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

Anonymous authors
Paper under double-blind review

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 will be made available.

1 Introduction

Unsupervised Domain Adaptation (UDA) (Ben-David et al., 2010; Ganin & 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 & 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 et al., 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 & Gall, 2017; Bucci et al., 2020; Jang et al., 2022). Various criteria based on instance-level predictions have been proposed, including entropy-based (Feng et al., 2021; Saito et al., 2020) and confidence-based (Saito & 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. Although some Source-free Domain Adaptation (SF-DA) methods have demonstrated effectiveness in addressing SF-OSDA for classification tasks (Liang et al., 2020; Yang et al., 2022; Wan et al., 2024), semantic segmentation (Choe et al., 2024), and graph applications (Wang et al., 2024b), 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 **R**ecall and **R**efine for **D**omain **A**daptation (**RRDA**) for 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 et al., 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.

2 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 et al., 2023) or adversarial training across various spaces, including image input space (Murez et al., 2018; Pizzati et al., 2020), feature space (Ganin & 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 et al., 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 & Gall, 2017; Dong et al., 2024a;b; 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 & 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 et al., 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 et al., 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 et al. (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 et al., 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.

3 Methodology

3.1 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 $h_\theta^s : \mathbb{R}^X \to \mathbb{R}^D$ is a feature extractor and $g_\theta^s : \mathbb{R}^D \to \mathbb{R}^K$ 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

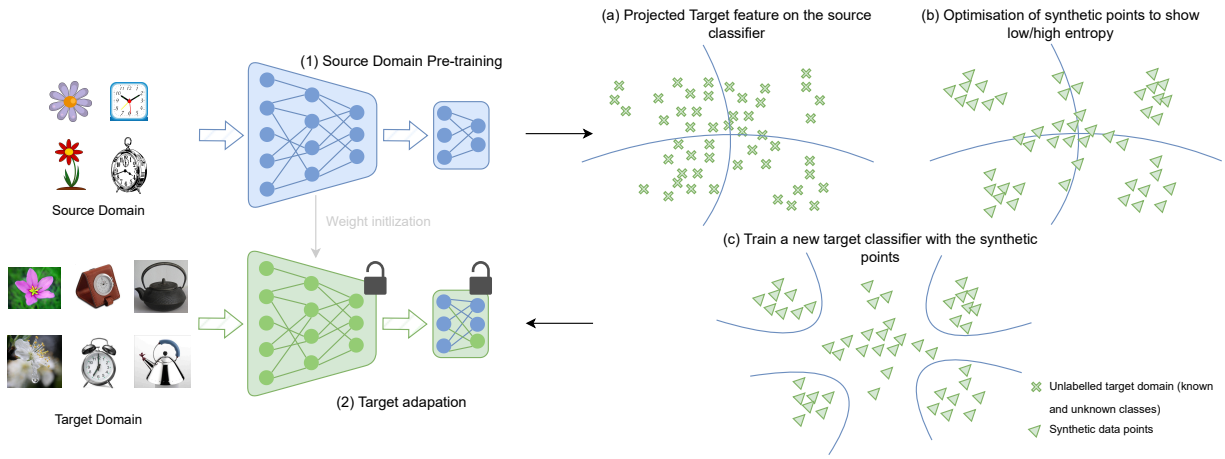


Figure 1: Overview of RRDA for Source-free Open-set Adaptation. Unlike conventional methods that overlook unknown class semantics, RRDA explicitly incorporates this information by generating synthetic points for both known and unknown classes from projected target features, enabling the training of a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

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.*

3.2 RRDA

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

1. **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.
2. **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.
3. **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.

