Gradual Domain Adaptation via Self-Training of Auxiliary Models

Yabin Zhang\textsuperscript{1} Bin Deng\textsuperscript{2} Kui Jia\textsuperscript{2} Lei Zhang\textsuperscript{1}
\textsuperscript{1}Hong Kong Polytechnic University \textsuperscript{2}South China University of Technology
\{csyzhang,cslzhang\}@comp.polyu.edu.hk bindeng.scut@gmail.com kuijia@scut.edu.cn

Abstract

Domain adaptation becomes more challenging with increasing gaps between source and target domains. Motivated from an empirical analysis on the reliability of labeled source data for the use of distancing target domains, we propose self-training of auxiliary models (AuxSelfTrain) that learns models for intermediate domains and gradually combats the distancing shifts across domains. We introduce evolving intermediate domains as combinations of decreasing proportion of source data and increasing proportion of target data, which are sampled to minimize the domain distance between consecutive domains. Then the source model could be gradually adapted for the use in the target domain by self-training of auxiliary models on evolving intermediate domains. We also introduce an enhanced indicator for sample selection via implicit ensemble and extend the proposed method to semi-supervised domain adaptation. Experiments on benchmark datasets of unsupervised and semi-supervised domain adaptation verify its efficacy.

1. Introduction

Deep neural network (DNN) has achieved great success on various tasks. However, it requires large amounts of labeled training data and generalizes poorly to new data domains. If we directly apply the trained DNN to a new data domain, degenerated performance is probably encountered. At the same time, it is expensive to collect labeled training data for the new domain. Therefore, there is a strong motivation to transfer knowledge from the labeled source domain to the unlabeled target one, which falls in the realm of transfer learning [35] or domain adaptation (DA) [29, 15].

Seminal DA theories [2, 1, 53] suggest that the target error could be minimized by reducing the source error and the distribution discrepancy across domains. Inspired by these theoretical results, DA methods are typically proposed to minimize the domain discrepancy by learning domain invariant representations [29, 15, 30, 40, 54]. For example, measurable distance metrics are calculated and minimized across domains [29, 44]. However, the DA problems are getting more difficult as domain gaps between source and target domains enlarge, which brings new challenges to traditional DA methods [3].

We empirically investigate the reliability of labeled source data for the use of distancing target domains in Section 3. As the distance between the source and target domains enlarges, the model trained on labeled source data gives the decreasing performance on the unlabeled target data, as showed in Figure 1. This indicates that DA could be facilitated and may have improved results if some reliable auxiliary models for intermediate domains are available.

Fortunately, as theoretically justified in [24], given two domains with small distribution divergence and a reliable model on one domain, the reliable model for the other one could be achieved by self-training. In other words, reliable auxiliary models could be achieved via self-training if intermediate domains, where the divergence between consecutive domains is small, are available. In the literature [47, 3, 24], such expected intermediate domains are assumed to be readily available. However, the evolving intermediate domains may be not given in practice, such as in standard benchmark datasets [46, 36].

To this end, we introduce intermediate domains as combinations of certain proportions of source data and target data, inspired by [7]. Specifically, starting from source data and a well trained source model, we introduce an intermediate domain with small domain divergence to the source one by combining the majority of source data and a few number of target data. A reliable auxiliary model for the introduced intermediate domain could be achieved via self-training [24]. Given the previous intermediate domain and its reliable model achieved via self-training, we alternate between introducing another intermediate domain with small domain divergence to the previous one by combining less number of source data and more number of target data and getting the auxiliary model for the new intermediate domain via self-training. We finally end with the target data and gradually adapt the source model for it.

Considering that there may be an intra-domain divergence in one dataset [31, 6], thus selecting which part of target and source data to construct intermediate domains mat-
lers. Given the starting point of labeled source data, target samples with smaller domain shift to source data should be selected first to minimize the domain divergence between consecutive domains; similarly, source samples with larger domain shift to target data should be dropped first, considering that target domain is the terminal of intermediate domains. We achieve this goal based on an empirical observation of the correlation between the domain shift and maximum prediction probability. As illustrated in Figure 1, based on a model trained on labeled source data, the samples with smaller domain distance to the labeled one tend to present higher prediction probability. Therefore, we could construct the expected intermediate domain by selecting target samples with higher prediction probability based on the current auxiliary model, and dropping the source samples with lower prediction probability based on an introduced target prototype classifier. This sampling strategy significantly improves over the previous one [7], where samples are randomly selected, as showed in Section 5.

