One Ring to Bring Them All: Towards Open-Set Recognition under Domain Shift

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Abstract

In this paper, we investigate open-set recognition with domain shift, where the final goal is to achieve Source-free Universal Domain Adaptation (SF-UNDA), which addresses the situation where there exist both domain and category shifts between source and target domains. Under the SF-UNDA setting, the model cannot access source data anymore during target adaptation, which aims to address data privacy concerns. We propose a novel training scheme to learn a \((n+1)\)-way classifier to predict the \(n\) source classes and the unknown class, where samples of only known source categories are available for training. Furthermore, for target adaptation, we simply adopt a weighted entropy minimization to adapt the source pretrained model to the unlabeled target domain without source data. In experiments, we show: 1) After source training, the resulting source model can get excellent performance for open-set single domain generalization and also open-set recognition tasks; 2) After target adaptation, our method surpasses current UNDA approaches which demand source data during adaptation on several benchmarks. The versatility to several different tasks strongly proves the efficacy and generalization ability of our method. 3) When augmented with a closed-set domain adaptation approach during target adaptation, our source-free method further outperforms the current state-of-the-art UNDA method by 2.5\%, 7.2\% and 13\% on Office-31, Office-Home and VisDA respectively.

1 Introduction

Modern deep learning models excel at close-set recognition tasks across various computer vision application areas. However, there are several inevitable obstacles lying on the path to deploying those methods to the challenging real world environments. For example, there may be 1) some unseen categories in practical scenarios, or 2) distributional shift between training and testing data. The first problem is usually defined as open-set recognition (OSR) \([1, 6, 15, 42, 61, 77, 59, 65]\) where the model should be able to distinguish samples as coming from unseen categories. The second problem is mostly investigated in the domain generalization (DG) \([56, 50, 66, 17, 69]\) and domain adaptation (DA) community \([37, 38, 40, 63, 78, 33, 62, 8]\). DG aims to tackle the domain shift problem in the absence of target domains, while DA seeks to transfer knowledge from labeled source domains to unlabeled target domains with training on them with utilizing both labeled source and unlabeled target data, there is distribution/domain shift between source and target domains. In recent years, several works introduce open-set recognition into DG and DA, which are formalized as open

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Table 1: Related setting. $C_s$ and $C_t$ denote label set of source and target domain (for evaluation), $P_s$ and $P_t$ denote source and target distribution, transductive means model can be trained on target data.

| Task                                      | $C_s = C_t$ | $P_s = P_t$ | Transductive |
|-------------------------------------------|-------------|-------------|--------------|
| Open-set Recognition (OSR)                | X           | ✓           | ✓            |
| Domain Generalization (DG)                | ✓           | X           | ✓            |
| Open Domain Generalization (ODG)          | X           | X           | X            |
| Domain Adaptation (DA)                    | ✓           | X           | ✓            |
| Open-set and Universal Domain Adaptation (ODA/UNDA) | X           | X           | ✓            |

Domain generalization (ODG) \cite{58, 82}, open-set domain adaptation (OSDA) \cite{55, 2, 35, 45, 19, 12} and universal domain adaptation (UNDA) \cite{13, 29, 76, 52, 53}, respectively.

The various settings described above are summarized in Tab. 1. Usually one method tailored for a specific setting in Tab. 1 does not work well under a different setting. Most existing works in Open-set Recognition are computationally demanding, either requiring the generation of unknown categories \cite{42} or conducting additional learning \cite{21, 61, 6}. Additionally, those methods are likely to suffer from performance degradation if test data are from different distributions. The recent CrossMatch \cite{82} tackles Open Domain Generalization problem when training on a single source domain. It proposes to use multiple open class detectors which are put on top of existing single domain generalization methods, and it achieves good results at the expense of introducing multiple open-set detectors and auxiliary unknown sample generation. For Universal Domain Adaptation, most works are based on an explicitly designed unknown-sample rejection module, which typically requires various hyper-parameters. More importantly, those UNDA methods all require access to source data during target adaptation, which is infeasible if having data privacy issues and deployed on devices of low computation capacity.

In this paper we investigate how to detect open classes efficiently even under the domain shift. Thus, a question arises, how to build a model training from only known categories aiming to learn to distinguish samples of unknown categories? Since we have no access to unknown class data, we can only use the known class data to train this classifier. We hypothesize that the closest (most similar) class to any known class is an unknown class. Given the open-endedness of the unknown class this is a reasonable assumption. This hypothesis allows us to train the classifier, enforcing the most probable class to be the ground truth class, and the runner-up class to be the background class for all source data. This is achieved by introducing an extra category in the classifier which represents the unknown classes, during training on samples of known categories (yielding a $(n + 1)$-way classifier where $n$ is the number of known classes), the classifier is expected to output the largest score for the ground truth class, and the second-largest score for unknown class. This way, the model can learn to reject samples of unknown categories by only training with known classes. The resulting model training on source data can be directly deployed to open-set recognition and open-set single domain generalization, in other words, it can detect open class efficiently whether there is domain shift or not.