3.2.1 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:

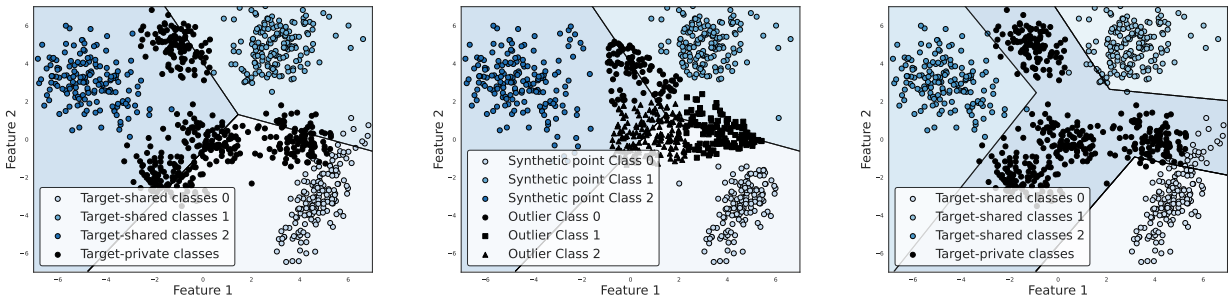
$$\min_{\mathbf{z}^t} \quad -H(\sigma(g_\theta^s(\mathbf{z}^t))) + \lambda \cdot \max(0, 1 - \sqrt{\mathrm{Var}(\mathbf{z}^t)}), \tag{1}$$

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, $\hat{y}_{unk}^{*t} \in \{K+1, ..., K+K'\}$, 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 et al., 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 $k \in [1, ..., K]$). 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:

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

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.



(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.

3.2.2 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 $k \in \{1, ..., K\}$, and the *unknown* classes ($\mathbf{z}_{unk}^{*t}$, $\hat{y}_{unk}^{*t}$). The supervised training objective is defined as:

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

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.

3.2.3 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 et al., 2020) and AaD (Yang et al., 2022), using their respective training objectives for adaptation. SHOT (Liang et al., 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:

$$\mathcal{L}_{\text{shot}} = -\frac{\lambda_{ent}}{n_t} \sum_{i=1}^{n_t} \sum_{k=1}^{K+K'} p_{k,i} \log p_{k,i} + \lambda_{\text{div}} \cdot \sum_{k=1}^{K+K'} \bar{p}_k \log \bar{p}_k + \lambda_{\text{ps}} \cdot \mathcal{L}_{\text{pseudo}}, \tag{4}$$

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 et al. (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:

$$\mathcal{L}_{\text{AaD},i} = -\sum_{j \in \mathcal{C}_i} p_i^T p_j + \lambda \sum_{m \in \mathcal{B}_i} p_i^T p_m, \tag{5}$$

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.

4 Experiments

4.1 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 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 et al., 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 ($\mathbf{z}_k^{*t}$) and unknown ($\mathbf{z}_{unk}^{*t}$) 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 the 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 $[K+1, K+K']$ 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 et al., 2024a). 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).

4.2 Experimental Results

From Table 6 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 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 6 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. Similarly, 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.

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.

Methods	SF	Office-31						
		A2D	A2W	D2A	D2W	W2A	W2D	Avg
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**

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 a 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.

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

Methods	SF	Office-Home													
		Ar2Cl	Ar2Pr	Ar2Rw	Cl2Ar	Cl2Pr	Cl2Rw	Pr2Ar	Pr2Cl	Pr2Rw	Rw2Ar	Rw2Cl	Rw2Pr	**Avg**	
CMU	✗	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	ResNet-50
DANCE	✗	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	✗	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	✗	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	✗	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	72.8	73.5	59.0	74.9	69.9	59.5	58.3	71.2	64.5	64.8	73.2	66.9	
		+3.7	+4.6	-1.9	+0.2	+9.2	+0.9	+4.9	+5.4	-1.1	-1.3	+7.7	+1.0	**+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	74.2	77.2	63.1	71.4	71.3	67.7	59.1	76.7	70.2	67.4	76.7	**70.0**	
		+7.4	+8.8	+7.3	+5.0	+8.8	+7.0	+7.2	+6.3	+5.6	+5.8	+13.9	+36.1	**+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	ViT
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	77.2	81.2	71.4	71.5	76.1	73.9	63.8	78.5	74.8	67.5	75.0	**73.2**	
		+9.6	+1.5	-1.5	+17.5	+2.9	+5.3	+21.4	+18.0	+1.7	+4.2	+9.3	-2.7	+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	75.0	81.4	71.2	73.8	73.6	71.9	60.4	79.2	76.5	66.2	77.5	**73.0**	
		+5.3	+1.5	-0.3	+4.5	+4.0	-2.1	+5.4	+4.2	+0.2	+3.0	+3.6	+2.9	**+2.7**	

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 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.

