A STUDY OF THE EFFECTS OF TRANSFER LEARNING ON ADVERSARIAL ROBUSTNESS

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ABSTRACT

The security and robustness of AI systems are critical in real-world deployments. While prior works have developed methods to train robust networks, these works implicitly assume that sufficient labeled data for robust training is present. However, in deployment scenarios with insufficient training data, robust networks cannot be trained using existing techniques. In such low-data regimes, non-robust training methods traditionally rely on *transfer learning*. First, a network is pre-trained on a large, possibly labeled dataset and then fine-tuned for a new task using the smaller set of training samples. The effectiveness of transfer learning with respect to adversarial robustness, though, is not well-studied. It is unclear if transfer learning can improve adversarial performance in low-data scenarios. In this paper, we perform a broad analysis of the effects of pre-training with respect to empirical and certified adversarial robustness. Using both supervised and self-supervised pre-training methods across a range of downstream tasks, we identify the circumstances necessary to train robust models on small-scale datasets. Our work also represents the first successful demonstration of training networks with high certified robustness for small-scale datasets.

1 INTRODUCTION

Transfer learning has been extensively studied for improving standard generalization in machine learning systems across various data availability scenarios (Yosinski et al., 2014; Kornblith et al., 2019; He et al., 2019). In the context of adversarial robustness, however, there are only limited works that studied the benefits of transfer learning (Hendrycks et al., 2019; Chen et al., 2020a). These works generally limit themselves to empirical robustness by solely using adversarial training (Madry et al., 2018) in their experiments. Furthermore, they only study the scenario where abundant data is available for the downstream tasks, *i.e.,* well-represented tasks (*e.g.,* CIFAR-10, CIFAR-100). The exact effect of transfer learning on empirical robustness when there is a lack of abundant data for the downstream tasks, *i.e.,* under-represented tasks, is therefore unknown.

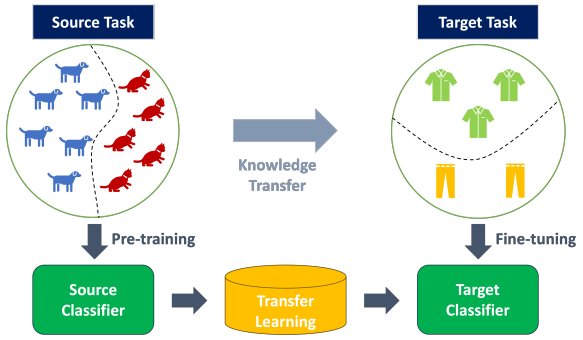

Figure 1: Through transfer learning, one can obtain high-performance networks in settings where it would otherwise be infeasible, *i.e.,* low-data regimes. First, the user trains a classifier on a source task with a large dataset to learn generalizable features. Next, the classifier is fine-tuned on a target task with a small dataset.

It is also unclear whether the findings in context of empirical robustness would apply to certified robustness training methods, specifically randomized smoothing based methods (Cohen et al., 2019; Salman et al., 2019; Zhai et al., 2020; Jeong & Shin, 2020; Jeong et al., 2021) which provide state-of-the-art certified robustness in the ℓ_2-space. This is because both these class of methods rely on fundamentally different ways of measuring and encoding adversarial robustness, and so classifiers

Table 1: Summarizing the findings of prior works regarding the usefulness of transfer learning towards standard generalization and adversarial robustness.

		Is Transfer Learning Useful?			
		Supervised		Self-Supervised	
		Low-Data	High-Data	Low-Data	High-Data
Standard Generalization		✔ (Kornblith et al., 2019)	✘ (He et al., 2019)	✔ (Chen et al., 2020b)	✔ (Chen et al., 2020b)
Adversarial Robustness	Empirical	?	✔ (Hendrycks et al., 2019)	?	✔ (Chen et al., 2020a)
	Certified	?	?	?	?

trained using them inherit different properties. Case in point, Kireev et al. (2022) demonstrated that empirical and certified training methods exhibit dissimilar levels of robustness against common image corruptions. Finally, there is little work that studies effect of self-supervised pre-training on adversarial robustness, with existing works limiting themselves to well-represented tasks.

