Highlights

Co-Teaching for Unsupervised Domain Adaptation and Expansion

Kaibin Tian, Qijie Wei, Xirong Li†

• We propose Co-Teaching (CT) for unsupervised domain adaptation and expansion.

• CT improves the generalizability of a student model by learning from two teachers.

• CT is generic, simple to implement and open source.

• Evaluation on Office-Home & DomainNet shows CT’s efficacy on image classification.

• Evaluation on Cityscapes & ACDC shows CT’s efficacy on driving-scene segmentation.
Co-Teaching for Unsupervised Domain Adaptation and Expansion

Kaibin Tian\textsuperscript{a,*}, Qijie Wei\textsuperscript{a,b,*}, Xirong Li\textsuperscript{†a}

\textsuperscript{a}Renmin University of China, China
\textsuperscript{b}Vistel AI Lab, Beijing Visionary Intelligence Ltd., China

Abstract

Unsupervised Domain Adaptation (UDA) essentially trades a model’s performance on a source domain for improving its performance on a target domain. To resolve the issue, Unsupervised Domain Expansion (UDE) has been proposed recently. UDE tries to adapt the model for the target domain as UDA does, and in the meantime maintains its source-domain performance. In both UDA and UDE settings, a model tailored to a given domain, let it be the source or the target domain, is assumed to well handle samples from the given domain. We question the assumption by reporting the existence of cross-domain visual ambiguity: Given the lack of a crystal-clear boundary between the two domains, samples from one domain can be visually close to the other domain. Such sorts of samples are typically in minority in their host domain, so they tend to be overlooked by the domain-specific model, but can be better handled by a model from the other domain. We exploit this finding, and accordingly propose Co-Teaching (CT). The CT method is instantiated with knowledge distillation based CT (kdCT) plus mixup based CT (miCT). Specifically, kdCT transfers knowledge from a leading-teacher network and an assistant-teacher network to a student network, so the cross-domain ambiguity will be better handled by the student. Meanwhile, miCT further enhances the generalization ability of the student. Extensive experiments on two image classification datasets and two driving-scene segmentation datasets justify the viability of CT for UDA and UDE.

Keywords: UDA, UDE, co-teaching, knowledge distillation, multi-class

*Equal contribution
†Corresponding author
E-mail addresses: \{tikibi,qijie.wei,xirong\}@ruc.edu.cn

Preprint submitted to arXiv September 17, 2023
1. Introduction

Unsupervised Domain Adaptation (UDA), aiming to adapt a model trained on a labeled source domain for an unlabeled target domain with no need of re-labeling any data, is a crucial technique for real-world pattern recognition [1]. Applications of this technique include cross-view person re-ID [2], cross-device medical image analysis [3], and cross-condition autonomous scene segmentation [4, 5], to name just a few. Thanks to the advent of novel methods for UDA [6, 7], we witness an ever-growing performance on the target domain, as demonstrated by public benchmark evaluations such as Office-Home [8] and DomainNet [9] for multi-class image classification and ACDC [10] for driving scene segmentation. However, it has been documented recently in the context of image classification that UDA in fact trades the model’s performance on the source domain for improving its performance on the target domain [11, 12]. Such a finding is disturbing, as it suggests that one may have to deploy simultaneously two models to support both domains. Even putting the doubled deployment cost aside, how to swiftly switch between the models is nontrivial, as from which domain a test sample comes is unknown. The degeneration of the source-domain performance puts the real-world applicability of UDA into question.

To remedy the issue, GSFDA [12] resorts to continual learning to preserve a model’s ability on the source domain while being adapted to the target domain. Since the method assumes zero availability of the source-domain samples, it has little chance to recover once degeneration occurs. Indeed, our evaluation shows that GSFDA also suffers source-domain performance loss.

To explicitly quantify the issue, a variant of UDA termed Unsupervised Domain Expansion (UDE) is introduced by Wang et al. [11]. UDE has the same starting point as UDA, i.e. a set of labeled training samples from the source domain and a set of unlabeled training samples from the target domain. The key difference is that UDE explicitly reports the source-domain performance and consequently the performance on an expanded domain which combines the source and target domains. Besides, the KDDE method by [11] assumes that a model tailored to a given domain, let it be the source or the target domain, can well handle samples from the given domain. Accordingly, KDDE runs in two steps, where two domain-specific models are first trained.
for the source and target domains, respectively. It then performs knowledge
distillation, where the dark knowledge of the source-specific (target-specific)
teacher is transferred to a student model via source-domain (target-domain)
samples exclusively.

We question the assumption of [11] by reporting the existence of cross-
domain visual ambiguity. We consider a test image in a specific domain \( A \) being \textit{cross-domain ambiguous} if the test image is wrongly predicted by a model well-trained on domain \( A \) but can be correctly classified by a model well-trained on a different domain \( B \). Tab. [1] shows the percentage of such ambiguous images on Office-Home and DomainNet, respectively. With the number ranging from 1.9\% to 7.5\%, the result consistently shows the universal existence of inter-domain ambiguity across different datasets.

| Office-Home | Domain A    | Domain B |
|-------------|-------------|----------|
|             | Art | Clipart | Product | Real |
| Art         | --  | 3.9     | 2.4     | 3.9  |
| Clipart     | 5.0 | --      | 1.9     | 4.1  |
| Product     | 6.0 | 4.0     | --      | 3.9  |
| Real        | 7.5 | 4.6     | 2.6     | --   |

| DomainNet  | Domain A   | Domain B |
|------------|------------|----------|
|             | clipart | painting | sketch | real |
| clipart     | --      | 3.4      | 2.6     | 3.8  |
| painting    | 3.9     | --       | 2.7     | 2.6  |
| sketch      | 4.5     | 4.4      | --      | 3.3  |
| real        | 4.3     | 2.9      | 1.9     | --   |

The cross-domain ambiguity is also exemplified in Fig. [1]. While the source and target domains are known to be distinct, there lacks a crystall boundary between the two. Hence, samples from one domain can be visually close to the other domain. As such sorts of samples are in minority in their host domain, they tend to be overlooked by the domain-specific model. However, they are likely to be better handled by the model targeted at the other domain. Departing from this observation, we propose in this paper Co-Teaching (CT) which exploits the domain-specific models in a more effective and easy-to-implement manner. Our major contributions are as follows:

- We propose CT as a generic method for unsupervised domain adaptation and expansion. CT consists of knowledge distillation based
CT (kdCT) and mixup based CT (miCT). Specifically, kdCT transfers knowledge from a leader-teacher network and an assistant-teacher network to a student network, to let the student better resolve cross-domain ambiguity, while miCT further enhances the generalization ability of the student.

- Comprehensive experiments on two image-classification benchmarks, i.e. Office-Home [8] and DomainNet [9], and two driving-scene-segmentation benchmarks, i.e. Cityscapes [13] and ACDC [10], justify the viability of the proposed method and its superior performance against competitive baselines. CT is open-source at https://github.com/TheEighthDay/Co-teaching.

Figure 1: Illustration of cross-domain visual ambiguity. Samples from a target domain (Clipart) can be visually realistic as samples from a source domain (Art), and vice versa. This points out an overlooked fact that there lacks a crystal clear boundary between the source and target domains. Data from Office-Home [8].