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

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	ResNet-50
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	85.7	34.5	37.6	92.2	46.4	71.7	68.4	
	+9.2	+15.9	-17.0	-1.1	+7.9	+20.4	+6.2	**+6.0**	
Shot-O	82.1	67.0	78.6	57.3	72.2	17.9	50.7	56.0	
Shot + RRDA	88.6	82.2	66.8	47.3	87.2	74.3	**83.5**	**78.7**	
	+6.5	+15.2	-11.8	-10.0	+15.0	+56.4	+32.8	**+22.7**	
Source-only	62.3	17.9	17.7	50.7	0.0	0.6	90.8	39.1	ViT
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	91.1	84.8	39.4	94.2	97.5	81.7	**82.9**	
	+10.3	+13.5	+37.1	+2.6	+33.0	+80.9	+14.1	+22.5	
Shot-O	96.7	77.0	80.4	75.9	3.0	4.7	80.1	66.1	
Shot + RRDA	95.4	84.8	74.1	48.7	85.1	82.3	79.3	**78.9**	
	-1.3	+7.8	-6.3	-27.2	+82.1	+77.6	-0.8	+ 12.8	

5 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.

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

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

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

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

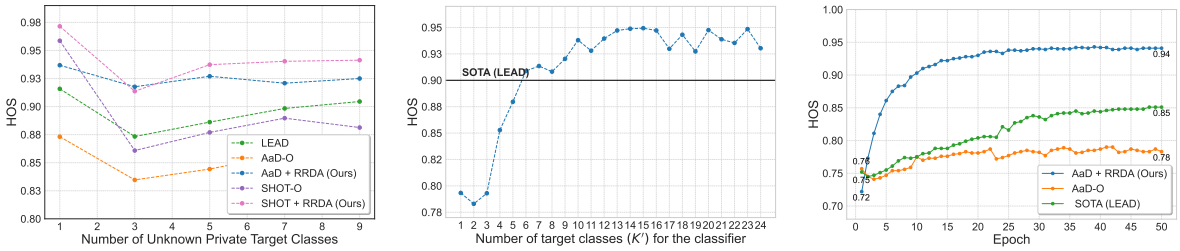
Methods	0.1/0.9	0.2/0.8	**0.25/0.75**	0.3/0.7	0.4/0.6	0.5/0.5
SHOT	93.3	91.3	91.1	91.1	91.1	91.9
AaD	90.9	89.5	90.0	89.7	90.1	90.0

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 large 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 $K' = K = 10$.

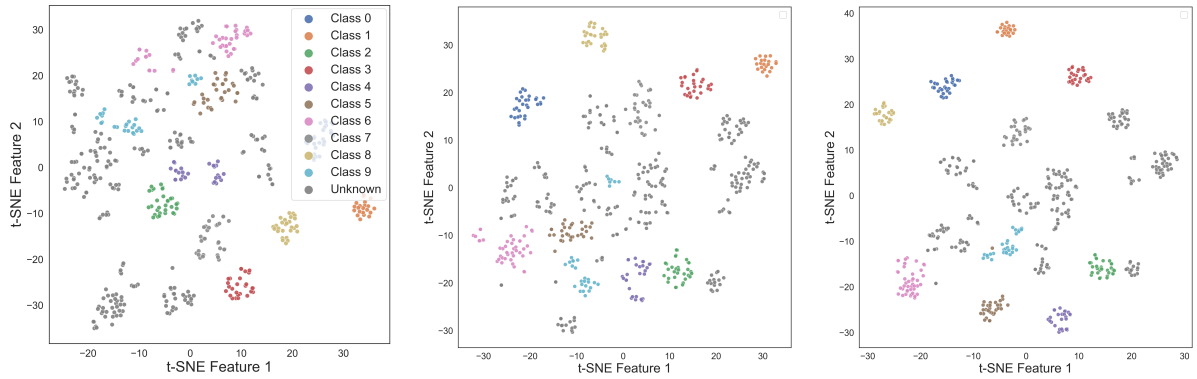
Training Stability. Figure 3c illustrates the training curves for the A2W task on the Office-31 dataset. Our method shows consistent HOS improvement on the test set, with steadily increasing before plateauing. In contrast, AaD-O exhibits unstable training, with noticeable performance fluctuations throughout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



(a) Various openness settings (b) Sensitivity to K' (c) HOS convergence

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.

