Unsupervised Domain Adaptation of Black-Box Source Models

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Abstract

Unsupervised domain adaptation (UDA) aims to learn a model for unlabeled data on a target domain by transferring knowledge from a labeled source domain. In the traditional UDA setting, labeled source data are assumed to be available for the use of model adaptation. Due to the increasing concerns for data privacy, source-free UDA is highly appreciated as a new UDA setting, where only a trained source model is assumed to be available, while the labeled source data remain private. However, exposing details of the trained source model for UDA use is prone to easily committed white-box attacks, which brings severe risks to the source tasks themselves. To address this issue, we advocate studying a subtly different setting, named Black-Box Unsupervised Domain Adaptation ($B^2$UDA), where only the input-output interface of the source model is accessible in UDA; in other words, the source model itself is kept as a black-box one. To tackle the $B^2$UDA task, we propose a simple yet effective method, termed Iterative Noisy Label Learning (IterNLL). IterNLL starts with getting noisy labels of the unlabeled target data from the black-box source model. It then alternates between learning improved target models from the target subset with more reliable labels and updating the noisy target labels. Experiments on benchmark datasets confirm the efficacy of our proposed method. Notably, IterNLL performs comparably with methods of the traditional UDA setting where the labeled source data are fully available.

1. Introduction

Although deep neuron network has achieved success on various tasks, it is difficult to generalize the model learned from the labeled training data to a target domain of slightly shifted data distribution. At the same time, it is expensive to collect a new target dataset with a large number of labeled training data. Therefore, the unsupervised domain adaptation (UDA) \cite{28, 21, 4} is introduced to learn an efficient target model by transferring knowledge from the labeled source domain to the unlabeled target domain.

Motivated by the seminal theories of UDA \cite{2, 40}, the popular methods \cite{21, 4, 33, 22, 41} target at learning domain invariant feature representations across domains. The underlying motivation is that the source classifier could be safely applied to the target data, once the domain invariant feature representations are achieved. In all these methods, the labeled source data are assumed to be readily available for the use of the target domain.

Although remarkable success has been achieved in UDA, nowadays increasing concerns for data privacy post new challenges to this task. Specifically, the data of source and target domains are typically captured and stored on different devices and contain private information. Thus it is risky to expose the source data to the target domain, and vice versa. In other words, the labeled source data may not be available for the use of target domain, which prevents the application of popular UDA methods \cite{21, 4, 33, 22, 41}. For this reason, a novel task, source-free UDA, is introduced \cite{39, 10, 20} to facilitate the model adaptation and protect the data privacy simultaneously.

Different from the vanilla UDA, a well-trained source model, instead of the labeled source data, is provided to the unlabeled target domain in the source-free UDA \cite{39, 20}. Specifically, a white-box source model is available for the target domain; thus we term this task as “white-box unsupervised domain adaptation” (in abbreviation WBUDA) to distinguish it from our proposed one in the later paragraphs. In WBUDA, the adaptation could be achieved by fine-tuning the source model on the unlabeled target data with well-designed objectives \cite{39, 20}.

Although the labeled source data remain private in WBUDA, exposing details of the trained source model is prone to easily committed white-box attacks, which brings severe risks to the source tasks themselves \cite{34, 6}. Supposing the source model is the recognition system of a self-driving car, attackers could easily generate adversarial examples to make the self-driving car misjudge the traffic signs, given the white-box source model.

To address this issue, we advocate studying a subtly dif-
ferent setting of source-free UDA, where only the input-output interface of the source model is accessible for the target domain. In other words, the source model itself is kept as a black-box one; thus we term this task as “black-box unsupervised domain adaptation” (in abbreviation B^2UDA). The potential attacks of source tasks are therefore downgraded from the white-box level in WBUDA to a less dangerous black-box one in B^2UDA [34, 6], making the B^2UDA a more safe way for adaptation.