2. Related Work

**Progress on UDA.** The major line of research on UDA is to learn domain-invariant feature representations, either by domain discrepancy reduction [14, 15, 16] or by adversarial training [17, 18, 19]. In Deep Domain Confusion (DDC) [14], the domain discrepancy between features from the source / target domains is defined as the maximum mean discrepancy (MMD)
on the last layers of a deep image classification network. Contrastive Adaptation Network (CAN) \cite{16} takes class information into account, measuring both intra-class and inter-class domain discrepancy. Domain Adversarial Neural Network (DANN) \cite{17} is among the first to introduce adversarial training for UDA. CDAN \cite{18} extends DANN by taking the multiplicative interaction of feature representations and class predictions as the input of its discriminator. SRDC \cite{6} enhances its discriminator by clustering features from intermediate layers of the network. More recently, the mixup technique, originally developed for supervised deep learning \cite{20}, has been actively leveraged for learning domain-invariant features \cite{21, 22}. To that end, DM-ADA \cite{21} aims for a better domain discriminator by training on domain-mixed samples with soft domain labels. FixBi \cite{22} bridges the domain gap by using fixed ratio-based mixup to first train a source-biased classifier and a target-biased classifier. Consistency regularization is then performed to let the two classifiers predict consistently on equally domain-mixed samples. Our mixup based CT (miCT) is motivated differently and thus uses the common mixup technique in a different manner: On recognizing the intrinsic discrepancy between the source and target models, miCT utilizes domain-mixed samples to pass the knowledge of the domain-specific models to a student network.

We note an increasing interest in extending image-level UDA to the pixel level for cross-domain semantic image segmentation. AdaSegNet \cite{23} and Advent \cite{24} use adversarial training at the output space, while pixel-level adaptation is performed in DCAN \cite{25} and Cycada \cite{26}. More recently, FDA \cite{7} uses self-predicted labels for self-supervised training.

Our proposed CT conceptually differs from the above works as it essentially performs meta learning on top of a specific UDA method. Moreover, in contrast to the prior art which cares only the target-domain performance, CT aims for a broader scope that covers the source and target domains both. Previously, GSFDA \cite{12} tries to prevent performance deterioration on the source domain by continual learning. LDAuCID \cite{27} conducts continual learning by consolidating the learned internal distribution to improve classifier generalization on the target domain. PDA \cite{28} attempts to balance the source supervised loss and the cross-domain alignment loss by pareto optimal solution. Our experiment indicates that the deterioration remains. CT works better for both image classification and semantic segmentation.

**Progress on UDE.** CT is inline with KDDE \cite{11}, as both aim for training a model that suits the expanded domain by knowledge distillation (KD). However, KDDE uses its teacher networks in a relatively limited manner,
where the knowledge of the teacher network trained for the source (target) domain is transferred to the student network via the source (target) samples exclusively. Consequently, KDDE lacks the ability to fully exploit the potential of the teacher network derived from one domain in handling the cross-domain ambiguity for the other domain.

**Multi-Teacher Knowledge Distillation (MTKD).** MTKD has been used in the context of multi-source UDA, where multiple domain-adapted teacher models are trained by pairing the target domain with each of the multiple source domains [29, 30]. Such a tactic is inapplicable to single-source UDA as this paper works on. In the context of standard supervised learning, MultiT [31] transfers the dark knowledge of multiple pre-trained teacher networks to a student network by minimizing the KL divergence between the averaged prediction of the teachers and the prediction of the student. Treating the teachers equally, MultiT is suboptimal for UDA/UDE. Different from MultiT whose teacher networks are all fully supervised, the teachers in CT are trained by supervised and semi-supervised learning, respectively. Moreover, to deal with the labeled and unlabeled training samples in an unbiased manner, CT exclusively uses the label-free KL divergence loss.

**Co-Teaching.** It is worth pointing out that the term co-teaching has been used in other contexts which conceptually and technically differ from ours. For supervised learning, Decoupling [32] and Co-Teach [33] aim for label denoising within a single domain. Decoupling simultaneously trains two models $h_1$ and $h_2$, updating them with samples having $h_1(x) \neq h_2(x)$ in a given mini-batch. Co-Teach alternately uses samples correctly classified by one model to train the other model. Since both methods are fully supervised, they are inapplicable for UDA/UDE where the target domain is unlabeled. For multi-target domain adaptation, CGCT [34] proposes a co-teaching strategy that uses a dual classifier head to provide pseudo labels for unlabeled target-domain samples. As our CT is model-agnostic, any UDA method including CGCT can in principle be used as CT’s UDA module.

3. Proposed Co-Teaching Method

3.1. Problem Formalization

We use $x$ to indicate a specific sample. For a manually labeled sample, we use $y$ to indicate its manual annotation, which can be a one-hot vector for multi-class image classification or a multi-dimensional binary mask for semantic image segmentation. Let $\mathcal{N}$ be a deep neural network, which is
Figure 2: Proposed Co-Teaching (CT) method for unsupervised domain adaptation and expansion. Given a set of labeled samples \( \{(x_s, y_s)\} \) from a source domain and unlabeled data \( \{x_t\} \) from a target domain, CT obtains a domain-expanded network \( N_u \) by two-stage training. In the first stage, two domain-specific teacher networks \( N_s \) and \( N_t \) are obtained, where \( N_s \) for the source domain is trained on \( \{(x_s, y_s)\} \) by standard supervised learning, whilst \( N_t \) for the target domain is trained on \( \{(x_s, y_s)\} \) and \( \{x_t\} \) by an existing UDA method. In the second stage, \( N_s \) and \( N_t \) are used in a cooperative manner to teach \( N_u \), achieved by knowledge distillation based CT (kdCT) that minimizes \( L_{kdct}(\{x_s\}) + L_{kdct}(\{x_t\}) \), and mixup based CT (miCT), minimizing \( L_{mict}(\{x_m\}) \) for mixup instances \( \{x_m\} \). Once trained, only \( N_u \) is needed for inference. CT is easy to implement and works for both image classification and semantic image segmentation.

supposed to output \( N(x) \) that well matches the (unknown) label of a novel sample. Following [1], we formalize the UDE task as follows. Given a set of \( n_s \) labeled samples \( \{(x_s, y_s)\} \) randomly sampled from a source domain \( D_s \) and a set of \( n_t \) unlabeled samples \( \{x_t\} \) sampled randomly from a target domain \( D_t \), the goal of UDE is to train \( N \) that works for an expanded domain covering both \( D_s \) and \( D_t \). Accordingly, we use \( D_{s+t} \) to indicate the expanded domain.

The previous approach to UDE, as aforementioned, is Knowledge Distillation Domain Expansion (KDDE) [1]. At a high level, KDDE works in two stages. In the first stage, two domain-specific teacher networks \( N_s \) and \( N_t \) are trained, where \( N_s \) for \( D_s \) is learned from the labeled set \( \{(x_s, y_s)\} \) by standard supervised learning, while \( N_t \) for \( D_t \) is trained on \( \{(x_s, y_s)\} \) and \( \{x_t\} \) by an off-the-shelf UDA method. In the second stage, knowledge distillation
(KD) is performed to inject the dark knowledge of the teacher networks into a student network \( N_u \), which will be eventually used for inference. Depending on the domain identity of a training sample, KDDE selectively uses the two teachers, i.e. \( N_s \) to deal with samples from \( D_s \) and \( N_t \) for samples from \( D_t \), see Eq. (1).

\[
\begin{align*}
N_s & \leftarrow \text{supervised-learning}\{(x_s, y_s)\} \\
N_t & \leftarrow \text{UDA}\{(x_s, y_s), \{x_t\}\} \\
N_u & \leftarrow \begin{cases} \\
\text{KD}(N_s, \{x\}), & x \in D_s \\
\text{KD}(N_t, \{x\}), & x \in D_t \\
\end{cases}
\end{align*}
\]

The two-stage property of KDDE ensures flexibility in choosing UDA methods for implementing \( N_t \). We therefore opt to inherit this property, but introduce a novel Co-Teaching (CT) method into the second stage.