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.



(a) Source Only (b) AaD-O (c) AaD + RRDA (Ours)

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

6 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.

References

Shai Ben-David, John Blitzer, Koby Crammer, Alex Kulesza, Fernando Pereira, and Jennifer Wortman Vaughan. A theory of learning from different domains. *Machine learning*, 79:151–175, 2010.

Silvia Bucci, Mohammad Reza Loghmani, and Tatiana Tommasi. On the effectiveness of image rotation for open set domain adaptation. In *European conference on computer vision*, pp. 422–438. Springer, 2020.

Liang Chen, Yihang Lou, Jianzhong He, Tao Bai, and Minghua Deng. Geometric anchor correspondence mining with uncertainty modeling for universal domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 16134–16143, 2022.

Seun-An Choe, Ah-Hyung Shin, Keon-Hee Park, Jinwoo Choi, and Gyeong-Moon Park. Open-set domain adaptation for semantic segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 23943–23953, 2024.

Tong Chu, Yahao Liu, Jinhong Deng, Wen Li, and Lixin Duan. Denoised maximum classifier discrepancy for source-free unsupervised domain adaptation. In *Proceedings of the AAAI conference on artificial intelligence*, volume 36, pp. 472–480, 2022.

Hao Dong, Ismail Nejjar, Han Sun, Eleni Chatzi, and Olga Fink. SimMMDG: A simple and effective framework for multi-modal domain generalization. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2023.

Hao Dong, Eleni Chatzi, and Olga Fink. Towards multimodal open-set domain generalization and adaptation through self-supervision. In *European Conference on Computer Vision*, 2024a.

Hao Dong, Yue Zhao, Eleni Chatzi, and Olga Fink. MultiOOD: Scaling Out-of-Distribution Detection for Multiple Modalities. *arXiv preprint arXiv:2405.17419*, 2024b.

Yuqi Fang, Pew-Thian Yap, Weili Lin, Hongtu Zhu, and Mingxia Liu. Source-free unsupervised domain adaptation: A survey. *Neural Networks*, pp. 106230, 2024.

Zeyu Feng, Chang Xu, and Dacheng Tao. Open-set hypothesis transfer with semantic consistency. *IEEE Transactions on Image Processing*, 30:6473–6484, 2021.

Bo Fu, Zhangjie Cao, Mingsheng Long, and Jianmin Wang. Learning to detect open classes for universal domain adaptation. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XV 16*, pp. 567–583. Springer, 2020.

Yaroslav Ganin and Victor Lempitsky. Unsupervised domain adaptation by backpropagation. In *International conference on machine learning*, pp. 1180–1189. PMLR, 2015.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778, 2016.

Lukas Hoyer, Dengxin Dai, Haoran Wang, and Luc Van Gool. Mic: Masked image consistency for context-enhanced domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 11721–11732, June 2023.

Jiaxing Huang, Dayan Guan, Aoran Xiao, and Shijian Lu. Model adaptation: Historical contrastive learning for unsupervised domain adaptation without source data. *Advances in Neural Information Processing Systems*, 34:3635–3649, 2021.

JoonHo Jang, Byeonghu Na, Dong Hyeok Shin, Mingi Ji, Kyungwoo Song, and Il-Chul Moon. Unknown-aware domain adversarial learning for open-set domain adaptation. *Advances in Neural Information Processing Systems*, 35:16755–16767, 2022.

Mengmeng Jing, Jingjing Li, Lei Zhu, Zhengming Ding, Ke Lu, and Yang Yang. Balanced open set domain adaptation via centroid alignment. In *Proceedings of the AAAI conference on artificial intelligence*, volume 35, pp. 8013–8020, 2021.

Guoliang Kang, Lu Jiang, Yi Yang, and Alexander G Hauptmann. Contrastive adaptation network for unsupervised domain adaptation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 4893–4902, 2019.

Youngeun Kim, Donghyeon Cho, Kyeongtak Han, Priyadarshini Panda, and Sungeun Hong. Domain adaptation without source data. *IEEE Transactions on Artificial Intelligence*, 2(6):508–518, 2021.

