Pre-training also Transfers Non-Robustness

Jiaming Zhang  
Beijing Jiaotong University  
jiamingzhang@bjtu.edu.cn

Jitao Sang  
Beijing Jiaotong University  
jtsang@bjtu.edu.cn

Qi Yi  
Beijing Jiaotong University  
tinybooke@gmail.com

Huiwen Dong  
Beijing Normal University  
donghw.dhw@gmail.com

Jian Yu  
Beijing Jiaotong University  
jianyu@bjtu.edu.cn

Abstract

Pre-training has enabled many state-of-the-art results on many tasks. In spite of its recognized contribution to generalization, we observed in this study that pre-training also transfers the non-robustness from pre-trained model into the fine-tuned model. Using image classification as an example, we first conducted experiments on various datasets and network backbones to explore the factors influencing robustness. Further analysis is conducted on examining the difference between the fine-tuned model and standard model to uncover the reason leading to the non-robustness transfer. Finally, we introduce a simple robust pre-training solution by regularizing the difference between target and source tasks. Results validate the effectiveness in alleviating non-robustness and preserving generalization.

1 Introduction

Benefited from both algorithmic development and adequate training data, deep neural networks (DNNs) have achieved state-of-the-art performance across a range of tasks. However, in many real-world applications, it is still expensive or impossible to label sufficient training data. In these cases, a well-established paradigm has been to pre-train models using large-scale data (e.g., ImageNet) and then to fine-tune on target tasks. Pre-training these days is becoming the default setting not only in researches [39, 35, 21], but in many industry solutions [6, 16, 5].

What’s wrong with pre-training?  With the gradual popularization of pre-training in addressing real-world tasks, it is vital to consider beyond the accuracy on experimental data, especially for tasks with high-reliability requirements. As illustrated in Figure 1, we find in typical pre-training enabled scenarios, the fine-tuned models tend to have an unsatisfactory performance on robustness. While confidently recognizing the original input, the fine-tuned models are very sensitive to trivial perturbation and incorrectly classify the adversarial input. The success of pre-training in substantially improving generalization seems to cover its defect in decreasing robustness. In this work, we will investigate the robustness of pre-training by systematically demonstrating the performance on robustness, discuss how non-robustness is transferred, and attempt to find ways towards robust pre-training.

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2.1 Notations and Settings

Pre-training  Pre-training is commonly used to initialize the network for target task. We decompose the networks for target task into two parts: feature extractor $f$ with parameters $\theta_f$, and classifier $g$ with parameters $\theta_g$. Given an original input $x$, $f(x; \theta_f)$ denotes the mapping from $x$ to its embedding representation $e_x$, and $g(e_x; \theta_g)$ denotes the mapping from $e_x$ to its predicted label. Typical pre-training involves with two fine-tuning settings: partial fine-tuning, in which only fully connected

### Table 1: Comparison of confidence on original and adversarial inputs

| Model Type     | Confidence on Original Input | Confidence on Adversarial Input |
|----------------|------------------------------|--------------------------------|
| Standard Model | 0.99/0.80                    | 1.00/0.00                      |
| Fine-tuned Model| 0.89/0.80                    | 0.92/0.10                      |

Figure 1: Example of three typical scenarios using pre-training. Regarding the true label, the fine-tuned model obtains higher confidence on original input yet lower confidence on adversarial input than the standard model.

**How different factors influence the robustness?** Using image classification as a testing case, we compare the performance between the fine-tuned model and standard model on a series of datasets. Results suggest that pre-training contributes to both generalization improvement and robustness decrease. Inspired by the studies on generalization, we examine how the pre-trained model influences the robustness of fine-tuned model by reviewing its model capacity and task difficulty [36, 3, 1]. It is observed that limited model capacity and difficult source task basically lead to non-robust fine-tuned model.

**What transferred feature accounts for the robustness decrease?** We then delve into the reasons of the non-robustness by examining the similarities and differences between fine-tuned model and standard model. By quantifying the learned knowledge, we find that the fine-tuned model is more similar to the pre-trained model than the standard model. The difference between fine-tuned model and standard model positively correlates to the robustness decrease. Furthermore, we use Universal Adversarial Perturbation (UAP) [26, 30] as a tool to analyze what features lead to the differences and how these features affect robustness. The non-robust features in the fine-tuned model are demonstrated to be mostly transferred from the pre-trained model.