### 3.2. Framework

As illustrated in Fig. 2, CT consists of knowledge distillation based CT (kdCT) and mixup based CT (miCT). Both kdCT and miCT are introduced to exploit the domain-specific advantages of the two teacher networks. In particular, kdCT allows the student network to simultaneously learn the two teacher networks’ dark knowledge about every training sample. Meanwhile, miCT improves the generalization ability of the student network by using the mixup technique in a cross-domain manner. As the two implementations of CT are orthogonal to each other, they can be used either alone or jointly.

#### 3.2.1. Knowledge Distillation based Co-Teaching

We depart from a standard KD process with one student network \( N_u \) and one teacher network, either \( N_s \) or \( N_t \). Let us consider \( N_s \) for instance. Given a set of samples \( \{x\} \), KD from \( N_s \) to \( N_u \) is achieved by minimizing the Kullback-Leibler (KL) divergence between \( N_s(\{x\}) \) and \( N_u(\{x\}) \), denoted as \( KL(N_s(\{x\}), N_u(\{x\})) \). Similarly, we have the loss of KD from \( N_t \) to \( N_u \) as \( KL(N_t(\{x\}), N_u(\{x\})) \). To perform multi-teacher KD, a straightforward solution is to average the two losses. In the context of UDA / UDE, however, the two teachers are supposed to specialize in handling samples from their targeted domains. Therefore, we shall not treat them equally. To be more precise, for training samples from \( D_s \), we expect that \( N_s \) leads the teaching process, while the \( N_t \) acts as an assistant. The opposite is true when exploiting training examples from \( D_t \). To that end, we introduce a parameter \( \gamma \) to
weigh the importance of each teacher in the kdCT process as:

$$L_{kdct}(\{x\}) = \begin{cases} 
\gamma \cdot KL(N_s, N_u) + (1 - \gamma) \cdot KL(N_t, N_u) & x \in D_s \\
\gamma \cdot KL(N_t, N_u) + (1 - \gamma) \cdot KL(N_s, N_u) & x \in D_t 
\end{cases}$$

(2)

Given Eq. (2), KDDE can now be viewed as a special case of kdCT with \(\gamma = 1\). By extending the loss of KDDE to exploit multiple teachers in a biased manner, kdCT enables the possibility of making correct decisions on samples of domain ambiguity. Such a compensation mechanism is missing from KDDE.

Concerning the choice of \(\gamma\), in principle we shall take a value larger than 0.5 to emphasize the leading-teacher network, i.e. \(N_s\) for samples from \(D_s\) and \(N_t\) for samples from \(D_t\). It has been recognized that introducing certain randomness into the process of deep network training can make the network more resistant to noise and thus improve its robustness \[35, 36\]. Therefore, we let \(\gamma\) follow a probability distribution, instead of using a fixed value. Since the beta distribution can produce diversified probability distributions with ease by adjusting two positive shape parameters denoted by \(\alpha\) and \(\beta\), we choose to use \(\gamma \sim Beta(\alpha, \beta)\). The randomness is introduced at a mini-batch level, by sampling randomly a specific \(\gamma\) from the beta distribution per batch.

Given the two domain-specific losses \(L_{kdct}(\{x_s\})\) and \(L_{kdct}(\{x_t\})\) computed by Eq. (2), we define the overall loss \(L_{kdct}\) as their sum.

### 3.2.2. Mixup based Co-Teaching

The mixup technique \[20\], synthesizing a new training sample by a convex combination of two real samples, is shown to be effective for improving image classification networks. We thus re-purpose this technique to generate new domain-expanded samples denoted by \(\{x_m\}\). In particular, \(x_m\) is obtained by blending \(x_s\) randomly chosen from \(D_s\) with \(x_t\) randomly chosen from \(D_t\).

Our mixup based Co-Teaching (miCT) is implemented by transferring the two-teacher knowledge via mixed samples to the student network. The teachers’ joint knowledge w.r.t. \(x_m\) is naturally reflected by their combined prediction denoted as \(\hat{y}_m\). Hence, the loss of miCT \(L_{miCT}\) is computed as

$$\begin{cases}
x_m = \lambda \cdot x_s + (1 - \lambda) \cdot x_t \\
\hat{y}_m = \lambda \cdot N_s(\{x_s\}) + (1 - \lambda) \cdot N_t(\{x_t\}) \\
L_{miCT} = KL(\hat{y}_m, N_u(\{x_m\}))
\end{cases}$$

(3)

with \(\lambda \sim Beta(1, 1)\).
Both $L_{kdct}$ and $L_{mict}$ are KL-divergence based losses for knowledge distillation. So they can be directly added and minimized together for the joint use of kdCT and miCT.

3.3. Applications

As Fig. 2 shows, CT is a generic method for UDA and UDE. Depending on the choice of the network and the loss function, the method can be used with ease for multi-class image classification and semantic image segmentation. For the former task, a classification network shall be used with the KD losses computed at the image level. For the latter, a segmentation network shall be adopted with the KD losses computed at the pixel level. In this paper, we use ResNet-50 \cite{he2016deep} as the structure of the student network for image classification, and DeepLabv2 \cite{chen2017rethinking} for semantic segmentation, unless otherwise stated.

4. Experiments

We evaluate the viability of the proposed CT method in the context of two tasks, i.e. multi-class image classification and driving scene segmentation. It is worth pointing out that UDE as an emerging topic is less studied. We shall naturally include methods directly targeted at UDE, namely KDDE \cite{rodriguez2019unsupervised}. Meanwhile, as our method is built based on two teacher networks ($\mathcal{N}_s$ and $\mathcal{N}_t$), methods used for obtaining these networks, e.g. SRDC for image classification \cite{sun2018deep} and FDA \cite{sun2016return} for semantic segmentation, shall be treated as baselines. In addition, methods developed for other purposes yet technically applicable for UDE, e.g. MultiT \cite{xie2020multit} which performs knowledge distillation given multiple teachers is also included. So for a fair and comprehensive evaluation, we organize the competitor methods into the following three groups: methods targeted at UDE, methods targeted at UDA, and methods technically related. All experiments are run within the PyTorch framework with two NVIDIA Tesla P40 cards.

4.1. Task 1. Multi-Class Image Classification

4.1.1. Experimental Setup

We adopt two public collections, Office-Home \cite{venkateswara2017match} and DomainNet\cite{peng2019moment}. Office-Home contains 15,588 images of 65 object classes common in office and home scenes, e.g. chair, table and TV. There are four different domains, i.e. artistic images (A), clip art (C), product images (P), and real-world images (R). DomainNet, previously used in the Visual Domain Adaptation
Challenge at ICCV 2019[1] has 362,470 images of 345 object classes from four domains, i.e. clipart, painting, real, and sketch. In order to evaluate a model’s performance on both source and target domains, we adopt the data split provided by [11], where images per domain have been divided at random into two disjoint subsets, one for training and the other for test[2]. A specific UDE task is defined with one domain as $D_s$ and another domain as $D_t$. Per collection, by pairing its individual domains, we define 12 tasks in total.

**Competitor methods.** We include as a baseline ResNet-50 trained by standard supervised learning on $D_s$. As mentioned above, we compare with existing methods from the following three groups:

- **Method for UDE:** KDDE [11].
- **Methods for UDA:** DDC[14], DANN[17], DAAN[39], CDAN[18], SRDC[6], PDA[28], GSFDA[12], CGCT[34], FixBi[10,22], SDAT[11,40] and ELS[13,41].
- **Method technically related:** MultiT [31].