Jogendra Nath Kundu, Naveen Venkat, R Venkatesh Babu, et al. Universal source-free domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 4544–4553, 2020a.

Jogendra Nath Kundu, Naveen Venkat, Rahul M V, and R. Venkatesh Babu. Universal source-free domain adaptation. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020b.

Jogendra Nath Kundu, Naveen Venkat, Ambareesh Revanur, R Venkatesh Babu, et al. Towards inheritable models for open-set domain adaptation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 12376–12385, 2020c.

Christoph H Lampert, Hannes Nickisch, and Stefan Harmeling. Learning to detect unseen object classes by between-class attribute transfer. In *2009 IEEE conference on computer vision and pattern recognition*, pp. 951–958. IEEE, 2009.

Jonghyun Lee, Dahuin Jung, Junho Yim, and Sungroh Yoon. Confidence score for source-free unsupervised domain adaptation. In *International conference on machine learning*, pp. 12365–12377. PMLR, 2022.

Guangrui Li, Guoliang Kang, Yi Zhu, Yunchao Wei, and Yi Yang. Domain consensus clustering for universal domain adaptation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 9757–9766, 2021.

Rui Li, Qianfen Jiao, Wenming Cao, Hau-San Wong, and Si Wu. Model adaptation: Unsupervised domain adaptation without source data. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 9641–9650, 2020.

Wuyang Li, Jie Liu, Bo Han, and Yixuan Yuan. Adjustment and alignment for unbiased open set domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 24110–24119, 2023.

Jian Liang, Dapeng Hu, and Jiashi Feng. Do we really need to access the source data? source hypothesis transfer for unsupervised domain adaptation. In *International conference on machine learning*, pp. 6028–6039. PMLR, 2020.

Jian Liang, Dapeng Hu, Jiashi Feng, and Ran He. Umad: Universal model adaptation under domain and category shift. *arXiv preprint arXiv:2112.08553*, 2021.

Hong Liu, Zhangjie Cao, Mingsheng Long, Jianmin Wang, and Qiang Yang. Separate to adapt: Open set domain adaptation via progressive separation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 2927–2936, 2019.

Mingsheng Long, Yue Cao, Jianmin Wang, and Michael Jordan. Learning transferable features with deep adaptation networks. In *International conference on machine learning*, pp. 97–105. PMLR, 2015.

Yadan Luo, Zijian Wang, Zhuoxiao Chen, Zi Huang, and Mahsa Baktashmotlagh. Source-free progressive graph learning for open-set domain adaptation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2023.

Yawei Luo, Liang Zheng, Tao Guan, Junqing Yu, and Yi Yang. Taking a closer look at domain shift: Category-level adversaries for semantics consistent domain adaptation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 2507–2516, 2019.

Zak Murez, Soheil Kolouri, David Kriegman, Ravi Ramamoorthi, and Kyungnam Kim. Image to image translation for domain adaptation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4500–4509, 2018.

Ismail Nejjar, Qin Wang, and Olga Fink. Dare-gram: Unsupervised domain adaptation regression by aligning inverse gram matrices. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 11744–11754, 2023.

Poojan Oza, Vishwanath A Sindagi, Vibashan Vishnukumar Sharmini, and Vishal M Patel. Unsupervised domain adaptation of object detectors: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2023.

Pau Panareda Busto and Juergen Gall. Open set domain adaptation. In *Proceedings of the IEEE international conference on computer vision*, pp. 754–763, 2017.

Xingchao Peng, Ben Usman, Neela Kaushik, Judy Hoffman, Dequan Wang, and Kate Saenko. Visda: The visual domain adaptation challenge. *arXiv preprint arXiv:1710.06924*, 2017.

Fabio Pizzati, Raoul de Charette, Michela Zaccaria, and Pietro Cerri. Domain bridge for unpaired image-to-image translation and unsupervised domain adaptation. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pp. 2990–2998, 2020.

Sanqing Qu, Guang Chen, Jing Zhang, Zhijun Li, Wei He, and Dacheng Tao. Bmd: A general class-balanced multicentric dynamic prototype strategy for source-free domain adaptation. In *European conference on computer vision*, pp. 165–182. Springer, 2022.

