

Recall and Refine: A Simple but Effective Source-free Open-set Domain Adaptation Framework

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Abstract

Open-set Domain Adaptation (OSDA) aims to adapt a model from a labeled source domain to an unlabeled target domain, where novel classes — also referred to as target-private unknown classes — are present. Source-free Open-set Domain Adaptation (SF-OSDA) methods address OSDA without accessing labeled source data, making them particularly relevant under privacy constraints. However, SF-OSDA presents significant challenges due to distribution shifts and the introduction of novel classes. Existing SF-OSDA methods typically rely on thresholding the prediction entropy of a sample to identify it as either a known or unknown class but fail to explicitly learn discriminative features for the target-private unknown classes. We propose Recall and Refine (RRDA), a novel SF-OSDA framework designed to address these limitations by explicitly learning features for target-private unknown classes. RRDA employs a two-step process. First, we enhance the model’s capacity to recognize unknown classes by training a target classifier with an additional decision boundary, guided by synthetic samples generated from target domain features. This enables the classifier to effectively separate known and unknown classes. In the second step, we adapt the entire model to the target domain, addressing both domain shifts and improving generalization to unknown classes. Any off-the-shelf source-free domain adaptation method (e.g., SHOT, AaD) can be seamlessly integrated into our framework at this stage. Extensive experiments on three benchmark datasets demonstrate that RRDA significantly outperforms existing SF-OSDA and OSDA methods. The source code is publicly available¹.

Introduction

Unsupervised Domain Adaptation (UDA) (Ben-David et al. 2010; Ganin and Lempitsky 2015; Long et al. 2015) adapts a model from a labeled source domain to an unlabeled target domain (Oza et al. 2023), effectively addressing the issue of domain shift where the source and target distributions differ. UDA strategies typically align feature distributions between domains using metric learning techniques (Long et al. 2015; Kang et al. 2019) or adversarial training (Ganin and Lempitsky 2015; Tzeng et al. 2017; Luo et al. 2019), and more recently, self-training approaches (Sun et al. 2022; Hoyer et al. 2023; Zhu, Bai, and Wang 2023). Despite their success, most

current domain adaptation approaches operate under the assumption of a shared label set between the source and target domains (i.e., $C_s = C_t$), referred to as Closed-set Domain Adaptation (Saenko et al. 2010). However, this assumption is often impractical in real-world scenarios.

In contrast, Open-set Domain Adaptation (OSDA) extends the target label space beyond that of the source domain (i.e., $C_s \subset C_t$) (Saito et al. 2018; Liu et al. 2019), thereby adding complexity to the DA task. OSDA aims to align target samples from known classes with those from the source domain while effectively identifying target samples belonging to categories not observed in the source domain, referred to as unknown classes (Panareda Busto and Gall 2017; Bucci, Loghmani, and Tommasi 2020; Jang et al. 2022). Various criteria based on instance-level predictions have been proposed, including entropy-based (Feng, Xu, and Tao 2021; Saito et al. 2020) and confidence-based (Saito and Saenko 2021; Fu et al. 2020) methods.

Additionally, privacy and legal considerations increasingly limit access to labeled source data for adaptation purposes. To address this, source-free adaptation methods (Fang et al. 2024) have emerged, enabling adaptation without reliance on labeled source data (Kim et al. 2021; Kundu et al. 2020a; Li et al. 2020). In this paper, we focus on Source-free Open-set Domain Adaptation (SF-OSDA), where only a pre-trained source model is available for knowledge transfer, without access to labeled source data. While some Source-free Domain Adaptation (SF-DA) methods have demonstrated effectiveness in addressing SF-OSDA for classification tasks (Liang, Hu, and Feng 2020; Yang et al. 2022; Wan et al. 2024), semantic segmentation (Choe et al. 2024), and graph applications (Wang et al. 2024), they primarily focus on the semantics of known classes in the source domain, often overlooking the crucial aspect of novel-class semantics. These methods focus on segregating target samples with low entropy, categorizing them as known classes, and subsequently optimizing specific objectives such as entropy minimization or clustering. In this process, data points associated with known classes are prioritized, while those with high entropy are typically excluded from training, leading to a semantic disparity between the known and unknown classes.

To effectively adapt a pre-trained source model to a target domain facing both category and distribution shifts, we propose **Recall and Refine for Domain Adaptation (RRDA)** for

¹<https://github.com/ismailnejjar/RRDA>

robust SF-OSDA. RRDA employs a two-step strategy. First, we propose to leverage the semantics of the *unknown* classes by introducing a novel target classifier with $K + K'$ decision boundaries. These boundaries extend the K classes from the source domain with K' additional classes for the *unknown* categories. To achieve this, synthetic samples are generated in the feature space from target domain features. These synthetic points are optimized to exhibit low entropy for *known* classes and high entropy for *unknown* classes, which are then clustered into K' categories. The synthetic data are used to refine the decision boundaries of the source classifier, enabling the target classifier to accommodate the unknown classes. In the second step, any off-the-shelf source-free domain adaptation method (e.g., SHOT (Liang, Hu, and Feng 2020), AaD (Yang et al. 2022)) can be integrated into our framework to adapt the entire model to the target domain. RRDA directly learns to classify target unknown classes. The framework introduces K' as a hyper-parameter, which we set to $K' = K$ for simplicity. Sensitivity analysis shows that performance improves with higher values of K' , though results remain robust across a range of settings. Extensive experiments on three SF-OSDA benchmark datasets demonstrate the effectiveness of our approach, significantly outperforming existing methods.

