Towards Corruption-Agnostic Robust Domain Adaptation

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Big progress has been achieved in domain adaptation in decades. Existing works are always based on an ideal assumption that testing target domains are i.i.d. with training target domains. However, due to unpredictable corruptions (e.g., noise and blur) in real data like web images, domain adaptation methods are increasingly required to be corruption robust on target domains. In this paper, we investigate a new task, Corruption-agnostic Robust Domain Adaptation (CRDA): to be accurate on original data and robust against unavailable-for-training corruptions on target domains. This task is non-trivial due to large domain discrepancy and unsupervised target domains. We observe that simple combinations of popular methods of domain adaptation and corruption robustness have sub-optimal CRDA results. We propose a new approach based on two technical insights into CRDA: 1) an easy-to-plug module called Domain Discrepancy Generator (DDG) that generates samples that enlarge domain discrepancy to mimic unpredictable corruptions; 2) a simple but effective teacher-student scheme with contrastive loss to enhance the constraints on target domains. Experiments verify that DDG keeps or even improves performance on original data and achieves better corruption robustness than baselines.

CCS Concepts:
• Computing methodologies → Transfer learning; Unsupervised learning; Machine learning algorithms;
• Computer systems organization → Neural networks;

Additional Key Words and Phrases: domain adaptation, corruption robustness, transfer learning

ACM Reference Format:
Yifan Xu, Kekai Sheng, Weiming Dong, Baoyuan Wu, Changsheng Xu, and Bao-Gang Hu. 2021. Towards Corruption-Agnostic Robust Domain Adaptation. ACM Trans. Multimedia Comput. Commun. Appl. 1, 1, Article 1 (January 2021), 15 pages.

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1551-6857/2021/1-ART1 $15.00
https://doi.org/
Fig. 1. Instances of corruption-agnostic robust domain adaptation (CRDA). To our surprise, existing domain adaptation method (CDAN+TN [42]) and corruption robust method (AugMix [17]), even their combination, suffer from unseen corruptions on target domain.

1 INTRODUCTION

Domain adaptation (DA) [31] is a promising technique to transfer knowledge from well-labeled source domain to assist unlabeled target domain learning with domain shift. Tremendous efforts on domain adaptation [23, 24, 26, 42] and domain generalization (DG) [20, 29, 41] indicate the significant progress on domain shift. Besides domain shift, given unpredictable corruptions (e.g., noise and blur) in real data, domain adaptation methods are increasingly required to be corruption robust on target domain (see Fig. 1). However, most DA or DG works only consider transferring source domain knowledge to some specific target datasets, while corruption robustness works [15–17, 37] usually focus on corruptions without domain shift. Thus, there is a question worth considering: how to conduct robustness against unpredictable corruptions in cross domain scenarios?

According to this question, we propose a new task: Corruption-agnostic Robust Domain Adaptation (CRDA), i.e., DA models are required to not only achieve high performance on original target domains, but also be robust against common corruptions that are unavailable for training. Popular DA methods, even combining with existing corruption robustness modules, will get sub-optimal results (see Fig. 1) because they cannot handle well two challenges of CRDA: (1) unpredictable corruptions with large domain discrepancy; (2) weak constraints for robustness on unlabeled target domains. More specifically, previous augmentation robustness methods [17, 44] for corruption-agnostic robustness are always conducted in supervised scenarios with strong classification loss, which may lose effectiveness with domain discrepancy loss on target domains. We first show that after taking into domain information, we can construct more generalized augmentation in cross-domain scenarios. To our knowledge, our work is among the first attempt to unify robustness on domain shift and common corruptions.

To address the above challenges, we propose a novel mechanism towards corruption-agnostic robust domain adaptation called Domain Discrepancy Generator (DDG). Specifically, DDG generates augmentation samples that most enlarge domain discrepancy. Based on several assumptions (detailedly discussed in Section 4.1), these generated samples are proved to be able to represent unpredictable corruptions. Besides, to enhance the constraints on target domains and tackle with unstable features in the early training stage, we propose a teacher-student warm-up scheme via contrastive loss. Specifically, a teacher model is first pre-trained to learn the original representations and then a student model further distills from the teacher model to learn robustness against samples generated by DDG via contrastive loss drawn from contrastive learning [3]. Our code is available at https://github.com/Mike9674/CRDA.
Table 1. Comparison of related research topics.

| Setting                                      | Domain Shift | Target Domain Available | Visual Corruption |
|----------------------------------------------|--------------|-------------------------|------------------|
| Unsupervised Domain Adaptation [23, 26, 31]  | ✓            | ✓                       |                  |
| Domain Generalization [20, 29, 41]           | ✓            |                         |                  |
| Corruption Robustness [15–17, 35]            | ✓            |                         | ✓                |
| Corruption-Agnostic Robust Domain Adaptation | ✓            | ✓                       | ✓                |

Our work makes the following contributions:

- We investigate a new scenario called corruption-agnostic robust domain adaptation (CRDA) to equip domain adaptation models with corruption robustness.
- We take use of information of domain discrepancy to propose a novel module Domain Discrepancy Generator (DDG) for corruption robustness that mimic unpredictable corruptions.
- Experiments demonstrate that our method not only significantly improves corruption robustness for DA models but also maintains or even improves classification results on original target domains.

2 RELATED WORK

**Unsupervised Domain Adaptation.** Tremendous DA methods have made progress in cross-domain applications like recognition [12], object detection [5], and semantic segmentation [38]. The core idea is to seek domain-invariant features among source and target domains [31]. A mainstream methodology is distribution alignment, which is mainly based on Maximum Mean Discrepancy (MMD) [1, 2, 23, 25, 30] or adversarial methods [9, 11, 26, 45, 46]. Besides, some works further make improvement by pseudo-labeling [33], co-training [45], entropy regularization [36], and evolutionary-based architecture design [34]. Recently, increasing researchers focus on more realistic scenarios: considering user privacy, [22, 24] investigate the scenario where only source domain models instead of data available while training. Label corruptions in source domain [13] is proposed to address the low quality labeling problem in DA. Besides, domain generalization [20, 29, 41] aims to learn domain-invariant representations for unseen target domains. Different from existing literature (see Table 1), we propose a new and realistic topic: corruption-agnostic robust domain adaptation, which investigates corruption robustness in domain adaptation.