Furthermore, our source model with strong capacity to distinguish unknown categories can be easily adapted to target domain without access to source data under the challenging source-free universal domain adaptation setting, where both source and target domains have their private classes. We propose to simply use a weighted entropy minimization to achieve the adaptation.

We summarize our contributions as below:

- We propose a simple method called One Ring, which excels at recognising open class without demanding extra data or additional learning, it can be directly deployed to open-set recognition (OSR) and open-set single domain generalization (OS-SDG).
- We can easily adapt the source model to target domain by using weighted entropy minimization under source-free universal domain adaptation setting (SF-UNDA).
- In experiments, we show our method is on par with or outperform current state-of-the-art approaches on several benchmarks for various different tasks, which proves the efficacy and generalization ability of our method. Augmented with a close-set DA approach, our source-free method surpasses current universal domain adaptation methods by a significant margin.
2 Related Works

Open-set Recognition. Open-set recognition (OSR) aims to recognize samples of unknown categories which do not exist in the training set. Several recent methods in OSR do not utilize extra data for training, which setting is denoted as controlled OSR. To address OSR, OpenHybrid [77] introduces a flow-based density estimation module, and ARPL [6, 5] proposes to learn a reciprocal point per category, which is intuitively regarded as the farthest point from the corresponding feature group. More recently [65] shows that actually OSR performance is enhanced when improving the model performance on the training set, for example by using improved data augmentation and other training tricks. In this paper, we propose a simple model training directly with two cross entropy losses without either auxiliary data or an extra learning process.

Domain Generalization. In Domain Generalization, a model is typically trained on multiple labeled source domains. It is expected to have good generalization ability on unseen target domains with which domain shift exists. A typical solution for domain generalization is to learn domain invariant features, which can be achieved by meta learning [27, 28, 10] or additional data generation [81, 80]. In recent years, there are several DG works that only use a single source domain. This setting is known as single domain generalization (SDG) [49, 69, 11, 30]. While most of those methods only consider the situation where source and target domains share the same label space, Open Domain Generalization (ODA) [58] is recently proposed to deal with the problem where the target domain contains open classes. More recently, CrossMatch [82] introduces an even more challenging setting called Open-set Single Domain Generalization (OS-SDG) which only relies on one source and where the target domains contains unknown categories. CrossMatch is built on a complex network model and needs to synthesize samples of unknown categories. It also applies entropy-based unknown class rejection with a manually set threshold. In this paper, our simple method can be directly deployed for OS-SDG task and gets surprisingly decent results.

Domain Adaptation. Early methods to tackle domain adaptation (DA) conduct feature alignment [38, 60, 64] to eliminate the domain shift. DANN [14], CDAN [49] and DIRT-T [57] further resort to adversarial training to learn domain invariant features. Similarly, [25, 31, 54] are based on multiple classifier discrepancy to achieve alignment between domains. Other methods like SRDC [62], CST [36] address domain shift from the perspective of either clustering or improved pseudo labeling. In addition to the closed-set DA, there are several methods that consider the setting where source and target domains have different label spaces. They can be grouped into partial-set DA [34, 44], open-set DA [46, 55, 35, 2] and open-partial/universal DA [76, 29, 53, 13, 52] depending on the intersection degree of source and target label space. However, the aforementioned DA methods demand source data when adapting to target domain. Recently, several works address source-free domain adaptation (SFDA), where only a source pretrained model instead of source data is available during target adaptation. SHOT [32] proposes to use mutual information maximization along with pseudo labeling. BAIT [23] adapts MCD [54] to source-free setting. 3C-GAN [31] resorts to (ODA) [58] is recently proposed to deal with the problem where the target domain contains open classes. In this paper, we show that our source pretrained model can be adapted to the target domain easily by simply minimizing entropy under the source-free universal DA setting.

3 Method

3.1 Preliminary

In this paper, we divide data samples into two groups/domains: the labeled source domain with $N_s$ samples as $D_s = \{ (x_i^s, y_i^s) \}_{i=1}^{N_s}$ on which the model will be first trained, and the unlabeled target domain with $N_t$ samples as $D_t = \{ x_i^t \}_{i=1}^{N_t}$. $D_t$ is used for evaluation. We denote $C_s$ and $C_t$ as the label set of the source and target domain, and $P_s$ and $P_t$ as the distribution of source and
3.2 Source Training: One Ring to Find Unknown Categories

The first stage is to train a model on the labeled source domain which has $|C_s|$ categories. We expect the resulting model to have the ability to detect unknown categories which do not exist in the source data. To achieve this, we build a classifier head as a $(|C_s| + 1)$-way classifier, where the additional dimension aims to distinguish unknown categories. Then the following problem arises: how to train a $(|C_s| + 1)$-way classifier without any sample from the last/unknown category? Note, if only training with the normal cross entropy (CE) loss on the source data, the model cannot directly give prediction to unknown categories.