Table 1 summarizes the findings of prior works in regards to improving performance/robustness in a range of data availability scenarios. The effects of transfer learning on adversarial robustness is largely unexplored (limited to empirical robustness and well-represented tasks). Furthermore, we note that self-supervised pre-training has become an important component of the transfer learning framework of late as it alleviates the need for labeled data for pre-training. The models fine-tuned using pre-trained weights generated via self-supervised learning have exhibited unprecedented generalization ability, unlocking large-scale commercial applications that were infeasible only a few years back. However, using self-supervision to train highly secure ML models is a topic that has largely been overlooked. Therefore, in this paper, we make adversarial robustness our primary focus and broadly study the effects of transfer learning on it. Our findings serve as a useful tool for ML practitioners wanting to deploy highly robustness models in a range of data availability scenarios.

Our **contributions** can be summarized as follows:

- We perform a comprehensive study on the utility of transfer learning towards certified and empirical robustness across a range of downstream tasks. First, a model is robustly pre-trained on a large-scale dataset (*i.e.,* ImageNet) using supervised or self-supervised methods and then robustly fine-tuned on the downstream task. Our experimental results show that such pre-training is beneficial toward improving adversarial performance on downstream tasks compared to training on the downstream task directly.
- We further show that during transfer learning, only the fine-tuning portion of the pipeline needs to rely on robust training methods. This finding eases the overhead of training robust models. Also, regardless of the amount of labeled data available for either pre-training or fine-tuning, models with high adversarial robustness can be trained on downstream tasks.
- Finally, our work demonstrates the first successful demonstration of training models with high certified robustness on downstream tasks irrespective of the amount of labeled data available, either during pre-training or fine-tuning.

2 Background

In this paper, we focus on transfer learning for image classification tasks. More specifically, we explore whether transfer learning can be used to train deep neural network-based image classifiers with high (empirical and certified) adversarial robustness in a range of data availability scenarios. In this section, we provide readers with the necessary background regarding transfer learning (Section 2.1) and adversarial robustness of deep neural networks (Section 2.2).

2.1 TRANSFER LEARNING

In transfer learning (Caruana, 1994; Pan & Yang, 2009; Bengio et al., 2011; Bengio, 2012; Yosinski et al., 2014; Huh et al., 2016), a network is pre-trained on a source task and then fine-tuned on a target task. Through pre-training, the network learns features that enable it to generalize better when fine-tuned on the target task (Yosinski et al., 2014). This is true even when the source and target tasks are dissimilar. For example, prior works (Sermanet et al., 2013; Girshick et al., 2014) re-purposed networks trained for ImageNet (Deng et al., 2009) classification task to achieve breakthroughs on object detection tasks. Pre-training has also been shown to be an effective solution for training high-performance networks when available training data is insufficient for standard training (Pan & Yang, 2009). However, He *et al.* (He et al., 2019) showed that, in the presence of abundant training data, similar levels of generalization can be achieved whether pre-training is performed or not. In such cases, the only benefit of transfer learning then is faster convergence and, therefore, savings in training time. Other studies found that transfer learning effectively transfers other desirable properties like shape bias (Utrera et al., 2020), robustness to common image corruptions (Yamada & Otani, 2022) and adversarial perturbations (Hendrycks et al., 2019).

2.1.1 SELF-SUPERVISED PRE-TRAINING

Traditionally, pre-training was performed in a supervised fashion on large-scale labeled datasets, which can be challenging to acquire in many domains. However, unlabeled data tends to be widely available. To leverage these unlabeled datasets, self-supervised pre-training was proposed to enable models to learn generalizable features by optimizing a custom training objective. Contrastive learning (Chen et al., 2020b; Grill et al., 2020; He et al., 2020; Caron et al., 2020; Goyal et al., 2022) is one such approach. Models are trained to maximize the similarity between positive pairs (semantically similar data samples) while minimizing the similarity between negative pairs (semantically dissimilar data samples) in the feature space. SimCLR (Chen et al., 2020b), one of the most popular contrastive learning method, generates the positive pairs by applying two different sets of input transformations (like cropping, color distortion, and blurring) to the same image. Negative pairs are generated using transformed versions of different images. Self-supervised methods often achieve state-of-the-art results in a range of applications such as image classification, object detection, and sentiment analysis after fine-tuning on relatively small amounts of labeled data.

2.2 ADVERSARIAL ROBUSTNESS

Neural networks are known to be susceptible to adversarial evasion attacks, which attempt to modify a given input imperceptibly with the goal of triggering misclassification. Since the discovery of this vulnerability, several methods have been proposed to train neural networks that are robust against such attacks. These methods can be broadly classified as *empirical* and *certified* methods based on the nature of the robustness guarantees they provide.

