Abstract

Present domain adaptation methods usually perform explicit representation alignment by simultaneously accessing the source data and target data. However, the source data are not always available due to the privacy preserving consideration or bandwidth limitation. Source-free domain adaptation aims to solve the above problem by performing domain adaptation without accessing the source data. The adaptation paradigm is receiving more and more attention in recent years, and multiple works have been proposed for unsupervised source-free domain adaptation. However, without utilizing any supervised signal and source data at the adaptation stage, the optimization of the target model is unstable and fragile. To alleviate the problem, we focus on semi-supervised domain adaptation under source-free setting. More specifically, we propose uncertainty-guided Mixup to reduce the representation’s intra-domain discrepancy and perform inter-domain alignment without directly accessing the source data. We conduct extensive semi-supervised domain adaptation experiments on various datasets. Our method outperforms the recent semi-supervised baselines and the unsupervised variant also achieves competitive performance. The experiment codes will be released in the future.

1. Introduction

Deep neural networks (DNNs) typically suffer significant degradation when the distribution of test data is different from training data, which is commonly-encountered in machine learning practice. Domain Adaptation (DA) has been shown to be an important technique to address such distribution shift or domain shift. In the common setting of DA, the source domain has sufficient examples with labels, the target domain has different but related examples with no or few labels provided. Based on the above setting, most methods simultaneously access the data from both domains and propose to reduce the domain gap by learning domain-invariant features. However, due to concerns of data privacy or the limitations of communication bandwidth, these methods could be infeasible in practice because of the unavailability of source data.

Recently, source-free domain adaptation is receiving increasingly popularity. These methods generally follow a pre-train and fine-tune paradigm, i.e., pre-training models on the source domain, and performing fine-tuning adaptation using target data only. In unsupervised setting, there have been several methods performing source-free adaptation on the target domain, such as fixing the pre-trained classifier layer with updating the others (SHOT, [20]), updating the Batch Normalization layer with fixing the others (Tent, [35]), updating all layers with augmented target data [19]. However, due to the unavailability of any labels for supervision, most of these methods depends on predicted pseudo labels, which are inherently unreliable and generally lead the model optimization to be unstable and fragile with false feature alignments. In this paper, we approach source-free domain adaptation in a semi-supervised manner by assuming few labeled target data is additionally available, which is quite reasonable in practice and achieves significantly im-

Figure 1. The illustrations of our motivation. The source domain data are not available at the adaptation stage due to privacy preserving consideration. We firstly select the unlabeled target data most similar with the source domain, then generate new examples around the selected data to explore the vicinal structure and bridge the domain gap.
Semi-Supervised DA (SSDA) aims to boost the adaptation quality with a few labeled target data and has a long research history [17, 36, 30]. To solve the source-free SSDA, two essential problems must be considered. The first is how to reduce the representation’s intra-domain discrepancy between the labeled target data and the unlabeled target data. This problem arises because of different training objectives for the labeled target data and the unlabeled target data. To reduce this intra-domain discrepancy, traditional semi-supervised learning methods usually need a considerable proportion of labeled examples. However, performing source-free SSDA makes a great challenge for these traditional techniques. Because in the common setting [30], only one or three labeled examples per class can be utilized. As the basics of our solution, we consider linear interpolation between the labeled target examples and the unlabeled target examples, making the model exploring the structure between the two parts. The linear interpolation methods for deep neural networks were proposed by Mixup [38], which trains a neural network on convex combinations of pairs of examples and their labels.

The second problem is how to perform effective domain alignment while not accessing the source domain. We use a common assumption that domain shift makes the target distribution different but related with the source distribution. Inspired by the semi-supervised setting, our motivation is to estimate the related part, in which the unlabeled target examples have a similar representation with the source examples. To this end, we propose source-like selection based on uncertainty estimation considering the uncertainty of data and model. The unlabeled target examples with low uncertainty have two merits for the adaptation task: 1) the model usually produces high quality pseudo labels for the unlabeled target examples with low uncertainty, and these high quality pseudo labels directly provide a substantial supplement for the labeled target examples. 2) the unlabeled target examples with low uncertainty are usually similar with source examples in representation space, hence pushing the representation of the high uncertainty examples toward the low uncertainty examples nearly equals aligning the cross-domain representations.