Considering that the maximum prediction probability may be not reliable since DNNs may produce high probability for inputs far away from training data [33], we propose an implicit ensemble scheme to improve the quality of predictive uncertainty to domain shift [25]. As combinations of source and target data are adopted as intermediate domains in our AuxSelfTrain, we could easily extend the AuxSelfTrain to semi-supervised domain adaptation (SSDA) tasks [39], where a few labeled target data are available, by treating the combination of source data and labeled target data as a pre-given intermediate domain and beginning our method from it. Empirical results on DA and SSDA benchmark datasets justify the efficacy of our AuxSelfTrain. We summarize our contributions as follows:

- Motivated from an empirical analysis on the reliability of labeled source data for the use of distancing target domains, we propose for DA the self-training of auxiliary models (AuxSelfTrain) that learns auxiliary models for intermediate domains and gradually combats the distancing shifts across domains.

- To technically implement AuxSelfTrain, we propose simple yet efficient sample selection strategies to select decreasing proportion of source data and increasing proportion of target data to construct evolving intermediate domains. We also introduce an enhanced selection indicator by improving the quality of predictive uncertainty to domain shift via implicit ensemble.

- We conduct careful analyses on AuxSelfTrain and extend it to SSDA task. Empirical results on standard benchmark datasets of DA and SSDA justify the efficacy of our method.

### 2. Related Works

**Representative methods for domain adaptation** The seminal DA theories [2, 1, 53] suggest that we could minimize the target error by reducing the source error and the cross-domain discrepancy. Motivated by them, the distance minimization-based methods [29, 44] and adversarial training-based ones [15, 30, 40, 54] have been proposed to minimize the domain discrepancy. In the former one, the domain discrepancy is measured and minimized by measurable distance metrics, such as the maximum mean discrepancy [29] and correlation distance [44]. The latter one minimizes the domain discrepancy by playing minimax optimization [17] between the feature extractor and domain classifiers [15, 30] or task classifiers [40, 54]. However, as the domain gap enlarges, the performance of seminal DA methods degrades significantly [3]; additionally, there are potential risks in the discrepancy minimization process [5, 55]. In contrary, we tackle DA by gradually adapt the source model for the use of target domain via self-training of auxiliary models on evolving intermediate domains.

**Domain adaptation with intermediate domains** To facilitate the adaptation across source and distancing target domains, researches typically utilize intermediate domains as a bridge. In the literature [47, 3, 24], intermediate domains are assumed to be readily available for the adaptation use. Although promising success has been achieved, the assumption of readily available intermediate domains may be not met and constrains its practical applications. Some methods [16, 10] try to introduce intermediate domains with generation models, and the generated intermediate samples are typically used as an additional regularization, rather than supporting auxiliary models as in our AuxSelfTrain. The work of [7] is closest to our method, but there are two crucial differences. Chopra et al. [7] randomly sample target and source data to construct intermediate domains and the corresponding models are introduced with unsupervised learning, while we propose simple yet efficient sampling strategies for both domains and achieve auxiliary models via self-training, as suggested by [24].

**Self-training** As a basic technique, self-training is initially introduced for semi-supervised learning (SSL) [27], and then widely adopted in unsupervised learning [4], SSL [43], and DA [57, 32, 22]. DA methods [57, 32, 22] typically adopt self-training to adapt source model to target domain directly, while we, together with [24], emphasize evolving intermediate domains for the success of self-training on DA.

**Semi-supervised domain adaptation** As a task with practical value, the SSDA is investigated with regularization [11], subspace learning [50] and smooth constraint [13]. Recently, state-of-the-art results are achieved in [39, 23] by conducting adversarial entropy minimization with deep networks. We conduct experiments following [39] to justify the extension of AuxSelfTrain to SSDA.
We randomly split the each sample in MNIST, where the domain shift is thus expected to be controlled. We introduce auxiliary models via self-training. As justified in [24], given two datasets with small distribution diver-

Fortunately, the reliable auxiliary models for intermediate domains could be achieved through self-training, as theoretically proofed in [24]. Specifically, given an initial model with the low loss on the labeled training data and unlabeled data of a new domain with small domain distance to the labeled one, we could get a reliable model on the new domain via self-training (cf. Theorem 3.2 in [24]). Thus, if intermediate datasets with gradually shifted distributions are available, we could gradually adapt the source model to the target domain along this path.