**How can we improve robustness of pre-training?** With the observation that the difference between target and source tasks largely encourages non-robust feature transfer, we are motivated to bridge the gap between the pre-trained model and target data towards robust pre-training. Specifically, we introduce steepness to measure how the features extracted from pre-trained model fit to the images of target task. A simple robust pre-training solution is then proposed by adversarially training the pre-trained model and then regularizing steepness at the fine-tuning stage. Experimental comparison validates the effectiveness of regularizing the difference between target and source tasks.

2 Pre-training Is Non-robust

2.1 Notations and Settings

Pre-training  Pre-training is commonly used to initialize the network for target task. We decompose the networks for target task into two parts: feature extractor $f$ with parameters $\theta_f$, and classifier $g$ with parameters $\theta_g$. Given an original input $x$, $f(x; \theta_f)$ denotes the mapping from $x$ to its embedding representation $e_x$, and $g(e_x; \theta_g)$ denotes the mapping from $e_x$ to its predicted label. Typical pre-training involves with two fine-tuning settings: partial fine-tuning, in which only fully connected
Table 1: Comparison of generalization and robustness between standard model, partial fine-tuned model and full fine-tuned model. For each model, we report accuracy of original inputs (AOI), accuracy of adversarial inputs (AAI), and decline ratio (DR) on 7 different target datasets.

| Model               | Pets   | NICO   | Flowers | Cars   | Food   | CIFAR10 | Alphabet |
|---------------------|--------|--------|---------|--------|--------|---------|----------|
| Standard            | AOI    | 35.98  | 65.79   | 52.61  | 26.56  | 53.98   | 86.38    | 100.00   |
|                     | AAI    | 4.93   | 26.68   | 40.27  | 3.33   | 4.76    | 50.71    | 100.00   |
|                     | DR     | 86.28  | 59.43   | 23.46  | 87.45  | 91.17   | 41.29    | 0.00     |
| Partial Fine-tuned  | AOI    | 86.45  | 91.03   | 85.44  | 35.83  | 56.39   | 78.48    | 55.54    |
|                     | AAI    | 3.38   | 10.34   | 4.90   | 0.02   | 0.50    | 0.00     | 0.00     |
|                     | DR     | 96.09  | 88.64   | 94.27  | 99.93  | 99.10   | 100.00   | 100.00   |
| Full Fine-tuned     | AOI    | 88.74  | 92.71   | 89.17  | 60.63  | 71.80   | 92.38    | 100.00   |
|                     | AAI    | 10.19  | 20.15   | 18.38  | 0.31   | 1.50    | 0.02     | 2.90     |
|                     | DR     | 88.51  | 78.26   | 79.39  | 99.48  | 97.90   | 99.97    | 97.10    |

layer corresponding to the classifier \( g(\cdot; \theta_g) \) is updated; and full fine-tuning, in which both \( f(\cdot; \theta_f) \) and \( g(\cdot; \theta_g) \) of pre-trained model are fine-tuned on the target dataset.

Adversarial robustness Adversarial robustness, i.e., robustness, measures model’s stability to adversarial example when small perturbation (often imperceptible) is added to the original input. To generate the adversarial example, given an original input \( x \) and the corresponding true label \( y \), the goal is to maximize the loss \( L(x + \delta, y) \) for input \( x \), under the constraint that the generated adversarial example \( x' = x + \delta \) should look visually similar to the original input \( x \) (by restricting \( \|\delta\|_p \leq \epsilon \)) and \( g(f(x')) \neq y \). In this work, we restrict \( \|\delta\|_{\infty} \leq \epsilon \) and set \( \epsilon = 0.5 \), and robustness is evaluated against PGD-10 attack [20] unless otherwise specified.