**Corruption Robustness.** Convolutional networks are proved fragile to simple corruptions by several studies [8, 19]. Assuming corruptions are known beforehand, Quality Resilient DNN [7] learns robustness against specific corruptions via a mixture of corruption-specific experts. Instead of knowing testing corruptions beforehand, we propose CRDA to learn general robustness against unseen corruptions. In recent years, increasing works begin to focus on robustness against unseen corruptions. [39] shows that fine-tuning on blurred images fails to generalize to unseen blurs. Several benchmarks [14, 15, 18, 21] are constructed to measure generalization to unseen corruptions. Self-supervised learning is found beneficial to corruption robustness [4, 16]. CutMix [43], Mixup [44], Patch Gaussian [27], Randaugment [6] and AugMix [17] are under the mainstream that aggregates several general transformations to implicitly represent unseen corruptions. However, current benchmarks and mainstream methods all take it for granted that training and testing data are from the same domain distribution, while CRDA also requires consideration of domain shift, as illustrated in Table 1. Furthermore, instead of aggregating transformations, we propose a new idea that utilize domain discrepancy information to mimic unseen corruptions.
3 PRELIMINARIES

3.1 Problem definition for CRDA

In this paper, we investigate CRDA in the scope of unsupervised domain adaptation for classification. Given labeled source domain $D_s = \{(X_s, Y_s)\}$, unlabeled target domain $D_t = \{X_t\}$ ($Y_t$ is unavailable while training), models are required to be robust on corrupted target domain samples $T(X_t)$ while maintaining the performance on original target domain, where $T$ denotes a corruption set unavailable for training. Note that $Y_s = Y_t = \{1, \ldots, S\}$ and $P(D_s) \neq P(D_t)$.

3.2 Definition of corruption robustness

The concept of corruption robustness is drawn from [15] with slight modification. Given an input sample set $X$ with the corresponding label set $Y$, a corruption set $T$ and a model $m = f \circ c$, where $f$ and $c$ respectively denote a feature extractor and a classifier, the corruption robustness is measured by:

$$\mathbb{E}_{t \sim T} \left[ P_{(x,y) \sim (X,Y)} (m(t(x)) = y) \right], \quad (1)$$

where we can derive the robustness by aligning features as:

$$\max \left\{ \mathbb{E}_{t \sim T} \left[ P_{x \sim X} (f(t(x)) = f(x)) \right] \right\}. \quad (2)$$

Here $T$ denotes corruptions derived from [15], which contains 15 kinds of corruptions for $T$ and 5 severities $t$ for each kind (see Fig. 2).

4 METHODOLOGY

4.1 Domain Discrepancy Generator

In CRDA setting, the key challenge is that testing corruptions are unavailable during training. Besides, previous data augmentation only encourages networks to memorize the specific corruptions seen during training and leaves models unable to generalize to new corruptions [10, 39]. In this section, we attempt to utilize domain information given by domain adaptation to solve this challenge. Thus, Domain Discrepancy Generator (DDG) is proposed to generate samples that most enlarge
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Classifier

Transfer Loss 
($\ell_{\text{trans}}$)

Contrastive Loss
($\ell_{\text{con}}$)

Domain Discrepancy Generator

Feature extractor

Classifier

$\mathbf{x}_s$

$\mathbf{x}_t$

$f_{\text{stu}}(\mathbf{x})$

$f_{\text{tea}}(\mathbf{x})$

$x_t^{(\text{DDG})}$

$\Delta \mathbf{x}_t$

Fig. 3. Overall structure of DDG. The yellow part is the classic structure of DA, while the green part is DDG. The gradient of transfer loss is inversely added to the target domain inputs by Projected Gradient Descent (PGD) [28] in Algorithm 1 to generate augmentation samples $x_t^{(\text{DDG})}$ which is aligned with the original domain-invariant feature extracted by a pretrained teacher model with contrastive loss.

domain discrepancy to mimic unpredictable corruptions. Fig. 3 illustrated the overall mechanism of DDG. The following is reasonable derivation.

We first assume that corrupted target domain samples hold larger domain discrepancy to source domain than corresponding original target domain samples, which is empirically proved in the supplementary material. Thus, our core idea is to find the points near the original images in sample space that most increase domain discrepancy to represent the most severe corruptions. In domain adaptation, the domain discrepancy is always measured by transfer loss, which is commonly realized by Maximum Mean Discrepancy (MMD) [1, 23, 25, 30] or adversarial methods [9, 26].

The followings are three basic assumptions for our method, where distance $d_s(t(x), x)$ denotes distance between the corrupted images and corresponding original images:

**Assumption 1.** The corrupted versions are within the $\delta$-range neighborhood of the original image in sample space ($\delta$ neighborhood for precise) and distance in sample space $d_s(t(x), x)$ becomes larger with increase of the severity level of corruption $t$.

**Assumption 2.** Within the $\delta$ neighborhood, the severity level $t$ of a corruption $T$ is positively correlated to distance in feature space $d_f(f(t(x)), f(x))$.

**Assumption 3.** Within the $\delta$ neighborhood, the severity level $t$ of a corruption $T$ is positively correlated to the value of transfer loss $\ell_{\text{trans}}(t(x))$.

The empirical proof can be seen in supplementary material. Assumption 2 is drawn from an interesting finding in Section 5.3 that networks always learn order-invariant representations for different severity levels of corruptions.