To solve the above two problems under an unified framework, we also use linear interpolation to reduce the domain gap. Figure 1 illustrates our motivation and proposed solution for domain alignment. We conduct extensive semi-supervised domain adaptation experiments on various datasets such as large scale dataset DomainNet and two small size datasets Office-31, Office-Home. The results show that our method outperforms the recent baselines of SSDA. Moreover, our unsupervised version using source-like selection also outperforms the recent unsupervised baselines under source-free setting. We formulate our method as Uncertainty-guided Intra-Domain Mixup (UIDM). Our contributions are summarized as follows:

- We summarize the recent domain adaptation methods considering source-free setting, and found that the optimization of target model is easy to corrupt without any supervised signal and source data. This motivates us to propose a semi-supervised version under this setting.
- For the source-free SSDA, we propose uncertainty-guided mixup by leveraging uncertainty estimation to reduce the intra-domain discrepancy and inter-domain representation gap.
- We evaluate the performances against different baselines on various domain adaptation datasets. Compared with the recent SSDA methods using both domains for adaptation, our framework outperforms these methods in almost all the tasks while not accessing the source domain at the adaptation stage.

2. Related Work

2.1. Source-Free Domain Adaptation

Domain Adaptation aims to deal with distribution shift problem by transferring knowledge from a source domain to a different but related target domain. Deep neural networks have been recognized with better representation ability compared to traditional methods. Among the recent deep learning techniques, Adversarial Deep Learning [9] gets strong performance in many adaptation scenarios by minimizing the domain gap with generative models. We recommend referring to the surveys [41] for more details.

In the meantime, data privacy is becoming more important as deep neural networks get success in domain adaptation. There exist various methods aiming at source-free for source data such as Federated Learning [27]. However, these methods lack the flexibility to be deployed in practical tasks, because of the requirement to access source data.

Recently, some works such as [4] show the possibility to perform adaptation on target domain while not accessing source data. Concretely, [4] proposes source-free domain adaptation and set the basic framework of pre-training and finetuning. Based on the framework, SHOT [20] adopts the Source Hypothesis Transfer, which fixes the pre-trained classifier and finetunes other modules at adaptation stage. [19] propose model adaptation methods by iteratively generating the source-style examples and updating the model. Tent [35] updates normalization layer and fixes others when performing adaptation.

2.2. Semi-Supervised Learning for DA

Semi-Supervised Learning aims to use the labeled and the unlabeled data together to facilitate the overall learn-
ing performance. Typical methods can be classified into three categories: i) consistency regularization, encouraging the model to have stable outputs when applying perturbations to examples \cite{33, 24}. ii) entropy minimization, encouraging the model to make a confident prediction for unlabeled examples \cite{11} iii) data augmentation, by performing linear interpolation \cite{38, 2} or self-supervised learning with more data transformations \cite{23}. In the traditional semi-supervised setting, where a considerable amount of labeled examples are available. However, there are only one or three labeled target examples in the setting of Semi-supervised Domain Adaptation (SSDA) \cite{30}. To solve domain shift challenge in semi-supervised setting, \cite{17} proposed a co-regulation based approach for SSDA, based on the notion of augmented space; \cite{36} proposed a kernel matching method mapping the labeled source data to the target data. Recently, MME \cite{30} proposed minimax entropy method and works well on DomainNet \cite{26}, which is used as a large domain adaptation dataset. Furthermore, many recent works follow the setting of MME and get more strong performance, e.g., \cite{13, 15}. Among the published methods, none of them solves the problem under source free setting.

### 2.3. Uncertainty Estimation

Estimating the noise from input data or models is important for the deep learning community. Among existing estimation methods, Bayesian networks\cite{3} are typical tools to predict the uncertainty of weights in the network. Using Bayesian theory, \cite{14} attempt to provide prediction results with confidence. \cite{28} propose an uncertainty-aware pseudo-label selection framework to improve pseudo labeling accuracy. In domain adaptation tasks, \cite{40} get strong performance on the domain adaptive semantic segmentation with uncertainty. Unlike the previous works, we only consider the prediction uncertainty on the target domain using entropy metric, which means lower prediction entropy indicates lower uncertainty. Further, we consider not only the data uncertainty brought by random transformation and linear interpolation, but also the model uncertainty brought by the Dropout operation.