However, intermediate datasets with evolving domain shift may be not available in practice, which prevents the application of such a promising strategy. For example, the well ordered intermediate domains are not provided in standard DA benchmark datasets [46, 56]. To this end, we make an empirical analysis and find that, based on a well-trained model, the maximum prediction probability (3) of unlabeled data gets smaller as their domain distance to the labeled training data gets larger, as illustrated in Figure 1; this provides useful clues for evolving intermediate domains and exactly motivates our method to be presented shortly.

4. The Proposed Method

In DA tasks, we have \( n_s \) labeled source data \( S = \{x_i^s, y_i^s\}_{i=1}^{n_s} \) randomly sampled from a source domain \( \mathcal{P} \) and \( n_t \) unlabeled target data \( T = \{x_i^t\}_{i=1}^{n_t} \) randomly sampled from a related but different target domain \( \mathcal{Q} \), where \( y_i^t \in \{1, \cdots, K\} \) and \( K \) is the number of categories. The goal of DA is to minimize the target risk \( \mathbb{E}_{(x^t, y^t) \sim \mathcal{Q}} \mathcal{L}(f(x^t), y^t) \) for a certain loss \( \mathcal{L} \) by learning a model \( f : \mathcal{X} \to [0, 1]^K \) that maps any input instance \( x \in \mathcal{X} \) to the category probabilities.

Self-training is a popular method in both DA [57, 24] and SSL [27, 43]. Take the DA task as an example, the self-trained method starts with a model \( f_s \) trained on the labeled source data:

\[
    f_s = \arg\min_{f \in \mathcal{F}} \mathbb{E}_{(x^s, y^s) \in S} \mathcal{L}(f(x^s), y^s),
\]

where \( \mathcal{F} \) is the space of the model and \( \mathcal{L}(f(x), y) = -\log f_y(x) \) is the cross-entropy loss; \( f_k(x) \) denotes the \( k \)-th entry of \( f(x) \).

Given the pre-trained model \( f_s \) and unlabeled data \( T \), self-training assigns a pseudo label to each sample \( x^t \in T \) as \( o(f_s(x^t)) = \arg\max_k f_s(x^t) \). Then the target model \( f_t \) could be achieved with this pseudolabeled dataset \( \{x^t_i, o(f_s(x^t_i))\}_{i=1}^{n_t} \) as:

\[
    f_t = \arg\min_{f \in \mathcal{F}} \mathbb{E}_{x^t \in T} \mathcal{L}(f(x^t), o(f_s(x^t))).
\]
gence and a reliable model on one dataset, we could obtain a reliable model for the other one via self-training. Therefore, reliable auxiliary models could be achieved via self-training if intermediate domains, where the domain divergence between consecutive domains is small, are available. In the literature [47, 3, 24], the expected evolving intermediate domains are assumed to be readily available, which is usually not met in practice. To this end, we propose the following strategy to generate such expected intermediate domains.

**Intermediate domains introduction** Inspired by [7], we start from the source data $S$, generate successive intermediate datasets by gradually increasing the proportion of samples drawn from $T$ and decreasing the proportion of samples drawn from $S$, and end with the target dataset $T$. Specifically, we introduce $M + 1$ datasets $\{M_m\}_{m=0}^{M}$, where $M_0 = S$ and $M_M = T$; the $M_m$, where $1 \leq m \leq (M−1)$, is composed of the $\frac{m}{M}$ proportion of the target data $T$ and $\frac{M−m}{M}$ proportion of the source data $S$. Chopra et al. [7] randomly select these samples from $T$ and $S$. We argue that selecting which part of $T$ or $S$ may make a difference, since there may be an intra-domain divergence in one dataset [31, 6]. In other words, a specific part of target data may have smaller domain shift to source data, and vice versa. Thus we propose the following sample selection strategies and justify their effectiveness in Section 5.