The unavailable of the source data and white-box source model in B^2UDA prevents the application of all existing DA methods. To this end, we propose a simple yet effective method, termed Iterative Noisy Label Learning (IterNLL), to tackle this challenging setting. Starting with the noisy labels of the unlabeled target data from the black-box source model, our IterNLL alternates between learning improved target models from the target subset with more reliable labels [9, 37] and updating the noisy target labels. The sampling strategy of the target subset is motivated by the memorization effect of deep neuron networks [1], which suggests that clean patterns could be first learned even on the noisy dataset and small-loss instances are probably the ones with reliable labels [9]. Experiments on benchmark datasets confirm the efficacy of our proposed method. Notably, our IterNLL performs comparably with the methods of traditional UDA setting where the labeled source data are fully available. We conclude our contributions as follows:

- Considering the risks of exposing the white-box source models, we advocate the B^2UDA setting, where only a black-box source model rather than the white-box one is available for the adaptation use. In this way, we retain the privacy of source data and downgrade the potential attacks of source tasks from the white-box level to a less dangerous black-box one.
- To tackle the B^2UDA problem, we propose a simple yet effective method, termed Iterative Noisy Label Learning (IterNLL). IterNLL performs comparably with methods of traditional UDA setting where the labeled source data are fully available on benchmark datasets, justifying its efficacy.

2. Related Work

Settings of Unsupervised Domain Adaptation. In the traditional UDA problem [21, 4], the labeled source data and the unlabeled target data are provided and we investigate how to transfer knowledge from the source domain to the unlabeled target one. Due to the increasing concerns for data privacy, source-free UDA [20, 19, 10, 14, 39, 15] is highly appreciated as a new UDA setting, where only a trained white-box source model is assumed to be available for the use of the target domain, while the labeled source data remain private. However, exposing details of the trained source model for UDA use is prone to easily committed white-box attacks, bringing severe risks to source tasks themselves. To this end, we advocate studying a subtly different setting where only the input-output interface of the source model is accessible for the target domain; in other words, the source model itself is kept as a black-box one. A black-box source model is also adopted in [25]; however, they assume that a limited number of labeled target examples are available, which distinguishes it from our proposed one. The various source-free UDA settings are discussed in [3] based on simple models (e.g., a linear classifier).

Noisy Label Learning. In practical problems, the labels of training data may be noisy due to various reasons, such as the error of manual annotations. In this consideration, methods of noisy label learning are proposed. One popular pipeline of noisy label learning is to sample instances with more reliable labels for training, where the small-loss instances are regarded as the reliable ones [9, 37]. We adopt the same strategy for the B^2UDA by treating the predictions of target data on the black-box source model as noisy labels. We recommend the readers to refer [8] for other methods of noisy label learning.

Black-box Attack and White-box Attack. The white-box attacks [6] and the black-box attack [29] are introduced based on whether the details, e.g., structure and weight parameters, of the model to be attacked are available. Note that the white-box attack is more dangerous than the black-box one since more information about the model to be attacked is provided to the attacker, which is also empirically verified in [24, 35].

Federated Learning. Researchers [38] aim to learn from multiple users without exposing their private training data in federated learning. Recently, the federated DA is proposed in [31], where the knowledge is transferred from the decentralized source domains to a new target domain. Peng et al. [31] assumes the availability of gradients of multiple source domains, while we only use the black-box source model of one source domain, which may prevent the application of Peng’s method in our advocated task.

3. Problem Statement

Given unlabeled target data \( \mathcal{T} = \{x_i^t\}_{i=1}^{n_t} \) sampled from a distribution \( Q \), our problem of interest is to learn a model \( F : \mathcal{X}^t \rightarrow [0, 1]^K \) such that the empirical target risk \( \frac{1}{n_t} \sum_{i=1}^{n_t} \mathcal{L}(F(x_i^t), y_i^t) \) (or ideally, the expected risk \( \mathbb{E}_{(x', y') \sim Q} [\mathcal{L}(F(x'), y')] \)) could be minimized, where \( K \) is the category number, \( \mathcal{L} \) is the loss function of the task, and \( y_i^t \in \{1, \ldots, K\} \) is the target label to be estimated. Depending on how much knowledge one may have from a source domain, the problem can fall in different established realms of unsupervised learning.
[36], unsupervised domain adaptation (UDA) [21, 4], and source-free UDA [39, 20]. While the first one assumes no the source knowledge and is of machine learning foundations, in this work, we focus on different problem settings of UDA. By the convention of deep learning models, a feature extractor \( G : \mathcal{X}^t \rightarrow \mathcal{Z} \) is usually used that lifts any input \( x^t \in \mathcal{X}^t \) into the space \( \mathcal{Z} \). We thus write \( F = C \circ G \), and \( C : \mathcal{Z} \rightarrow [0, 1]^K \) is the classifier defined in \( \mathcal{Z} \).