### 3. Proposed Framework

#### 3.1. Problem Formulation

Here we introduce the adaptation process of source-free DA. On the source domain, we have labeled data $X^s \in \mathbb{R}^{n \times d}$ and corresponding labels $Y^s \in \mathbb{R}^{n \times l}$. On the target domain, we have a few labeled data $X^t \in \mathbb{R}^{o \times d}$ with corresponding labels $Y^t \in \mathbb{R}^{k \times l}$, and the unlabeled data $X^t_u \in \mathbb{R}^{m \times d}$. Here the superscripts $s$ and $t$ denote the source domain and the target, respectively. $n$, $o$ and $m$ denote the number of the source data, the labeled target data and the unlabeled target data, respectively. The universal setting of DA is training a model to predict the labels of $X^t_u$, with the help of $X^s$ and $Y^s$. Inspired by the framework of HTL, we firstly define a encoder function $f(x) : \mathbb{R}^d \rightarrow \mathbb{R}^h$ and an objective function $L_w(x, y)$ with learnable parameters $W \in \mathbb{R}^{k \times h}$.

On the source domain, we optimize function $f$ and $W$ by:

$$L_w(X^s, Y^s) = -\mathbb{E}_{(x,y) \sim X^s,Y^s} \sum_{k=1}^{K} y_k \log S_k(W \times f(x)), \quad (1)$$

where $K$ is the class number, $S_k$ is Softmax function. Note that in the origin work of HTL \cite{20}, $W$ is the parameters of classifier consisting of one fully connected layer. We regard $W$ as a part of loss function $L_w$ for the sake of analysis.

On the target domain, we fix $W$ that has captured the statistics of the source data, and update the encoder with the proposed UIDM method. The next contents are organized as follows: we firstly introduce the mixup operation and its extension applied on the target domain. Then we analyze what the model can transfer from the source to the target and design the source-like selection methods using uncertainty estimation. Finally, we put all the processes into an unified framework including Self-Mixup and Hybrid-Mixup. Figure\cite{2} demonstrates the proposed framework.

#### 3.2. Target Mixup

To reduce the intra-domain discrepancy between the labeled target examples and the unlabeled target examples, we try to use Mixup \cite{38} to explore the structure of the two parts. Mixup aims to train a neural network on convex combinations of pairs of examples and their labels. The simple method has been shown powerful ability to improve robustness to adversarial examples, and reduce corruption risk for training generative adversarial networks \cite{10}. Therefore in earlier works \cite{37}, domain mixup is used to boost Adversarial Domain Adaptation and get satisfactory performances. However, the Adversarial Domain Adaptation needs source domain to be accessible, which conflicts with our source-free setting. In our setting, we only consider mixup operation on the target domain. The new example $\{x, y\}$ generated by mixup $M((X_1, Y_1), (X_2, Y_2))$ can be defined as:

$$
\begin{align*}
x &= \lambda x_1 + (1 - \lambda) x_2; x_1 \in X_1, x_2 \in X_2 \\
y &= \lambda y_1 + (1 - \lambda) y_2; y_1 \in Y_1, y_2 \in Y_2,
\end{align*}
$$

where $\lambda$ denotes the mixup coefficient. For implementation, we adopt MixMatch \cite{2}, a improved version of mixup which performs linear interpolation by $M((X^t_l, Y^t_l), (X_u, \hat{Y}_u))$ and $M((X^t_u, \hat{Y}_u), (X_u, \hat{Y}_u))$ where $X_u$ is the union of augmented $X^t_l$ and $X^t_u$, $\hat{Y}_u$ is the label set corresponding to $X_u$, $\hat{Y}_u$ is the soft labels of $X^t_u$. However, the original Mixmatch above can not cope with our situation well. In our setting, only one labeled target examples making $M((X^t_l, Y^t_l), (X_u, \hat{Y}_u))$ often lost its
function. This impels us to select some source-like examples from $X_u^t$ as the labeled data. In the following section, we will define what is the source-like examples and design selection methods by uncertainty estimation.