As each method is provided with the same training data and eventually yields a specific ResNet-50 network for inference, such an experimental setup enables a head-to-head comparison between the different methods.

In order to study whether CT also works with the latest Transformer-based method, we try to improve CDTrans[42] with CT. Different from the previous baselines, CDTrans uses DeiT-Base[43] as its backbone. We simply use the same training protocol (optimizer, initial learning rate, learning rate adjustment strategy, etc.) as used for CNN.

**Details of implementation.** Following [11], we train networks by SGD with a momentum of 0.9, an initial learning rate of 0.005, and a weight decay

---

[1]http://ai.bu.edu/visda-2019  
[2]https://github.com/li-xirong/ude  
[3]https://github.com/jindongwang/transferlearning/tree/master/code/DeepDA  
[4]https://github.com/fungtion/DANN  
[5]https://github.com/thuml/CDAN  
[6]https://github.com/Gorilla-Lab-SCUT/SRDC-CVPR2020  
[7]https://github.com/BIT-DA/ParetoDA  
[8]https://github.com/Albert0147/G-SFDA  
[9]https://github.com/Evgeneus/Graph-Domain-Adaptaion  
[10]https://github.com/NaJaeMin92/FixBi  
[11]https://github.com/val-iisc/SDAT  
[12]https://github.com/yfzhang114/Environment-Label-Smoothing
of 0.0005. The learning rate is decayed by 0.1 every 30 epochs on Office-Home and every 10 epochs on DomainNet. A fixed number of training epochs is used, which is 100 for Office-Home (with batch size 32) and 30 on DomainNet (with batch size 96) as the latter is much larger. Models obtained at the last epoch are used for evaluation. Each method is run independently three times with averaged performance reported.

Note that not all methods are compared on DomainNet due to their high demand on GPU computational resources that are beyond our capacity. Also notice that the performance of the baselines appear lower than that reported in their original papers. Our data split follows [11], “for each domain, we randomly divide its images into two disjoint subsets, one for training and the other for test, at a ratio of 1:1”, while other works typically use much more training data, e.g. [6] uses “all labeled source samples and all unlabeled target samples as the training data”. Such difference results in the performance gap.

Performance metric. We report accuracy (%), i.e. the percentage of test images correctly classified.

4.1.2. Results on Office-Home

Tab. 2 shows the performance of the different methods on the source ($D_s$), target ($D_t$) and expanded ($D_s+t$) domains, respectively. The UDA method consistently show performance degeneration on $D_s$. Even though GSFDA is meant for maintaining a model’s performance on $D_s$, it suffers from a performance drop of 2.53% (from 82.43 to 79.90). Among the three UDE methods, the proposed CT performs the best. Given DDC as $N_t$, CT even outperforms $N_s$ on $D_s$. When evaluated in the UDA setting to which only the performance on $D_t$ matters, CT again compares favorably against the best UDA method, i.e. GSFDA. CT is also better than KDDE and MultiT. As for the UDE setting, the lower performance of MultiT than KDDE and CT confirms our hypothesis that the two teacher networks shall not be treated equally in the knowledge distillation process. Given DDC / SRDC as $N_t$, CT outperforms KDDE by 0.52% (72.47 → 72.99 / 74.37 → 74.89). When using CDAN as $N_t$, a larger gain of 1.36% (72.00 → 73.36) is obtained on Office-Home. As Tab. 3 shows, the proposed CT steadily surpasses KDDE for all the 12 tasks on the expanded domain.

On addressing the cross-domain ambiguity. While the above experiments have shown that the student network derived by kdCT is better than its KDDE / MultiT counterparts, it remains not entirely conclusive that kdCT can better handle the cross-domain ambiguity. In that regard, we
Table 2: Multi-class image classification in the UDA/UDE setting. Cells with n.a. indicate that running the specific methods is beyond our computational capacity.

| Method         | Office-Home | DomainNet |
|----------------|-------------|------------|
|                | $D_s$ | $D_t$ | $D_{s+t}$ | $D_s$ | $D_t$ | $D_{s+t}$ |
| ResNet-50 ($N_s$) | 82.43 | 57.84 | 70.13 | 74.59 | 41.49 | 58.04 |
| Choice of $N_t$: | | | | | | |
| CDAN [18]      | 80.36 | 61.57 | 70.96 | 69.73 | 45.21 | 57.47 |
| DANN [17]      | 81.36 | 60.65 | 71.01 | 67.37 | 44.53 | 56.95 |
| DDC [14]       | 82.35 | 60.51 | 71.43 | 72.44 | 46.20 | 59.32 |
| DAAN [39]      | 82.38 | 60.84 | 71.62 | n.a.  | n.a.  | n.a.  |
| SRDC [6]       | 78.68 | 65.30 | 71.99 | n.a.  | n.a.  | n.a.  |
| GSFDA [12]     | 79.90 | 66.53 | 73.22 | n.a.  | n.a.  | n.a.  |
| CGCT [34]      | 79.70 | 61.44 | 70.57 | n.a.  | n.a.  | n.a.  |
| DDC as $N_t$:  | | | | | | |
| KDDE [11]      | 82.74 | 62.19 | 72.47 | 73.78 | 48.04 | 60.91 |
| PDA [28]       | 76.90 | 54.01 | 65.46 | n.a.  | n.a.  | n.a.  |
| CT             | 82.92 | 63.06 | 72.99 | 74.63 | 48.42 | 61.53 |
| CDAN as $N_t$: | | | | | | |
| KDDE           | 81.03 | 62.96 | 72.00 | 72.98 | 47.65 | 60.32 |
| PDA            | 78.44 | 57.65 | 68.04 | n.a.  | n.a.  | n.a.  |
| CT             | 82.17 | 64.55 | 73.36 | 73.26 | 49.33 | 61.29 |
| SRDC as $N_t$: | | | | | | |
| MultiT [31]    | 82.23 | 61.66 | 71.94 | n.a.  | n.a.  | n.a.  |
| KDDE           | 81.54 | 67.20 | 74.37 | n.a.  | n.a.  | n.a.  |
| CT             | 82.32 | 67.45 | 74.89 | n.a.  | n.a.  | n.a.  |

group all test samples w.r.t. to the prediction (in)consistency between the two teacher networks. In particular, depending on whether the predictions of $N_s$ and $N_t$ are consistent (=) or inconsistent (≠), samples are exclusively grouped. The inconsistent group covers the visually ambiguous samples. The fine-grained result is shown in Tab. 4. We can mostly attribute the success of kdCT to its superior performance on the inconsistent group, which confirms the effectiveness of compensation mechanism from CT. As Fig. 3 shows, the activated regions w.r.t. kdCT is more precise than the others. Both quantitative and qualitative results justify the efficacy of CT.