2.2.1 EMPIRICAL ADVERSARIAL ROBUSTNESS

Empirical adversarial robustness is traditionally measured using the strongest possible attack within a pre-determined threat model. Robustness training methods that rely on this strategy train the neural network to be robust against this strongest attack and, in turn, gain robustness against all possible attacks within the same threat model. However, such robustness is not provable in nature and can be challenged by an adaptive adversary (Carlini & Wagner, 2017; Athalye et al., 2018; Tramer et al., 2020). Adversarial training (Madry et al., 2018), is one of the most promising empirical robustness methods, as is evident from the fact that the current state-of-the-art methods (Zhang et al., 2019; Wu et al., 2020) are derived from the basic framework proposed by Madry *et al.* (Madry et al., 2018). This framework involves generating adversarial inputs on the fly during training and updating the neural network's weights using them. Furthermore, several works (Tsipras et al., 2019; Ilyas et al., 2019; Augustin et al., 2020) still study the models trained by Madry *et al.* to learn more about adversarial robustness in general. Due to its prominence and in an attempt to fall in line with prior works, we use adversarial training as a representative of empirical robustness training methods.

2.2.2 CERTIFIED ADVERSARIAL ROBUSTNESS

Despite the progress made towards developing empirical robustness methods with strong robustness guarantees, the lack of provability remains an issue. Provably/certifiably robust training methods remedy this concern by maximizing the lower bound of a neural network's output corresponding to the correct class within a certain range of input perturbations. If, for a given input, the lower bound of the correct class output is higher than the upper bound of all other class outputs, the neural network is provably robust for that input. Computing and maximizing this lower bound for a multi-layer neural network is an NP-hard problem (Katz et al., 2017). In recent literature, several methods have been proposed to approximately compute this lower bound and incorporate it in the training process of the neural network in a scalable manner. Of these, randomized smoothing based methods (Cohen et al., 2019; Salman et al., 2019; Zhai et al., 2020; Jeong & Shin, 2020; Jeong et al., 2021) yield state-of-the-art robustness in the ℓ_2-space for modern neural networks. Therefore, in this paper, we focus on these methods.

First formalized by Cohen *et al.* (Cohen et al., 2019), randomized smoothing defines the concept of a smooth classifier. Given a base classifier f_θ, the **smooth classifier** g_θ, is defined as follows:

$$g_\theta(x) = \arg\max_{c \in \mathcal{Y}} P_{\eta \sim \mathcal{N}(0,\sigma^2 I)}(f_\theta(x+\eta) = c) \tag{1}$$

Simply put, the smooth classifier returns the class c, which has the highest probability mass under the Gaussian distribution $\mathcal{N}(x, \sigma^2 I)$. If, for a given input x, the smooth classifier's output c is equal to the ground truth label y, it is said to be certifiably robust (with high probability) at x. The **certified radius**, *i.e.,* the input radius in which x's prediction is consistent, is given by:

$$\begin{aligned} CR(g_\theta; x, y) = \frac{\sigma}{2}[&\Phi^{-1}(P_\eta(f_\theta(x+\eta) = y)) - \\ &\Phi^{-1}(\max_{y' \neq y} P_\eta(f_\theta(x+\eta) = y'))] \end{aligned} \tag{2}$$

Randomized smoothing-based robustness training methods focus on maximizing the average certified radius for a given dataset (Cohen et al., 2019; Salman et al., 2019; Zhai et al., 2020; Jeong et al., 2021). Cohen *et al.* (Cohen et al., 2019), simply augmented the training data with Gaussian noise when training the base classifier. Salman *et al.* (Salman et al., 2019) modified the adversarial training objective to work in this new framework. Zhai *et al.* (Zhai et al., 2020) derived a differentiable approximation of the certified radius and directly maximized it during training. Jeong *et al.* (Jeong & Shin, 2020) find that the certified robustness of a smooth classifier can be greatly improved by enforcing the base classifier's outputs over several noisy copies of a given input to be consistent. They achieve this consistency by using a regularization loss that forces the output for a noisy copy of the input to be closer to the expected output over several noisy copies. Finally, Jeong *et al.* (Jeong et al., 2021) identified that the certified radius of the smooth classifier is aligned with its prediction confidence and used a combination of adversarial training and *mixup* (Zhang et al., 2018) to favorably calibrate the prediction confidence.

