Robustified Domain Adaptation

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Abstract

Unsupervised domain adaptation (UDA) is widely used to transfer a model trained in a labeled source domain to an unlabeled target domain. However, with extensive studies showing deep learning models being vulnerable under adversarial attacks, the adversarial robustness of models in domain adaptation application has largely been overlooked. In this paper, we first conducted an empirical analysis to show that severe inter-class mismatch is the key barrier against achieving a robust model with UDA. Then, we propose a novel approach, Class-consistent Unsupervised Robust Domain Adaptation (CURDA), for robustified unsupervised domain adaptation. With the introduced contrastive robust training and source anchored adversarial contrastive loss, our proposed CURDA is able to effectively conquer the challenge of inter-class mismatch. Experiments on two public benchmarks show that, compared with vanilla UDA, CURDA can significantly improve model robustness in target domains for up to 67.4% costing only 0% to 4.4% of accuracy on the clean data samples. This is one of the first works focusing on the new problem of robustifying unsupervised domain adaptation, which demonstrates that UDA models can be substantially robustified while maintaining competitive accuracy.

1. Introduction

Unsupervised domain adaptation (UDA) is often used to transfer a machine learning model trained with data from a source domain to a target domain, where annotation labels are not available in the latter domain for direct supervised training or adaptation [33]. UDA attempts to generalize the model performance from labeled source domain to the unlabeled target domain by reducing the domain shift, which is commonly achieved by aligning source and target domain data distributions [2, 31]. UDA based methods have been successful in transferring knowledge obtained in a source domain to a target domain in many applications [13, 38, 37]. However, it has come to our attention that the existing UDA methods overlook the network stability issues and thus the adapted deep learning model can be highly unstable even the model is robustified in the source domain.

Adversarial robustness of deep learning models has been intensively studied in the past few years. Many works have shown that deep learning models are vulnerable to adversarial examples that contain imperceptible perturbations specifically designed to attack trained models [30, 10, 36]. To address this issue, various robust training approaches have been proposed trying to make deep learning models immune to adversarial attacks. While many of these approaches perform well, they assume that adversarial samples in the training and testing phases are all generated from normal or so-called clean samples under a same distribution, i.e., in a same domain. When such an assumption is violated, as in our above-mentioned case of UDA, the robustness may not be transferred together with the gained knowledge. As shown in Fig. 1a, when a well-trained robust model from a source domain (referred as source-robust model) is applied to a related but different target domain, a shift of the data distribution between the domains would degrade the model’s performance in the target domain, as reported by the abundant literature [2, 9, 33]. Obviously, the source-robust model would be vulnerable to the adversarial samples generated from the target domain data.

One straightforward solution to the above problem may be to apply UDA on the source-robust model instead in the hope of transferring the robustness to the target domain. However, our empirical study shows that even though aligning the data distributions of the two domains by using UDA can improve the model performance on the clean samples from the target domain, the performance on the adversarial examples, i.e., the model robustness in the target domain, doesn’t get better because of the lack of robustness constraint as shown in Fig. 1b. The relevant experimental results are presented in Section 4.4.

Another possible way of dealing with the problem of
model instability in a target domain is to use label-free robust training [15, 36], which improves models’ robustness by constraining the difference in predictions between corresponding clean- adversarial sample pairs. However, incorporating target domain robust training into UDA would further complicate the issue and worsen the situation. Without data labels in the target domain, existing domain adaptation methods rely on narrowing the discrepancy between the data distributions of the two domains. It may cause inter-class mismatch, where the overall distributions of the two domains are aligned but the feature representations of different classes from the source and target domains may be matched together as illustrated in Fig. 1c. Furthermore, the label-free robust training methods generally increase the model’s robustness by regularizing the prediction consistency between clean-adversarial pairs with distance metrics, such as KL-divergence or L2 distance. As the adversarial samples are intentionally generated to fool the model, such a robust regularization term may encourage the model to map clean samples into wrong locations and thus cause severe mismatch.