Unsupervised Domain Adaptation. UDA [21, 4] assumes that labeled source data \( S = \{x^s_i, y^s_i\}_{i=1}^n \) sampled from a distribution \( P \) are available for a transferable use. Given the labeled \( S \), UDA algorithms typically learn the model \( F \) by simultaneously minimizing a task loss \( L_{\text{task}} \) on \( S \) and reducing the distribution divergence across the two domains:

\[
\min_{F=C \circ G} L_{\text{task}}(F, S) + L_{\text{div}}(G, S, \mathcal{T}),
\]

where we notice that the model \( F \) is shared by both the source and target data; \( L_{\text{div}} \) measures the distribution divergence between the two domains in the feature space \( \mathcal{Z} \), and the task loss \( L_{\text{task}} \) is typically instantiated as:

\[
L_{\text{task}}(F, S) = \frac{1}{n^s} \sum_{i=1}^{n^s} -\log(F_{y^s_i}(x^s_i)),
\]

where \( F_{k}(x) \) stands for the \( k^{th} \) entry of \( F(x) \).

Source-free Unsupervised Domain Adaptation. Source-free UDA [39, 20] is proposed recently due to the increasing concerns for the data privacy. Indeed, we are in an era of cloud computing, and the source and target data are usually captured and privately stored on different devices; it is thus risky to expose the source data for a transferable use to the target domain. Source-free UDA proposes to use a well trained white-box source model \( F^s \), instead of the labeled source data \( S \), to accomplish the UDA objective, which is formalized as:

\[
\min_{F} L_{\text{white}}(F, \mathcal{T}, F^s) \quad \text{s.t.} \quad F^s = \arg \min_{F} L_{\text{task}}(F, S).
\]

The target model is typically achieved by fine-tuning the white-box source model \( F^s \) on the unlabeled target data \( \mathcal{T} \) using a proper loss \( L_{\text{white}} \), e.g., the information maximization loss used in [20].

3.1. The Proposed Study for Black-Box Unsupervised Domain Adaptation

Although the source data remain private in the source-free UDA [39, 20], exposing the white-box source model for UDA use is prone to easily committed white-box attacks, bringing severe risks to the source tasks themselves [34, 6]. To this end, we advocate a subtly different setting of source-free UDA, where only the input-output interface of the source model is accessible for the target domain and the source model itself is kept as a black-box one. We denote the proposed task as “black-box unsupervised domain adaptation” (in abbreviation B\(^2\)UDA) to distinguish it from the previous setting of “white-box unsupervised domain adaptation” (in abbreviation WBUDA) [39, 20]. The potential attacks are downgraded from the white-box level in WBUDA to a less dangerous black-box one [24, 35] in
Figure 2. Framework of our IterNLL, where only a black-box source model is required by the target domain.

\[ \min_{F} \mathcal{L}_{\text{black}}(F, T, \hat{F}^s) \]
\[ \text{s.t. } F^s = \arg \min_{F} \mathcal{L}_{\text{task}}(F, S), \]

where \( \hat{F}^s \) provides the input-output interface of \( F^s \). Specifically, we could get the output of \( F^s(x) \) with respect to a sample \( x \) via \( \hat{F}^s(x) \) and the source model \( F^s \) itself is kept as a black-box one.

In WBUDA [39, 20] and our proposed B²UDA, the labeled source data are not accessible for the target domain, which protects the privacy of source data in the knowledge transfer process. Taking it a step further, our proposed B²UDA downgrades the potential attacks of source tasks from the white-box level in WBUDA to a less dangerous black-box one, making the B²UDA more attractive in practical applications. We compare different UDA settings in Figure 1.

The labeled source data \( S \) are necessary for the distribution divergence minimization across domains in the UDA tasks [21, 4] and methods of WBUDA typically fine-tune the white-box source models for the use of the target domain [39, 20]. Therefore, the unaccessible of the source data and white-box source models for the target domain in B²UDA prevents the application of all existing methods of UDA and WBUDA. To this end, we propose a simple yet effective method termed Iterative Noisy Label Learning (IterNLL) for B²UDA, as illustrated in the next section.