3 TRANSFER LEARNING FOR ADVERSARIALLY ROBUST ML

Commercial systems are becoming increasingly reliant on AI. However, adversarial attacks remain an ever-present issue when considering the trustworthiness of these systems. Training models with high adversarial robustness using current methods, however, requires access to large amounts of labeled data (Schmidt et al., 2018), which is hard to achieve in many deployment scenarios, even in the image domain. Except for public datasets such as ImageNet, most vision tasks may only have a handful of labeled data samples for training.

In non-robust scenarios, transfer learning is one solution to alleviate the need for abundant training data for a given task. It involves pre-training on a data-rich (source) task followed by fine-tuning on the low-data downstream task to achieve state-of-the-art performance. Unfortunately, the relationship between transfer learning and adversarial robustness has only been studied in one specific scenario, when the downstream task has abundant labeled training samples and *empirical* adversarial robustness is the property of interest. To our knowledge, there are no works that explore using transfer learning to enable the deployment of empirically robust models on small-scale datasets. Furthermore, there are no works that study the relationship between transfer learning and *certified* adversarial robustness.

We present the first comprehensive study on the utility of transfer learning towards adversarial robustness. In Section 3.1, we describe our experiment setup. In Sections 3.2 and 3.3, we examine the benefits of transfer learning in the context of empirical and certified robustness in a range of data availability scenarios. Here, we use different pre-training methods (robust and non-robust), and perform fine-tuning robustly. In Section 4, we will examine the need for robustness training during the different phases of transfer learning, *i.e.,* pre-training and fine-tuning.

3.1 SETUP

In this section, we describe our experimental setup. Additional implementation details are available in Appendix A.

Dataset and Model. For pre-training (supervised and self-supervised), we use the standard ImageNet dataset. For fine-tuning, we use a suite of 12 downstream datasets (Kornblith et al., 2019) often used in transfer learning literature. Training is done using a ResNet-50 classifier. All images are scaled to 224×224 in order to be compatible with ImageNet pre-trained weights.

Threat Model. We measure the adversarial robustness with respect to a white-box ℓ_2 adversarial attack. Our choice of adversary is motivated by the fact that randomized smoothing (Cohen et al., 2019), our choice of certified robustness method, defines robustness in the ℓ_2 space. This enables us to easily compare both adversarial metrics during evaluation.

Supervised Training. As a baseline for comparison, for every downstream task, we train a randomly initialized model using only the downstream task's labeled data. When studying the effects of transfer learning on empirical robustness, we use Adversarial Training (**AT**) (Madry et al., 2018) for baseline training, pre-training, and fine-tuning. AT uses a PGD attack with $\epsilon = 0.5$, step size = $2\epsilon/3$, and 3 steps. We note that higher values of ϵ will only result in reducing the overall performance of the models. When studying the effects of transfer learning on certified robustness, we use Consistency Regularization (**CR**) (Jeong & Shin, 2020) for baseline training, pre-training, and fine-tuning. For CR, we use $\sigma = 0.5$, number of Gaussian noise samples $m = 2$, $\lambda = 5$, and $\eta = 0.5$.

Self-supervised Training. Due to its popularity in current literature, we study the benefits of self-supervised pre-training on adversarial robustness. Unfortunately, most existing adversarially robust self-supervised methods (Jiang et al., 2020; Fan et al., 2021; Luo et al., 2022) have not been evaluated on ImageNet, but on smaller datasets instead. The one method we found that uses ImageNet (Gowal et al., 2020) does not have code publicly available. Thus, we use the SimCLR (Chen et al., 2020b) training method, a contrastive learning approach.

Evaluation. For measuring the robustness of empirically robust models during evaluation, we measure accuracy against the autoPGD attack (Croce & Hein, 2020) with $\epsilon = 0.5$, *i.e.,* robust accuracy (**RA**). Prior work (Croce & Hein, 2020) has demonstrated that AutoAttack, a more comprehensive attack for evaluating, only slightly reduces the robust accuracy (only a difference of $\mathbf{0.71}\%$ in RA computed using AutoAttack and AutoPGD) and we found AutoAttack is significantly slower.