**CT versus Transformer-based UDA.** As Tab. 5 shows, CT exceeds CDTrans on the target domain, and obtains better performance on the expanded domain (82.07→83.62). Also note that the issue of source-performance degeneration is alleviated (85.37→88.04). The above result allows us to conclude that CT can also work with the transformer-based UDA.
Table 3: Multi-class image classification result on Office-Home in the UDA/UDE setting. A specific task denoted by A→C means the artificial image set (A) is used as the source domain, while the clip art image set (C) is used as the target domain. All methods have been independently trained and evaluated three times, with its average performance and standard deviation reported. Top performers are highlighted in red font.

| Method | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|-------|---------|---------|---------|---------|---------|---------|
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
|       | A→C     | A→P     | A→R     | R→A     | R→P     | P→A     |
|       | A       | P       | R       | R       | P       | A       |
Table 4: **Performance of different methods on two groups of test samples.** Given a specific test set, say $D_s$, it can be divided into two disjoint subsets, i.e. consistent and inconsistent, where each sample $x$ in the consistent set has $N_s(x) = N_t(x)$, while each sample in the inconsistent set has $N_s(x) \neq N_t(x)$. The classification accuracy score is calculated per subset. The gain of kdCT against KDDE and MultiT is mostly attributed to the method’s better performance on the inconsistent group.

| Task $\rightarrow$ P | $D_s$ | $D_t$ | $D_{s+t}$ |
|----------------------|--------|--------|------------|
| $N_s$                | 90.00  | 42.75  | 87.54 21.88 | 88.80 30.20 |
| $N_t$                | 90.00  | 30.07  | 87.54 48.31 | 88.80 41.04 |
| KDDE                 | 88.96  | 42.39  | 87.32 51.20 | 88.16 47.69 |
| MultiT               | 88.96  | 44.57  | 86.61 41.59 | 87.81 42.77 |
| kdCT                 | 89.53  | 47.46  | 87.54 52.88 | 88.56 50.72 |

| Task $\rightarrow$ C | $D_s$ | $D_t$ | $D_{s+t}$ |
|----------------------|--------|--------|------------|
| $N_s$                | 85.19  | 43.30  | 66.50 16.13 | 74.41 22.90 |
| $N_t$                | 85.19  | 18.30  | 66.50 27.61 | 74.41 25.31 |
| KDDE                 | 81.90  | 36.14  | 65.13 29.99 | 72.26 31.52 |
| MultiT               | 83.87  | 40.19  | 65.45 27.51 | 73.25 30.67 |
| kdCT                 | 82.98  | 43.30  | 66.75 32.78 | 73.62 35.40 |

Table 5: **Comparison with transformer-based UDA method on Office-Home.**

| Method                | $D_s$ | $D_t$ | $D_{s+t}$ |
|----------------------|--------|--------|------------|
| DeiT-Base\[43\] as $N_s$ | 88.31  | 72.38  | 80.35      |
| CDTrans\[42\] as $N_t$  | 85.37  | 78.78  | 82.07      |
| CT(CDTrans)           | 88.04  | 79.19  | 83.62      |

**CT versus state-of-the-art.** As shown in Tab. 6, among the three SOTA methods evaluated, SDAT is the best in terms of its overall performance, followed by ELS and FixBi. Note that the performance of ELS and FixBi is lower than that reported in the original papers, where the evaluation is performed in a transductive setting that all the test data from the target domain is also used for training. CT is consistently better per baseline.

4.1.3. **Results on DomainNet**

As DomainNet is much larger than Office-Home in terms of classes and samples, we are only able to train the following UDA methods, i.e. CDAN, DANN and DDC. As Tab. 2 shows, using either DDC or CDAN as $N_t$, our CT method again achieves the best performance on $D_s$, $D_t$ and $D_{s+t}$. In
Figure 3: Grad-CAM [44] visualization of ResNet-50 trained by different methods. The top three rows are from a source domain (Art), while the bottom three rows are from a target domain (Clipart). Texts under heatmaps are predicted labels with scores.

**4.1.4. Ablation Study**

We choose Office-Home for ablation study, simply because the set is more computationally friendly than DomainNet.

particular, CT exceeded KDDE on 11/12 tasks, see Tab. 7. 
Table 6: **Comparison with state-of-the-art UDA methods.** We found that training FixBi on DomainNet does not converge, so its result on this dataset is omitted.

| Method     | Office-Home | DomainNet |
|------------|-------------|-----------|
|            | $D_s$ | $D_t$ | $D_{str}$ | $D_s$ | $D_t$ | $D_{str}$ |
| FixBi [22] | 77.10 | 64.31 | 70.71 | – | – | – |
| CT(FixBi)  | 80.88 | 65.46 | 73.17 | – | – | – |
| SDAT [40]  | 81.48 | 68.42 | 74.95 | 75.41 | 51.15 | 63.28 |
| CT(SDAT)   | 81.87 | 68.86 | 75.37 | 75.94 | 51.47 | 63.70 |
| ELS [41]   | 81.74 | 68.51 | 75.13 | 75.17 | 49.83 | 62.50 |
| CT(ELS)    | **82.10** | **68.82** | **75.46** | **75.83** | 50.35 | 63.09 |

**The influence of kdCT and miCT.** As shown in Tab. 8, kdCT is better than miCT when they are used alone. Their joint use is recommended for the image classification task. The lower performance of miCT is because we train on mixup samples exclusively, without using original samples. Similar to a standard mixup, mixup samples shall not be used alone.

![Beta distributions](image.png)

Figure 4: **Beta distributions** parameterized by different $\alpha$ and $\beta$. $E(\gamma)$ represents the distribution expectation.

**The influence of $\gamma$.** Tab. 9 reports the performance of kdCT given $\gamma$ specified in varied manners. The stochastic strategy with $\gamma \sim Beta(10, 1)$ leads to the best performance on the expanded domain. In particular, we also tried fixing $\gamma$ to 0.909, which is the expectation value of $Beta(10, 1)$, see Fig. 4. Comparing the first row and the last second row in Tab. 9, we observe that using the fixed value results in lower performance consistently.
Table 7: Multi-class image classification on DomainNet in the UDA/UDE setting. Top performers are highlighted in red font.

| Method          | c→p | c→r | c→s | p→c | p→r | p→s |
|-----------------|-----|-----|-----|-----|-----|-----|
|                 | c   | p   | c+p | c   | r   | c+s |
| ResNet-50(Ns)   | 77.16 | 32.07 | 54.62 | 77.16 | 38.50 | 57.83 |
|                 | c+p | c   | r   | c   | s   | c+s |
|                 | 48.22 | 62.69 | 77.16 | 38.50 | 57.83 | 69.71 |
|                 | p   | c   | r   | c   | s   | p+c |
|                 | 54.72 | 69.71 | 69.71 | 43.99 | 62.51 | 56.05 |
|                 | r   | c   | r   | c   | s   | p+s |
| Choice of Nt:   |     |     |     |     |     |
| DDC             | 75.36 | 36.52 | 55.94 | 75.77 | 54.09 | 64.93 |
| DANN            | 71.35 | 33.51 | 52.43 | 73.92 | 52.98 | 63.45 |
| CDAN            | 72.45 | 34.33 | 53.39 | 73.34 | 53.23 | 63.29 |
|                 |     |     |     |     |     |
| DDC as Nt:      |     |     |     |     |     |
| KDDE            | 76.57 | 37.71 | 57.14 | 76.77 | 55.52 | 66.15 |
| DANN            | 71.25 | 38.67 | 57.68 | 77.40 | 57.56 | 67.48 |
| CDAN            | 79.10 | 50.99 | 65.05 | 80.34 | 43.25 | 63.47 |

| Method          | r→c | r→p | r→s | s→c | s→p | s→r |
|-----------------|-----|-----|-----|-----|-----|-----|
|                 | r   | c   | r+c | r   | p   | r+p |
|                 | c   | r+p | r+s | s   | c   | s+c |
|                 | s   | p   | s+p | s   | r   | s+r |
| Choice of Nt:   |     |     |     |     |     |     |
| DDC             | 81.16 | 50.08 | 65.62 | 82.14 | 46.50 | 64.32 |
| DANN            | 77.25 | 49.32 | 63.29 | 78.34 | 43.25 | 60.80 |
| CDAN            | 79.10 | 50.99 | 65.05 | 80.34 | 46.30 | 63.47 |
|                 |     |     |     |     |     |     |
| DDC as Nt:      |     |     |     |     |     |     |
| KDDE            | 82.19 | 52.68 | 67.44 | 83.28 | 48.77 | 66.03 |
| DANN            | 82.45 | 52.88 | 67.67 | 83.11 | 51.16 | 67.14 |
| CDAN            | 81.37 | 53.56 | 67.47 | 82.68 | 49.00 | 65.84 |
|                 |     |     |     |     |     |     |
| CDAN as Nt:     |     |     |     |     |     |     |
| KDDE            | 81.37 | 53.56 | 67.47 | 82.68 | 49.00 | 65.84 |
| DANN            | 82.45 | 52.88 | 67.67 | 83.11 | 51.16 | 67.14 |
| CDAN            | 81.97 | 55.56 | 68.77 | 82.47 | 51.23 | 66.85 |
Table 8: Ablation Study of Co-Teaching on Office-Home.