### 3.3. Source-Like Selection

To produce high quality pseudo labels and push the target representation towards the source representation, we want to select the unlabeled targets which have similar representation with source examples as the agents of source domain. Before the introducing for selection operation, we analyze what the model can transfer from the source domain to the target domain. Let $W$ denote the parameter matrix of the model’s fully connected classifier. Though the training on the source domain, the estimated matrix $\hat{W}$ can capture the expected representations for each class when the model is optimized. If $W_k$ denote the $k$-th vector corresponding to $k$-th class, $f(x)$ denotes the representation of input $x$, the following equation will be hold when the model is fully optimized:

$$\hat{W}_k = E_{x_k \in \mathcal{X}}[f(x_k)],$$

(3)

where $x_k$ denote the example with class $k$. If we transfer $\hat{W}$ to the target domain, we can get the following objective function:

$$\mathcal{L}_{\text{cos}}(X^t, Y^t) = -E_{(x,y) \sim \mathcal{X^t}, Y^t} \sum_{k=1}^{K} y_k \log S_k (\hat{W} \times f(x)),$$

(4)

Due to $\hat{W}$ is fixed when transferred to the target domain. Equation 8 indicates we can get lower $\mathcal{L}_{\text{cos}}(X^t, Y^t)$ when the representation of an unlabeled target example similar to a vector of $\hat{W}$, i.e., the example is close to a class of source data in representation space. This gives us the motivation to explore and exploit the unlabeled target examples which have high confidence close to the source data in representation space.

Next, we introduce a simple method to select high confidence target examples based on uncertainty estimation. If we let $p(x) = S(\hat{W} \times f(x))$ denote the class probability vector, we can use the entropy $e = \sum_{k=1}^{K} P_k \log P_k$ to estimate the uncertainty of sample $x$, where $P$ is derived from:

$$P = 1/2 \times n_r \times \sum_{i=1}^{n_r} D_i(p(x_1) + p(x_2))$$

(5)

Note that we use random transformation to consider the uncertainty from data, i.e., $x_1$ and $x_2$ are two different random transformation examples from input sample $x$. Furthermore, to consider the uncertainty brought from the model, we repeat $n_r$ times Dropout operation $D_i$ to calculate $p(x)$ using MC-Dropout method. MC-Dropout is an uncertainty estimation method opening Dropout in $f(x)$ and calculate the mean of repeated outputs in the estimation stage.

Finally, we consider how to select the unlabeled target examples from their estimated uncertainty. Let $I_k$ denote the unlabeled target examples with predicted class $k$. For each $k$, we sort $I_k$ according to their uncertainty with ascending order, and select top-$h$ samples. Compared with SHOT, the source-like selection can produce high quality pseudo labels for a part of target examples and avoid redundancy noises. Furthermore, these selected examples can be
set as the agents of source domain to perform domain alignment.

3.4. Model Training

In this section, we provide the overall objective function training our model. We split $X_u^i$ into the selected samples $\{I, \hat{Y}\}$ and the rest samples $\{I_r, \hat{Y}_r\}$, where $\hat{Y}$ and $\hat{Y}_r$ are predicted soft labels. Derived from MixMatch[2], the interpolation of examples can be re-defined as:

$$ (X, Y) = M_{hybrid}\left((X^i_j + I, Y_j^i + \hat{Y}), (I_r, \hat{Y}_r)\right), \quad (6) $$

$$ (U, Y_u) = \bigcup_i M_{self}\left((\hat{X}_i, \hat{Y}_i), (\hat{X}_i, \hat{Y}_i)\right), \quad (7) $$

where $\hat{X}_i$ includes $X^i_j$, $I$ and $I_r$, and $\hat{Y}_i$ denotes corresponding ground truth labels or soft labels. Following [2], the loss for $(U, Y_u)$ can be defined using Mean Squared Error:

$$ L_{mse}(U, Y_u) = -\mathbb{E}_{(x,y)\sim U,Y_u} \sum_{k=1}^{K} y_k - S_k\left(\hat{W} \times f(x)\right)^2, \quad (8) $$

Therefore, we get the mixup loss:

$$ L_m = L_{cos}(X, Y) + \alpha L_{mse}(U, Y_u), \quad (9) $$

where $\alpha$ is the weight of $L_{mse}$. Algorithm[1] demonstrates the implementation of the UIDM at the adaptation stage.