For measuring the robustness of certifiably robust models, we use the certification process proposed by Cohen et al. (2019) and report the fraction of inputs with certified radius (Equation 2) greater than $\epsilon = 0.5$, called certified robust accuracy. Additionally, we report the average radius around an input within which the model's prediction remains consistent, denoted Average Certified Radius (**ACR**). For both evaluations, we also report the accuracy on the clean test set, *i.e.,* standard accuracy (**SA**).

3.2 EMPIRICAL ADVERSARIAL ROBUSTNESS

Prior work (Hendrycks et al., 2019; Chen et al., 2020a) have demonstrated that, unlike with standard generalization, empirical robustness benefits from transfer learning for well-represented downstream tasks. We begin our study by validating their findings and then extending them to a wider range of data availability scenarios. On a suite of 12 target tasks, we train three versions of a ResNet-50 classifier: (i) using randomly initialized weights, (ii) using pre-trained weights obtained by performing Adversarial Training (AT) (Madry et al., 2018) on ImageNet, and (iii) using pre-trained weights obtained by performing SimCLR (Chen et al., 2020b) on ImageNet. The standard accuracy (SA) and robust accuracy (RA) of the resultant classifiers are reported in Table 2.

Table 2: Evaluating the benefits of pre-training for empirical adversarial robustness. Given a target task, we train three ResNet-50 classifiers: one using random weight initialization and two using weights pre-trained on a source task (ImageNet). Pre-training is performed using supervised (adversarial training) and self-supervised (SimCLR) objectives. During fine-tuning, the full network is trained using AT. Pre-training improves empirical adversarial robustness across all target tasks.

Target Task	**Random Init.**		**Sup. Pre-Training**		**Self-Sup. Pre-Training**	
	SA (%)	**RA** (%)	**SA** (%)	**RA** (%)	**SA** (%)	**RA** (%)
Food	74.5	62.3	81.6	69.2	82.2	68.6
CIFAR-100	71.8	62.5	80.1	70.6	80.9	70.3
CIFAR-10	93.3	88.8	95.8	91.7	95.9	91.2
Birdsnap	65.2	50.8	61.8	48.3	60.4	44.4
SUN397	51.0	41.7	55.5	44.4	59.0	44.3
Caltech-256	61.4	54.4	70.6	62.5	76.8	65.4
Cars	88.3	83.0	87.9	82.2	85.8	76.1
Aircraft	76.4	68.6	77.9	69.6	76.3	64.6
DTD	54.3	48.1	65.8	59.7	72.6	58.9
Pets	73.2	63.3	86.9	78.4	88.6	74.5
Caltech-101	66.7	61.5	88.5	83.1	91.9	83.6
Flowers	78.0	72.6	93.7	90.1	93.7	86.1

First, we see that, as prior work also demonstrated (Hendrycks et al., 2019; Chen et al., 2020a), transfer learning using a model pre-trained using AT improves performance (SA) and robustness (RA) on well-represented downstream tasks (*i.e.,* CIFAR-10, CIFAR-100, and Food). However, our experiments also show that pre-training with AT improves SA and RA even on under-represented downstream tasks (*e.g.,* Flowers, Pets, and Caltech-101). On average, across all tasks, pre-training with AT improves SA and RA relative to random initialization by 11.4% and 12.6%, respectively. We also note that SimCLR pre-training yields consistent improvements in SA and RA, averaging to 14.1% and 9.9%, respectively. While improvements in SA were expected, the improvements in RA are surprising given that SimCLR, unlike other self-supervised methods we surveyed (Jiang et al., 2020; Fan et al., 2021; Luo et al., 2022), does not specifically design its objective function with adversarial robustness in mind.

We suspect that improvements in RA due to transfer learning are largely due to the overall improvement in SA rather than the robustness being "transferred" from the source task (ImageNet) to the target tasks. On Birdsnap, for example, both pre-training methods result in lower SA, which is mirrored by lower RA compared to random initialization. In Figure 2, we plot the relative increase in RA vs. the relative increase in SA due to pre-training. We observe a strong linear correlation between the two quantities for both the pre-training methods, with R^2 value of 0.98 for AT and 0.94 for SimCLR.