Related Work

Unsupervised Domain Adaptation (UDA) aims to adapt a model originally trained on a labeled source domain to perform effectively in an unlabeled target domain. This adaptation process assumes access to data from both the source and target domains during training (Oza et al. 2023). UDA strategies often align feature distributions between domains using metric learning techniques (Long et al. 2015; Kang et al. 2019; Nejjar, Wang, and Fink 2023) or adversarial training across various spaces, including image input space (Murez et al. 2018; Pizzati et al. 2020), feature space (Ganin and Lempitsky 2015), and output space (Luo et al. 2019; Vu et al. 2019). Additionally, various techniques incorporate pseudo-labeling or self-training algorithms (Sun et al. 2022; Dong et al. 2023; Yue, Sun, and Zhang 2024), which generate pseudo-labels for unlabeled samples in the target domain. However, existing approaches assume that label spaces are identical across both domains, limiting their applicability in real-world scenarios.

Open-set Domain Adaptation (OSDA) addresses scenarios where the target domain may contain classes not present in the source domain (Panareda Busto and Gall 2017; Dong, Chatzi, and Fink 2024; Dong et al. 2024; Li et al. 2021). Various approaches have been proposed to tackle this challenge, including assigning target domain images to source categories while discarding unrelated target domain images (Panareda Busto and Gall 2017), and using adversarial training to separate unknown target samples (Saito et al. 2018; Jang et al. 2022). Separate to Adapt (STA) approach (Liu et al. 2019) progressively separates unknown and known class samples using a coarse-to-fine weighting mechanism and proposes evaluating OSDA on diverse levels of openness. Rotation-based Open Set (ROS) (Bucci, Loghmani, and Tommasi 2020) explores the use of self-

supervised tasks such as rotation recognition for unknown class detection. (Jing et al. 2021) project features to a hyperspherical latent space to reject known samples based on angular distance. Adjustment and Alignment for Unbiased Open Set Domain Adaptation (ANNA) (Li et al. 2023) addresses semantic-level bias in OSDA by designing Front-Door Adjustment and Decoupled Causal Alignment modules. However, these approaches all assume the availability of labeled source data, which can pose challenges due to privacy concerns in real applications.

Source-free Domain Adaptation (SFDA) leverages only a source-trained model and unlabeled target data for adaptation to the target domain. SFDA approaches can be categorized into data-based and model-based methods (Yu et al. 2023). One of the data-driven methods, SHOT, was introduced by Liang et al. (Liang, Hu, and Feng 2020). It adapts a pre-trained source model via information maximization with self-supervised pseudo-labeling to implicitly align target domain representations to the source hypothesis. Building on this approach, subsequent works(Chu et al. 2022; Lee et al. 2022; Qu et al. 2022) refine the adaptation through self-training techniques. Other works explore different training procedures. For example, historical Contrastive Learning (HCL) (Huang et al. 2021) compensates for the absence of source data by leveraging historical models and contrasting current and historical embeddings of target samples. Some methods (Yang et al. 2021, 2022) enforce consistency between local neighbors by considering local feature density, with Attract and Disperse (AaD) (Yang et al. 2022) treating SFDA as an unsupervised clustering problem. Additionally, Zhang, Wang, and He (2023) explore leveraging source model classifier weights as class prototypes to embed class relationships into a similarity measure for a target sample.

Source-free Open-set Domain Adaptation (SF-OSDA) extends SFDA to scenarios where the target domain contains novel classes not present in the source domain. While methods like SHOT (Liang, Hu, and Feng 2020), AaD (Yang et al. 2022), and Uncertainty-guided Source-free Domain Adaptation (U-SFAN) (Roy et al. 2022) have been adapted for SF-OSDA, they primarily focus on the *known* class semantics in the source domain, which can lead to suboptimal handling of target-private unknown classes. Universal Domain Adaptation (UniDA) aims to handle domain shifts and label set differences between source and target domains, encompassing open, partial, and open-partial set scenarios (Liang et al. 2021; Qu et al. 2023, 2024). Recent SF-UniDA methods proposed one-vs-all clustering approaches (Qu et al. 2023) and subspace decomposition (Qu et al. 2024) to separate and identify common and private target classes in a source-free setup. Similarly, Progressive Graph Learning (Luo et al. 2023) decomposes the target hypothesis space into shared and unknown subspaces for SF-OSDA. However, current methods either require specific training for the source model to incorporate the unknown classes (Kundu et al. 2020b,c), which is usually impractical, or rely on thresholding a metric to distinguish known classes from unknown ones during training and inference, making the prediction sensitive to different thresholds.