Dataset and experimental setting We carry out our study on several widely-used image classification datasets including Pets [29], NICO [11], Flowers [28], Cars [18], Food [4], and CIFAR10 [19]. In addition, we craft a new Alphabet dataset as comparing example with low semantic complexity and relatively sufficient training data. The Alphabet dataset is constructed by offsetting the 26 English letters and adding random noise, resulting in 1,000 training images and 200 testing images for each letter class. Example images of these datasets are illustrated in Figure 2. We use ImageNet dataset [7] as source dataset unless otherwise specified. ResNet-18 [10] backbone is employed as default architecture for pre-trained, fine-tuned and standard models. ADAM optimizer is used with a learning rate of \( 1e^{-5} \) for features extractor \( f(\cdot) \) and \( 1e^{-3} \) for classifier \( g(\cdot) \). More experimental settings are reported in Supplement A.

Figure 2: Example images of Pets, NICO, Flowers, Cars, Food, CIFAR10 and Alphabet, respectively.

2.2 Experimental Results on Robustness

To examine whether pre-training transfers non-robustness, we compare the performance of standard model, partial fine-tuned model and full fine-tuned model. Regarding adversarial robustness, we introduce decline ratio (DR) as additional evaluation metric. Given the recognition accuracy of original inputs (AOI) and adversarial inputs (AAI), DR is defined as \( DR = (AOI - AAI) / AOI \). DR serves as a more balanced indicator of model robustness than AAI, especially when two models perform quite differently on original inputs (i.e., AOI). Large DR indicates sharp accuracy decrease in case of input perturbation, and thus inferior robustness. The results of ResNet-18 backbone are summarized in Table 1. More results of ResNet-50 and WideResNet-50-2 models are shown in Supplement B.
Table 2: The performance of fine-tuned model with different pre-training architectures (from left to right, the model size increases gradually). All results are averaged over all 7 datasets.

| Model            | RN-18   | RN-50   | RN-101  | WRN-50-2 | WRN-101-2 |
|------------------|---------|---------|---------|----------|-----------|
| Model Size       | 42.7MB  | 90.1MB  | 162.8MB | 255.4MB  | 477.0MB   |
| AOI              | 79.43   | 77.48   | 82.64   | 82.30    | 83.46     |
| AAI              | 9.45    | 19.04   | 24.67   | 25.63    | 28.02     |
| DR               | 84.88   | 80.18   | 69.97   | 68.86    | 66.42     |

Table 3: The performance of fine-tuned model using different source pre-training datasets.

| Dataset          | Pets     | NICO     | Flowers  | Cars     | Food     | CIFAR10  | Alphabet |
|------------------|----------|----------|----------|----------|----------|----------|----------|
| ImageNet-R       | AOI      | 54.41    | 71.31    | 72.48    | 22.04    | 44.23    | 81.43    | 99.08    |
|                  | AAI      | 7.93     | 20.07    | 28.59    | 1.68     | 3.24     | 2.12     | 71.52    |
|                  | DR       | 85.45    | 71.85    | 60.56    | 92.38    | 92.67    | 97.40    | 27.81    |
| Alphabet-E       | AOI      | 16.46    | 44.99    | 16.15    | 4.71     | 38.04    | 80.17    | 100.00   |
|                  | AAI      | 8.56     | 24.32    | 7.76     | 2.01     | 12.34    | 36.55    | 100.00   |
|                  | DR       | 48.01    | 45.95    | 51.96    | 57.26    | 67.57    | 54.41    | 0.00     |

It is shown that: (1) For most of the examined datasets, fine-tuned models (both partial fine-tuned and full fine-tuned) achieve better generalization (AOI), but worse robustness (AAI and DR) than standard model. This demonstrates that pre-training not only improves the ability to recognize original input of target task, but also transfers non-robustness and makes the fine-tuned model more sensitive to adversarial perturbation. (2) Within the two pre-training settings, full fine-tuning consistently obtains better robustness as well as generalization than partial fine-tuning setting. This suggests that full fine-tuning is preferable when employing pre-training in practical applications to alleviate the decrease in robustness. In the rest of the paper, we deploy full fine-tuning as the default pre-training setting. (3) For CIFAR10 and Alphabet when standard models trained on target dataset already achieve good AOI, pre-training contributes to trivial improvement on generalization (even with decreased AOI when partially fine-tuned on CIFAR10) but severe non-robustness to the fine-tuned model. In this view, instead of improving fine-tuned model, pre-training actually plays a role as poisoning model [15, 24]. This further demonstrates the risk of arbitrarily employing pre-training and the necessity to explore the factors influencing the performance of pre-training in subsequent target tasks.