3.5. Generalization Analysis

In this section, we try to theoretically explain why UIDM works and the differences between UIDM and traditional mixup methods. We use Integral Probability Metric [25] to denote the expected distance between the source domain and the target domain:

$$ \gamma_H(S, T) := \sup_{h \in H} |\mathbb{E}_S h(z) - \mathbb{E}_T h(z)|, \quad (10) $$

where $h : \mathcal{X} \times \mathcal{Y} \rightarrow R$ is a real-value function and $S$ and $T$ denote the distribution of the source domain and the target domain respectively. If we only consider binary classification, according to [11], for any $B$-uniformly bounded and $L$ Lipchitz function $\Gamma$, for all $h \in H$, with probability at least $1 - \delta$:

$$ \gamma_H(S, T) \leq \gamma_H(\hat{S}, \hat{T}) + 2L \mathcal{R}(h|Z) + B \sqrt{\frac{\log(1/\delta)}{2n}}, \quad (11) $$

where $\mathcal{R}(h|Z)$ is the Rademacher Complexity [11] of the function class $H$ w.r.t the target examples $Z$, $\hat{S}$, $\hat{T}$ are the empirical distributions of source domain and target domain,

\textbf{Algorithm 1} The Adaptation Stage of UIDM

\textbf{Input}: The pre-trained encoder $f$ and transform matrix $\hat{W}$, the labeled target data $X_t^i$, $Y_t^i$ and the unlabeled target data $X_u^i$

\textbf{Output}: the updated encoder $f$.

1: \textbf{while} not convergence \textbf{do}
2: \hspace{1em} Compute uncertainty $e_i$ for each unlabeled target example in $X_t^i$ by Equation[5]
3: \hspace{1em} Compute soft labels for $X_t^i$ and split them into low uncertainty set $\{I, \hat{Y}\}$ and high uncertainty set $\{I_r, \hat{Y}_r\}$ using source-like selection.
4: \hspace{1em} for Step $= 0 \rightarrow T$ do
5: \hspace{2em} Sample batch data $x \in X_t^i \cup I$, $y \in Y_t^i \cup \hat{Y}$ and $i \in I_r, y_r \in \hat{Y}_r$
6: \hspace{2em} Generate interpolated examples $\{x, y\}$ and $\{u, y_u\}$ using Equation[6][7][8] and [9]
7: \hspace{2em} Update the encoder $f$ using $\{x, y\}$ and $\{u, y_u\}$ with Equation[9]
8: \hspace{1em} \textbf{end for}
9: \textbf{end while}

$n$ is the number target examples. [39] has proved that the original Mixup reduces $\gamma_H(S, T)$ by minimizing $\mathcal{R}(h|Z)$. Derived from the original Mixup, our mixup framework further minimizes $\gamma_H(\hat{S}, \hat{T})$ by implicit domain alignment with the help of estimated $\hat{W}$.

4. Experiments

4.1. Datasets

We adopt three public datasets including DomainNet [26], Office-Home [14] and Office-31 [29].

DomainNet is a large dataset containing six domains including Clipart, Infograph, Painting, Real, Quickdraw [26]. Following MME [30], we also pick 4 domains (Real, Clipart, Painting, Sketch), and 126 classes for each domain.

Office-Home consists of images from 4 domains: Art, Clipart, Product and Real-World images. For each domain, the dataset contains images of 65 object categories built typically from office and home environments.

Office-31 dataset is a small size dataset containing 3 domains (Amazon, Webcam and Dslr) and 31 categories in each domain.

4.2. Baselines

The baselines including three categories: None Adaptation (S+T [30]), Semi-Supervised Learning (ENT [11] [30]), Unsupervised Domain Adaptation (DANN [8], ADR [31], CDAN [21], SHOT [20]), and Semi-Supervised Domain Adaptation (MME [30], BiAT [13], Meta-MME [18], APE [13]). For the unsupervised domain adaptation...
methods, the labeled target data were put with the source data during the adaptation process. S+T trains a model with labeled source and labeled target data without using unlabeled data from target domain. ENT is a direct semi-supervised method that minimizes the entropy of the unlabeled target data. MME proposed minimax entropy loss for the SSDA problem. Based on MME, Meta-MME achieves better generalization with the help of Meta Learning [5][22]. BiAT uses bidirectional adversarial training for generating samples between the source and target domain. APE uses data perturbation and exploration to reduce the intra-domain discrepancy. We reproduce the APE method with model selection according to the original code, in which the model selection process is ignored. Besides, SHOT is an unsupervised domain adaptation methods via Source Hypothesis Transfer. We also reproduce SHOT method including the semi-supervised and the unsupervised version from their original codes.