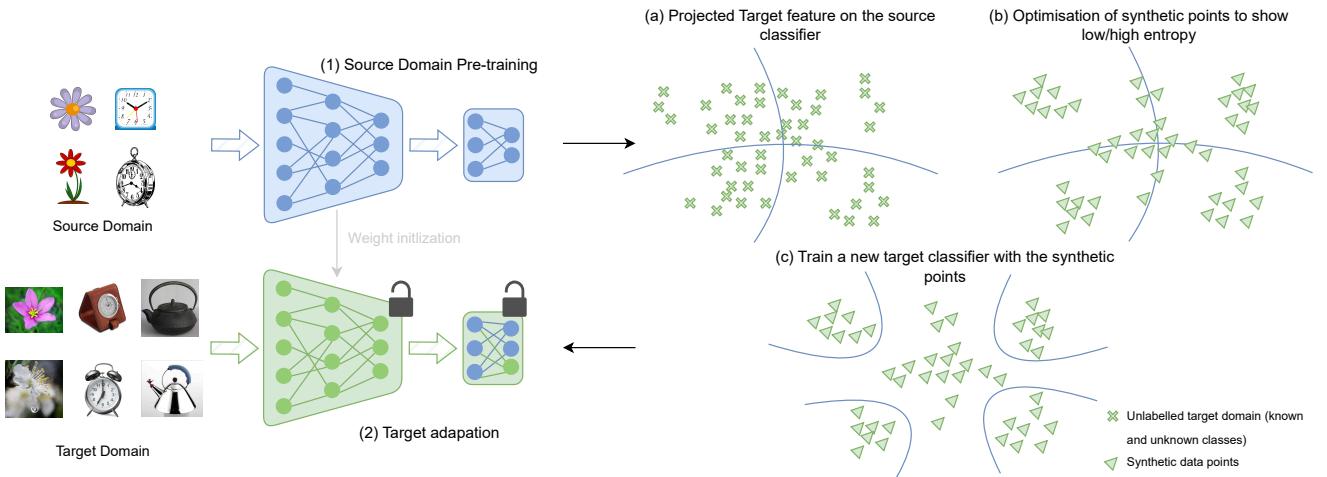


Figure 1: Overview of RRDA for Source-free Open-set Adaptation. Unlike conventional methods that overlook unknown class semantics, RRDA explicitly incorporates this information by generating synthetic points for both known and unknown classes from projected target features, enabling the training of a new target classifier that captures the semantics of all classes. The adaptation is then achieved using standard closed-set domain adaptation methods.

Methodology

Preliminary

For SF-OSDA, we are given a source pre-trained model f_θ^s and an unlabeled target domain with n_t samples, denoted as $\mathcal{D}_t = \{(x_i^t)\}_{i=1}^{n_t}$, where $x_i^t \in \mathcal{X} \subset \mathbb{R}^X$. The target domain follows a distinct data distribution ($P^t \neq P^s$) from the source domain, reflecting both distribution and label shifts. Let \mathcal{C}^s and $\mathcal{C}^t \subset \mathcal{Y}$ represent the label sets for the source and target domains, respectively, where $\mathcal{C}^s \subset \mathcal{C}^t$. Both domains share K common classes referred to as *known* classes ($\mathcal{C}_k^t = \mathcal{C}^s$). Additionally, the target domain includes target-private novel classes, jointly considered as a single *unknown* class ($\mathcal{C}_{unk}^t = \mathcal{C}^t \setminus \mathcal{C}^s$).

The primary objective of SF-OSDA is to classify both *unknown* and *known* classes, relying exclusively on the target domain data and a pre-trained source model. The pre-trained model can be decomposed as $f_\theta^s = h_\theta^s \circ g_\theta^s$, where $h_\theta^s : \mathbb{R}^X \rightarrow \mathbb{R}^D$ is a feature extractor and $g_\theta^s : \mathbb{R}^D \rightarrow \mathbb{R}^K$ is the source classifier. Unlike previous works, which freeze the source classifier (e.g., SHOT) during adaptation, we propose training a new target classifier g_θ^t to explicitly account for target-private unknown classes.

One of the challenges in open-set scenarios is the ability to distinguish known from unknown classes in the target domain. Different approaches have been proposed for distinguishing between known and unknown classes, including hand-crafted thresholding criteria and clustering strategies. However, paradigms such as vendor-to-client (Kundu et al. 2020c) are more effective, as they incorporate an auxiliary out-of-distribution classifier during source training, enabling better handling of unknown classes in the target domain.

In this paper, we propose a novel approach to address this limitation by adapting the source classifier post hoc to include new decision boundaries for unknown classes. Our method enables the seamless adaptation of any off-the-shelf

source pre-trained model to a target domain, even in the presence of novel classes. Motivated by the idea that learning from *unknown* class samples can improve performance in open-set scenarios, *our objective is to simplify adaptation and eliminate the dependency on threshold-based methods during inference*.

RRDA

Our proposed Recall and Refine framework for SF-OSDA consists of three main steps:

- Synthetic Data Generation:** Referring to step (b) in Figure 1, synthetic feature points are generated for both *known* and *unknown* classes. This involves optimizing target feature representations using entropy objectives.
- Target Classifier Training:** Referring to step (c) in Figure 1, the synthetic feature points are used to train a new target classifier g_θ^t with extended decision boundaries to accommodate unknown classes.
- Target Domain Adaptation:** The entire model is adapted using any off-the-shelf source-free domain adaptation methods (e.g., SHOT, AaD) on target domain data.

This allows the model to (1) learn the semantics of both known and unknown classes in the target domain, (2) treat OSDA as a simple closed-set scenario, and (3) directly output predictions for unknown classes.

Synthetic Data Generation. The first step of our proposed approach involves generating synthetic features for both *known* and *unknown* classes using the source classifier g_θ^s . Specifically, we optimize the target feature representation $\mathbf{z}^t = h_\theta^s(x^t)$ to generate synthetic samples that exhibit low entropy for *known* classes and high entropy for the *unknown* class. We denote these optimized synthetic features as \mathbf{z}_k^{*t} and \mathbf{z}_{unk}^{*t} . The unknown features are then clustered in K' classes, and a new target classifier g_θ^t is introduced

with $K + K'$ classes. In this section, we describe the process for obtaining feature representations for both *known* and *unknown* classes. We use standard gradient descent optimization to generate the desired feature representations.

Synthetic Unknown Classes Generation: To effectively identify points near the source classifier’s decision boundary, we aim to find \mathbf{z}_{unk}^{*t} that maximizes entropy while ensuring diverse feature representations, thereby reducing the risk of collapsing to a single-point representation. To prevent feature collapse, we introduce a variance regularization term in the form of a hinge function applied to the standard deviation of features across the batch dimension. Specifically, we initialize the optimization with a noisy version of the original features \mathbf{z}^t . This process is formulated as follows:

$$\min_{\mathbf{z}^t} -H(\sigma(g_\theta^s(\mathbf{z}^t))) + \lambda \cdot \max(0, 1 - \sqrt{\text{Var}(\mathbf{z}^t)}), \quad (1)$$

where $H(p) = -\sum_{k=1}^K p_k \log(p_k)$ represents the entropy, and σ is the softmax activation function, and λ was set to 1 for all the experiments. After optimization, only the points satisfying $H(g_\theta^s(\mathbf{z})) > 0.75 \cdot \log(K)$ (see Ablation section for threshold discussion) are considered as \mathbf{z}_{unk}^{*t} . The selected features \mathbf{z}_{unk}^{*t} are then clustered into K' unknown classes using K-means. Each cluster is assigned a pseudo-label corresponding to a new class index, $\hat{y}_{unk}^{*t} \in \{K+1, \dots, K+K'\}$, representing the specific unknown class assigned to the synthetic features. These synthetic features and their associated pseudo-labels ($\mathbf{z}_{unk}^{*t}, \hat{y}_{unk}^{*t}$) will be used in the subsequent training of the target classifier. This approach is motivated by the observation in the literature (Lampert, Nickisch, and Harmeling 2009) that it is possible to generate meaningful semantics for novel classes using known classes.