3.3 Certified Adversarial Robustness

To the best of our knowledge, there exist no works that explicitly study the utility of transfer learning in the context of certified adversarial robustness for either supervised or self-supervised pre-training. As before, we train three versions of a ResNet-50 classifier on each target task: (i) using randomly initialized weights, (ii) using pre-trained weights obtained by performing Consistency Regularization (CR) (Jeong & Shin, 2020) on ImageNet, and (iii) using pre-trained weights obtained by performing SimCLR on ImageNet. In order to achieve certified robustness during inference, we convert the ResNet-50 classifiers into smooth classifiers following Equation 1. The standard accuracy (SA), certified robust accuracy (RA), and Average Certified Radius (ACR) of the smooth classifiers are reported in Table 3. We compute these quantities using the prediction and certification process described by Cohen et al. (2019).

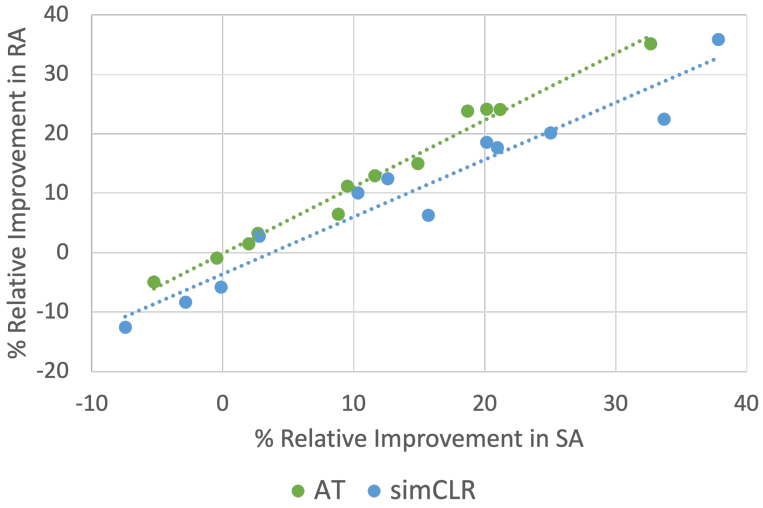

Figure 2: Plotting the improvement (%) introduced by pre-training relative to random initialization across all 12 target tasks. Improvement in RA is linearly correlated with improvement in SA for both pre-training methods, with R^2 value of 0.98 for AT and 0.94.

Table 3: Evaluating the benefits of pre-training on certified adversarial robustness. Given a target task, we train three ResNet-50 classifiers: one using random weight initialization and two using weights pre-trained on a source task (ImageNet). Pre-training is performed using supervised (consistency regularization) and self-supervised (SimCLR) objectives. During fine-tuning, the full network is trained using CR. In all three cases, training on target tasks is performed using consistency regularization. Similar to empirical adversarial robustness, pre-training improves certified adversarial robustness across all target tasks.

Target Task	**Random Init.**			**Sup. Pre-Training**			**Self-Sup. Pre-Training**		
	SA (%)	**RA** (%)	**ACR** (ℓ_2)	**SA** (%)	**RA** (%)	**ACR** (ℓ_2)	**SA** (%)	**RA** (%)	**ACR** (ℓ_2)
Food	63.0	53.9	0.891	63.2	53.5	0.874	64.4	57.6	0.923
CIFAR-100	70.0	62.8	1.075	70.8	65.2	1.101	72.8	65.0	1.089
CIFAR-10	89.6	86.0	1.508	93.4	89.2	1.601	93.2	90.4	1.619
Birdsnap	42.0	34.7	0.538	41.6	32.4	0.504	41.0	35.3	0.541
SUN397	37.0	32.5	0.519	42.3	37.4	0.586	44.1	36.2	0.585
Caltech-256	54.0	47.4	0.835	60.9	57.3	1.001	65.4	58.5	1.000
Cars	81.9	77.5	1.358	79.1	73.9	1.285	77.7	70.1	1.158
Aircraft	70.1	63.4	1.065	68.1	60.9	1.022	69.0	61.4	0.991
DTD	44.9	39.4	0.699	50.2	45.3	0.790	55.5	49.8	0.849
Pets	66.7	61.8	1.068	70.8	64.5	1.088	75.2	67.2	1.089
Caltech-101	62.8	58.3	1.019	78.6	76.0	1.339	80.3	73.7	1.300
Flowers	75.2	72.7	1.306	87.5	82.0	1.538	84.6	78.7	1.407

* The above results are generated by evaluating a smooth classifier. This entails performing the computationally expensive process of certification, which scales poorly with input dimension. Since all our datasets are ImageNet size (*i.e.,* 224×224), we follow the standard practice (Cohen et al., 2019) and perform certification using only 500 evenly spaced images in the test set.