4. A Simple Baseline for the Proposed Study

Although the source data and the white-box source model are not accessible for the target domain in B²UDA, we could get the label prediction of the target sample \( x^t_i \) with the black-box source model \( \hat{F}^s \) as \( \hat{F}^s(x^t_i) \). Due to the distribution shift between the source and target domains, the empirical target risk with the \( \hat{F}^s \), i.e., \( \frac{1}{n^t} \sum_{i=1}^{n^t} \mathcal{L}(\hat{F}^s(x^t_i), y^t_i) \), could be high. In other words, the target predictions are highly noisy, which reminds us of the noisy label learning [8].

Noisy Label Learning. One popular method of noisy label learning is to sample instances with more reliable labels for training [9, 37]. As illustrated in [9], the performance could be improved by selecting samples with more reliable labels, while we would get low accuracy if too many samples are dropped. Therefore the sampling strategy is of vital importance.

Existing sampling strategies [9, 37] are mostly motivated by the memorization effects of deep models [1]. Given training data with noisy labels, the deep models tend to learn the clean patterns at the beginning, where the test accuracy increases and reaches a peak; then the deep models gradually memorize the noisy patterns as the training proceeds, where the test accuracy drops gradually, as illustrated in the “w/o NLL” in Figure 3. Inspired by this phenomenon, researchers typically use all the noisy data at the beginning of training, where clean patterns are first learned even with the existence of noisy labels; then samples with less reliable labels are gradually dropped as the training proceeds. The target samples with larger losses are typically regarded as
these with less reliable labels [9, 8], where the loss for the target sample $x_i^t$ is defined as:

$$-\log(F_{\hat{y}_i}(x_i^t)), \quad (5)$$

where $F$ is the model to learn and $\hat{y}_i$ is the pseudo label of $x_i^t$. Given a black-box model $\hat{F}$, e.g., the black-box source model $\hat{F}^n$, the pseudo label $\hat{y}_i^t$ of the sample $x_i^t$ is defined as: $\hat{y}_i^t = \arg\max_k P_k(x_i^t)$.

Figure 3. An illustration of the training accuracy on the noisy labeled target training data (i.e., solid lines) and test accuracy on the target test data with clean labels (i.e., dash lines) on the USPS->MNIST task. When we adopt all the noisy labeled target data in the training process (i.e., w/o NLL), the training accuracy keeps increasing and the test accuracy gradually decreases since the model gradually memorizes all the target data, including that with wrong labels. When we adopt the noisy label learning strategy (6) (i.e., with NLL), the training accuracy stabilizes at a relatively lower level while the test accuracy stabilizes at a relatively higher level, compared to the w/o NLL setting, since the samples with less reliable labels are dropped. Note that we start our plot from the iteration 100 since the low accuracy (e.g., 10%) in the beginning stage affects the presentation of accuracy changes. We also provide the test accuracy of the source model as “Source Only” for reference.

Following [9], we adopt the $R(n) \in [1 - \tau, 1]$ proportion of pseudo labeled target samples with smaller losses (5) in the $n$-th iteration for training. We define $R(n)$ as:

$$R(n) = 1 - \tau \min\left(\left(\frac{n_k}{n}\right)^p, 1\right), \quad (6)$$

where $n \in [1, N]$, $n_k \leq N$ and $N$ is the total number of iterations; $\tau$, $n_k$ and $p$ are hyperparameters. We set $n_k = 0.5N$ and $p = 1$ by default and analyze the influence of different $p$ values in Section 5.1. The value of $\tau$ plays an important role in the adopted strategy (6), since it decides the proportion of samples to be dropped. We propose the following two strategies to set the value of $\tau$.

It is intuitive that less samples should be dropped as data with noisy labels if the model $\hat{F}$ is more reliable for the target domain. Inspired by this assumption, we empirically set:

$$\tau = k(1 - \text{acc}_{\text{val}}), \quad (7)$$

where acc$_{\text{val}}$ is the accuracy based on a small-sized labeled target validation set and $k$ is the hyperparameter. Note that it is a common manner to adopt the labeled validation set for tuning hyperparameters and not model parameters [27].