Synthetic Known Classes Generation: A similar optimization approach is employed to generate synthetic data points for the *known* classes. The optimization is performed iteratively K times, once for each known class k (where $k \in \{1, \dots, K\}$). The objective is to minimize the cross-entropy for each class directly from \mathbf{z}^t . The optimization problem for generating a sample for class k is defined as:

$$\min_{\mathbf{z}^t} \mathcal{L}_{CE}(g_\theta^s(\mathbf{z}^t), I_k) + \lambda \cdot \max(0, 1 - \sqrt{\text{Var}(\mathbf{z}^t)}), \quad (2)$$

where I_k is the identity function for the k -th class (i.e., a one-hot vector), and λ controls the regularization term, set to 1 in all experiments. After optimization, only the points satisfying $\mathcal{L}_{CE}(g_\theta^s(\mathbf{z}), I_k) < 0.25 \cdot \log(K)$ (see Ablation section for threshold discussion) are considered as \mathbf{z}_k^{*t} . Each selected synthetic feature \mathbf{z}_k^{*t} is assigned the pseudo-label $\hat{y}_k^{*t} = k$, forming the pairs $(\mathbf{z}_k^{*t}, \hat{y}_k^{*t})$. These synthetic data points and their corresponding pseudo-labels are then used to train the target classifier. By iteratively generating feature points for each known class, our method enhances the decision boundaries without requiring access to the original source data or labels.

Target Classifier Training. In the second step, we introduce a new target classifier g_θ^t with $K + K'$ classes, where

K is the number of known classes and K' is the number of unknown classes. The weights for the known classes $g_{\theta[1:K]}^t$ are initialized using the source classifier’s weights g_θ^s , while the weights for the unknown classes $g_{\theta[K+1:K+K']}^t$ are randomly initialized. The target classifier g_θ^t is trained using the synthetic feature-label pairs for the *known* classes $(\mathbf{z}_k^{*t}, \hat{y}_k^{*t})$ for $k \in \{1, \dots, K\}$, and the *unknown* classes $(\mathbf{z}_{unk}^{*t}, \hat{y}_{unk}^{*t})$. The supervised training objective is defined as:

$$\min_{\theta} \mathcal{L}_{CE}(g_\theta^t(\mathbf{z}^{*t}), \hat{y}^{*t}), \quad (3)$$

where \mathbf{z}^{*t} represents the combined synthetic features for both known and unknown classes, and \hat{y}^{*t} represents their corresponding labels. The results of the previous steps, including the refined decision boundaries achieved by RRDA, are illustrated in Figure 2.

Target Domain Adaptation. Any source-free unsupervised domain adaptation method (originally designed for closed-set scenarios) can be integrated into our approach to address open-set scenarios, provided it incorporates a diversity loss or a similar mechanism to facilitate self-learning of unknown classes. To empirically validate this hypothesis, we consider SHOT (Liang, Hu, and Feng 2020) and AaD (Yang et al. 2022), using their respective training objectives for adaptation. SHOT (Liang, Hu, and Feng 2020) employs information maximization and self-supervised pseudo-labeling to adapt the source model to the target domain. Its objective function can be expressed as:

$$\begin{aligned} \mathcal{L}_{\text{shot}} = & -\frac{\lambda_{ent}}{n_t} \sum_{i=1}^{n_t} \sum_{k=1}^{K+K'} p_{k,i} \log p_{k,i} + \lambda_{\text{div}} \cdot \sum_{k=1}^{K+K'} \bar{p}_k \log \bar{p}_k \\ & + \lambda_{\text{ps}} \cdot \mathcal{L}_{\text{pseudo}}, \end{aligned}$$

where $\bar{p}_k = \frac{1}{n_t} \sum_{i=1}^{n_t} p_k(x_i; \theta)$, and $\mathcal{L}_{\text{pseudo}}$ is the pseudo-labeling loss function from (Liang, Hu, and Feng 2020). During adaptation, only the feature encoder is updated while the classifier remains frozen. AaD (Yang et al. 2022) leverages local consistency and global dispersion. The objective function for feature i is formulated as:

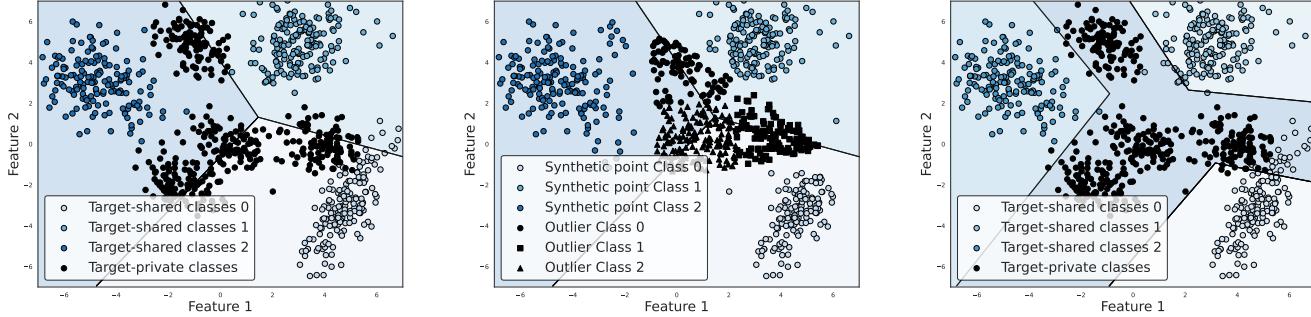
$$\mathcal{L}_{\text{AaD},i} = -\sum_{j \in \mathcal{C}_i} p_i^T p_j + \lambda \sum_{m \in \mathcal{B}_i} p_i^T p_m,$$

where \mathcal{C}_i represents the local neighborhood of feature i and \mathcal{B}_i is the mini-batch feature not in \mathcal{C}_i . Unlike SHOT, AaD updates the entire model weights during adaptation.