We observe that supervised and self-supervised pre-training improves performance (SA) and certified robustness (RA and ACR) on downstream tasks. Pre-training with CR results in an average relative improvement of 7.1%, 7.5%, and 7.3% compared to no pre-training on SA, RA, and ACR, respectively. Similarly, Pre-training with SimCLR results in an average relative improvement of 9.9%, 9.1%, and 6.9% compared to no pre-training on SA, RA, and ACR, respectively. As before, we note that the improvements in RA and ACR are not necessarily due to the "transfer" of robustness of the pre-trained model. Rather, the improvement in SA seems to result in an overall increase in RA and ACR. In Figure 3, we plot both the relative improvement in SA vs. RA and SA vs. ACR from pre-training and see a strong linear correlation between these quantities. For CR pre-training, the R^2 value for linear

correlation between SA and RA is 0.92, and between SA and ACR is 0.94. For SimCLR pre-training, the R^2 value for linear correlation between SA and RA is 0.89, and between SA and ACR is 0.86.

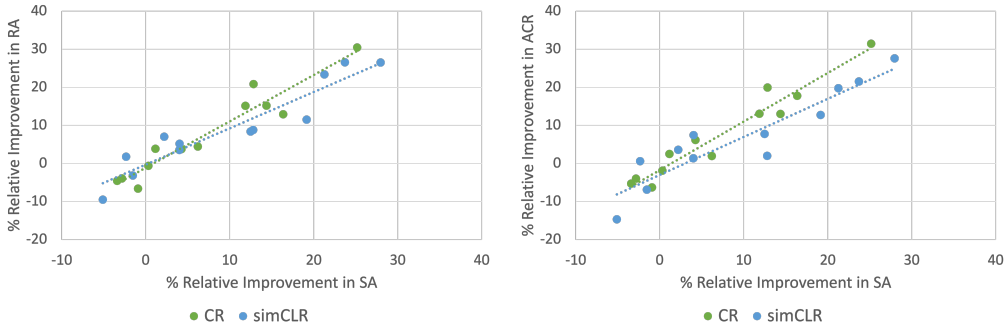

Figure 3: Plotting the improvement (%) introduced by pre-training relative to random initialization across all 12 target tasks. Improvements in both RA (left) and ACR (right) are linearly correlated with improvement in SA for both pre-training methods. For the left plot, R^2 values for CR and SimCLR are 0.92 and 0.89. For the right plot, R^2 values are 0.94 and 0.86.

4 Discussion

In Section 3, we demonstrated that a robust transfer learning pipeline is an effective method to train robust models, especially on downstream tasks with small amounts of labeled data. In fact, our self-supervised pre-training results highlight that a large **labeled** pre-training dataset is also unnecessary. However, there remains a question as to which parts of the robust transfer learning pipeline need to use robust training methods. As robust training methods impose a higher training overhead compared to non-robust training methods (Shafahi et al., 2019a; Vaishnavi et al., 2022), we perform two additional experiments to understand which parts of the transfer learning pipeline must use robust training methods.

4.1 Is Robust Pre-training Necessary?

Transfer learning is designed to improve standard performance on downstream tasks. In Section 3, we observed a strong linear correlation between improvements in SA and RA. This observation suggests that the robustness of the pre-trained model may be irrelevant. The SimCLR results provide further evidence as this training method does not optimize for robustness, and the models trained with it are not empirically or certifiably robust. Using the same experimental setup as in Section 3, we pre-train a ResNet-50 model using standard training (**ST**), *i.e.,* minimizing the cross entropy loss, which is also a non-robust pre-training method like SimCLR. We still use robust fine-tuning of the full network. In Table 4, we measure the empirical and certified robustness of models pre-trained with ST on two downstream datasets and compare it to pre-training with SimCLR and the respective robust pre-training method. We only see minor performance differences when using ST and SimCLR compared to a robust pre-training method, suggesting that robust pre-training is unnecessary for improving robustness on the downstream task.