Despite the common usage of the validation set for hyperparameter tuning, adopting the target validation set is not elegant in UDA tasks since target data are assumed to be totally unlabeled. Thus we propose another strategy to set $\tau$ without the validation data. As illustrated in [18, 42], there is a close correlation between the accuracy and the prediction confidence. In other word, if the predictions of $\hat{F}$ present high confidence on target data, high prediction accuracy is expected. We first calculate the proportion of target data $T$ with large prediction confidence as:

$$\hat{P} = \frac{1}{n} \sum_{i=1}^{n} \mathbb{I}[\max(\hat{F}(x_i^t)) > \gamma], \quad (8)$$

where $\gamma \in [0, 1]$ is the score threshold and $\mathbb{I}[\text{var}] = \begin{cases} 1, & \text{var} = \text{True} \\ 0, & \text{Otherwise} \end{cases}$. One may opt for replacing the acc$_{\text{val}}$ in (7) with $\hat{P}$ (8). However, considering that the deep models are prone to make over-confident predictions [7], we rescale $\hat{P}$ from $[0, 1] \rightarrow [\tau_1, \tau_h]$ as:

$$P = \tau_1 + \max\left(\frac{\hat{P} - \tau_1}{1 - \tau_1}(\tau_h - \tau_1), 0\right), \quad (9)$$

where $0 \leq \tau_1 < \tau_h \leq 1$. An intuitive example of the rescaled $P$ is presented in Figure 4. We therefore set $\tau = k(1 - P)$ and justify its effectiveness in Section 5.

Iterative Learning Strategy. As illustrated in Figure 3, given a black-box model with the low target test accuracy and its introduced noisy-labeled target training data, we could train a model of relatively higher accuracy from the
visda-c with its k prior assumption for all categories and refine the classified as one category [12, 5], we adopt the uniform Prediction Refinement via Uniform Prior Assumption. We replace the \( \tilde{Y} \) as zero, the closed-form solution [5] of \( f \in \{0, 1\}^K \) is a vector with its \( k \)-th entry \( f_k = \frac{1}{n^t} \sum_{i=1}^{n^t} \tilde{F}_k(x^t_i) \) and \( \mathbf{u} \in \left[ \frac{1}{K} \right]^K \) is the uniform distribution with its \( k \)-th entry \( u_k = \frac{1}{K} \). By setting the gradient of (10) as zero, the closed-form solution [5] of \( \tilde{Y} = \{ \tilde{F}(x^t_i) \}_{i=1}^{n^t} \) could be achieved as:

\[
\tilde{F}_k(x^t_i) = \frac{\tilde{F}_k(x^t_i) / (\sum_j \tilde{F}_k(x^t_j))^{\frac{1}{2}}}{\sum_{k'} \tilde{F}_{k'}(x^t_i) / (\sum_j \tilde{F}_{k'}(x^t_j))^{\frac{1}{2}}}. \tag{13}
\]

We replace the \( \tilde{F}_k(x^t_i) \) and the corresponding \( \tilde{y}^t_i \) in the IterNLL with the \( \tilde{F}_k(x^t_i) \) and \( \tilde{y}^t_i \), where \( \tilde{y}^t_i = \arg \max_k \tilde{F}_k(x^t_i) \).

5. Experiment

Datasets. We conduct four adaptation tasks with the Digits datasets and one with the VisDA-C [32] dataset. The digits datasets consist of MNIST [16], Street View House Numbers (SVHN) [26], and USPS [11]. There are 10 classes shared by 50,000 training samples, 10,000 validation samples and 10,000 test samples in the MNIST dataset (M), where all the images are black-and-white handwritten digits. The SVHN dataset (S) contains 73,257 training and 26,032 test images with colored backgrounds, and the USPS dataset (U) contains 6,652 training and 1,860 test images with black backgrounds. We adopt two settings for the adaptation task U \( \leftrightarrow \) M: following [23], we sample 2,000 images from M and 1,800 images from U, resulting in the U \( \leftrightarrow \) M; following [33], we adopt all in the training data in U and M, leading to the U \( \uparrow \leftrightarrow \) M. In the VisDA-C dataset, the source domain contains synthetic images while the target domain contains real world images, which results in a large domain gap; there are 152K synthetic images and 55K real images shared by 12 classes. We visualize the sample examples of the two tasks in Figure 5.