2.3 Factors Influencing Robustness of Fine-tuned Model

To provide more guidelines in practically employing pre-training for robust target tasks, this subsection studies how the training of pre-trained model influences the robustness of fine-tuned model. A simple hypothesis is that: when the model capacity is too limited or the source task is too difficult, the pre-trained model itself tends to rely more on non-robust features and represents more risk to affect the robustness of fine-tuned models. The following reports our observations in view of pre-trained model’s capacity and the source task difficulty.

2.3.1 Pre-trained Model Capacity

We employ network size as example to examine the influence of model capacity. Table 2 shows the results for 5 ResNet-based backbones as pre-training architecture: ResNet-18 (RN-18), ResNet-50 (RN-50), ResNet-101 (RN-101), WideResNet-50-2 (WRN-50-2), and WideResNet-101-2 (WRN-101-2). It is easy to find that as network size increases, both the generalization and robustness consistently improve (with DR value decreasing from 84.88 to 66.42). This indicates that the high capacity of the pre-trained model alleviates the non-robustness transfer to the fine-tuned models.

2.3.2 Source Task Difficulty

Task difficulty largely depends on the dataset. In this work, we measure task difficulty as the amount of semantics in the dataset necessary to solve the task. Specifically, we select 2 source datasets
with very different amount of semantics for comparison: reduced ImageNet (ImageNet-R) and expanded Alphabet (Alphabet-E) with the equal number of training images (200,000 images). The performance of fine-tuning on different target datasets is reported in Table 3. It is unsurprising that employing ImageNet-R as pre-training dataset gives rise to fine-tuned models with higher AOL. However, the fine-tuned models transferred from Alphabet-E achieves lower DR (better robustness), which indicates that the source dataset with more semantics improves generalization yet has more risk to transfer non-robustness. Therefore, the guideline in selecting source dataset for robust fine-tuned models seems not that straightforward. Uncovering the paradox between generalization improvement and robustness decrease of pre-training needs to further examine the similarities and differences between fine-tuned model and standard model.

3 Difference between Fine-tuned Model and Standard Model

3.1 On the Learned Knowledge

To understand the performance difference between the fine-tuned model and standard model, we start from examining their learned knowledge. Motivated by many studies on model knowledge measurement [31, 27, 22, 37, 17, 23], we employ a recognized metric, SVCCA [31], to quantify the representation similarity between two networks by finding permutations of neurons with maximal correlation. Specifically, feature extractor \( f(\cdot; \theta_f) \) consists of 4 layers, and we compare the SVCCA value between fine-tuned model and standard model using the output of bottom-layer feature (only \( \text{conv}^2 x \)) and the output of total feature extractor (considering features of all 4 layers) respectively. More detailed experimental settings are reported in Supplement C.

As shown in Figure 3, the fine-tuned model is more similar to the pre-trained model than to the standard model, both on bottom-layer and all-layer features for all the examined datasets. Since the pre-trained model and standard model are trained on source dataset and target dataset separately, this result seems to tell that more knowledge learned in the fine-tuned model is transferred from the source task data, than from the fine-tuning target task data. By further comparing Figure 3(a) with Figure 3(b), we find that the bottom-layer features of the fine-tuned model and standard model are relative similar than all-layer features, suggesting that the bottom-layer features (e.g., edges, simple textures) extract some shared semantics between the source and target tasks. This on one hand justifies the role of initialization of pre-training and its contribution to generalization improvement, on the other hand partially explains the result in Section 2.3.2 that difficult source dataset is capable of learning more semantics and thus sharing with target tasks.