4.3. Implementation Details

Data preparation. At the pre-training stage, we split the source data into the training data and the validation data, because of no access to the target domain. Specifically, on Office-31 and Office-Home, we split the training data and the validation data as 0.9 : 0.1; on DomainNet, we split the training data and the validation data as 0.98 : 0.02. We use the standard data augmentation methods consisting of random horizontal flip, random crop, and data normalization. For a fair comparison with baselines, we use the same partition for the target domain data as [30] corresponding to the labeled training data, the unlabeled training data, and the labeled validation data. Except for the final performance evaluation stage on the unlabeled data, we also use the same data augmentation methods when performing adaptation.

Model Architecture. We select three encoder backbones including AlexNet [16], VGGNet [32] and the ResNet-34 [12]. For the AlexNet and the VGGNet, we add a bottleneck layer after the last layer of the encoder. For the ResNet-34, we drop the last layer of the model and add a bottleneck layer like the former backbones. Finally, we use a classifier with one normalized fully connected layer.

Training Setting. We set the learning rate as 0.001 for all encoders and 0.01 for the rest layers. According to validation set, the selected numbers of examples per class for Office-31, Office-home, DomainNet are [3, 5, 20]. Following SHOT, we freeze the classifier at the adaptation stage and apply entropy constraints for the smaller dataset Office-31 and Office-Home. Furthermore, for all datasets, the

Table 1. The accuracies of semi-supervised domain adaptation on DomainNet dataset with ResNet34. R: real, S: sketch, P: painting, C: clipart. We repeat three times per task and report the mean with a standard variance. The variance 0.0 denotes missing the value reported by the original paper.
Table 2. The accuracies of semi-supervised domain adaptation on Office-31 dataset with AlexNet and Office-Home dataset VGGNet. The missing values are denoted by ‘-’. On Office-31, we focus on Dslr to Amazon and Webcam to Amazon. On Office-Home, 12 adaptation tasks are performed across 4 domains.

| Methods   | Office-31 | Office-Home |
|-----------|-----------|-------------|
|           | 1-shot    | 3-shot      | 1-shot    | 3-shot      |
| S+T       | 50.2±0.0  | 61.8±0.0    | 57.4±0.0  | 62.9±0.0    |
| DANN      | 55.8±0.0  | 64.8±0.0    | 60.0±0.0  | 63.9±0.0    |
| ADR       | 50.6±0.0  | 61.3±0.0    | 57.4±0.0  | 63.0±0.0    |
| CDAN      | 49.4±0.0  | 60.8±0.0    | 55.8±0.0  | 61.8±0.0    |
| SHOT      | 51.7±2.7  | 63.3±0.0    | 59.9±0.1  | 66.2±0.1    |
| ENT       | 48.1±0.0  | 65.5±0.0    | 51.6±0.0  | 64.8±0.0    |
| MME       | 56.5±0.0  | 67.5±0.0    | 62.7±0.0  | 67.6±0.0    |
| BiAT      | 56.2±0.0  | 68.3±0.0    | -         | -           |
| UIDM      | 58.3±0.4  | 68.2±0.3    | 64.3±0.1  | 69.1±0.2    |

Mixup coefficients λ is sampled from a Beta Distribution Beta(2, 0.5), the weight α of ℓ_mse is set to 200. The repeat times n_r is empirically set to 5. For all experiments, we randomly select three different seeds to repeat the experiments and report the mean results with a standard variance. Besides, our experiment was implemented with Pytorch and running on one RTX 3090 GPU.

4.4. Results

We focus on the evaluation of 1-shot/3-shot domain adaptation on the large scale dataset DomainNet (see Table[1] and Figure[3]). Our method outperforms the others on most semi-supervised domain adaptation tasks. Compared to the BiAT method that generates adversarial examples between two domains, our method performs target adaptation without accessing the source domain but gets stronger performance by generating interpolated examples only in the target domain. Similarly, APE uses data perturbation and exploration to reduce the intra-domain discrepancy. Our mixup strategy can effectively explore the data structure compared to data perturbation and exploration strategy.

Compared to SHOT (see Table[1]), which is an unsupervised domain adaptation method proposed with privacy preserving consideration. Our method outperforms SHOT on all the tasks except the simple task Painting to Real. The reason is that the diversity-promoting objective in SHOT is suboptimal when dealing with large scale dataset. Because this objective has multiple solutions which bring more uncertainty for the optimization as the class increasing. Recent work for multi-source domain adaptation [5] also verifies that SHOT is suboptimal on large scale dataset like DomainNet. We also conduct unsupervised domain adaptation using SHOT and our unsupervised version (See Table[3]). Under the unsupervised setting, no labeled target examples are available. Instead, we use the selected target examples with low uncertainty to replace the labeled target examples.