**Target samples selection** To minimize the domain divergence between the expected $M_{m+1}$ and the previous $M_m$, target samples with smaller domain shift to the $M_m$ should be selected for $M_{m+1}$. Inspired by the analysis in Section 3 that samples with smaller domain shift to the labeled data tend to present higher prediction probability based on the model trained with the labeled data, we could achieve this goal by selecting the $\frac{m+1}{M}$ proportion of the target data $T$ with higher prediction probability based on the $f_m$, which is trained with the $m$-th intermediate dataset $M_m$ and will be presented shortly. The maximum prediction probability of a sample $x^t_i$ is:

$$c_t(x^t_i, f_m) = \max(f_m(x^t_i)).$$

Given the prediction probability of all unlabeled target data $C_t = \{c_t(x^t_i, f_m)\}_{i=1}^{n_t}$, we introduce the binary indicator $v^t_i \in \{0, 1\}$ to indicate whether the sample $x^t_i$ should be selected for the $M_{m+1}$:

$$v^t_i = \begin{cases} 1, & c_t(x^t_i, f_m) \in TOP_{(m+1)n_t/M}(C_t), \\ 0, & Otherwise \end{cases}$$

where $TOP_N(C_t)$ is the subset with $N$ highest scores in $C_t$. **Source samples selection** Given the target domain $T$ as the terminal of intermediate domains, source data with larger domain shift to the target one should be dropped first. In other words, the source data with smaller domain shift to the target one should be selected for the intermediate domains. Similar to the selection strategy of target samples, we could achieve this goal by introducing a target classifier and selecting source data with higher prediction probability on this classifier.

To introduce the target classifier, we instantiate the auxiliary model $f_m$ as a standard DNN with the decomposed feature extractor $\phi_m: K \rightarrow Z$ and the classifier $\psi_m: Z \rightarrow [0, 1]^K$, where $Z$ is the feature space. Based on the auxiliary model $f_m$, we could introduce a target prototype classifier [42] with the prototype $p_k$ of the $k$-th target category as:

$$p_k = \frac{\sum_{i=1}^{n_t} 1_{y(f_m(x^t_i))=k} \phi_m(x^t_i)}{\sum_{i=1}^{n_t} 1_{y(f_m(x^t_i))=k}}$$

where $1_{y=k} = \begin{cases} 1, & y = k \\ 0, & Otherwise \end{cases}$.

Given target prototypes $\{p_k\}_{k=1}^K$, we calculate the prediction probability of a labeled source sample $(x^s_i, y^s_i)$ as:

$$c_s(x^s_i, f_m) = \frac{\exp(1 + ||\phi_m(x^s_i) - p_{y^s_i}||^2)^{-1}}{\sum_{k=1}^{K} \exp(1 + ||\phi_m(x^s_i) - p_k||^2)^{-1}}.$$  

Given the prediction probability of all labeled source data $C_s = \{c_s(x^s_i, f_m)\}_{i=1}^{n_s}$, we also introduce a binary indicator
Auxiliary models via self-training

Given the auxiliary and (4), and empirically ablated in Table 1. The enhanced indicator is introduced as:

\[
v_i^* = \begin{cases} 
1, & c_s(x_i^t, f_m) \in TOP_{(M-m-1)n_s/M}(C_s) \\
0, & \text{Otherwise}
\end{cases}.
\] (7)

The effectiveness of the proposed sample selection strategies (i.e., (4) and (7)) is intuitively presented in Figures 3 and 4, and empirically ablated in Table 1.

**Auxiliary models via self-training**

Given the auxiliary model \(f_m\) and the \((m + 1)\)-th intermediate dataset \(M_{m+1}\) defined with the target indicator \(\{v_i^s\}_{i=1}^{n_t}\) and the source indicator \(\{v_i^s\}_{i=1}^{n_s}\), the auxiliary model \(f_{m+1}\) could be achieved with the following self-training objective:

\[
f_{m+1} = \arg\min_{f \in \mathcal{F}} \frac{1}{n_s} \sum_{i=1}^{n_s} v_i^s \mathcal{L}(f(x_i^s), y_i^s) + \frac{1}{n_t} \sum_{i=1}^{n_t} v_i^t \mathcal{L}(f(A(x_i^t)), o(f_m(x_i^t))),
\] (8)

where we utilize the advanced data augmentation \(A(\cdot)\) [8] for unlabeled data following [43]. We initialize \(f_0 = f_s\) (1) as the model trained on the labeled source data. Note that training each auxiliary model from scratch is time consuming. However, given evolving domains, minor selection is required to adapt the learned \(f_m\) to \(f_{m+1}\). In this way, our method only doubles the training iterations of the Source Only baseline (including the training of \(f_s\) (1)), leading to an efficient implementation.