|      | kdCT | miCT | $D_s$ | $D_t$ | $D_{s+t}$ |
|------|------|------|------|------|-----------|
| DDC as $N_t$ |      |      |      |      |           |
| ✓    | 82.85| 62.42| 72.63|      |           |
| ✓ ✓  | 82.92| 63.06| 72.99|      |           |
| SRDC as $N_t$ |      |      |      |      |           |
| ✓    | 82.52| 67.19| 74.86|      |           |
| ✓ ✓  | 82.32| 67.45| 74.89|      |           |

on $D_s$ (82.81 versus 82.85), $D_t$ (61.67 versus 62.42) and $D_{s+t}$ (72.24 versus 72.63). The results justify the benefit of using $\gamma$ in a stochastic manner.

Table 9: The influence of $\gamma$ on kdCT. Best performance is obtained by sampling $\gamma$ from Beta$(10,1)$ with an expectation of 0.909. Fixing $\gamma$ to 0.909 results in lower performance consistently on $D_s$, $D_t$ and $D_{s+t}$. Choice of $N_t$: DDC. Data: Office-Home.

|      | $D_s$ | $D_t$ | $D_{s+t}$ |
|------|------|------|-----------|
| $(\alpha, \beta)$ of the beta distribution |      |      |           |
| 10, 1 | 82.85| 62.42| 72.63     |
| 5, 1  | 82.84| 62.02| 72.43     |
| 1, 1  | 82.86| 61.54| 72.20     |
| 1, 5  | 82.78| 60.61| 71.70     |
| 1, 10 | 82.65| 60.61| 71.63     |
| Fixed | 0.5  | 82.75| 61.41     |
|       | 0.909| 82.81| 61.67     |
|       | 1    | 82.74| 62.19     |
|       |      |      | 72.47     |

4.2. Task 2. Driving Scene Segmentation

4.2.1. Experimental Setup

We follow the setup of [10], using Cityscapes [13] as $D_s$ and ACDC [10] as $D_t$. Both datasets have pixel-level ground truth w.r.t. 19 traffic-related labels such as bicycle, road and sidewalk. Different from Cityscapes consisting of normal lighttime driving scenes, ACDC have four adverse conditions, i.e. fog, nighttime, rain and snow, see Fig. 5. For both datasets, we adopt their official data splits, i.e. 2,975 training and 500 test images in Cityscapes and 1,600 training and 406 test images in ACDC.
Baselines. We again compare with KDDE [11]. Our choice of $\mathcal{N}_s$ is DeepLabv2 [38] with ResNet-101 as its backbone, as has been used in the previous work [10]. As for $\mathcal{N}_t$, we adopt the classic AdaSegNet [23] and the more recent FDA [7], which is found to be the most effective on ACDC [10].

Implementation. Following [38], we adopt SGD with an initial learning rate of 0.001, a momentum of 0.9, and a weight decay of 0.0005. We train 75000 iterations with batch size 1. Previous work on semantic image segmentation [45] reports the Mixup technique has an adverse effect on the performance, which is also observed in our preliminary experiment on driving scene segmentation. We therefore use kdCT for this task.

Performance metric. We report Intersection over Union (IoU) per class, and mean IoU (mIoU) for measuring the overall performance.

4.2.2. Results

On the source domain, we observe that the performance of the AdaSegNet and FDA decreases in Tab. 10, which confirms the necessity of the UDE for semantic segmentation. Two-stage methods can alleviate the decline, and CT outperforms KDDE. Under the UDA setting, CT boosts both UDA methods and achieves the best performance on the target domain. As Fig. 5 shows, for the adverse conditions, CT produces more accurate segmentation, e.g. reducing misclassification of the sky into buildings. On the expanded domain, CT achieves the best performance on the most categories in Tab. 10 and CT(FDA) achieves the best average performance for UDE. This demonstrates our method’s applicability to cross-condition driving scene segmentation.

In addition, we provide pixel-level classification accuracy in Tab. 11. The superior performance of CT on the pixels with inconsistent $\mathcal{N}_s$ and $\mathcal{N}_t$ predictions shows the effectiveness of CT for tackling the cross-domain ambiguity in the context of driving scene segmentation.

5. Conclusions and Remarks

We present Co-Teaching (CT), a new method for unsupervised domain adaptation and expansion. Our multi-class image classification experiments on two public benchmarks, i.e. Office-Home and DomainNet, and semantic image segmentation experiments on another two public sets, i.e. Cityscapes and ACDC, support our conclusions as follows. Due to the existence of cross-domain ambiguity, a domain-specific model is not universally applicable to handle samples from its targeted domain. Our proposed CT method, with its
| Method         | road | side. | build. | wall | fence | pole | light | sign | veget. | terrain | sky | person | rider | car | truck | bus | train | motor | bicycle | mIoU  |
|----------------|------|-------|--------|------|-------|------|-------|------|--------|---------|-----|--------|-------|-----|-------|-----|-------|-------|---------|-------|

*Tested on the source domain $D_s$, i.e. Cityscapes:*

DeepLabv2 96.22 73.58 87.39 42.65 40.08 40.35 45.01 60.11 88.17 49.38 89.95 67.67 47.61 90.74 61.81 66.51 43.66 50.57 63.05 63.34

AdaSegNet 96.20 72.73 87.53 32.48 41.48 40.82 41.06 60.01 87.30 41.70 90.99 67.22 48.21 89.83 68.98 62.07 31.05 50.39 62.14 61.69

FDA 95.99 71.38 86.37 43.45 37.29 38.67 41.82 57.03 86.69 48.03 88.65 64.97 44.05 88.56 69.24 58.28 30.21 45.60 61.46 60.93

AdaSegNet as $N_t$:

KDDE 96.20 72.94 87.30 36.50 40.16 40.26 40.12 58.78 87.65 45.05 90.24 66.64 47.75 90.63 69.72 64.40 31.27 49.66 62.33 61.98

CT 96.15 73.47 87.39 36.69 42.00 41.77 41.60 59.49 87.64 41.57 90.11 67.39 47.57 90.46 63.71 48.76 44.50 62.29 62.72

FDA as $N_t$:

KDDE 96.20 73.69 87.09 43.19 41.32 39.72 37.16 57.19 87.73 47.30 89.99 66.84 47.22 90.34 67.56 47.35 35.95 45.05 61.46 62.09

CT 95.97 73.58 87.09 37.59 42.79 40.73 39.55 59.28 87.41 42.91 90.38 66.34 47.81 90.40 72.15 61.20 37.34 47.06 61.78 62.18

*Tested on the target domain $D_t$, i.e. ACDC:*

DeepLabv2 59.60 20.09 43.67 10.16 12.90 22.86 39.94 34.11 66.24 17.00 58.13 17.31 8.20 52.93 38.28 45.06 51.22 23.83 23.80 39.47