Implementation Details. All experiments are conducted on the PyTorch [30] and all parameters are updated by the SGD optimizer. Following [33], we adopt a model composed of three convolutional layers and three fully connected layers for the Digits dataset; we randomly pick 10 samples per class to build a small-sized validation set, which is used to set the hyperparameter \( \tau \) in (7). In VisDA-C experiments, we randomly pick 30 samples per class to build a validation set, which occupies less than 1% of the entire target data. We set the batch size as 64, the total number of iterations \( N \) as 10,000, and \( k \) in (7) as 1. In experiments without the validation data, we set \( \gamma \) in (8) as 0.95, and set \( \tau_1 \) and \( \tau_0 \) in (9) as 0.5 and 0.8 respectively. Following [4], we adopt the learning strategy of \( \eta_p = \frac{\eta_0}{(1 + 10t)^{\omega}}, \) where \( \eta_0 = 0.01 \) and \( \omega \) is the process of training iterations linearly changing from 0 to 1.

Algorithm 1 Iterative Noisy Label Learning Algorithm.

**Input:** Black-box source model \( \tilde{F}^s \), target data \( \mathcal{T} = \{x_i^t\}_{i=1}^{n^t} \),

1: Initialize \( \tilde{F} \) with \( \tilde{F}^s \)
2: for \( m = 1 \) to \( M \) do
3: Acquire noisy labels \( \tilde{Y} \) of \( \mathcal{T} \) as their predictions on \( \tilde{F} \)
4: Refine \( \tilde{Y} \) to \( \tilde{\mathcal{Y}} \) using (10)
5: Decide the sampling strategy (6) with (7) or (9)
6: Acquire improved \( F \) (and the corresponding black-box \( \tilde{F} \)) by noisy label learning
7: end for

Figure 5. Sample examples in MNIST, SVHN and USPS datasets (a) and the VisDA-C dataset (b).
5.1. Analysis

Ablation Study. To investigate the effects of components in IterNLL, we conduct the following ablation experiments on the VisDA-C dataset. In the baseline of “Source Only”, we get the results on the target domain based on the black-box source model $F^s$. To illustrate the effectiveness of the iterative learning strategy, we conduct our IterNLL by setting $M = 1$ in the Algorithm 1, leading to the “IterNLL w/o Iter”. To investigate the noisy label learning strategy (6), we introduce the “IterNLL w/o u.p.” by setting $R(n) = 1$ (6). To study the efficacy of the prediction refinement with the uniform prior assumption (10), we remove the refinement from the Algorithm 1, resulting in the “IterNLL w/o u.p.”. As for the “IterNLL”, we adopt the setting where the $\tau$ is determined by the accuracy on target validation set (7).

As illustrated in Table 1, our “IterNLL” improves over the results of “IterNLL w/o Iter”, “IterNLL w/o u.p.” and “IterNLL w/o u.p.”, verifying the effectiveness of the iterative learning strategy, the noisy label learning strategy and the refinement with the uniform prior assumption, respectively. Specifically, we find that the accuracy of “IterNLL w/o u.p.” on the ‘knife’ and ‘truck’ classes are zero, since the low results of “Source Only” on the two classes lead to few samples selected for them in the noisy label learning; this problem could be significantly alleviated by the adopted prediction refinement with the uniform prior assumption and boosting performance has been observed.

Results with Various $k$. To investigate the influence of the hyperparameter $k$ in (7), we set $k$ to different values. As illustrated in Figure 6(a), although the best $k$ of different tasks varies, a value around 1 consistently gives good results. Accuracy of different $k$ fluctuates relatively slightly in tasks of U→M and M→U, but it fluctuates rapidly in the M→S task, which means that $k$ plays an important role especially when the accuracy of Source Only is low. Empirically, we set $k = 1$ in all experiments.

Results with Various $p$. We set the hyperparameter $p$ (6) to different values to study its influence. As illustrated in Figure 6(b), the results vary little as the value of $p$ changes. We set $p = 1$ in all experiments.