In this paper, to tackle the challenging problem of robust unsupervised domain adaptation, a new method called Class-consistent Unsupervised Robust Domain Adaptation (CURDA) is proposed. First, we propose Contrastive Robust Training (CORTrain) in source domain to train a source-robust model, which can map input images into a more discriminative space, where the intra-class distance is significantly smaller than the inter-class distance. As features in this discriminative space are pushed away from the decision boundary, the inter-class mismatch can be alleviated during UDA. Second, we introduce a Source Anchored Adversarial (SAA) contrastive loss to conduct class-aware adversarial domain alignment during UDA. SAA-contrastive loss is a specified contrastive loss, where source domain representations are used as fixed anchors and target domain representations are pulled to or pushed away from anchors depending on whether their potential labels. Since target domain labels are not available in UDA, we further propose a strategy to generate pseudo labels in target domain for SAA-contrastive loss. Fig. 2 shows an overview of the architecture of CURDA.

We validated the proposed CURDA on two public UDA benchmarks, 1) DIGITS benchmark (MNIST, USPS and MNIST-M) and 2) CIFAR-STL benchmark (CIFAR10 and STL10). The experimental results show that CURDA can efficiently align both unlabeled target clean and adversarial samples to their corresponding classes, which brings a great improvement of model’s robustness in target domain while maintaining competitive accuracy on target clean data. Major contributions of our work are summarized as follows.

1. To the best of our knowledge, this is the first work focusing on robust unsupervised domain adaptation. With empirical analysis, we show that robustifying UDA is a valuable but challenging problem due to the lack of target labels and the existence of inter-class mismatch.
2. We propose a new method of Class-consistent Unsupervised Robust Domain Adaptation (CURDA) with Contrastive Robust Training (CORTrain) on source domain and a Source Anchored Adversarial contrastive loss (SAA-contrastive loss) for robust UDA.
3. The evaluation results on two public benchmarks (DIGITS and CIFAR-STL) demonstrate that the proposed CURDA can achieve strong robustness yet with competitive classification accuracy.
a. Contrastive Robust Training (CORTrain) in Source Domain

![Diagram of Contrastive Robust Training (CORTrain) in Source Domain]

b. Adaptation to Target Domain

![Diagram of Adaptation to Target Domain]

Figure 2: The architecture of the proposed Class-consistent Unsupervised Robust Domain Adaptation (CURDA).

2. Related work

Unsupervised Domain Adaptation (UDA). UDA aims at generalizing the model from labeled source domain to unlabeled target domain by reducing domain shift. Ben-David et al. [2] first provided upper bounds on a domain-adapted classifier in the target domain. Subsequently, Mansour et al. [23] extend the theory in [2] to handle the case of multiple source domains. In practice, the domain discrepancy is measured by the maximum mean discrepancy (MMD) [3] in [32, 20]. In addition, the deep correlation alignment (Deep CORAL) [29] minimizes the domain discrepancy by matching the mean and covariance of different domains. Recent UDA methods train deep neural network (DNN) encoders that can extract domain-invariant features shared by both domains. Ganin et al. [9, 8] proposed domain adversarial neural networks (DANN) using adversarial training to find domain-invariant representations by a single DNN encoder. In comparison, also with adversarial training, Adversarial discriminative domain adaptation (ADDA) network [31] maps source and target samples to a domain-invariant representation space with two different DNN encoders.

Adversarial attack and defense. Szegedy et al. [30] first reported that deep neural networks can be fooled by adversarial examples (AE), which heralded the era of adversarial attacks and model robustness for deep learning. Fast gradient sign method (FGSM) [10] was soon proposed to efficiently find such AE. Meanwhile, in the same paper [10], Goodfellow et al. also proposed robust training that introduce AE into DNN training to defense such adversarial attacks. More effective attack and defence approaches, including C&W [4], PGD [21], BIM [17], MIM [7], DeepFool [25], and JSMA [26], were later proposed to identify the instabilities of deep neural networks, which further encourage the area.

As most of robust training approaches requires labels, the first label-free robust training strategy, adversarial logit pairing (ALP), is proposed by Kannan et al. [15]. It applies an additional loss term that constraints the pairwise logit feature distance between a clean sample and adversarial sample. Further, Zhang et al. [36] proposed tradeoff-inspired adversarial defense via surrogate-loss minimization (TRADES) which separates model accuracy on clean data and model robustness into two loss terms based on theoretical derivation. Label-free robust training approaches has been utilized in semi-supervise learning to train robust models [1, 5]. In our work we also apply one of label-free robust training approaches to enhance the model robustness on target domain.