Experiments

Experimental Setup

Datasets. **Office-Home** (Venkateswara et al. 2017) comprises 65 labeled image categories from four distinct domains: Art (Ar), Clipart (Cl), Product (Pr), and Real World (Rw). We designate the first 25 alphabetically ordered categories as known classes, with the remaining 40 as unknown. **Office-31** (Saenko et al. 2010) consists of 31 classes across three domains: Amazon (A), Dslr (D), and Webcam (W). We assign the first 10 as known and the last 10 classes as unknown. **VisDA** (Peng et al. 2017) have 12 categories across



(a) Unlabeled target domain projected onto the decision boundary of the source classifier.

(b) Optimized synthetic points for known and unknown classes.

(c) Unlabeled target domain projected onto the new decision boundary of the target classifier.

Figure 2: Visualization of the synthetic data generation process and the resulting target classifier boundary on a toy example with $K = K' = 3$ classes.

two domains: Real (R) and Synthetic (S). The first 6 classes are categorized as known and the remaining 6 as unknown.

Evaluation Metrics. To assess model performance, we adopt standard evaluation metrics widely used in previous OSDA studies (Bucci, Loghmani, and Tommasi 2020; Liu et al. 2019; Li et al. 2023). The Harmonic Open-set (HOS) accuracy balances performance on known and unknown classes and can be calculated as $HOS = \frac{2 \times OS^* \times UNK}{OS^* + UNK}$, where OS^* represents the accuracy of known classes, and UNK denotes the accuracy of unknown classes. The HOS metric provides a comprehensive measure, by equally weighting the model’s ability to classify known classes and detect unknown classes.

Implementation Details. All experiments are conducted on a single A100 GPU using PyTorch. For synthetic data generation, we employ the Adam optimizer with a learning rate of 0.001 for 1000 steps, for both known (\mathbf{z}_k^{st}) and unknown (\mathbf{z}_{unk}^{st}) classes. In all main experiments, we set $K' = K$. To maintain class balance, we cap the sample size at 1000 for known classes in Office-Home and Office-31, and 10,000 for VisDA. The target classifier is trained for 50 epochs using SGD with a learning rate of 0.01, momentum of 0.9, weight decay of 0.001, and a fixed batch size of 128. During target model adaptation, we use SGD with momentum 0.9, a batch size of 64, and train for 50 epochs. The learning rate is set to 0.001 for Office-31 and Office-Home, and 0.0001 for VisDA, when using Resnet-50 (He et al. 2016) as backbone. When using ViT-B (Wu et al. 2020) as the backbone, we set the learning rate to 0.0001 for all experiments. For SHOT, we freeze the target classifier and train only the feature extractor and backbone. For AaD, all model parameters are trained, with the feature extractor’s learning rate set to 10 times lower. During inference, samples belonging to the new K' classes are considered unknown target samples. λ_{ps} was set to 0.1, 0.3, and 0.4 for Office-Home, Office-31, and VisDA respectively. The hyper-parameters λ_{div} and λ were set to 1 and λ_{ent} was set to 0.5 in all our experiments.

During inference, samples assigned to any of the new K' classes are treated as unknown target samples. Following the standard open-set protocol, predictions in the range $[1, K]$ correspond to known classes, while predictions in

Methods	SF	Office-31						Avg
		A2D	A2W	D2A	D2W	W2A	W2D	
CMU	✗	52.6	55.7	76.5	75.9	65.8	64.7	65.2
DANCE	✗	84.9	78.8	79.1	78.8	68.3	78.8	79.8
OSLPP	✗	91.5	89.0	79.3	92.3	78.7	9.6	87.4
GATE	✗	88.4	86.5	84.2	95.0	86.1	96.7	89.5
ANNA	✗	83.8	85.5	82.5	99.5	81.6	98.4	88.6
Source-only	✓	78.2	72.1	44.2	82.2	52.1	88.8	69.6
UMAD	✓	88.5	84.4	86.8	95.0	88.2	95.9	89.8
LEAD	✓	84.9	85.1	90.9	94.8	90.3	96.5	90.3
GLC	✓	82.6	74.6	92.6	96.0	91.8	96.1	89.0
AaD-O	✓	82.3	79.0	84.3	93.1	84.8	95.0	86.4
AaD + RRDA	✓	91.1	94.3	94.1	96.6	94.0	96.2	94.4
		+8.8	+15.3	+9.8	+3.5	+9.2	+1.2	+8.0
SHOT-O	✓	89.5	83.0	85.9	91.4	84.0	95.2	88.2
SHOT+ RRDA	✓	90.0	92.2	92.6	98.2	91.6	98.2	93.8
		+0.5	+9.2	+6.7	+6.8	+7.6	+3.0	+5.6

Table 1: HOS (%) results on Office-31 (ResNet-50). SF denotes source-free methods. AaD-O and SHOT-O are the adapted open-set methods of AaD and SHOT. RRDA uses standard AaD and SHOT versions (closed-set scenario).

$[K + 1, K + K']$ are aggregated into a single $K + 1$ class, representing the unknown class.