AdaSegNet 49.36 30.92 68.16 24.50 22.09 31.33 51.08 38.85 55.53 26.40 34.39 28.18 12.58 64.73 36.94 40.10 50.11 27.02 22.56 38.20

FDA 75.00 38.31 61.23 22.10 23.75 30.26 47.74 37.00 66.35 25.73 68.17 38.54 13.31 65.37 33.03 52.77 44.34 16.84 21.32 41.11

AdaSegNet as $N_t$:

KDDE 59.45 29.49 69.18 23.45 22.17 31.74 52.88 39.40 67.02 26.02 53.10 30.82 10.02 52.93 38.28 45.06 51.22 23.83 23.80 39.47

CT 64.25 27.03 68.58 23.53 23.02 31.28 53.96 39.96 67.82 27.10 62.96 32.06 12.09 69.17 39.19 36.27 49.04 21.99 27.45 40.88

FDA as $N_t$:

KDDE 76.35 33.10 62.02 18.95 25.15 30.49 52.94 35.98 68.74 25.96 71.15 31.02 10.69 70.99 30.92 48.93 50.32 26.86 25.26 41.83

CT 77.72 35.76 60.12 15.86 24.34 30.29 51.46 38.08 70.15 26.48 74.38 35.80 13.48 69.74 40.50 48.28 48.81 28.55 22.83 42.77

*Tested on the expanded domain $D_{s+t}$, i.e. Cityscapes + ACDC:*

DeepLabv2 84.31 48.39 63.59 20.35 23.24 34.22 42.96 52.54 75.83 25.66 61.98 56.57 45.45 78.06 42.97 45.79 34.24 41.97 58.46 49.29

AdaSegNet 75.53 52.73 79.63 27.38 30.04 37.48 45.45 53.68 75.07 32.78 41.38 60.69 46.21 83.92 50.60 51.65 47.12 42.72 58.18 52.22

FDA 88.95 54.76 75.28 29.32 28.56 35.68 44.29 51.51 74.97 34.28 70.70 62.17 42.86 83.31 47.17 55.61 42.11 35.12 56.58 53.33

AdaSegNet as $N_t$:

KDDE 81.63 52.03 79.83 28.31 29.40 37.31 45.64 53.13 75.58 34.03 57.68 61.14 45.27 80.39 51.98 55.49 48.35 41.55 58.81 53.55

CT 84.07 51.45 79.54 28.53 30.65 58.20 46.87 53.77 76.08 33.34 66.32 62.23 45.24 85.74 52.59 50.77 49.00 37.50 59.18 54.27

FDA as $N_t$:

KDDE 89.59 53.08 75.84 27.35 31.23 36.52 44.11 51.18 76.96 34.99 73.44 62.27 45.25 86.08 44.60 56.16 48.21 39.07 57.35 54.38

CT 89.99 54.79 74.59 23.48 31.28 37.14 44.67 53.32 77.80 33.68 76.34 63.01 46.26 85.81 54.50 54.89 47.20 41.32 57.55 55.14
Table 11: **Pixel-level classification accuracy.** CT performs the best on samples for which $N_s$ and $N_t$ disagrees.

| Method            | $D_s$  | $D_t$  | $D_{s+t}$ |
|-------------------|--------|--------|-----------|
| DeepLabv2 as $N_s$ | 95.99  | 3.06   | 86.31     | 9.92      | 92.20     | 5.74      |
| FDA as $N_t$      | 95.99  | 2.55   | 86.31     | 21.30     | 92.20     | 9.89      |
| CT (FDA)          | 95.29  | 3.49   | 86.66     | 26.13     | 91.91     | 12.35     |

Figure 5: **Qualitative results of driving scene segmentation.** The first row is from $D_s$ (normal condition in the sunlight), while the other rows are from $D_t$ (adverse conditions in the nighttime, fog, snow and rain). Important difference between the results is marked out by white bounding boxes.

ability to resolve such ambiguity, provides a simple and unified framework to improve a model’s performance on the target domain, and meanwhile maintain mostly its performance on the source domain. Consequently, CT beats strong baselines on unsupervised domain adaptation, *i.e.* GSFDA and CDTrans, for image classification and FDA for driving scene segmentation. CT is also better than the prior art on unsupervised domain expansion, *i.e.* KDDE, for both image classification and semantic segmentation.

This study has the following limitations. First, in our current implementation of CT, the parameter $\gamma$, which weighs the importance of two teachers, is fixed per batch. Since a teacher’s importance varies over samples, such an implementation may limit the method’s ability to fully exploit the teachers. How to adaptively relate $\gamma$ to the teachers’ performance is worth pursuing in future research. Second, CT has shown its potential for image classification and semantic segmentation, yet its viability for cross-domain object detec-
tion [46] remains to be verified. Third, our study follows the conventional setup of UDA, where one has access to labeled training data from a specific source domain and unlabeled training data from a given target domain. Several novel setups have emerged, e.g. source data-free UDA [47], which aims for model transfer with no need of accessing the source-domain data, multi-target UDA [48], which attempts to obtain a single model that works across multiple target domains, and partial domain adaptation [49] where the target label space is subsumed to the source label space. How to extend CT to these new setups requires further investigation. With its UDA module replaced by a semi-supervised learning (SSL) module [50], we also see the possibility of exploiting CT for SSL. Lastly, our evaluation does not cover large pre-trained vision-language models. Popularized by OpenAI’s CLIP network [51], these sorts of models are remarkably good at learning generic visual representations. For leveraging such models for UDA, domain-specific prompt learning techniques are being developed [52, 53]. By performing meta learning on top of a specific UDA method, the CT method is naturally complementary to this new line of research. While addressing the aforementioned is beyond the scope of this paper, we believe the discussion helps foresee what comes next.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was supported by the National High Level Hospital Clinical Research Funding (2022-PUMCH-C-61), NSFC (No.62172420), and Public Computing Cloud, Renmin University of China.

References

[1] S. J. Pan, Q. Yang, A survey on transfer learning, IEEE Transactions on Knowledge and Data Engineering 22 (10) (2009) 1345–1359.

[2] D. Zheng, J. Xiao, K. Chen, X. Huang, L. Chen, Y. Zhao, Soft pseudo-label shrinkage for unsupervised domain adaptive person re-identification, Pattern Recognition 127 (2022) 108615.
[3] S. Yang, X. Zhou, J. Wang, G. Xie, C. Lv, P. Gao, B. Lv, Unsupervised domain adaptation for cross-device OCT lesion detection via learning adaptive features, in: ISBI, 2020.

[4] C. Sakaridis, D. Dai, L. Van Gool, Map-guided curriculum domain adaptation and uncertainty-aware evaluation for semantic nighttime image segmentation, IEEE Transactions on Pattern Analysis and Machine Intelligence 44 (6) (2022) 3139–3153.

[5] A. Valada, J. Vertens, A. Dhall, W. Burgard, Adapnet: Adaptive semantic segmentation in adverse environmental conditions, in: ICRA, 2017.

[6] H. Tang, K. Chen, K. Jia, Unsupervised domain adaptation via structurally regularized deep clustering, in: CVPR, 2020.

[7] Y. Yang, S. Soatto, FDA: Fourier domain adaptation for semantic segmentation, in: CVPR, 2020.

[8] H. Venkateswara, J. Eusebio, S. Chakraborty, S. Panchanathan, Deep hashing network for unsupervised domain adaptation, in: CVPR, 2017.

[9] X. Peng, Q. Bai, X. Xia, Z. Huang, K. Saenko, B. Wang, Moment matching for multi-source domain adaptation, in: ICCV, 2019.

[10] C. Sakaridis, D. Dai, L. Van Gool, ACDC: The adverse conditions dataset with correspondences for semantic driving scene understanding, in: ICCV, 2021.