Sanqing Qu, Tianpei Zou, Florian Röhrbein, Cewu Lu, Guang Chen, Dacheng Tao, and Changjun Jiang. Upcycling models under domain and category shift. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 20019–20028, 2023.

Sanqing Qu, Tianpei Zou, Lianghua He, Florian Röhrbein, Alois Knoll, Guang Chen, and Changjun Jiang. Lead: Learning decomposition for source-free universal domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 23334–23343, 2024.

Subhankar Roy, Martin Trapp, Andrea Pilzer, Juho Kannala, Nicu Sebe, Elisa Ricci, and Arno Solin. Uncertainty-guided source-free domain adaptation. In *European Conference on Computer Vision*, pp. 537–555. Springer, 2022.

Kate Saenko, Brian Kulis, Mario Fritz, and Trevor Darrell. Adapting visual category models to new domains. In *Computer Vision–ECCV 2010: 11th European Conference on Computer Vision, Heraklion, Crete, Greece, September 5-11, 2010, Proceedings, Part IV 11*, pp. 213–226. Springer, 2010.

Kuniaki Saito and Kate Saenko. Ovanet: One-vs-all network for universal domain adaptation. In *Proceedings of the ieee/cvf international conference on computer vision*, pp. 9000–9009, 2021.

Kuniaki Saito, Shohei Yamamoto, Yoshitaka Ushiku, and Tatsuya Harada. Open set domain adaptation by backpropagation. In *Proceedings of the European conference on computer vision (ECCV)*, pp. 153–168, 2018.

Kuniaki Saito, Donghyun Kim, Stan Sclaroff, and Kate Saenko. Universal domain adaptation through self supervision. *Advances in neural information processing systems*, 33:16282–16292, 2020.

Tao Sun, Cheng Lu, Tianshuo Zhang, and Haibin Ling. Safe self-refinement for transformer-based domain adaptation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 7191–7200, 2022.

Eric Tzeng, Judy Hoffman, Kate Saenko, and Trevor Darrell. Adversarial discriminative domain adaptation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7167–7176, 2017.

Hemanth Venkateswara, Jose Eusebio, Shayok Chakraborty, and Sethuraman Panchanathan. Deep hashing network for unsupervised domain adaptation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 5018–5027, 2017.

Tuan-Hung Vu, Himalaya Jain, Maxime Bucher, Matthieu Cord, and Patrick Pérez. Dada: Depth-aware domain adaptation in semantic segmentation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 7364–7373, 2019.

Fuli Wan, Han Zhao, Xu Yang, and Cheng Deng. Unveiling the unknown: Unleashing the power of unknown to known in open-set source-free domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 24015–24024, 2024.

Qian Wang, Fanlin Meng, and Toby P Breckon. Progressively select and reject pseudo-labelled samples for open-set domain adaptation. *IEEE Transactions on Artificial Intelligence*, 2024a.

Yu Wang, Ronghang Zhu, Pengsheng Ji, and Sheng Li. Open-set graph domain adaptation via separate domain alignment. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 9142–9150, 2024b.

Bichen Wu, Chenfeng Xu, Xiaoliang Dai, Alvin Wan, Peizhao Zhang, Zhicheng Yan, Masayoshi Tomizuka, Joseph Gonzalez, Kurt Keutzer, and Peter Vajda. Visual transformers: Token-based image representation and processing for computer vision, 2020.

Shiqi Yang, Yaxing Wang, Joost Van De Weijer, Luis Herranz, and Shangling Jui. Generalized source-free domain adaptation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 8978–8987, 2021.

Shiqi Yang, Shangling Jui, Joost van de Weijer, et al. Attracting and dispersing: A simple approach for source-free domain adaptation. *Advances in Neural Information Processing Systems*, 35:5802–5815, 2022.

Zhiqi Yu, Jingjing Li, Zhekai Du, Lei Zhu, and Heng Tao Shen. A comprehensive survey on source-free domain adaptation. *arXiv preprint arXiv:2302.11803*, 2023.

Zhongqi Yue, Qianru Sun, and Hanwang Zhang. Make the u in uda matter: Invariant consistency learning for unsupervised domain adaptation. *Advances in Neural Information Processing Systems*, 36, 2024.