Baselines. We compare our method against open-set domain adaptation approaches, including both non-source-free and source-free methods. The non-source-free methods include OSBP (Saito et al. 2018), CMU (Fu et al. 2020), STA (Liu et al. 2019), DANCE (Saito et al. 2020), GATE (Chen et al. 2022), ANNA (Li et al. 2023), and OSLPP (Wang, Meng, and Breckon 2024). For source-free methods, we consider UMAD (Liang et al. 2021), GLC (Qu et al. 2023), SF-PGL (Luo et al. 2023), and LEAD (Qu et al. 2024).

Experimental Results

From Table 1 to 3, we compare our method against state-of-the-art (SOTA) OSDA methods in both source-free and non-source-free setups. We include non-SF methods to provide a comprehensive performance benchmark, despite our focus on SF scenarios. We use RRDA alongside AaD and

Methods	SF	Office-Home												
		Ar2Cl	Ar2Pr	Ar2Rw	Cl2Ar	Cl2Pr	Cl2Rw	Pr2Ar	Pr2Cl	Pr2Rw	Rw2Ar	Rw2Cl	Rw2Pr	Avg
CMU	X	55.0	57.0	59.0	59.3	58.2	60.6	59.2	51.3	61.2	61.9	53.5	55.3	57.6
DANCE	X	6.5	9.0	9.9	20.4	10.1	9.2	28.1	15.8	12.6	14.2	7.9	13.7	12.9
OSLPP	X	61.0	72.8	74.3	60.9	66.9	70.4	63.6	59.3	74.0	67.2	59.0	74.4	67.0
GATE	X	63.8	70.5	75.8	66.4	67.9	71.7	67.3	61.3	76.0	70.4	61.8	75.4	69.0
ANNA	X	69.0	73.7	76.8	64.7	68.6	73.0	66.5	63.1	76.6	71.3	65.7	78.7	70.7
Source-only	✓	46.1	63.3	72.9	42.8	54.0	58.7	47.8	36.1	66.2	60.8	45.3	68.2	55.2
UMAD	✓	59.2	71.8	76.6	63.5	69.0	71.9	62.5	54.6	72.8	66.5	57.9	70.7	66.4
LEAD	✓	60.7	70.8	76.5	61.0	68.6	70.8	65.3	59.8	74.2	64.8	57.7	75.6	67.2
GLC	✓	65.3	74.2	79.0	60.4	71.6	74.7	63.7	63.2	75.8	67.1	64.3	77.8	69.8
AaD-O	✓	58.0	68.2	75.4	58.8	65.7	69.0	54.6	52.9	72.3	65.8	56.3	72.2	64.1
AaD + RRDA	✓	61.7 +3.7	72.8 +4.6	73.5 -1.9	59.0 +0.2	74.9 +9.2	69.9 +0.9	59.5 +4.9	58.3 +5.4	71.2 -1.1	64.5 -1.3	64.8 +7.7	73.2 +1.0	66.9 +2.8
SHOT-O	✓	57.2	65.4	69.9	58.1	62.6	64.3	60.5	52.8	71.1	64.4	53.5	40.6	61.9
SHOT + RRDA	✓	64.6 +7.4	74.2 +8.8	77.2 +7.3	63.1 +5.0	71.4 +8.8	71.3 +7.0	67.7 +7.2	59.1 +6.3	76.7 +5.6	70.2 +5.8	67.4 +13.9	76.7 +36.1	70.0 +8.1
Source-only	✓	57.1	69.5	79.9	50.2	62.5	66.0	52.2	45.7	75.1	69.3	56.4	73.7	63.1
LEAD	✓	58.6	74.7	82.7	58.9	74.6	74.3	59.0	47.1	78.3	71.9	58.7	77.4	68.0
AaD-O	✓	57.8	74.9	82.7	53.9	68.6	70.8	52.5	45.8	76.8	70.6	58.2	77.7	65.9
AaD + RRDA	✓	67.4 +9.6	77.2 +1.5	81.2 -1.5	71.4 +17.5	71.5 +2.9	76.1 +5.3	73.9 +21.4	63.8 +18.0	78.5 +1.7	74.8 +4.2	67.5 +9.3	75.0 -2.7	73.2 +7.3
SHOT-O	✓	63.6	73.5	81.7	66.7	69.8	75.5	66.5	56.2	79.0	73.5	62.6	74.6	70.3
SHOT + RRDA	✓	68.9 +5.3	75.0 +1.5	81.4 -0.3	71.2 +4.5	73.8 +4.0	73.6 -2.1	71.9 +5.4	60.4 +4.2	79.2 +0.2	76.5 +3.0	66.2 +3.6	77.5 +2.9	73.0 +2.7

Table 2: HOS (%) results on Office-Home (ResNet-50 and ViT). $|C_s| = 25$, $|C_t| = 65$. SF denotes source-free methods.

Methods	VisDA							
	Bic	Bus	Car	Mot	Tra	Tru	UNK	HOS
OSBP	35.6	59.8	48.3	76.8	55.5	29.8	81.7	62.7
STA	50.1	69.1	59.7	85.7	84.7	25.1	82.4	71.0
Source-only	16.3	7.9	24.9	48.0	6.1	0.0	72.7	27.9
LEAD	83.5	65.2	57.7	35.7	82.1	79.5	82.7	74.2
SF-PGL	91.5	90.1	74.1	90.3	81.9	74.8	72.0	77.4
AaD-O	86.8	69.8	51.5	38.7	84.3	26.0	65.5	62.4
AaD + RRDA	96.0 +9.2	85.7 +15.9	34.5 -17.0	37.6 -1.1	92.2 +7.9	46.4 +20.4	71.7 +6.2	68.4 +6.0
Shot-O	82.1	67.0	78.6	57.3	72.2	17.9	50.7	56.0
Shot + RRDA	88.6 +6.5	82.2 +15.2	66.8 -11.8	47.3 -10.0	87.2 +15.0	74.3 +56.4	83.5 +32.8	78.7 +22.7
Source-only	62.3	17.9	17.7	50.7	0.0	0.6	90.8	39.1
LEAD	87.6	65.3	49.8	30.5	70.9	54.4	98.2	74.3
AaD-O	87.9	77.6	47.7	36.8	61.2	16.6	67.6	60.4
AaD + RRDA	98.2 +10.3	91.1 +13.5	84.8 +37.1	39.4 +2.6	94.2 +33.0	97.5 +80.9	81.7 +14.1	82.9 +22.5
Shot-O	96.7	77.0	80.4	75.9	3.0	4.7	80.1	66.1
Shot + RRDA	95.4 -1.3	84.8 +7.8	74.1 -6.3	48.7 -27.2	85.1 +82.1	82.3 +77.6	79.3 -0.8	78.9 +12.8