Table 3. Performances of unsupervised domain adaptation on DomainNet with ResNet34. No labeled target examples are used in the adaptation of UIDM and SHOT. Instead, we use the selected target examples with low uncertainty to replace the labeled target examples.

| Methods             | C→S | R→S | S→P |
|---------------------|-----|-----|-----|
| Source-Only         | 49.2±0.5 | 54.6±0.3 | 51.3±0.4 |
| SHOT                | 60.3±0.1 | 59.3±0.1 | 64.2±0.1 |
| UIDM (Ours)         | 63.9±0.5 | 63.5±0.1 | 66.0±0.2 |

For Office-31 and Office-Home, recent baselines such as BiAT and Meta-MME lack uniform evaluation on the two datasets. The average performance for 1-shot/3-shot adaptation tasks can be seen in Table[3].

4.5. Ablation Study

Table[4] demonstrates different performances by removing multiple operations in turn. When removing the source-like selection, our method equals to original Mixmatch [2], which overfits on 1-shot domain adaptation tasks. When hybrid-mixup is removed, the performance also suffers large degradation, because only performing mixup on the unlabeled data can not performing efficient domain alignment. Besides, self-mixup has smaller contribution to the overall performance.

Table 4. Ablation results of 1-shot adaptation on DomainNet with ResNet34. Source-Only denotes not using adaptation and evaluating with pre-trained models. Selection hybrid-M and Self-M denote source-like selection. hybrid mixup operation and self-mixup operation.

| Methods             | S→P | C→S | R→S |
|---------------------|-----|-----|-----|
| Source-Only         | 51.3±0.4 | 49.2±0.5 | 54.0±0.3 |
| UIDM w/o Selection  | 52.4±0.5 | 45.6±1.4 | 51.5±0.8 |
| UIDM w/o hybrid-M   | 58.5±0.1 | 53.5±0.1 | 53.2±0.1 |
| UIDM w/o Self-M     | 62.3±0.3 | 58.8±0.2 | 60.5±0.1 |
| UIDM full           | 67.0±0.2 | 64.5±0.6 | 63.5±0.1 |

4.6. Sensitivity Analysis

The selected number of example per class (SNPC) and the mixup coefficient λ are critical hyper-parameters for our framework.

To demonstrate the robustness of our method on different SNPC, we conduct three adaptation tasks on large-
Figure 3. T-SNE visualization for the encoder’s outputs of the source domain Real and the target domain Sketch on DomainNet. For clarity, we randomly select 1000 examples from each domain. (a) The visualization of the source domain and target domain using the model trained on the source domain. The magenta dots denote the data of the source domain Real, and the cyan dots denote the data of the target domain Sketch. (b) After adaptation, the target domain’s representation becomes more compact and is clustered to the source domain. (c) The class level visualization of the target domain Sketch before adaptation. Each class is denoted by one color. (d) After adaptation, the representation of each class is more compact.

Figure 4. The performances when selecting different number of examples per class on DomainNet with ResNet34.

Figure 5. The performances when selecting different mixup coefficient $\lambda$ on DomainNet with ResNet34.

scale dataset DomainNet, given multiple SNPC varying 5 to 30. Figure 4 demonstrates the adaptation accuracies corresponding to each setting. Compared to SNPC=0, SNPC=5 improves the performance with a large margin. When given larger SNPC, the performance is becoming flattened. Even so, we hope more elegant way to decide which part is important in mixup. When $\lambda > 0.5$, the performance is improved with acceptable standard variance.

5. Conclusion and Future Work

In this paper, we propose Uncertainty-guided Intra-Domain Mixup (UIDM) method to perform semi-supervised target domain adaptation without accessing the source data. With the help of uncertainty estimation, we split the target examples into three groups: the unlabeled target examples with high uncertainty, the unlabeled target examples with low uncertainty and the labeled target examples. Then Self-Mixup and Hybrid-Mixup are used to perform intra-group and inter-group data interpolation, respectively. Compared to standard mixup methods like Mixmatch, our framework still works well when only given only one or three labeled examples in virtue of the mechanism of source-like selection. In the future, we hope to select optimal source-like examples for each class to improve the semi-supervised and even unsupervised domain adaptation under source-free setting.

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