Based on the above assumptions, we can construct the bridge between domain discrepancy and unpredictable corruptions. Given an input target domain data $x_t$, source domain $D_s$, transfer loss $\ell_{\text{trans}}$ and a corruption set $T (t \in T)$ whose corresponding corrupted data $t(x_t)$ is within the $\delta$
Algorithm 1 PGD: Projected Gradient Descent

**Input:** Target and source domains data \(x_t, x_s\); Feature extractor \(f\); Parameters: shift range \(\delta\), update stride \(\eta\), update step number \(n\).

**Output:** augmented target samples by DDG \(x_t^{(DDG)}\)

1: \(i = 0, x_t^{(DDG)} = x_t\)
2: repeat:
3: Transfer loss:
   
   \[ \ell = \ell_{\text{trans}}(f(x_t^{(DDG)}), f(x_s)) \]
4: Update \(x_t^{(DDG)}\) by the gradients of transfer loss:
   
   \[ x_t^{(DDG)} \leftarrow x_t^{(DDG)} + \eta \cdot \text{sign}\left( \frac{\partial \ell}{\partial x_t^{(DDG)}} \right) \]
5: Clamp \(x_t^{(DDG)}\) within
   
   \[ \|x_t^{(DDG)} - x_t\| \leq \delta \]
6: \(i \leftarrow i + 1\)
7: until \(i = n\)
8: return \(x_t^{(DDG)}\)

neighborhood of \(x_t\), DDG generates

\[
x_t^{(DDG)} = \arg \max_{\|x_t^{(DDG)} - x_t\| \leq \delta} \ell_{\text{trans}}(f(x_t^{(DDG)}), f(D_s))
\]

\[
\Rightarrow \arg \max_{t \in T} \ell_{\text{trans}}(f(t(x_t)), f(D_s)) = t_{\text{max}}(x_t),
\]

which means the point \(x_t^{(DDG)}\) near the original target domain sample in sample space that most increases transfer loss (denoting domain discrepancy) can represent the most severe corruption. The proof of Equation (3) can be seen in the supplementary material. In practice, Domain Discrepancy Generator generates such samples via Project Gradient Descent (PGD) [28] in Algorithm 1.

It is worthy noting that the generated samples look similar to adversarial samples [28]. However, there exists few evidence that domain discrepancy could help corruption robustness in cross domain scenarios like domain adaptation ever before. We first show that it significantly improves corruption robustness on the basis of the bridge between corruptions and domain discrepancy constructed by Equation (3). Meanwhile, DDG works in an unsupervised way while common adversarial training always needs ground-truth labels.

### 4.2 Overall Learning Framework

The last question is how to learn robustness in unlabeled target domains. Since there is no strong constraints like classification loss in target domains, simply merging samples generated by DDG with the original data may lose the effectiveness. Thus, we utilize contrastive loss [3] to enhance the constraints on target domains. The core idea is simple, i.e., minimizing the feature distance between corrupted samples with their original versions. Besides, to tackle with the unstable features in the early training stage, we further propose a warm-up scheme like teacher-student framework. The teacher model is first trained to extract the original features, while the student model then extracts corrupted features to minimize the distance to corresponding original features. Algorithm 2 shows the overall process of DDG. The proposed contrastive loss is introduced as followed.

ACM Trans. Multimedia Comput. Commun. Appl., Vol. 1, No. 1, Article 1. Publication date: January 2021.
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Algorithm 2 Overall process for Domain Discrepancy Generator

Input: Data and source labels: \(X_s, X_t, Y_s\); Original DA model \(f + c\); Parameters: \(\delta = 60/255, \eta > 2\delta, n = 2\)

Output: Robust student model \(f^{(stu)} + c^{(stu)}\)

1: Train the original model as a teacher model \(f^{(tea)} + c^{(tea)}\). Fix the parameters.
2: Construct a student network \(f^{(stu)} + c^{(stu)}\) with same structure of \(f + c\).
3: repeat:
   4: Draw \(x_s, x_t, y_s\) from \(X_s, X_t, Y_s\).
   5: Generate augmentation samples according to Equation (3) and Algorithm 1:
      \[x_i^{(DDG)} = \text{PGD} (x_t, x_s, f^{(stu)} + c^{(stu)}, \delta, \eta, n)\]
   6: Update \(f^{(stu)} + c^{(stu)}\) according to Equation (10).
7: until Convergence
8: return \(f^{(stu)} + c^{(stu)}\)

Given a batch of samples \(\{x_i\}_1^N\), we use feature extractor \(f^{(tea)}\) and \(f^{(stu)}\) introduced in Algorithm 2 to get \(2N\) representation feature vectors:

\[
Z^{(tea)} = \left\{ z_i^{(tea)} | z_i^{(tea)} = f^{(tea)}(x_i) \right\}_1^N, \\
Z^{(stu)} = \left\{ z_i^{(stu)} | z_i^{(stu)} = f^{(stu)}(x_i) \right\}_1^N, \tag{4}
\]

where we define \(Z = Z^{(tea)} \cup Z^{(stu)} = \{z_i\}_1^{2N}\). The similarity loss of each two features can be calculated by:

\[
\ell_{\text{sim}} (z_i, z_j) = -\log \frac{\exp\left(\text{sim}(z_i, z_j) / \tau\right)}{\sum_{z_k \in Z, z_k \neq z_i} \exp\left(\text{sim}(z_i, z_k) / \tau\right)}, \tag{5}
\]

where \(\tau = 0.2\) is a temperature controller to control the similarity extent, and \(\text{sim}(z_i, z_j) = z_i^T z_j / \|z_i\| \|z_j\|\) is cosine distance between two vectors. Note that Equation (5) is asymmetric between \(z_i, z_j\). The final contrastive loss is defined by:

\[
\ell_{\text{con}} \left( Z^{(stu)}, Z^{(tea)} \right) = \frac{1}{2N} \sum_{i=1}^N \left[ \ell_{\text{sim}} \left( z_i^{(stu)}, z_i^{(tea)} \right) + \ell_{\text{sim}} \left( z_i^{(tea)}, z_i^{(stu)} \right) \right], \tag{6}
\]

where the goal is to minimize the distance between feature representations \(z_i^{(stu)}\) and \(z_i^{(tea)}\) of a same sample \(x_i\). The other kinds of losses defined by the original DA models \(\ell_{\text{ori}}\), usually containing source domain classification loss \(\ell_{\text{cls}}\) and transfer loss \(\ell_{\text{trans}}\) in Equation (7), also need to be calculated:

\[
\ell_{\text{ori}}(x_s, x_t, y_s) = \ell_{\text{cls}}(x_s, y_s) + \ell_{\text{trans}}(x_s, x_t). \tag{7}
\]

In fact, contrastive loss does not make \(Z^{(stu)}\) definitely same as \(Z^{(tea)}\). And thanks to corruptions, the final feature representation \(Z^{(stu)}\) has a further distillation on the basis of the teacher model, which may lead to not only improvement on robustness but also better performance on domain invariance.

