cartoon	34.6	30	28	25	28	17	30	27	27	31	39	65	44	36	44	47
	IN-Drawing	12.3	20	13	18	1	2	2	2	25	38	4	42	4	5	5	7
LP-FT (Kumar et al., 2022)	IN-V2	47.1	42	40	37	40	28	43	42	42	48	59	71	55	47	51	62
	IN-A	46.4	43	42	39	39	28	42	40	44	48	58	69	56	45	48	58
	IN-R	44.2	40	40	36	35	34	38	37	40	48	52	66	48	46	49	55
	IN-Sketch	24.2	21	19	17	15	13	18	19	27	29	32	41	23	23	30	35
	ObjNet	41.8	35	34	31	38	24	41	40	35	40	55	66	52	41	43	52
	IN-Cartoon	32.2	29	27	25	26	15	28	24	24	28	36	62	42	33	41	43
	IN-Drawing	16.7	26	21	22	1	4	6	5	23	37	7	48	5	14	13	19
WiSE-FT (Wortsman et al., 2022b)	IN-V2	48.1	42	40	37	42	28	43	43	42	48	60	73	59	48	53	63
	IN-A	48.9	44	43	40	43	29	43	44	45	48	61	72	60	48	52	61
	IN-R	49.3	45	44	41	43	34	43	43	43	50	59	72	57	50	53	62
	IN-Sketch	41.5	40	40	37	33	26	37	37	36	40	48	66	41	42	47	55
	ObjNet	46.8	41	40	36	43	27	44	44	40	45	59	71	58	46	50	59
	IN-Cartoon	42.8	37	35	32	37	22	38	35	37	40	51	72	53	46	50	57
	IN-Drawing	41.8	42	39	38	25	22	34	32	39	48	50	71	48	42	45	53
Model Soup PRE-FT-EWC-LwF (Wortsman et al., 2022a)	IN-V2	48.0	42	40	37	42	28	43	43	43	48	60	73	59	48	52	63
	IN-A	48.9	45	44	41	42	29	44	43	45	49	61	71	60	47	51	61
	IN-R	48.4	44	43	40	41	34	42	42	43	49	58	71	55	50	52	60
	IN-Sketch	38.7	36	35	33	29	22	32	33	37	40	46	63	37	39	45	52
	ObjNet	45.7	39	38	35	41	26	44	44	39	44	59	70	57	45	48	57
	IN-Cartoon	39.5	34	31	29	34	21	35	32	32	36	46	69	49	43	48	53
	IN-Drawing	28.9	38	32	34	6	11	14	13	35	46	29	64	24	26	26	35