**4.2. An Enhanced Indicator for Sample Selection**

Although the maximum prediction probability (3) is a valid indicator of domain shift, as showed in Figure 1, it is possible that unlabeled samples with high prediction probability may be distant from labeled ones, since DNNs may produce high probability for inputs far away from training data [33]. To this end, we propose an enhanced indicator for sample selection via implicit ensemble.

As presented in [25, 34] with a large scale empirical study, ensemble is a simple but efficient way to improve the quality of predictive uncertainty to domain shift. However, vanilla ensemble by training multiple models is computational expensive and memory consuming [25, 38, 34]. Therefore, we propose an implicit ensemble scheme by introducing two accessory models \(\tilde{f}_m\) and \(\hat{f}_m\), where all three models (i.e., \(f_m\), \(\tilde{f}_m\), and \(\hat{f}_m\)) share the same feature extractor \(\phi_m\). \(\tilde{f}_m\) and \(\hat{f}_m\) are parameter-free and computational efficient. The enhanced indicator is introduced as:

\[
f_m(x^t) = (f_m(x^t) + \tilde{f}_m(x^t) + \hat{f}_m(x^t))/3.
\] (9)

Note that the enhanced indicator \(f_m\) (9) is only adopted in training process (i.e., \(f_m\) in (4) and (8)), and we still use the vanilla \(f_m\) (i.e., without implicit ensemble) for the test. The details of \(\tilde{f}_m\) and \(\hat{f}_m\) are given as follows.

The \(\tilde{f}_m\) is a classifier constructed from the clustering method, which is widely adopted in DA [21, 45]. We first calculate source category centers \(\{O_s^{K}_{k}\}_{k=1}^{K}\) as: \(O_s^k = \frac{1}{\sum_{i=1}^{n_s} 1}_{i=1} 1 y_i^s = k \phi_m(x_i^s)\). Then we apply the k-means clustering on extracted target features \(\{\phi_m(x_i^t)\}_{i=1}^{n_t}\), and use source category centers \(\{O_s^{K}_{k}\}_{k=1}^{K}\) as initial cluster centers. After clustering, we could get the corresponding target cluster centers \(\{O_t^{K}_{k}\}_{k=1}^{K}\). The \(\tilde{f}_m\) is thus introduced with its \(k\)-th entry \(f_{m,k}(x^t)\) for any target sample \(x^t\):

\[
f_{m,k}(x^t) = \frac{\exp(1 + ||\phi(x^t) - O_t^k||^2)}{\sum_{k'=1}^{K} \exp(1 + ||\phi(x^t) - O_t^{k'}||^2)^{-1}}.
\] (10)

The \(\hat{f}_m\) is a classifier based on the label propagation [56], which is also widely adopted in DA [12, 52]. We could achieve \(f_m\) by minimizing the following objective:

\[
\sum_{i=1}^{n_t} \frac{||f_m(x_i^{st}) - y_i^{st}||^2}{\lambda} + \sum_{i,j} a_{ij} \frac{||f_m(x_i^{st}) - f_m(x_j^{st})||}{d_{ij}},
\] (11)

where \(n_{st} = n_s + n_t\), \(x_i^{st} = \begin{cases} x_i^s, & 1 \leq i \leq n_s \\
 x_i^t, & \text{others}, \end{cases}\) is a one-hot vector of \(K\) dimension with the \(y_i^{st}\)-th entry of 1 if \(i \leq n_s\) otherwise \(y_i^{st} = \{0\}^K\), the cosine similarity \(a_{ij} = \langle \phi_m(x_i^{st}); \phi_m(x_j^{st}) \rangle / \|\phi_m(x_i^{st})\| \|\phi_m(x_j^{st})\|\) between features \(\phi_m(x_i^{st})\) and \(\phi_m(x_j^{st})\) is the element of the affinity matrix \(A \in \mathbb{R}_{+}^{n_s \times n_s}\) and \(d_{ij}\) is the sum of \(i\)-th row of \(A\). The solution of (11) is given in the appendices. We normalize the output of \(\hat{f}_m\) as \(f_m(x^t) = f_m(x^t) / \sum_{i} f_m(x_i^t)\) for the use in (9).