Metric learning for model robustness. Our work is also related to the metric learning methods that explicitly enforce intra-class compactness and inter-class separabil-
ity of the extracted features. Two of the widely used metric learning strategies are contrastive loss [11] and triplet loss [28]. Several previous works have applied these metric learning methods in adversarial attack and defense [24, 19] and unsupervised domain adaptation [14]. Our proposed SAA-contrastive loss can be considered as a novel variant of contrastive loss to align target clean and adversarial samples with their corresponding source class samples.

3. Method

This section presents the problem formulation and details of the proposed Class-Consistent Unsupervised Robust Domain Adaptation (CURDA). The overall architecture of CURDA is shown in Fig. 2.

3.1. Problem Formulation and Overview

We begin with formulating the task of robust unsupervised domain adaptation. Let \( S = \{ (x_1, y_1), ..., (x_{N_S}, y_{N_S}) \} \) denote a labeled source domain dataset and \( T = \{ x'_1, ..., x'_{N_T} \} \) denote an unlabeled target domain dataset, where \( x \) represents an input data sample and \( y \) represents a label. The goal of robust UDA is to train a network, which can not only perform well on clean inputs \( x \) but also be robust against adversarial attacks \( x' \) at test-time on the target domain data \( T \). Here, \( x' = x + \eta \) denotes an adversarial sample of \( x \), where \( \| \eta \|_p < \epsilon \) is an imperceptible perturbation. As this paper focuses on classification tasks, we use \( y \in \{1, ..., M\} \) to denote a data label of \( M \) classes.

Fig. 2 shows the architecture of the proposed CURDA for tackling this problem with two major steps. First, an enhanced source-robust model including a source encoder \( E_s(\cdot) \) and a classifier \( C(\cdot) \) is trained by Contrastive Robust Training (CORTrain) in the source domain. Then, a target encoder \( E_t(\cdot) \) is initialized from the trained source encoder and adapted to the target domain through minimizing a joint loss consisting of Source Anchored Adversarial contrastive loss (SAA-contrastive), label-free robust consistency loss, and domain discriminative loss. Assembling \( E_t(\cdot) \) and \( C(\cdot) \) together leads to a robust target classification model \( C(E_t(\cdot)) \).

3.2. Contrastive Robust Training

As we discussed earlier in Section 1, inter-class mismatch is a key problem to be solved in order to achieve robust UDA. As the first step of CURDA shown in Fig. 2a, the proposed Contrastive Robust Training (CORTrain) incorporates contrastive loss into the robust training process of a deep learning model to reduce the inter-class mismatch in the source domain.

Specifically, an adversarial sample \( x'^s \) of a labeled source sample \( x^s \) can be generated by a supervised adversarial sample generator. Projected gradient descent (PGD) [21] attack is adopted in our work. Then two losses, the cross entropy loss \( \mathcal{L}_{ce} \) and the contrastive loss \( \mathcal{L}_{saa} \), are minimized on input samples \( x^s \) and corresponding labels \( y^s \) to train the classifier while constraining the intra-class compactness and inter-class sparsity. The cross entropy loss, \( \mathcal{L}_{ce} = - \sum_{i=1}^{M} \mathbb{1}[y_i=y^s] \log C(E_s(x^s)) \), guides \( C(E_s(\cdot)) \) to map the adversarial sample onto the right label. The contrastive loss imposes constraint on the encoded representations \( E_s(x'^s) \) to minimize the intra-class distance and maximize the inter-class distance. For a pair of samples in a mini-batch, \( \{(x_i^s, y_i^s), (x_j^s, y_j^s)\} \), the contrastive loss is defined as

\[
\mathcal{L}_{saa} = \frac{1}{2} \left[ \mathbb{1}[y_i^s=y_j^s] D_r^2 + \mathbb{1}[y_i^s \neq y_j^s] \max(0, m_s - D_r)^2 \right] \quad (1)
\]

where \( D_r = ||E_s(x_i'^s) - E_s(x_j'^s)||_2 \) is the Euclidean distance between two feature representations, and \( m_s > 0 \) is a margin to prevent over-fitting. The full loss function for CORTrain is given by \( \mathcal{L}_{corr} = \mathcal{L}_{ce} + \lambda_{con} \mathcal{L}_{saa} \) where \( \lambda_{con} \) is a positive weighting parameter.