We then investigate how the difference on the learned knowledge relates to the robustness decrease. Figure 4 compares the DR value of fine-tuned model (from Table 1) with the SVCCA value between fine-tuned model and standard model (from Figure 3(b)). We can see that basically DR and SVCCA value are in a negative correlation, i.e., the more different fine-tuned model is from standard model, the more non-robust the fine-tuned model is. Combing with the above observation that fine-tuned model learns knowledge more from the source task, we draw a rough conclusion that the deviation of the target task from the source task largely affects the robustness of fine-tuned model.
3.2 On Non-robust Features

In this subsection, we investigate what features lead to the difference in learned knowledge and how these features affect robustness. In particular, Universal Adversarial Perturbation (UAP) is employed as the feature probe. Different from standard adversarial perturbation which is sample-specific, UAP is fixed for a given model misleading most of the input samples. Therefore, UAP is model-dependent and can be used to explore the features that the model relies on and understand the model behavior [30, 43]. Figure 5(a) illustrates the UAP for fine-tuned and standard models on the crafted Alphabet dataset. It is shown that UAP of fine-tuned model expresses no semantics. Relying on these noise-alike features, fine-tuned models are more vulnerable to adversarial attacks. In contrast, the UAP of standard model contains clear semantics related to the attack class. Combining with the example adversarial images in Figure 5(b), we can see that misleading the standard model is non-trivial and needs to add more human-perceptible information (e.g., edge of "A"). This coincides with the superior robustness of standard model than fine-tuned model.

Figure 6: UAP attack results: (a) Using UAP of fine-tuned model and standard model to attack themselves at different training batches (on Alphabet). (b) Using UAP of pre-trained model to attack the fine-tuned model and standard model (on other datasets).
Next, we employ UAP to examine how the non-robust features are learned. Since the premise behind successful UAP attack is that the models actually extract the corresponding features, we are motivated to use the above obtained UAP to attack model during its training process to observe when the non-robust features are learned. As shown in Figure 6(a), we record the attack success rate (i.e., the perturbated images are misclassified as the attack letter) at different training batches for the fine-tuned model and standard model respectively. It is easy to perceive that the attack success rate of fine-tuned model remains at a very high level at the very beginning of training. This indicates that these non-robust features are more likely to be transferred from the pre-trained model than learned from the target data. Other observation includes that the UAP of fine-tuned model has a much stronger attack ability than that of standard model, which again demonstrates the inferior robustness of fine-tuned model compared with standard model.

We conduct further experiments to confirm whether the non-robust features are transferred from the source task. The idea is to generate UAP on the pre-trained model, and then use this UAP to attack the fine-tuned and standard model on different target tasks. The DR value is reported in Figure 6(b), showing the obvious robustness decrease for the fine-tuned model and trivial influence to the standard model. Note that UAP is model-dependent, the fact that UAP of pre-trained model succeeds in attacking the fine-tuned model validates our assumption that pre-training transfers non-robust features.

It has been recognized that the knowledge and features pre-training transfers are semantic-oriented [42, 9]. We find from the above analysis that pre-training transfers not only semantic but also non-robust features. Recent studies suggested that non-robust features can help to improve generalization [13] and belong to so-called "shortcut" features [8]. We speculate that the transferred non-robust features in pre-training also contributes to the generalization improvement, but imposes robustness problem at the same time. The difference between the target task and source task encourages the non-robust features transfer and increases the risk for robustness decrease.

## 4 Robust Pre-training via Steepness Regularization

In Section 2, we demonstrate that pre-training not only improves generalization but also transfers non-robustness. As recognized in previous studies [42, 9, 12], the fine-tuned model tends to obtain good initialization and generalization when the target and source tasks are similar. In our view, the improvement probably owes to the similarity that transfers semantic-oriented features to the fine-tuned model. In Section 3, we observe that the difference between target and source tasks encourages the transfer of non-robust features which largely account for the robustness decrease in fine-tuned model. Inspired by this, if we can constrict the difference between target and source tasks, it is expected that non-robust features are discouraged to alleviate robustness decrease and at the same time semantic features are reserved to guarantee generalization. In this section, we first introduce a trainable metric to quantify the difference between target and source tasks, and then design a simple method to employ the metric towards robust pre-training.