Given pre-trained feature extractor \(\phi_m\) of an auxiliary model \(m\) (8), accessory models \(\tilde{f}_m\) and \(\hat{f}_m\) could be achieved immediately and the diversity of ensemble members is naturally satisfied via different algorithms. Although better classification accuracy may be also introduced via implicit ensemble, we find that the performance improvement is mainly from the improved sample selection via improved quality of predictive uncertainty to domain shift, as illustrated in Table 1. The AuxSelfTrain algorithm is illustrated in Algorithm 1 and intuitively presented in Figure 2.

**4.3. Extension to SSDA**

Our AuxSelfTrain could be easily extended to SSDA tasks, where a few target data \(\{x_i^{t}\}_{i=1}^{n_t}\), \(n_t < n_s\) are manually assigned with category labels \(\{y_i^{t}\}_{i=1}^{n_t}\). As illustrated in Section 4.1, we introduce intermediate datasets as combinations of source and target samples. Therefore, the combination of labeled source data and labeled target data in SSDA could be treated as a pre-given intermediate domain. We could start our AuxSelfTrain from this intermediate domain.
Figure 3. An illustration of the intermediate domains learned by our AuxSelfTrain on the Rotating MNIST dataset, where we set $M = 24$. We randomly rotate source samples by an angle from 0 to 30 degrees, while the target samples are randomly rotated from 30 to 60 degrees.

![Fig3](image_url)

Algorithm 1 Algorithm Framework of AuxSelfTrain.

1. Input: Source data $S = \{x_i^s, y_i^s\}_{i=1}^{n_s}$, target data $T = \{x_i^t\}_{i=1}^{n_t}$, number of intermediate domains $M$
2. Initialize $f_0$ as source model $f_s$ (1)
3. for $m = 1; m \leq M; m + +$ do
4.  Acquire the enhanced $f_{m-1}$ using (9)
5.  Acquire intermediate dataset $M_m$ via (4) and (7)
6.  Acquire the auxiliary model $f_m$ using (8)
7. end for
8. Adopt $f_M$ for testing on the target domain

and replace $o(f_m(x_i^t))$ with $y_i^t$, $1 \leq i \leq n_t$, to utilize manual labels. Empirical results in Section 5 justify its efficacy.

5. Experiments

We first conduct control studies on the Rotating MNIST dataset. Then we evaluate our AuxSelfTrain on standard benchmark datasets of DA and SSDA.

5.1. Control Studies

Rotating MNIST is a semi-synthetic dataset from the MNIST [26], where the rotation degree of each sample is strictly controlled. Specifically, we randomly split the 50,000 training samples of the MNIST into the source and target domains of equal size. The source samples are randomly rotated by an angle from 0 to 30 degrees to construct the labeled source domain. We construct the unlabeled target domain by randomly rotating target samples with degrees of 30 ~ 60. A 3-layer convolutional network with dropout and batch normalization is adopted.

To illustrate the effectiveness of our method intuitively, we present the sample distribution in different intermediate domains learned by our AuxSelfTrain. As intermediate domains evolve from the source domain $M_0$ to target one $M_M$, source samples with smaller rotation degrees, which are far away from target domain, are firstly dropped and target samples with smaller rotation degrees are firstly selected, as illustrated in Figure 3. This makes the domain divergence between consecutive domains small although the divergence between source and target domains is large, as showed in Figure 4; the evolving intermediate domains support the successful self-training in AuxSelfTrain [24].