By utilizing the contrastive loss in Equation (6), we can minimize feature distance between samples \(x_i^{(DDG)}\) generated by DDG and original samples \(x_i\) in the target domain iteratively, which leads to features of the most severely corrupted images come closer to original ones, as:

\[
\min_{f} d_f \left( f(x_i^{(DDG)}), f(x_i) \right) \Rightarrow \min_{f} d_f \left( f(t_{\max}(x_t)), f(x_t) \right). \tag{8}
\]
In practice, Equation (8) is realized by minimizing:

$$\ell_{\text{con}}^{(DDG)}(x_t^{(DDG)}, x_t) = \ell_{\text{con}}^{(su)}(x_t^{(DDG)}, f^{(tea)}(x_t)),$$

(9)

Together with the loss defined by the original DA model $\ell_{\text{ori}}$ illustrated in Equation (7) and Fig. 3, the final total loss is:

$$\ell_{\text{total}} = \ell_{\text{ori}}(x_s, x_t, y_s) + \lambda \ell_{\text{con}}^{(DDG)}(x_t^{(DDG)}, x_t).$$

(10)

Note that DDG only generated samples on target domains and the generated samples are only processed by contrastive loss.

### 4.3 Further Explanation

Intuitively, DDG should loop many times like $n = 10$ in PGD to generates an augmented sample, which is time-consuming. In this section, we theoretically show that we only need to consider the edge point so that by setting $n = 2$ is enough, which effectively reduces the time consumption. We begin with the following proposition.

**Proposition 1.** Only aligning the edge points $\{x_t^{(DDG)} || x_t^{(DDG)} - x_t = \delta\}$ around the $\delta$ neighborhood in Equation (3) is enough to gain corruption robustness under the DDG framework.

Given input data $x$, a feature extractor $f$ and a corruption $T$ with continuous severity, we denote the distance in feature space $d_f(f(T(x)), f(x))$ as $d(T)$. Then Assumption 2 can be explained as $T$ is positively correlated with $d(T)$. Due to the properties of monotonic function, the upper bound of $d(T)$ is $d(T_{\text{max}})$:

$$0 \leq d(T) \leq d(T_{\text{max}}) = d_{\text{max}},$$

(11)

where $T_{\text{max}}$ denotes the most severe level of corruption $T$. By limiting $d_{\text{max}}$ to 0, we get:

$$\lim_{d_{\text{max}} \to 0} d(T) = \lim_{d_{\text{max}} \to 0} d_f(f(T(x)), f(x)) = 0,$$

(12)

which means for all severity levels of corruption $T$, features of corrupted data $T(x)$ and clean data $x$ are the same when $d_{\text{max}} \to 0$. Thus, robustness against a specific corruption is achieved.

Now the last issue is how to limit $d_{\text{max}}$ to 0. Note that:

$$d_{\text{max}} = d(T_{\text{max}}) = d_f(f(T_{\text{max}}(x)), f(x)).$$

(13)

Thus, by aligning features of the most severely corrupted samples $T_{\text{max}}(x)$ with original features $x$, we get $d_{\text{max}} \to 0$.

Considering Assumption 1, the shift in sample space increases as the increase of the severity level of a corruption $T$. Thus, the most severe corruption $T_{\text{max}}(x)$ is always achieved on the edge points of $\delta$ cycle. Then we can use $\{x_t^{(DDG)} || x_t^{(DDG)} - x_t = \delta\}$ to implicitly represent $T_{\text{max}}(x)$ due to the conclusion in Equation (3). By aligning features of these edge points with the original features via minimizing the contrastive loss defined in Equation (9), corruption robustness is achieved under DDG as :

$$\lim_{\ell_{\text{con}}^{(DDG)} \to 0} d(T) = \lim_{\ell_{\text{con}}^{(DDG)} \to 0} d_f(f(T(x)), f(x)) = 0.$$

(14)

Proposition 1 is derived.

Thus, by setting stride $\eta$ bigger than range $2\delta$, we can reach the edge point in one step. In practice, only step $n = 2$ gains enough good performance.
4.4 Metrics for corruption robustness

The commonly used standardized aggregate performance measure is the Corruption Error (CE) [15], which can be computed by:

\[ CE_f^T = \frac{\sum_{t=1}^{s} E_{t,T}^f}{\sum_{t=1}^{s} E_{t,T}^{\text{AlexNet}}} \]  

where \( E_{t,T}^f \) denotes the error rate of model \( f \) on target domain data transformed by corruption \( T \) with severity \( t \). The AlexNet is trained on clean source domain and tested on corrupted target domain.

The corruption robustness of model \( f \) is summarized by averaging Corruption Error values of 15 corruptions introduced in Section 3.2: CE\(_{\text{Gaussian Noise}}^f \), ..., CE\(_{\text{Glass Blur}}^f \). The results in the mean CE or mCE [15] for short. mCE is calculated by only one setting (e.g., the Ar:Rw setting in Office-Home). For average performance of corruption robustness on the whole dataset (e.g., Office-Home), we need to average mCE values of all settings.