### 4.1 Steepness of Feature Space

Since pre-training essentially serves as feature extractor for the target task, we propose to measure the difference by examining how the features extracted from pre-trained model fit to the images of target task. Specifically, steepness of feature space is a recognized property closely related to model robustness [41]. Local Lipschitz Function (LLF) is typically used to calculate steepness as following:

$$
\text{LLF}(f(x)) = \frac{1}{n} \sum_{i=1}^{n} \frac{\|f(x_i) - f(x'_i)\|_1}{\|x_i - x'_i\|_\infty}
$$

where \(n\) denotes the number of images, \(x\) is original image, and \(x'\) is the corresponding adversarial image constructed by solving the following optimization problem:

$$
\max_{x'} \text{LLF} \quad \text{s.t.} \|x'_i - x_i\|_\infty \leq \epsilon
$$

The lower value of LLF implies smoother feature space is usually with good robustness. We use ImageNet and Alphabet datasets as example to respectively train pre-trained models \(f^I(\cdot)\) and \(f^A(\cdot)\), and then use them to extract features for images \(x^A\) from Alphabet dataset. \(\text{LLF}(f^I(x^A))\) and
Table 4: Comparison results of robust pre-training.

| Method          | Pets   | NICO   | Flowers | Cars   | Food   | CIFAR10 | Alphabet |
|-----------------|--------|--------|---------|--------|--------|---------|----------|
| AOI             | 88.74  | 92.71  | 89.17   | 60.63  | 71.80  | 92.38   | 100.00   |
| AAI             | 10.19  | 20.15  | 18.38   | 0.31   | 1.50   | 0.02    | 2.90     |
| DR              | 88.51  | 78.26  | 79.39   | 99.48  | 97.90  | 99.97   | 97.10    |
| Full Fine-tuned |        |        |         |        |        |         |          |
| AOI             | 40.28  | 91.55  | 90.71   | 68.09  | 70.38  | 85.50   | 99.98    |
| AAI             | 21.37  | 31.97  | 42.06   | 4.75   | 5.43   | 44.28   | 74.53    |
| DR              | 75.64  | 65.19  | 53.63   | 93.02  | 92.71  | 53.17   | 10.48    |
| KD@fine-tuning  |        |        |         |        |        |         |          |
| AOI             | 86.02  | 92.31  | 86.23   | 61.87  | 70.48  | 95.78   | 99.94    |
| AAI             | 75.44  | 83.93  | 77.98   | 45.49  | 44.50  | 66.10   | 99.31    |
| DR              | 12.29  | 9.07   | 9.56    | 26.47  | 36.85  | 30.98   | 0.63     |
| AT@fine-tuning  |        |        |         |        |        |         |          |
| AOI             | 86.48  | 91.71  | 87.17   | 64.83  | 70.04  | 95.62   | 99.96    |
| AAI             | 77.73  | 85.50  | 81.41   | 53.46  | 47.93  | 88.63   | 99.90    |
| DR              | 10.11  | 6.77   | 6.60    | 17.53  | 31.56  | 7.31    | 0.05     |
| AT@pre-training |        |        |         |        |        |         |          |
| AOI             |        |        |         |        |        |         |          |
| AAI             |        |        |         |        |        |         |          |
| DR              |        |        |         |        |        |         |          |
| robustPT        |        |        |         |        |        |         |          |

LLF($f^A(x^A)$) thus represent how ImageNet-trained and Alphabet-trained features fit to the Alphabet images. The result is LLF($f^I(x^A)$) = 367.4 and LLF($f^A(x^A)$) = 32.9, indicating that the features pre-trained from ImageNet fail to fit to the Alphabet images. Note that this result is compatible with the DR value in the last column of Table 3. This relation between steepness and robustness motivates us to regularize steepness for robust pre-training.

4.2 Steepness Regularization

We propose to reduce the steepness of pre-trained feature space on the target samples to alleviate the influence of the difference between target and source tasks. Specifically, in addition to the traditional fine-tuning loss, LLF regularization term is added to derive the following objective function:

$$\min_{\theta_f, \theta_g} C(x, g(f(x))) + \lambda \cdot \text{LLF}(f(x))$$

(3)

where $C$ is the cross-entropy classification loss, LLF($f(x)$) is the steepness regularization term as defined in Equation (1), and $\lambda$ is the balancing parameter to control the trade-off between generalization and robustness. The above optimization problem can be easily solved by PGD-like procedure.