5.2. Analyses and Results

VisDA-2017 [37] is a dataset with large domain shift from synthetic data (Syn.) to real images (Real), which contains about 280K images across 12 categories. OfficeHome [46] is a standard benchmark dataset of DA, which contains 65 classes shared by 4 domains; we adopt it in both DA and SSDA experiments. DomainNet [36] is a large-scale benchmark dataset, containing 345 classes shared by six domains and about 0.6 million images. Following [39], we conduct SSDA on a subset of DomainNet, where 126 classes are selected and 7 tasks are defined. We use all labeled source data and all unlabeled target data for training in DA. In SSDA, we adopt the split strategy in [39], where one or three target data are manually labeled per class.

Implementation details We conduct experiments based on the ResNet model [18] and VGG16 model [41] using Pytorch. Given a model pre-trained on ImageNet dataset, we remove the last fully connect (FC) layer and construct the feature extractor $\phi(\cdot)$ with remaining parts; a new FC layer with $K$ neurons is adopted as the classifier $\phi(\cdot)$. We sample two batches with different sizes in each iteration; the first
Following [48, 43], we sample a large batch of unlabeled data with batch size of $uB$, where $u \geq 1$; we set $B = 64$ and $u = 7$ in all experiments. All parameters are updated by SGD with momentum of 0.9. Following [15], we set the learning rate as: $\eta = \eta_0 \frac{(1+\alpha p)^{\beta}}{\beta}$, where $\eta_0 = 0.01$, $\alpha = 10$, $\beta = 0.75$, and $p$ is linearly changing from 0 to 1 as the training proceeds.

### 5.2.1 Analyses

**Ablation studies** We investigate the target sample selection (4), source sample selection (7) and enhanced indicator (9) by removing the corresponding component from the overall objective. Specifically, setting $v_i^t = 1.1 \leq i \leq n_t$ in (4) (i.e., $\times$ in ‘Selection-T’ column) leads to a significant performance degradation; replacing our target selection scheme by randomly selecting the same number of target data (i.e., $R$ in ‘Selection-T’ column) achieves worse results than our AuxSelfTrain, although it improves over the setting without sample selection (i.e., $\times$ in ‘Selection-

| Selection-T | Selection-S | Selection-Enh. | Labeling-Enh. | plane | bicycle | bus | car | horse | knife | motorcycle | person | plant | skateboard | train | truck | mean |
|-------------|-------------|----------------|---------------|-------|---------|----|-----|------|------|------------|-------|------|-----------|------|-------|------|
| ✓           | ✓           | ✓              | ✓             | 95.0  | 86.9    | 84.8| 80.4| 95.5  | 90.5  | 93.1       | 84.6  | 95.1 | 85.6      | 89.8 | 40.6  | 85.2 |
| ×           | ✓           | ✓              | ✓             | 88.8  | 65.0    | 73.8| 73.0| 93.1  | 61.9  | 80.8       | 71.0  | 91.9 | 67.0      | 51.9 | 20.4  | 69.9 |
| R           | ✓           | ✓              | ✓             | 93.8  | 74.8    | 75.8| 72.6| 94.7  | 82.0  | 75.1       | 81.5  | 93.1 | 84.0      | 75.1 | 29.8  | 76.3 |
| ✓           | ×           | ✓              | ✓             | 95.0  | 84.1    | 85.9| 81.1| 95.2  | 80.1  | 92.8       | 83.8  | 94.9 | 80.4      | 88.6 | 31.8  | 82.8 |
| ✓           | ✓           | ×              | ✓             | 95.0  | 85.4    | 85.2| 81.1| 95.4  | 88.3  | 93.1       | 84.6  | 94.7 | 85.9      | 89.3 | 38.3  | 84.7 |
| ✓           | ✓           | ×              | ×             | 93.9  | 85.1    | 87.3| 83.2| 95.8  | 74.0  | 93.4       | 84.5  | 93.3 | 77.9      | 90.1 | 39.4  | 83.2 |
| ✓           | ✓           | ✓              | ×             | 94.3  | 85.8    | 85.5| 80.9| 95.7  | 86.5  | 93.1       | 83.6  | 93.3 | 85.9      | 90.7 | 39.7  | 84.6 |

| Methods                 | Syn. $\rightarrow$ Real (%) |
|-------------------------|-----------------------------|
| Source Only [18]        | 45.6                        |
| DANN [15]               | 55.0                        |
| MCD [40]                | 69.8                        |
| MDD [53]                | 74.6                        |
| GSDA [19]               | 81.5                        |
| RWOT [49]               | 84.0                        |
| AuxSelfTrain            | 85.2                        |