5 EXPERIMENTS

5.1 Setups

Datasets. Office-Home and Office-31 are two benchmark datasets widely adopted for visual domain adaptation algorithms. Experiments are mainly conducted on Office-Home, a relatively challenging dataset. Office-Home [40] is a challenging medium sized benchmark, which contains 15588 images from 4 domains (Artistic images (Ar), Clip Art (Cl), Product images (Pr), and Real-World images (Rw)). Each domain consists of 65 object classes under daily life environment. Office-31 [32] is a standard benchmark with 4110 images and 31 classes under office environment. There are totally three domains: Amazon (A), Webcam (W) and DSLR (D).

Corruption. To check the corruption robust of one given DA model, we create the corrupted version of Office-31 and Office-Home by using the corruption types defined by ImageNet-C [15], a widely used benchmark for corruption robustness. For each image, there exists 15 corruption types with 5 levels of severity as illustrated in Fig. 2.

Baselines. To illustrate the improvement on CRDA, we apply our method to CDAN+TN [26, 42], a classic baseline model for domain adaptation. We further apply our method to a SOTA DA model DCAN [23]. Note that the domain discrepancies of CDAN+TN and DCAN are respectively measured by adversarial methods [11] and MMD [1]. We compare our DDG method with AugMix [17], a SOTA method for corruption robustness, which aggregates several general transformations such as contrast, equalization and posterization for data augmentation.

Implementation details. For contrastive loss in Equations (10), the trade-off \( \lambda \) is set to 0.5. For DDG, we conduct Algorithm 2 with \( \delta = 60/255 \), \( \eta = 6 \), \( n = 2 \). Network structures and other hyper-parameters are the same as the original DA models.

5.2 Experiments in CRDA

We compare DDG with AugMix and the original DA models on both corruption robustness and original performance. In addition, we further set an empirical lower bound for CRDA calculated by simply replacing DDG-generated samples in Algorithm 2 with corresponding corrupted samples, which means models that reach the lower bound can be robust against unpredictable corruptions as if they are already known beforehand.
Table 2. Accuracy (%) on clean Office-Home data (ResNet-50).

| Method   | Ar→Cl | Ar→Pr | Ar→Rw | Cl→Ar | Cl→Pr | Cl→Rw | Pr→Ar | Pr→Cl | Pr→Rw | Rw→Ar | Rw→Cl | Rw→Pr | Avg (%) |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|---------|
| ResNet   | 34.9  | 50.0  | 58.0  | 37.4  | 41.9  | 46.2  | 38.5  | 31.2  | 60.4  | 53.9  | 41.2  | 59.9  | 46.1    |
| DAN      | 43.6  | 57.0  | 67.9  | 45.8  | 56.5  | 60.4  | 44.0  | 43.6  | 67.7  | 63.1  | 51.5  | 74.3  | 56.3    |
| DANN     | 45.6  | 59.3  | 70.1  | 47.0  | 58.5  | 60.9  | 46.1  | 43.7  | 68.5  | 63.2  | 51.8  | 76.8  | 57.6    |
| JAN      | 45.9  | 61.2  | 68.9  | 50.4  | 59.7  | 61.0  | 45.8  | 43.4  | 70.3  | 63.9  | 52.4  | 76.8  | 58.3    |
| DWT      | 50.3  | 72.1  | 77.0  | 59.6  | 69.3  | 70.2  | 58.3  | 48.1  | 77.3  | 69.3  | 53.6  | 82.0  | 65.6    |
| CDAN     | 50.7  | 70.6  | 76.0  | 57.6  | 70.0  | 70.0  | 57.4  | 50.9  | 77.3  | 70.9  | 56.7  | 81.6  | 65.8    |
| TADA     | 53.1  | 72.3  | 77.2  | 59.1  | 71.2  | 72.1  | 59.7  | 53.1  | 78.4  | 72.4  | 60.0  | 82.9  | 67.6    |
| SymNets  | 47.7  | 72.9  | 76.7  | 64.2  | 71.3  | 74.2  | 64.2  | 48.8  | 75.9  | 74.5  | 52.6  | 82.7  | 67.6    |
| MDD      | 54.9  | 73.7  | 76.8  | 60.0  | 71.4  | 71.8  | 61.2  | 53.6  | 78.1  | 72.5  | 60.2  | 82.3  | 68.1    |
| CDAN+TN  | 54.1  | 70.3  | 77.9  | 62.2  | 74.4  | 73.7  | 62.4  | 53.1  | 81.0  | 72.8  | 56.9  | 82.5  | 68.4    |
| +AugMix  | 50.5  | 70.1  | 74.9  | 56.7  | 69.6  | 68.7  | 53.9  | 50.4  | 75.9  | 67.9  | 58.2  | 80.6  | 64.8    |
| +DDG     | 57.1  | 74.4  | 79.4  | 63.5  | 75.9  | 75.3  | 63.2  | 54.9  | 81.9  | 73.1  | 58.8  | 84.2  | 70.1    |
| DCAN     | 57.8  | 76.3  | 82.9  | 68.5  | 72.7  | 76.7  | 68.0  | 56.3  | 82.1  | 73.5  | 60.8  | 83.3  | 71.6    |
| +AugMix  | 55.8  | 74.8  | 82.5  | 67.6  | 72.1  | 76.1  | 67.5  | 55.0  | 82.5  | 73.4  | 59.0  | 82.5  | 70.7    |
| +DDG     | 58.1  | 75.2  | 82.9  | 68.7  | 75.0  | 77.6  | 68.1  | 56.6  | 81.8  | 73.9  | 60.6  | 83.1  | 71.8    |

Fig. 4. Error rate (%) on Ar→Rw of Office-Home for different corruptions with the most severe level under CRDA (ResNet-50).