To evaluate the effectiveness of steepness regularization in robust pre-training, we consider several baselines for comparison. Basically speaking, to improve the robustness of fine-tuned model involves with the two stages of fine-tuning and pre-training. Shafah et al. [33] conducted one pilot study to investigate the robustness problem in transfer learning. They implemented knowledge distilling at the fine-tuning stage to improve robustness. We implemented this method as the compared robust solution at the fine-tuning stage (denoted as KD@fine-tuning). Adversarial training [25] also provides an alternative way to improve robustness at the fine-tuning stage. We implemented adversarial training on the fine-tuned model to provide another solution at the fine-tuning stage (denoted as AT@fine-tuning). Salman et al. [32] introduced adversarial training into the pre-training stage. We implemented this method as the compared solution at the pre-training stage (denoted as AT@pre-training). Our proposed robust pre-training solution (denoted as robustPT) combines the two stages: at the pre-training stage we employ adversarial training as in [32] to obtain a robust pre-trained model, and at the fine-tuning stage we fine-tune on the target dataset according to Equation (3) to reduce the feature space steepness caused by the difference between target and source tasks.

The experimental results of ResNet-18 backbone are shown in Table 4. More results of ResNet-50 and WideResNet-50-2 models are shown in Supplement D. We have the following main findings:

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3The authors in this study attribute non-robustness to the forgetting knowledge from pre-trained model to the fine-tuned model. However, according to our observation, the transferred non-robust features resulted from the difference between target and source tasks should account for the non-robustness.
Regarding robustness, robustPT achieves superior AAI and DR in 6 of the 7 examined datasets, owing to regularizing the transferred feature space steepness; (2) Regarding generalization, robustPT guarantees performance as compared to the original fine-tuned model, and achieves comparable if not better performance than the baseline methods. This demonstrates the feasibility of regularizing the difference between target and source tasks in addressing the paradox between pre-training robustness and generalization.

5 Conclusion and Discussion

Conclusion In this work, we demonstrate that pre-training indeed transfers non-robustness. Using image classification as example, we first explore the influencing factors of model capacity and task difficulty to provide some practical guidelines for robust pre-training settings. Then we discuss the reason of robustness decrease that the difference between target and source tasks encourages the transfer of non-robust features from pre-trained model to fine-tuned model. Finally, we introduce a simple yet effective robust pre-training solution by regularizing the steepness of pre-trained feature space on target dataset. Experimental results further validate the role of target-source task difference in transferring non-robustness.

Discussion The practical and reliable employment of pre-training concerns more than accuracy. In addition to robustness, we are also interested to explore how pre-training affects interpretability. As illustrated in Figure 7, pre-training tends to deviate the model saliency map from the object of interest. We attribute this also to the difference between target and source tasks, and directly employ robustPT to modify the pre-training process. It is shown that mitigating the target-source task difference also contributes to improved interpretability of fine-tuned model, which also coincides with the recent discussions on the connection between robustness and interpretability [34]. More results are available in the supplementary material.

This paper studies pre-training as the example paradigm of transfer learning. Also of vital importance is to examine the reliability of other transfer learning paradigms like knowledge distillation and domain adaption. A particular phenomenon is the non-reliability accumulation in iterative transfer learning. For example, there has been an increasing attempt to automatically label data by a well-trained model [40, 44, 38, 14]. Since it is difficult to tell whether the data is labeled by human or by model, there exists a risk to iteratively transfer the pseudo label from one to another model. Without human intervention to correct the potentially faulty knowledge, the continuous transfer of knowledge among models likely leads to the so-called “echo chamber” situation in sociology [2]. As observed in this work, one single round of knowledge transfer can contribute to considerable reliability issues, and iterative transfer may result in catastrophic results. In summary, many works remain to explore the mechanisms behind non-reliability transfer, and we are working towards developing more reliable transfer learning solutions.

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