Table 1. Ablation experiments on VisDA-2017 dataset (ResNet50). The ✓, R, and × symbols in the ‘Selection-T’ column indicate adopting our target selection scheme (4), randomly selecting the same number of target data as our target selection scheme, and selecting all target data (i.e., $v_i^t = 1.1 \leq i \leq n_t$), respectively. The ✓, R, and × symbols in the ‘Selection-S’ column are similarly defined. The ✓ and × symbols in the ‘Selection-Enh.’ column indicate using the enhanced indicator (9) and the vanilla $f_m$ in the sample selection scheme (4), respectively; the ✓ and × symbols in the ‘Labeling-Enh.’ column indicate using the enhanced indicator (9) and the vanilla $f_m$ to provide pseudo labels of target data (i.e., $o(f_m(x_i^t))$ in (8)), respectively.

| Values of $M$ | Source Only | DANN | MCD | MDD | GSDA | RWOT | AuxSelfTrain |
|---------------|-------------|------|-----|-----|------|------|--------------|
| 0             | 45.6        | 55.0 | 69.8| 74.6| 81.5 | 84.0 | 85.2         |
| 10            |             |      |     |     |      |      |              |
| 20            |             |      |     |     |      |      |              |
| 30            |             |      |     |     |      |      |              |
| 40            |             |      |     |     |      |      |              |
| 50            |             |      |     |     |      |      |              |
| 60            |             |      |     |     |      |      |              |
| 70            |             |      |     |     |      |      |              |
| 80            |             |      |     |     |      |      |              |
| 90            |             |      |     |     |      |      |              |

Table 2. Results (%) on the VisDA-2017 dataset for the DA task (ResNet50).

**Figure 5.** (a) Two criteria measuring feature discriminability [5], where higher max $J(W)$ and lower average error rates imply stronger discriminability. Definitions of the two criteria are given in the appendices. (b) Results of AuxSelfTrain with various $M$ on the Rw→Cl task of OfficeHome dataset.
Analyses on number of intermediate domains We investigate the number of intermediate domains by setting $M$ as various values. As illustrated in Figure 5(b), the results get better as the $M$ increases in the beginning and gradually level off when $M$ reaches a relatively large value (e.g., 25). The results are as expected since larger $M$ indicates smaller changes between consecutive domains. We empirically set $M$ as a large value, e.g., 50, in experiments.

Analyses on the advanced data augmentation Replacing the advanced data augmentation $A$ [8] in (8) with a standard crop-and-flip one [18] leads to degraded results of 69.7% and 77.5% for the DA task on datasets of OfficeHome and VisDA-2017, respectively. To the best of our knowledge, we are the first one to investigate the advanced data augmentation [8] in DA problems.

Analyses on target feature discriminability Following [5], we investigate target feature discriminability on the VisDA-2017. As illustrated in Figure 5(a), target feature discriminability in AuxSelfTrain is enhanced compared to the ResNet50 baseline; this distinguishes AuxSelfTrain from the seminal discrepancy minimization method [15], where target feature discriminability is deteriorated [5].

5.2.2 Results
As illustrated in Tables 2, 3, and 5, our AuxSelfTrain achieve the new state of the art on all tested DA and SSDA benchmark datasets, justifying its efficacy on both DA and SSDA tasks and its generalization to different datasets and network structures.

6. Discussions
In contrast to popular distribution discrepancy minimization methods in DA [29, 15], we propose gradual self-training of auxiliary models, which is empowered by evolving intermediate domains via a simple yet efficient sample selection strategy. Together with [24], we stress the importance of gradually evolving intermediate domains for the success of self-training on DA. Two perspectives could be further investigated for the improvement. First, advanced indicators for sample selection could be explored. Moreover, the mix of source and target data could be conducted in other ways, such as pixel-level mixup [51]. Additionally, although the correlation between domain shift and the maximum prediction probability has been empirically observed...
in [34] and our paper, their underlying theoretical analysis is still an open problem and requires further investigation.

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