3.3. Source Anchored Adversarial Contrastive Loss

Applied on the output of encoders \( E_s(\cdot) \) and \( E_t(\cdot) \), Source Anchored Adversarial (SAA) contrastive loss aims to conquer inter-class mismatch by aligning the representations of both target clean and adversarial samples with the representations of corresponding classes in the source domain, as shown in the SAA-contrastive Loss block in Fig. 2b. It is worth noting that the SAA-contrastive loss uses source representations as anchors and only optimizes the inter- and intra-class distances between target domain representations (of both clean and adversarial samples) and source domain representations. During the process, the source domain encoder \( E_s(\cdot) \) is frozen. This is different from the standard contrastive loss, where the distances between any data pairs are used for constraining losses. In our work, SAA contrastive loss is defined as

\[
l(u,v,y_u,y_v) = \begin{cases} 
    D(u,v)^2, & \text{if } y_u = y_v \\
    \max(0, m_t - D(u,v))^2, & \text{if } y_u \neq y_v 
\end{cases} \quad (2)
\]

where \( D(\cdot, \cdot) \) denotes the Euclidean distance and \( m_t > 0 \) is a margin to prevent over-fitting. The full SAA-contrastive loss is formulated as

\[
\mathcal{L}_{saa} = \mathbb{E}_{(x^s, y^s) \sim \{S,T\}} \left[ l(E_s(x^s), E_t(x^s), y^s, \hat{y}) + l(E_s(x'^s), E_t(x'^t), y^s, \hat{y}' \} \right], \quad (3)
\]

where \( \hat{y}' \) denotes pseudo labels (details are discussed at the end of this section), \( x'^t \) denotes an adversarial sample of a target clean sample \( x^t \), which is generated by a label-free adversarial sample generator based on \( C(E_t(x^t)) \). In our
paper, we used the adversarial sample generator proposed in [36]. From Eq. (3), we can see that SAA-contrastive loss does not directly optimize any distance between \(x_t\) and \(x_{t}^\prime\). This prevents adversarial samples from dragging clean samples towards wrong class centers when no data annotation labels are available.

Since target labels are not available during UDA, to provide \(\hat{y}_t\) for SAA-contrastive loss, we introduce a strategy to generate pseudo labels for target samples. In the first \(\tau\) iterations of adaptation training, the performance of \(E_t(\cdot)\) may be unstable, so the source-robust model \(C(E_s(\cdot))\) with frozen parameters is used for pseudo label generation. To reduce the noise in the pseudo labels, only predictions with the largest softmax scores greater than a specific threshold \(P_{\text{pseudo}}\) are preserved. Samples with their largest softmax scores less than \(P_{\text{pseudo}}\), indicating uncertain estimation, would not be included in the SAA-contrastive loss. After the first \(\tau\) iterations, when the target encoder \(E_t(\cdot)\) becomes stable, the target domain model \(C(E_t(\cdot))\) is switched to generate pseudo labels. Note that the parameters of the classifier \(C(\cdot)\) remain fixed during the process no matter \(E_s(\cdot)\) or \(E_t(\cdot)\) is used.

### 3.4. Other Losses

Since SAA-contrastive loss uses only target samples with credible pseudo labels, we further include standard UDA and label-free robust training losses in the adaptation step of CURDA to make full use of all the unlabeled samples in the target domain. For UDA, domain discriminative losses proposed in ADDA [31] are used. The corresponding loss function used to train the domain discriminator \(D_{\text{dom}}(\cdot)\) is formulated as

\[
\mathcal{L}_{\text{dom}} = -\mathbb{E}_{x_t \sim S}[\log D_{\text{dom}}(E_s(x_t))] - \mathbb{E}_{x_t \sim T}[\log(1 - D_{\text{dom}}(E_t(x_t)))].
\]  

(4)

The target domain encoder \(E_t(\cdot)\) is trained by optimizing the loss function of

\[
\mathcal{L}_{\text{dis}} = -\mathbb{E}_{x_t \sim T}[\log D_{\text{dom}}(E_t(x_t))].
\]  

(5)