Fig. 4 shows the error rate on clean data and 15 different corruptions with the most severe severity in a single setting. It is reported that DDG achieves improvement over most kinds of corruptions with about 10 percentages in average than the original model and 3 percentages than AugMix. We observe that AugMix only achieves relatively high robustness on several corruptions such as Fog and Contrast. The reason possibly is that these corruptions can be implied by the aggregation of the general transformations defined by AugMix, however, corruptions like Pixelate may lie out of the implied set. Instead, our DDG achieves a much more generalizable implied set thanks to reasonable utilization of domain discrepancy information. It is worthy of noting that DDG can also improve the original accuracy, which is detailedly reported in Table 2.

Fig. 4 also shows that DDG gains no improvement over the Contrast corruption. We argue the reason probably is that this corruption conducts too much shift in sample space which goes beyond the scope of Assumption 1. Possible solutions include loosening the constraint in Assumption 1 and considering the invariant order of pixel values (Contrast does not change the order of pixel values). We leave them for future work.

We report the overall robustness under the whole Office-Home and Office-31 datasets in Table 3 and Table 4 with the standard robustness metric mCE. Results show that even the SOTA model
Table 3. mCE (%) on all cross-domain settings of Office-Home dataset under CRDA (ResNet-50).

| Settings   | CDAN+TN | DCAN | Lower Bound |
|------------|---------|------|-------------|
| Ar→Cl      | 69.7    | 69.3 | 59.8        |
| Ar→Pr      | 62.2    | 52.8 | 52.2        |
| Ar→Rw      | 59.2    | 56.0 | 48.0        |
| Cl→Ar      | 65.4    | 73.7 | 66.0        |
| Cl→Pr      | 58.7    | 56.6 | 51.9        |
| Cl→Rw      | 57.6    | 61.3 | 56.2        |
| Pr→Ar      | 65.5    | 72.2 | 63.6        |
| Pr→Cl      | 70.9    | 71.4 | 63.6        |
| Pr→Rw      | 55.0    | 55.3 | 48.8        |
| Rw→Ar      | 63.2    | 62.4 | 57.8        |
| Rw→Cl      | 70.4    | 61.4 | 64.4        |
| Rw→Pr      | 60.9    | 52.6 | 47.9        |
| Avg (↓)    | 63.2    | 62.1 | 56.7        |

Table 4. mCE (%) on all cross-domain settings of Office-31 dataset under CRDA (ResNet-50).

| Settings   | CDAN+TN | DCAN | Lower Bound |
|------------|---------|------|-------------|
| A→D        | 60.3    | 46.0 | 48.9        |
| A→W        | 59.6    | 65.2 | 46.9        |
| D→A        | 64.1    | 66.0 | 62.4        |
| D→W        | 83.5    | 59.9 | 69.7        |
| W→A        | 64.7    | 67.9 | 60.1        |
| W→D        | 120.2   | 64.3 | 70.9        |
| Avg (↓)    | 75.4    | 61.6 | 59.8        |

Table 5. mCE (%) on Ar→Rw for different update strides η in DDG

| δ         | η       | n  | mCE (↓) |
|-----------|---------|----|---------|
| 60/255    | > 2δ    | 2  | 48.0    |
| 60/255    | > 2δ    | 10 | 49.6    |
| 60/255    | 15/255  | 10 | 51.6    |
| 60/255    | 6/255   | 10 | 52.8    |

AugMix has sub-optimal results or even worse performance in some settings, which indicates the challenge of CRDA. Despite the challenging task, DDG still gains improvement with obvious margins. Meanwhile, there is still a long way for further study to reach the lower bound in CRDA. Besides robustness, DDG also maintains or improves the original accuracy of DA models. Results are shown in Table 2.

5.3 Empirical analysis

Ablation. In Section 4.3, we theoretically show only considering the edge points on the δ cycle is enough for DDG, which is realized by setting stride η > 2δ in Algorithm 2. Table 5 reports the mCE under CRDA with different strides η. Results show that the setting η > 2δ, which results in only considering the edge points, gains best performance. We conclude the reason why settings η ≪ δ perform relatively poorer is that they may wander in the δ cycle instead of reaching the large-shift
Fig. 5. Feature distance between a clean image and the versions corrupted by five severity levels of Gaussian Noise on the basis of different models: **Clean** (a ResNet-50 trained on clean data), **All levels** (trained on all severity levels of Gaussian Noise), **Clean + Level 5** (trained on clean data and severity level 5 Gaussian Noise), **Level 5** (trained on data only corrupted by severity level 5).

Table 6. Error rate (%) under a specific known corruption on the Ar→Rw setting of Office-Home dataset for teacher-student warm-up scheme.

| Corruption        | CDAN+TN | - DataAug | Ours |
|-------------------|---------|-----------|------|
| Clean             | 22.1    | 24.6      | 21.2 |
| Gaussian Noise    | 78.4    | 33.4      | 27.8 |
| Shot Noise        | 78.3    | 34.9      | 26.9 |
| Impulse Noise     | 83.4    | 33.4      | 24.4 |
| Defocus Blur      | 70.4    | 34.9      | 26.7 |
| Motion Blur       | 69.5    | 28.4      | 24.3 |
| Zoom Blur         | 53.6    | 29.4      | 23.1 |
| Fog               | 47.3    | 24.6      | 23.6 |
| Frost             | 55.7    | 30.6      | 25.5 |
| Snow              | 60.0    | 31.2      | 23.9 |
| Elastic Transform | 84.2    | 30.0      | 23.3 |
| Contrast          | 66.4    | 24.6      | 23.0 |
| Brightness        | 29.7    | 26.5      | 23.6 |
| JPEG Compression  | 37.6    | 29.0      | 23.2 |
| Pixelate          | 45.7    | 26.9      | 22.6 |
| Glass Blur        | 86.4    | 37.0      | 27.8 |

More ablation results can be seen in Appendix.

**Teacher-student warm-up scheme.** In this section, we aim to evaluate the effectiveness of the teacher-student warm-up scheme. To compare with simply augmenting samples with testing corruptions, we replace DDG-generated samples in Algorithm 2 with corresponding testing corruptions. Table 6 precisely reports the error rate on original data and corruptions with the most severe severity. Results show that our warm-up scheme can significantly improve the model’s robustness against a specific corruption. Furthermore, our scheme can further improves the model’s original performance instead of negative effect brought by pure data augmentation. In another word, the teacher-student warm-up scheme does not conduct trade-off over robustness and accuracy.