Visualization of Iterative Training. As illustrated in Figure 3, better results over the initial Source Only model could be achieved by the noisy label learning strategy. To better understand our proposed method, we plot the training accuracy and test accuracy in different iterative stages, i.e., with different $m$ in Algorithm 1. As illustrated in Figure 7, the results get better as the $m$ gets larger, which verifies the effectiveness of our proposed IterNLL. The results gradually stabilize as the $m$ increases, and we empirically set $M = 20$ and $M = 30$ for the datasets of Digits and VisDA-C, respectively.

5.2. Results

We first compare results of our IterNLL with different noisy label selection strategies, i.e., the IterNLL and IterNLL (w/o val). In IterNLL, we decide the noisy label selection (6) with a small-sized target validation set (7), and in IterNLL (w/o val), we adopt the noisy label selection (6) with (9). As illustrated in Table 2 and Table 3, both IterNLL

| method          | plane  | bcycl | bus   | car   | horse | knife | mcycl | person | plant | sktbrd | train | truck | Avg   |
|-----------------|--------|-------|-------|-------|-------|-------|-------|--------|-------|--------|-------|-------|-------|
| Source Only     | 65.9   | 31.2  | 24.7  | 75.5  | 55.6  | 3.9   | 73.0  | 7.5    | 66.7  | 26.5   | 89.1  | 1.0   | 43.4  |
| IterNLL w/o Iter| 84.0   | 54.4  | 48.1  | 74.7  | 76.2  | 16.8  | 79.9  | 30.6   | 85.7  | 50.6   | 89.7  | 10.9  | 58.5  |
| IterNLL w/o u.p.| 95.2   | 85.5  | 77.3  | 92.8  | 94.0  | 0.0   | 86.2  | 40.7   | 94.7  | 91.8   | 84.2  | 0.0   | 70.2  |
| IterNLL w/o NLL | 93.1   | 84.6  | 75.4  | 58.8  | 91.8  | 40.0  | 84.4  | 77.0   | 87.6  | 83.7   | 82.5  | 50.3  | 75.8  |
| IterNLL         | 95.9   | 86.8  | 82.8  | 75.9  | 95.1  | 96.2  | 86.9  | 84.7   | 94.0  | 89.3   | 85.9  | 50.0  | 85.3  |

Table 1. Ablation study on VisDA-C dataset, where all experiments are based on a ResNet-34 model. Please refer to the main text for definitions of these methods.
We compare our proposed IterNLL with other methods on datasets of Digits and VisDA-C in Table 2 and Table 3, respectively. Our IterNLL achieves comparable results with other methods, which either utilize the labeled source data directly [4, 33, 22, 13] or require the white-box source model [14, 19, 39, 20]. The unaccessible of source data and white-box source model in B^2UDA prevents the application of all existing UDA methods, resulting in the unfair comparison between these methods and our IterNLL. Nevertheless, we provide results of these methods for reference. We adapt the recent state-of-the-art WBUDA method SHOT [20] for the B^2UDA task to provide a fair comparison for IterNLL; specifically, to provide a white-box source model for SHOT, we approximate the source model by retraining a new model on the target data and their pseudo labels from the black-box source model; then we apply SHOT to B^2UDA by treating the retrained model as the white-box source one, resulting in the SHOT-BB. As illustrated in Table 2 and Table 3, our proposed IterNLL improves over the SHOT-BB in three of the four tasks on the Digits dataset and in the VisDA-C dataset, justifying the efficacy of our IterNLL. Especially, our IterNLL achieves promising results on tasks where the target domain is more complicated than the source one, e.g., the M→S task in the Digits dataset and the VisDA-C task, justifying the efficacy of IterNLL in this challenging setting.

6. Conclusion

Due to the increasing concerns for data privacy, source-free UDA is highly appreciated nowadays, where a trained source model is available for the use of the target domain, while the labeled source data remain private. In this paper, we advocate studying a subtly different setting where only the input-output interface of the source model is accessible by the target domain. By keeping the source model as a black-box one, we downgrade the potential attacks from the white-box level to a less dangerous black-box one. To tackle this challenging task, we propose a simple yet efficient method, termed Iterative Noisy Label Learning (IterNLL), and verify the effectiveness of the IterNLL on standard benchmark datasets of domain adaptation. We expect the proposed B^2UDA task could facilitate the practical application of domain adaptation in real world.
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