For label-free robust training, we applied the robustness regularization term presented in [36] as \(\mathcal{L}_{\text{trade}} = -\mathbb{E}_{x_t \sim T} KL(C(E_t(x_t)), C(E_t(x_t)))\) where \(KL(\cdot, \cdot)\) denotes the Kullback-Leibler divergence. With the SAA-contrastive loss pulling target samples towards source samples of the same classes, the inter-class mismatch problem caused by the label-free robust training loss can be greatly alleviated. Therefore, the loss can instead increase the model robustness in the target domain. The overall loss function for the adaptation step of CURDA is summarized into \(\mathcal{L}_{\text{curda}} = \lambda_{\text{saa}}\mathcal{L}_{\text{saa}} + \mathcal{L}_{\text{dis}} + \mathcal{L}_{\text{trade}},\) where \(\lambda_{\text{saa}}\) is positive weighting parameters.

### 4. Experiments

The proposed method of CURDA for robust UDA were evaluated across two public benchmarks, handwritten digits recognition and natural image classification, on both domain adaptation and adversarial defense. Models were evaluated in both clean data classification accuracy (referred as accuracy for conciseness) and adversarial robustness (referred as robustness) in target domain. This section mainly consists of two parts. First, quantitative experiments and qualitative visualizations are conducted on the two benchmarks to compare CURDA with three baseline models. Second, thorough ablation studies are applied on the digits recognition benchmark to evaluate the effectiveness of each proposed component in CURDA. In all of our quantitative analysis, robustness is evaluated by the classification accuracy on the adversarial samples.

#### 4.1. Datasets

All of our experiments follow the standard experimental setups in UDA [31, 8, 14], models are first trained on a labeled source domain dataset and then tuned on an unlabeled target domain dataset. The obtained models are validated on the same unlabeled target domain dataset.

**Handwritten Digits Recognition.** benchmark (DIGITS) includes three distinct domains commonly used for domain adaptation evaluation, i.e., MNIST [18], USPS [12] and MNIST-M [9]. The MNIST dataset is also frequently used for adversarial attack and defence evaluation. The samples of those datasets are imbalanced in classes and styles across domains, with 60,000 binary images in MNIST, 7,291 binary images in USPS and 68,002 RGB images in MNIST-M. In our experiments, samples in all three domains are re-scaled to the size of 28×28 pixels. A gallery of DIGITS benchmark is shown in Fig. 3a. On DIGITS, we conducted three domain adaptation tasks, including MNIST→USPS, USPS→MNIST and MNIST→MNIST-M.

**Natural Image Classification.** benchmark (CIFAR-STL) is composed by two colour image classification datasets, CIFAR-10 [16] with 60,000 images and STL-10 [6] with 1,300 images. Both STL-10 and CIFAR-10 are 10-class image datasets. These two datasets contain nine overlapping classes. We removed the non-overlapping classes, “frog” and “monkey” from the two datasets, respectively. A gallery of CIFAR-STL benchmark is shown in Fig. 3b. In our experiments, CIFAR-10 is used as the source domain and STL-10 is considered as the target domain.

#### 4.2. Baseline models

Since there are few existing work on robust UDA, we present three baseline models for comparison with the CURDA.
4.3. Implementation details

**Source-robust Model Only (SR).** With the robust training strategy proposed in PGD [21], we first trained source-robust models in source domains and directly evaluated them in target domains without any tuning. By SR, we intend to set a baseline on the original generalization ability of a model trained in a source domain.

**Source-robust Model + UDA (SR+UDA).** Based on the above source-robust models, we further applied a popular UDA approach, ADDA [31]. Similar to part of the architecture of CURDA, ADDA also splits the source model into an encoder and a classifier. The source encoder is used to initialize a target encoder. The classifier remained frozen. SR+UDA is set to test whether UDA approaches can transfer the robustness from a source domain to a target domain.

**Source-robust Model + UDA + Label-free Robust Training (SR+UDA+RT).** The third baseline model introduces label-free robust training into the UDA process intending to determine if label-free robust training may enhance the target domain model robustness. The robust regularization strategy proposed in [36] is deployed as the label-free robust training approach in this baseline model.