**Order-invariant representations of corruptions.** We empirically observe that the distance between the corrupted versions and the corresponding clean image in feature space (**feature distance** for...
precise) is always positively correlated to the severity of corruptions. Training details are shown in the supplementary material. Fig. 5 shows that even only trained on clean and corrupted samples with a single severity (Clean + Level 5), models still learn the positive correlation instead of relatively nearer feature distance on a specific severity. In a word, networks always learn order-invariant representations in feature space for different levels of severity, which contributes to Assumption 2 in Section 4.1.

6 CONCLUSION
In this paper, we throw a new sight to domain adaptation to investigate a more realistic new task, Corruption-agnostic Robust Domain Adaptation (CRDA). Taking domain information into consideration, we present a new idea for corruption robustness called Domain Discrepancy Generator (DDG) that mimic unpredictable corruptions via generating samples most enlarging domain discrepancy. Besides, we propose a teacher-student warm-up scheme via contrastive loss to enhance the constraints on unlabelled target domains and stabilize the early training stage feature. Empirical results justify that DDG outperforms existing baselines on original accuracy and achieves better corruption robustness.

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Supplementary Material for “Towards Corruption-Agnostic Robust Domain Adaptation”

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ACM Reference Format:
Yifan Xu, Kekai Sheng, Weiming Dong, Baoyuan Wu, Changsheng Xu, and Bao-Gang Hu. 2021. Supplementary Material for “Towards Corruption-Agnostic Robust Domain Adaptation”. ACM Trans. Multimedia Comput. Commun. Appl. 1, 1, Article 1 (January 2021), 6 pages.

In this supplementary material, we provide details omitted in the main manuscript, including:
- Section 1: Further explanation for the importance and challenge of the new task setting, CRDA.
- Section 2: Empirical proof for three assumptions in Section 4.1 of the main manuscript.
- Section 3: Proof for Equation (3) in the main manuscript.
- Section 4: More ablation study results.
- Section 5: Details of corruptions.
- Section 6: More details of experiments.

1 FURTHER EXPLANATION

In this section, we emphasize the challenge and importance of CRDA through the lower bound.
Corruption robustness is always an important subject. Previous works do not pay much care for corruptions because it has been addressed enough well in the setting of supervised learning. However, corruption robustness in domain adaptation is far from satisfactory.

As shown in Fig. 1, to estimate the status of current study, we further set an empirical lower bound for CRDA calculated by mCE of TSCL applied on CDAN+TN, which assumes testing corruptions are available while training. Models that reach the lower bound can be robust against unseen corruptions as if they are already known beforehand.

It is shown that current methods for CRDA still hold a large distance to the lower bound. In a word, instead of enough good progress in supervised learning, there is still a long way to go for CRDA.

2 PROOF FOR THREE ASSUMPTIONS IN SECTION 4.1 OF THE MAIN MANUSCRIPT

2.1 Proof for Assumption 1

We give the empirical proof for Assumption 1 via Average Shift. Given a clean image \( x \in \mathbb{R}^{c \times w \times h} \) and a corruption \( t \), the Average Shift is calculated by:

\[
\text{avg} = \frac{||x - t(x)||_1}{cwh} = \frac{1}{cwh} \sum_{i=1}^{c} \sum_{j=1}^{w} \sum_{k=1}^{h} |(x - t(x))_{ijk}|.
\]

(1)

Table 1 shows the Average Shift of an image under 15 corruptions with the most severe level. It is shown that most corruptions are within the shift range \( \delta = 0.26 \approx 60/255 \).

Fig. 2 verifies that the Average Shift in sample space increases with the increase of the severity level of most corruptions.

2.2 Proof for Assumption 2

It is shown in Section 5.4 of the main manuscript.

2.3 Proof for Assumption 3

Given input target domain \( D_t = \{(X_t, Y_t)\} \), source domain \( D_s = \{(X_s, Y_s)\} \), a corruption with 5 severity levels \( T = \{t_i\}_{i=1}^{5} \), an ideal transfer loss function \( \ell_{\text{trans}} \) and a DA model \( m = f \circ c \), we first make some notions for precise:
Table 1. Average Shift of different corruptions

| Corruption          | Avg shift | Corruption          | Avg shift |
|---------------------|-----------|---------------------|-----------|
| Gaussian Noise      | 0.22      | Snow                | 0.25      |
| Shot Noise          | 0.25      | Elastic Transform   | 0.19      |
| Impulse Noise       | 0.14      | Contrast            | 0.26      |
| Defocus Blur        | 0.08      | Brightness          | 0.25      |
| Motion Blur         | 0.13      | JPEG Compression    | 0.04      |
| Zoom Blur           | 0.12      | Pixelate            | 0.05      |
| Fog                 | 0.24      | Glass Blur          | 0.08      |
| Frost               | 0.21      |                     |           |

Fig. 2. Average Shift of different corruptions with 6 severity levels.

\[
\ell_{\text{trans}}(t_i) = \mathbb{E}_{x_t \sim X_t} \left[ \ell_{\text{trans}}(f(t_i(x_t)), f(X_t)) \right],
\]

\[
\text{Acc}(t_i) = \mathbb{P}_{(x_t, y_t) \sim D_t} (m(t_i(x_t)) = y_t),
\]

\[
\ell_{\text{total}}(t_i) = \ell_{\text{trans}}(t_i) + \ell_{\text{cls}}(X_s, Y_s),
\]

where \(\ell_{\text{trans}}(t_i)\) denotes the average transfer loss of corrupted target domain samples. \(\text{Acc}(t_i)\) denotes the classification accuracy of corrupted target domain samples. \(\ell_{\text{cls}}(X_s)\) denotes the classifier loss of source domain samples; \(\ell_{\text{total}}(t_i)\) denotes the total loss of a classic DA models, which usually correlated to \(\text{Acc}(t_i)\).