Table 3: Accuracy for each class (%) and HOS (%) results on VisDA (ResNet-50 and ViT), with $|C_s| = 6$, $|C_t| = 12$.

SHOT (vanilla methods for closed-set scenarios), as well as their open-set variants denoted as AaD-O and SHOT-O that rely on entropy-thresholding during training and inference. Results for comparison methods are sourced from (Qu et al. 2024; Li et al. 2023), and the mean HOS is reported.

Office-31. Table 1 presents results on the Office-31 dataset, where RRDA demonstrates significant improvements over threshold-based methods. AaD+RRDA achieves an average HOS of 94.4%, which is an 8.0% increase over AaD-O. Sim-

ilarly, SHOT+RRDA reaches 93.8%, representing a 5.6% improvement over SHOT-O. These results surpass all compared source-free and non-source-free SOTA methods.

Office-Home. On the Office-Home dataset (Table 2), RRDA consistently enhances the performance of both AaD-O and SHOT-O across most domain adaptation tasks. AaD+RRDA and SHOT+RRDA show average HOS improvements of +2.8% and +8.1% respectively. SHOT+RRDA achieves a competitive 70.0% average HOS, outperforming most methods, including both source-free and non-source-free approaches, while falling just slightly short of ANNA a non-source-free adaptation method. A similar observation can be made when using ViT as backbone, where RRDA consistently improves previous methods AaD+RRDA and SHOT+RRDA show average HOS improvements of +7.3% and +2.7% respectively, and surpass the other baselines.

VisDA. On the challenging VisDA dataset (Table 3), RRDA continues to demonstrate its effectiveness. AaD+RRDA improves upon AaD-O by +6.0% in HOS, significantly improving unknown sample recognition and overall class accuracy. Significant improvements are observed in classes such as "Bus" (+15.9%) and "Truck" (+20.4%). Similar improvements can be observed when applying RRDA to SHOT with an improvement of +22.7% in HOS. We observe that both methods improve over the same class and degrade the performances of the "car" and "motorcycles" classes.

These results demonstrate RRDA's consistent superiority across various domain adaptation scenarios. Our method significantly improves existing SF-OSDA techniques, as evidenced by the consistent performance gains across all datasets. The key advantage of RRDA lies in its novel approach to handling unknown classes. Unlike previous methods that rely on thresholding and discard unknown class

Entropy	Diversity	OS*	UNK	HOS
✓		95.6	79.8	86.5
	✓	95.0	91.8	93.4
✓	✓	95.8	91.9	93.8

Table 4: Ablation on the optimization objective to generate synthetic points. Results using SHOT+RRDA on Office-31.

Methods	0.1/0.9	0.2/0.8	0.25/0.75	0.3/0.7	0.4/0.6	0.5/0.5
SHOT	93.3	91.3	91.1	91.1	91.1	91.9
AaD	90.9	89.5	90.0	89.7	90.1	90.0

Table 5: Ablation on the optimization objective to generate synthetic points. Results using SHOT+RRDA on Office-31.

data during adaptation, RRDA actively learns the semantics of unknown classes through our adaptive target classifier, which evolves to accommodate the unknown class distribution. Furthermore, the consistent performance gains with both AaD and SHOT demonstrate RRDA’s versatility. These results underscore the importance of explicitly modeling unknown classes in open-set domain adaptation, rather than treating them as outliers to be discarded.

Ablation Study and Sensitivity Analysis

Optimization Process. We conducted ablation studies on Office-31 with three different settings to train the new classifier. The results are shown in Table 4. We compare the following scenarios: (1) selecting target features based on entropy threshold without optimization, (2) optimizing entropy without hinge loss for diversity, and (3) the full proposed method optimizing feature points based on entropy and diversity. Our findings are as follows: (1) Using target features based on entropy directly to train the target classifier leads to the worst results in terms of HOS. SHOT-O achieves an HOS of 88.2 %, while using features directly without optimization achieves an HOS of 86.5%. (2) Optimizing the points significantly improves performance. There is a slight additional improvement when using hinge loss during optimization to promote diversity. (3) The full proposed method, which optimizes feature points based on both entropy and diversity, yields the best performance. We used SHOT for adaptation in the experiment as it keeps the classifier frozen, allowing for a direct performance comparison with the new classifier.

Threshold Sensitivity Analysis. To further analyze the hyperparameter sensitivity and its impact on performance, we examined the effect of varying the entropy threshold used for feature selection during the optimization process. The thresholds were evaluated on the A2D task (ref Table 5).

We observe that the best-performing threshold on this task is $T = 0.1$. However, the HOS score remains consistent across different thresholds. For larger datasets, such as VisDA, where the domain shifts are more significant, lower thresholds (e.g., $T = 0.1$) can result in highly imbalanced datasets, with some classes being excluded entirely. For example, under such thresholds, a subset of classes may not meet the selection criteria. To ensure consistency across all datasets while maintaining a balanced feature distribution,

we report results using $T = 0.25$ throughout the experiments. This threshold provides a balance between maintaining sufficient class representation and achieving competitive performance, particularly in scenarios with significant domain shifts.