Yixin Zhang, Zilei Wang, and Weinan He. Class relationship embedded learning for source-free unsupervised domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7619–7629, 2023.

Jinjing Zhu, Haotian Bai, and Lin Wang. Patch-mix transformer for unsupervised domain adaptation: A game perspective. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 3561–3571, June 2023.

A Appendix

This supplementary material contains additional information and experiments to support our main paper on open-set domain adaptation. Specifically, it includes the pseudo-code for Synthetic Data Generation and an additional Ablation Study on the target classifier initialization.

B Pseudo code

We present the pseudo-code for our synthetic data generation algorithms used for training the target classifier:

Algorithm 1 Synthetic Known Classes Generation

Require: features, classifier, classDesired, numClass, numSteps

```
points ← Clone(features)
points.requiresGrad ← true
optimizer ← Adam([points], lr=0.001)
for step = 1 to numSteps do
    scores ← classifier(points)
    stdLoss ← Mean(ReLU(1 - sqrt(Var(points) + 1e-4)))
    entropies ← CrossEntropyLoss(scores, classDesired)
    loss ← Mean(entropies) + stdLoss
    Backpropagate(loss) and Update(optimizer)
end for
idx ← FindIndices(entropies < 0.25 log(numClass))
return points[idx], classDesired
```

Algorithm 2 Synthetic Unknown Classes Generation

Require: features, classifier, numClass, kPrime, numSteps

```
points ← Clone(features)
points.requiresGrad ← true
optimizer ← Adam([points], lr=0.001)
for step = 1 to numSteps do
    scores ← classifier(points)
    stdLoss ← Mean(ReLU(1 - sqrt(Var(points) + 1e-3)))
    probs ← Softmax(scores)
    entropies ← -Sum(probs * log(probs + 1e-8))
    loss ← -Mean(entropies) + stdLoss
    Backpropagate(loss) and Update(optimizer)
end for
idx ← FindIndices(entropies > 0.75 log(numClass))
kmeans ← KMeans(nClusters=kPrime).fit(points[idx])
return points[idx], kmeans.labels + numClass
```

The Synthetic Known Classes Generation function optimizes synthetic data points to be confidently classified into known classes shared between source and target domains. It minimizes cross-entropy loss while maintaining point diversity through a standard deviation loss term.

The Synthetic Unknown Classes Generation function creates synthetic data points for potential unknown classes in the target domain. It maximizes entropy to generate points that are difficult for the classifier to

Methods	Target Classifier	Office-31						
		A2D	A2W	D2A	D2W	W2A	W2D	Avg
SHOT-O		89.5	83.0	85.9	91.4	84.0	95.2	88.2
SHOT+ RRDA	Random Initialization	90.0	91.5	92.4	98.0	89.0	98.4	93.2
SHOT+ RRDA	Source Initialization	90.0	92.2	92.6	98.2	91.6	98.2	**93.8**

Table 6: HOS (%) results on Office-31 (ResNet-50). Comparison of the impact of the target classifier initialization on the final performance.

categorize, simulating unknown classes. The function also uses k-means clustering to assign synthetic labels to these unknown class points.

Both functions use gradient descent optimization to iteratively refine the synthetic points. The final selection of points is based on entropy thresholds, ensuring that known class points have low entropy (high confidence) and unknown class points have high entropy (low confidence).

C Ablation Study

We present an ablation study comparing the impact of known class initialization on the final performance of RRDA on the Office-31 dataset.

In our approach, we first generate synthetic points for both known and unknown classes. These synthetic points are then used to train the target classifier before performing the adaptation. Our main paper uses source initialization for the known classes in the target classifier before this training process.

As shown in Table 6, source initialization of the known classes yields a consistent improvement over random initialization. Importantly, both SHOT+RRDA variants (random and source initialization of the target classifier) significantly outperform the baseline SHOT-O method, with average improvements of 5.0% and 5.6%, respectively.

These findings demonstrate that our synthetic data generation process is robust and effective. Even when the target classifier is randomly initialized before training with the synthetic points, our method achieves strong performance. This underscores the quality of the generated synthetic points for both known and unknown classes.