**Backbone Architectures.** Following the same architecture as [31, 22], we use a modified LeNet [18] and a Wide ResNet (WRN) [35] as backbone networks in DIGITS and CIFAR-STL benchmarks, respectively. For DIGITS, the modified LeNet composed by two convolutional layers is applied as the source and target encoders. Same as [31], the domain discriminator consists three fully connected layers, with two hidden layers of 500 units. For CIFAR-STL, the WRN-34-10 is used as encoder. The domain discriminator is also composed by three fully connected layers but the size of two hidden layers is 2,048.

**Training Details.** Stochastic gradient descent (SGD) is used as optimizer in all training processes with a momentum of 0.9. On DIGITS, in the first step of CURDA, the source-robust model is trained for 80 epochs in total, starting with a learning rate of 0.001 for the first 50 epochs and changing it to 0.0001 for the rest 30 epochs. For the adaptation step, the target encoder is trained with a learning rate of 0.001 for 60 epochs. A weight decay of $5e-4$ and a batch size of 300 is used in both two steps. In pseudo label generation, we use $\tau = 20$ and $P_{\text{pseudo}} = 0.90$. In $L_{\text{con}}$ and $L_{\text{sa}}$, the margins $m_{s}$ and $m_{t}$ are set to be 10. In the loss function of CORTrain, we set $\lambda_{\text{con}} = 0.01$. In the loss function of the adaptation step, we set $\lambda_{\text{sa}} = 0.01$. On CIFAR-STL, as the WRN-34-10 is much larger than the LeNet, we train the source-robust model for 80 epochs with a learning rate of 0.001 in the first 55 and change the learning rate to 0.0005 for the rest epochs. The target encoder is trained for 70 epochs on a learning rate of 0.001. A weight decay of $2e-4$ and a batch size of 128 is used in both source training and adaptation. The pseudo label generator uses $\tau = 30$ and $P_{\text{pseudo}} = 0.90$. The margins $m_{s}$ and $m_{t}$ are all set to be 8. In the loss functions, we set $\lambda_{\text{con}} = \lambda_{\text{sa}} = 0.01$.

**Adversarial Attacks.** The PGD [21] attack is used for both CORTrain on source domains and robustness testing on target domains. The hyper-parameters for training and testing are consistent for each domain following the popular settings used in existing work [36, 34]. For binary image datasets, MNIST and USPS, the attack perturbation is 0.3, the perturbation step size is 0.01 and the number of perturbation steps is 20. For colour image datasets, MNIST-M, CIFAR-10 and STL-10, the attack perturbation is 0.031, the perturbation step size is 0.007 and the number of perturba-
Table 1: Clean data accuracy (clean acc (%)) and adversarial data robustness (adv rob (%)) on DIGITS benchmark. The bold number shows the best results in each column.

| Models       | MNIST→USPS |           | USPS→MNIST |           | MNIST→MNIST-m |           |
|--------------|------------|-----------|------------|-----------|----------------|--------|
|              | Clean Acc (%) | Adv Rob (%) | Clean Acc (%) | Adv Rob (%) | Clean Acc (%) | Adv Rob (%) |
| SR           | 77.7       | 26.3      | 68.7       | 23.4      | 38.8          | 22.3   |
| SR+UDA       | 86.8       | 10.1      | 83.6       | 12.8      | 71.2          | 28.8   |
| SR+UDA+RT    | 85.3       | 63.4      | 75.3       | 54.2      | 56.7          | 46.3   |
| Ours(CURDA)  | 86.8       | 77.5      | 80.3       | 70.2      | 66.8          | 60.6   |

Figure 5: Visualization by t-SNE on representations learnt by all models. The outputs of the second-to-last layer (activation layer) are used for this visualization.
Table 2: Results of Ablation Study. Columns 2-5 present the effect of 4 major losses used in CURDA. The column w s-lab gen represents pseudo label generation without switching encoders. The results on MNIST→USPS are reported.

| Models       | Clean Acc (%) | Adv Rob (%) |
|--------------|---------------|-------------|
| SR           | 70.6          | 38.0        |
| SR+UDA       | 76.4          | 10.3        |
| SR+UDA+RT    | <30           | <30         |
| Ours(CURDA)  | 74.2          | 47.9        |

Table 3: Clean data accuracy (clean acc (%)) and adversarial data robustness (adv rob (%)) on CIFAR-STL benchmark. The bold number shows the best results in each column.