4.2 Is Robust Fine-tuning Necessary?

In our initial experiments with a robust pre-trained model, we found that we could not use standard training and fine-tune the entire model. The resulting model exhibited neither empirical nor certified robustness as it was biased towards maximizing standard performance. However, Shafahi et al. (2019b) showed that it was possible to train an empirically robust network if standard fine-tuning was only done on the last model layer, thus freezing the rest of the model which was pre-trained using AT. The intuition is that the frozen layer of model pre-trained with AT act a robust feature extractor that can be fine-tuned non-robustly while preserving robustness. Their method results in a less robust model compared to robust fine-tuning, but is computationally more efficient. Thus, we replicate their experiments for certified robustness by first pre-training a ResNet-50 network on ImageNet using Consistency Regularization (CR) with $\sigma = 0.5$ and then fine-tuning the final layer only on CIFAR-10

Table 4: Effect of the pre-training method on empirical and certified robustness. The full network is fine-tuned using AT and CR, respectively. Robustness is not a requirement during pre-training in order to observe improvement in robustness on downstream tasks.

Task	**Empirical Robustness**			**Certified Robustness**			
	Pre-Training	**SA (%)**	**RA (%)**	**Pre-Training**	**SA (%)**	**RA (%)**	**ACR (ℓ_2)**
CIFAR-10	ST	95.4	91.2	ST	93.0	88.6	1.584
	SimCLR	95.9	91.2	SimCLR	93.2	90.4	1.619
	AT	95.8	91.7	CR	93.4	89.2	1.601
CIFAR-100	ST	78.5	68.1	ST	70.2	60.6	1.050
	SimCLR	80.9	70.3	SimCLR	72.8	65.0	1.089
	AT	80.1	70.6	CR	70.8	65.2	1.101

Table 5: Studying whether certified robustness is preserved on fine-tuning the final layer of a pre-trained model non-robustly using standard training (*i.e.,* $\sigma = 0$). Using different values of σ during training and inference causes the smooth classifier to exhibit poor SA, RA, and ACR.

Task	$\sigma = \mathbf{0.5}$			$\sigma = \mathbf{0.0}$		
	SA (%)	**RA (%)**	**ACR (ℓ_2)**	**SA (%)**	**RA (%)**	**ACR (ℓ_2)**
CIFAR-10	8.4	5.4	0.073	91.0	0.0	0.000
CIFAR-100	0.4	0.4	0.008	75.6	0.0	0.000

and CIFAR-100 using Standard Training. During inference, we convert the ResNet-50 classifier into a smooth classifier (with $\sigma = 0.5$) following Equation 1 to measure certified robustness.

In Table 5, we report the performance and robustness of our ResNet-50 classifiers when converted in a smooth classifier with $\sigma = 0.5$. We observe that on both datasets, non-robust fine-tuning of the last layer results in a classifier with trivial standard accuracy (SA), robust accuracy (RA), and average certified radius (ACR). Recall from Equation 1 that a smooth classifier g_θ performs prediction by taking majority voting over several copies of a given input x sampled from the distribution $\mathcal{N}(x, \sigma^2 I)$. Thus, the base classifier should be trained using a noisy distribution (*i.e.,* $\sigma = 0.5$). Standard fine-tuning is equivalent to training with $\sigma = 0$. Thus, the smooth classifier's performance suffers. We see that if we instead use $\sigma = 0$, the SA of the smooth classifier is restored, though it has zero RA and ACR (follows directly from Equation 2). From these results, we conclude that robust fine-tuning is a necessary step for robust transfer learning to avoid catastrophic forgetting of robustness on the downstream task. Although Shafahi et al. (2019b) demonstrate a potential alternative for this finding in context of empirical robustness, it significantly lowers the performance and robustness of the fine-tuned model, and as we demonstrated, it doesn't extend to certified robustness.

5 Conclusion

Transfer learning is traditionally used to train models with high standard generalization on tasks with insufficient labeled training data. In this paper, we showed that transfer learning can also be used to improve the adversarial robustness on downstream tasks. Although training adversarially robust models has even higher data requirements than training non-robust models, our study reveals that transfer learning can alleviate this issue. We propose a robust transfer learning pipeline composed of non-robust pre-training followed by robust fine-tuning on the downstream task. Furthermore, the pre-training step can be performed on large amounts of unlabeled data by leveraging self-supervised training methods. Across 12 downstream tasks, our robust self-supervised transfer learning pipeline improved the average empirical and certified robustness compared to no pre-training by 9.9% and 6.9% respectively. Our work also represents the first method to trained certifiably robust models on datasets with small amounts of labeled training data.

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