[11] J. Wang, K. Tian, D. Ding, G. Yang, X. Li, Unsupervised domain expansion for visual categorization, ACM Transactions on Multimedia Computing, Communications, and Applications 17 (4) (2021) 1–24.

[12] S. Yang, Y. Wang, J. van de Weijer, L. Herranz, S. Jui, Generalized source-free domain adaptation, in: ICCV, 2021.

[13] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, B. Schiele, The cityscapes dataset for semantic urban scene understanding, in: CVPR, 2016.
[14] E. Tzeng, J. Hoffman, N. Zhang, K. Saenko, T. Darrell, Deep domain confusion: Maximizing for domain invariance, ArXiv abs/1412.3474 (2014).

[15] Y. Chen, C. Yang, Y. Zhang, Deep domain similarity adaptation networks for across domain classification, Pattern Recognition Letters 112 (2018) 270–276.

[16] G. Kang, L. Jiang, Y. Yang, A. G. Hauptmann, Contrastive adaptation network for unsupervised domain adaptation, in: CVPR, 2019.

[17] Y. Ganin, E. Ustinova, H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, M. March, V. Lempitsky, Domain-adversarial training of neural networks, Journal of Machine Learning Research 17 (59) (2016) 1–35.

[18] M. Long, Z. Cao, J. Wang, M. I. Jordan, Conditional adversarial domain adaptation, in: NeurIPS, 2018.

[19] W. Chen, H. Hu, Generative attention adversarial classification network for unsupervised domain adaptation, Pattern Recognition 107 (2020) 107440.

[20] H. Zhang, M. Cisse, Y. N. Dauphin, D. Lopez-Paz, mixup: Beyond empirical risk minimization, in: ICLR, 2018.

[21] M. Xu, J. Zhang, B. Ni, T. Li, C. Wang, Q. Tian, W. Zhang, Adversarial domain adaptation with domain mixup, in: AAAI, 2020.

[22] J. Na, H. Jung, H. J. Chang, W. Hwang, Fixbi: Bridging domain spaces for unsupervised domain adaptation, in: CVPR, 2021.

[23] Y.-H. Tsai, W.-C. Hung, S. Schulter, K. Sohn, M.-H. Yang, M. Chandraker, Learning to adapt structured output space for semantic segmentation, in: CVPR, 2018.

[24] T.-H. Vu, H. Jain, M. Bucher, M. Cord, P. Perez, ADVENT: Adversarial entropy minimization for domain adaptation in semantic segmentation, in: CVPR, 2019.

[25] Z. Wu, X. Han, Y.-L. Lin, M. G. Uzunbas, T. Goldstein, S. N. Lim, L. S. Davis, Dcan: Dual channel-wise alignment networks for unsupervised scene adaptation, in: ECCV, 2018.
[26] J. Hoffman, E. Tzeng, T. Park, J.-Y. Zhu, P. Isola, K. Saenko, A. Efros, T. Darrell, CyCADA: Cycle-consistent adversarial domain adaptation, in: ICML, 2018.

[27] M. Rostami, Lifelong domain adaptation via consolidated internal distribution, in: NeurIPS, 2021.

[28] F. Lv, J. Liang, K. Gong, S. Li, C. H. Liu, H. Li, D. Liu, G. Wang, Pareto domain adaptation, in: NeurIPS, 2021.

[29] Y.-H. Liu, C.-X. Ren, A two-way alignment approach for unsupervised multi-source domain adaptation, Pattern Recognition 124 (2022) 108430.

[30] Z. Luo, X. Zhang, S. Lu, S. Yi, Domain consistency regularization for unsupervised multi-source domain adaptive classification, Pattern Recognition 132 (2022) 108955.

[31] S. You, C. Xu, C. Xu, D. Tao, Learning from multiple teacher networks, in: KDD, 2017.

[32] E. Malach, S. Shalev-Shwartz, Decoupling” when to update” from” how to update”, in: NeurIPS, 2017.

[33] B. Han, Q. Yao, X. Yu, G. Niu, M. Xu, W. Hu, I. Tsang, M. Sugiyama, Co-teaching: Robust training of deep neural networks with extremely noisy labels, in: NeurIPS, 2018.

[34] S. Roy, E. Krivosheev, Z. Zhong, N. Sebe, E. Ricci, Curriculum graph co-teaching for multi-target domain adaptation, in: CVPR, 2021.

[35] A. Fawzi, S.-M. Moosavi-Dezfooli, P. Frossard, Robustness of classifiers: From adversarial to random noise, in: NeurIPS, 2016.

[36] Z. He, A. S. Rakin, D. Fan, Parametric noise injection: Trainable randomness to improve deep neural network robustness against adversarial attack, in: CVPR, 2019.

[37] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: CVPR, 2016.
[38] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A. L. Yuille, DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs, IEEE Transactions on Pattern Analysis and Machine Intelligence 40 (4) (2017) 834–848.

[39] C. Yu, J. Wang, Y. Chen, M. Huang, Transfer learning with dynamic adversarial adaptation network, in: ICDM, 2019.

[40] H. Rangwani, S. K. Aithal, M. Mishra, A. Jain, V. B. Radhakrishnan, A closer look at smoothness in domain adversarial training, in: ICML, 2022.

[41] Y. Zhang, J. Liang, Z. Zhang, L. Wang, R. Jin, T. Tan, et al., Free lunch for domain adversarial training: Environment label smoothing, in: ICLR, 2023.

[42] T. Xu, W. Chen, P. Wang, F. Wang, H. Li, R. Jin, CDTrans: Cross-domain transformer for unsupervised domain adaptation, in: ICLR, 2022.

[43] H. Touvron, M. Cord, M. Douze, F. Massa, A. Sablayrolles, H. Jégou, Training data-efficient image transformers & distillation through attention, in: ICML, 2021.

[44] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, D. Batra, Grad-CAM: Visual explanations from deep networks via gradient-based localization, in: ICCV, 2017.

[45] E. Panfilov, A. Tiulpin, S. Klein, M. T. Nieminen, S. Saarakkala, Improving robustness of deep learning based knee MRI segmentation: Mixup and adversarial domain adaptation, in: ICCV Workshop, 2019.

[46] R. Qian, X. Lai, X. Li, 3d object detection for autonomous driving: A survey, Pattern Recognition 130 (2022) 108796.

[47] J. Liang, D. Hu, J. Feng, R. He, Dine: Domain adaptation from single and multiple black-box predictors, in: CVPR, 2022.

[48] T. Isobe, X. Jia, S. Chen, J. He, Y. Shi, J. Liu, H. Lu, S. Wang, Multi-target domain adaptation with collaborative consistency learning, in: CVPR, 2021.
[49] C. X. Ren, P. Ge, P. Yang, S. Yan, Learning target-domain-specific classifier for partial domain adaptation, IEEE Transactions on Neural Networks and Learning Systems 32 (5) (2020) 1989–2001.

[50] C. Ren, P. Ge, D. Dai, H. Yan, Learning kernel for conditional moment-matching discrepancy-based image classification, IEEE Transactions on Cybernetics 51 (4) (2019) 2006–2018.

[51] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, et al., Learning transferable visual models from natural language supervision, in: ICML, 2021.

[52] C. Ge, R. Huang, M. Xie, Z. Lai, S. Song, S. Li, G. Huang, Domain adaptation via prompt learning, arXiv preprint arXiv:2202.06687 (2022).

[53] Z. Zheng, X. Yue, K. Wang, Y. You, Prompt vision transformer for domain generalization, arXiv preprint arXiv:2208.08914 (2022).