| Models       | CIFAR→STL | Clean Acc (%) | Adv Rob (%) |
|--------------|-----------|---------------|-------------|
| Clean Acc (%)| 79.3      | 85.3          | 86.6        |
| Adv Rob (%)  | 67.2      | 63.4          | 76.1        |
| MNIST-USPS   | 82.4      | 86.8          | 73.3        |
| SR           | 70.6      | 38.0          | 47.9        |
| SR+UDA       | 76.4      | 10.3          |             |
| SR+UDA+RT    | <30       | <30           |             |
| Ours(CURDA)  | 74.2      | 47.9          |             |

high accuracy and robustness achieved by CURDA.

CIFAR-STL We also evaluated the effectiveness of the proposed CURDA on natural images. Tab. 3 lists the results of the CURDA in comparison with other three baseline models. Due to serious inter-class misalignment caused by the joint use of label-free robust training and UDA, the performance of SR+UDA+RT fluctuated significantly during tuning and the highest accuracy is lower than 30%. In comparison, with the help of CORTrain and SAA-contrastive loss, the proposed CURDA achieved strong robustness up to 47.9% with only 2.2% decrease on accuracy.

4.5. Ablation Studies

Tab. 2 examines all 5 components of CURDA. We perform ablation study by leaving-one-component-out of our framework at a time.

Effect of Using Contrastive Loss in Source Domain. The removal of source domain contrastive loss (Lcon) causes a significant drop on both target clean data and target adversarial data. The main reason is that only enforcing target domain inter-class sparsity and intra-class compactness is not enough to prevent the inter-class mismatch.

Effect of SAA-contrastive Loss Comparing the third and last columns of Tab. 2, we can see that, without SAA-contrastive loss, the clean data accuracy does not decrease much, but the target domain robustness degrades significantly. This phenomenon demonstrates that the SAA-contrastive loss plays an important role in CURDA model in terms of increasing target model robustness while remaining the accuracy of UDA.

Effect of Label-free Robustness Training Comparing column ‘w/o. Ltrade’ with the last column in Tab. 2, we observed a slight drop when we remove the Ltrade loss. This suggests our proposed SAA-contrastive loss itself is strong enough to force the adversarial samples to be close with clean samples of the same classes which satisfies the Ltrade loss consistency constraint.

Effect of Target Domain Discriminative loss We compared CURDA with/without the domain discriminator according to the fifth column and the last column in Tab. 2. Without domain discriminator, both model accuracy and robustness degrades dramatically. It indicates that although domain discriminator cannot guarantee the class-level feature alignment, it is able to utilize all unlabeled target samples to achieved the domain-level distribution alignment, while SAA-contrastive loss can only rely on the samples with trusty pseudo labels.

Effect of Switching Encoders in Pseudo Label Generation The quality of pseudo labels determine the effect of the SAA-contrastive loss. In the CURDA, as mentioned in Sec. 3.3, the trained source-robust encoder is used for pseudo label generation for the first few epochs and is changed by the target encoder when the target encoder becomes stable. We compare the impact of changing encoders in pseudo label generation. From the column ‘w s-lab gen’ in Tab. 2, it can be observed that switching encoders can bring 4.4% improvements on accuracy and 4.2% improvements on robustness. The reason is that a stable target domain model can generate better pseudo label than a source domain model. On MNIST→USPS, with same threshold of Ppseudo = 0.9, the source domain model can assign 43.8% target samples with trusty pseudo labels and the accuracy of which is 70%. However, a stable target domain model can make trusty predictions on 61.3% target samples and its accuracy of which is 91%.

5. Conclusion

In this paper, we presented a new problem, robustifying UDA, which concerns training an adversarial robust model in a target domain without data annotations. Correspondingly, we proposed a novel method of Class-consistent Unsupervised Robust Domain Adaptation(CURDA) to tackle this problem. With contrastive robust training (CORTrain) to enhance the source domain training and source anchored adversarial contrastive (SAA-contrastive) loss to perform class-aware adversarial domain alignment, CURDA conquered the challenge of inter-class mismatch. Experiments on handwritten digits and natural images bench-
marks demonstrate that the proposed CURDA can effectively adapt a source-robust model onto an unlabeled target domain while simultaneously achieving strong robustness and competitive accuracy.

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