It is observed that the classification accuracy decreases as the increase of the severity level, as:

\[i < j \Rightarrow \text{Acc}(t_i) > \text{Acc}(t_j).\]  

(3)

We make the proof by contradiction. If

\[i < j \Rightarrow \ell_{\text{trans}}(t_i) > \ell_{\text{trans}}(t_j)
\]

\[\Rightarrow \ell_{\text{total}}(t_i) > \ell_{\text{total}}(t_j),\]

(4)

the final classification accuracy should be \(\text{Acc}(t_i) < \text{Acc}(t_j)\). Conflict with Equation (3).

3 PROOF FOR EQUATION (3) IN THE MAIN MANUSCRIPT

According to Assumption 1, \(x_t^{(\text{DDG})}\) and \(t(x_t)\) are within the \(\delta\) neighborhood \(\{x | \|x - x_t\| \leq \delta\}\).
Table 2. mCE (%) for different parameters in TSCL-WC on the UDA task of Ar→Rw from Office-Home dataset.

| object | $\delta$ | $\eta$ | $n$ | mCE (%) |
|--------|---------|-------|-----|---------|
| $\eta$ | 60/255  | $> 2\delta$ | 2   | 48.0    |
|        | 60/255  | $> 2\delta$ | 10  | 49.6    |
|        | 60/255  | 15/255  | 10  | 51.6    |
|        | 60/255  | 6/255   | 10  | 52.8    |
| $\delta$ | 20/255  | $> 2\delta$ | 2   | 49.5    |
|         | 40/255  | $> 2\delta$ | 2   | 48.6    |
|         | 60/255  | $> 2\delta$ | 2   | 48.0    |
|         | 80/255  | $> 2\delta$ | 2   | 47.3    |
|         | 100/255 | $> 2\delta$ | 2   | 47.2    |
|         | 120/255 | $> 2\delta$ | 2   | 46.9    |
|         | 140/255 | $> 2\delta$ | 2   | 46.4    |
| $n$    | 60/255  | $> 2\delta$ | 1   | 47.4    |
|         | 60/255  | $> 2\delta$ | 2   | 48.0    |
|         | 60/255  | $> 2\delta$ | 5   | 49.9    |
|         | 60/255  | $> 2\delta$ | 10  | 49.6    |

Suppose $t_{\text{max}}$ as the most severe corruption in corruption set $T$. According to Assumption 3,

$$t_{\text{max}} = \arg \max_{t \in T} \ell_{\text{trans}}(f(t(x_t)), f(D_s)).$$

Due to the uncertainty of $T$, the corrupted versions $t(x_t)$ can be everywhere in $\delta$ neighborhood. Thus,

$$\ell_{\text{trans}}(f(x_t^{(\text{DDG})}), f(D_s)) = \ell_{\text{trans}}(f(t_{\text{max}}(x_t)), f(D_s)) = \ell_{\text{max}}. \tag{6}$$

Suppose that

$$X^{(\text{DDG})} = \{x_t^{(\text{DDG})} | \ell_{\text{trans}}(f(x_t^{(\text{DDG})}), f(D_s)) = \ell_{\text{max}}\}$$

$$X^{(\text{tm})} = \{t_{\text{max}}(x_t) | \ell_{\text{trans}}(f(t_{\text{max}}(x_t)), f(D_s)) = \ell_{\text{max}}\}. \tag{7}$$

We get

$$X^{(\text{DDG})} = X^{(\text{tm})}. \tag{8}$$

Thus, $x_t^{(\text{DDG})} \in X^{(\text{we})}$ can represent $t_{\text{max}}(x_t) \in X^{(\text{tm})}$, as:

$$x_t^{(\text{DDG})} \Rightarrow t_{\text{max}}(x_t). \tag{9}$$

4 MORE ABLATION ON $\delta$, $\eta$, AND $n$

Table 2 reports the mCE on different settings of hyper-parameter of DDG in Algorithm 2. Besides the conclusion of $\eta$ in the main text, it is shown that the final corruption robustness improves as the increase of shift range $\delta$ and decrease of the update step $n$. For stability, we set $\delta = 60/255$, $\eta > 2\delta$ and $n = 2$ in this paper.
5 DETAILS OF CORRUPTIONS

We follow the same types of corruptions as Hendrycks et al. proposed to investigate how neural networks are robust against to common corruptions and perturbations. The 15 types of corruptions are: Gaussian Noise, Shot Noise, Impulse Noise, Defocus Blur, Motion Blur, Zoom Blur, Fog, Frost, Snow, Elastic Transform, Contrast, Brightness, JPEG Compression, Pixelate, and Glass Blur. Fig. 3 illustrates examples of all the 15 kinds of corruptions. For each kind, there are 5 levels of severity as shown in Fig. 4.

6 OTHER DETAILS

Training details of Fig.5 of Section 5.3 in the main manuscript. All models are trained on a single domain (Real World of Office-Home). Given Gaussian Noise corruption set with five levels of severity $T = \{t^0, t^5\}$ ($t^0$ denotes clean images) and inputs $x$, the training details of the models are as follows.

- **Clean**: Supervised training on clean data.
- **All levels**: At the beginning of each iteration, we randomly select a corruption from $\{t^0, t^5\}$ to corrupt the inputs $x$. All corrupted inputs $t(x)$ are aligned with the original clean inputs $x$ in feature space by contrastive loss.
- **Clean + Level 5**: At the beginning of each iteration, we randomly select a corruption from $\{t^0, t^5\}$ to corrupt the inputs $x$. All corrupted inputs $t(x)$ are aligned with the original clean inputs $x$ in feature space by contrastive loss.
- **Level 5**: At the beginning of each iteration, we use level 5 corruption $t^5$ to corrupt the inputs $x$.

![Fig. 3. Examples of 15 kinds of corruptions.](image-url)
Fig. 4. Examples of 5 levels of severity.