Varying Unknown Classes. We investigated the robustness of our framework against an increased number of unknown private classes, which complicates the distinction between known and unknown classes. We compared our method to LEAD, SHOT-O, and AaD-O on the Office-31 dataset. As shown in Figure 3a, our RRDA method in combination with SHOT and AaD achieves stable results and consistently outperforms existing approaches. For consistency with our main results, we kept K' fixed at 10.

Sensitivity to K' . Figure 3b shows adaptation performance for different K' values of the target classifier on Office-31 dataset. The performance improves as K' increases, validating the benefit of inheriting class separability knowledge, before eventually reaching a plateau. In fact, $K' = 15$ yields the best results. For the main experiments, we reported Office-31 results using $K' = K = 10$.

Training Stability. Figure 3c illustrates the training curves for the A2W task on the Office-31 dataset. Our method shows consistent HOS improvement on the test set, with steadily increasing before plateauing. In contrast, AaD-O exhibits unstable training, with noticeable performance fluctuations throughout the training process.

Feature Space Visualization. Figure 4 shows t-SNE embeddings of pre-classifier features for the source-only model, AaD-O, and our method on the A2W task on the Office-31 dataset. The source-only model (Figure 4a) exhibits well-separated known class clusters but mixes unknown samples with known classes. AaD-O (Figure 4b) slightly improves known-unknown separation, but class overlap remains. Our method (Figure 4c) achieves superior separation of known and unknown classes, maintaining tight, well-defined known class clusters while isolating unknown samples. This demonstrates our method’s effectiveness in inheriting class separability during adaptation.

Conclusion

In this work, we introduce **R**ecall and **R**efine for **D**omain **A**daptation (RRDA), a simple but effective framework for SF-OSDA. RRDA enables the successful adaptation of off-the-shelf source pre-trained models to target domains, effectively addressing both distribution and category shift problems. RRDA achieves this by introducing a new target classifier that aids in classifying and learning the semantics of both known and unknown classes. This approach enables the direct use of source-free adaptation methods designed for closed-set scenarios in open-set contexts. Extensive experiments on three challenging benchmarks demonstrate that RRDA significantly outperforms existing SF-OSDA methods and even surpasses OSDA methods that have access to the source domain. Future work could explore its potential for continuous adaptation in the setup where new classes appear over time.

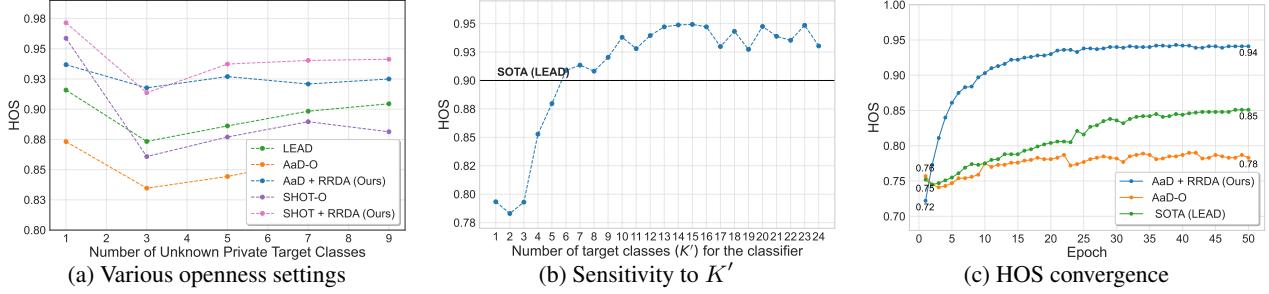


Figure 3: Sensitivity analysis on Office-31. (a) Adaptation performance across different openness levels (average across all transfer tasks). (b) Sensitivity to K' target classifier classes (average across all transfer tasks). (c) HOS curves for the A2W task.

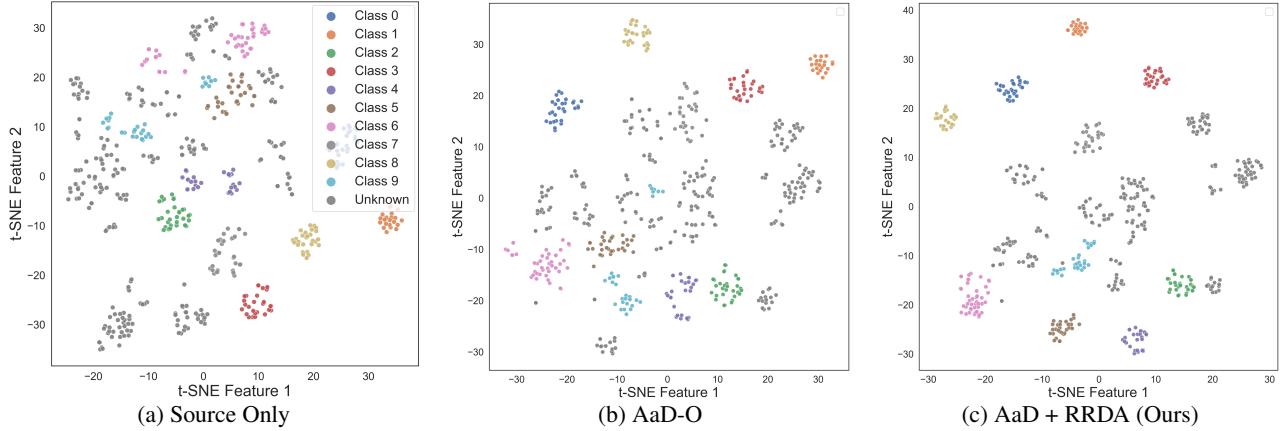


Figure 4: T-SNE visualization of the pre-classifier feature space for the A2W task on Office-31 dataset.

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