As mentioned in Sec. [1], we hypothesize that any non-ground-truth category could be regarded as unknown categories. This hypothesis gives us a feasible solution to train an open-set classifier without actually accessing open classes. Specifically, we propose to use a simple variant of cross entropy loss with only samples of known categories to train the $(|C_s| + 1)$-way classifier, which has 2 properties: 1) The largest output logit of the source samples corresponds to the ground truth class and 2) The second-largest output logit of source samples will be the unknown class $(|C_s| + 1)$-th class in classifier. This way, the model is expected to detect samples of unknown categories even without training on them. The proposed objective to achieve it is formalized as follows:

$$L_{source} = E_{x_i \sim D_s}[L_{ce}(p(x_i), y_i) + L_{ce}(\hat{p}(x_i), \hat{y}_i)]$$  \hspace{1cm} (1)

where $p(x_i) = g(f(x_i)) \in \mathbb{R}^{|C_s|+1}$ is the output vector of the $(|C_s| + 1)$-way classifier, while $\hat{p}(x_i) \in \mathbb{R}^{|C_s|}$ is the output vector removing the dimension corresponding to the ground truth class, and $\hat{y}_i \in \mathbb{R}^{|C_s|}$ is a one-hot label with unknown class as ground truth label. As illustrated in Fig. [1](right), if we have a sample $x_i$ belonging to the first class, the first CE loss in Eq. [1] is the typical CE loss on $p(x_i)$ with ground truth label, $\hat{p}(x_i)$ is produced by removing the first dimension and the second CE loss is applied on $\hat{p}(x_i)$ with unknown (last) category as label.

We adopt a toy example to illustrate it. As shown in upper part of Fig. [1](right), we generate isotropic Gaussian blobs with 4 categories, where the last one is treated as the unknown category (in Purple) and others as known classes (thus $|C_1| = 3$). We first train the $(|C_s| + 1)$-way classifier which contains 4 linear layers with the normal cross entropy loss on samples of known categories, and then evaluate
it on all classes. Upper part of Fig. 1(right) shows that the samples of the unknown category (Purple) are misclassified as there are only 3 prediction regions for 3 known categories. As shown in lower part of Fig. 1(right) that there are 4 prediction regions (3 known + 1 unknown categories), after training on 2 CE losses the classifier can detect samples of unknown category which is unseen before. We attach a demo video to show the difference between training the ($|C_s|+1$)-way classifier with only standard CE loss and those 2 CE losses.

An intuitive understanding of the proposed method is that, we can split the ($|C_s|+1$)-way classification into 2 levels: 1) if we check the prediction $p(x_i)$ we would say $x_i$ has to belong to category $y_i$; 2) if we check the prediction $p(x_i)$, we would say that $x_i$ is impossible to belong to all other categories except the potential unknown categories. Since in Eq. 1 the output score of unknown category (last dimension) will always rule other non-ground-truth categories, we call the last dimension of the classifier head as One Ring dimension and our model as One Ring. In the experimental section, we will show that our One Ring model trained on source data can be directly deployed to open-set recognition and open-set single domain generalization.

### 3.3 Target Adaptation: One Ring to Bind All Categories without the Source

Our source-pretrained One Ring model is empowered with the ability to recognition unknown classes in the target domain. We further posit that it can easily be adapted to target domains where domain shift and unknown categories exist. The key part is to rectify the wrong predictions due to the domain shift. We propose to simply use entropy minimization, which is widely used in DA [57, 39, 32, 52, 53], to achieve adaptation with only a slight but indispensable modification:

$$L_{target} = \frac{1}{|n_k|} \mathbb{E}_{y_i \in C_s} L_{ent}(p(x_i)) + \frac{1}{|n_u|} \mathbb{E}_{y_i \in C_u} L_{ent}(p(x_i))$$ (2)

where $\bar{y}_i$ is the predicted label, $n_k$ is the number of samples in the mini-batch which are predicted as known category, $n_u$ is the number of samples predicted as unknown category $C_u$. The only difference from the normal entropy minimization is the weights here ($\frac{1}{n_k}, \frac{1}{n_u}$), which aim to balance the samples from known and unknown classes according to predictions. By using this simple weighted entropy minimization, the source model can be adapted to the target domain efficiently.

**Augmented with Local Prediction Aggregation.** Since our One Ring method can equip models to efficiently detect unknown classes, it can be used as a baseline to be combined with methods in close-set source-free DA. Here we integrate our method with a simple state-of-the-art SFDA method Local Prediction Aggregation (LPA) [75], note LPA can not directly tackle the universal domain adaptation setting. LPA has an objective with only 2 dot product terms: $L_{dis}$ for discriminability and $L_{div}$ for diversity; more details can be found in LPA paper. The resulting objective is:

$$L_{target^+} = \frac{1}{|n_k|} \mathbb{E}_{y_i \in C_s} [L_{ent}(p(x_i)) + L_{dis} + L_{div}] + \frac{1}{|n_u|} \mathbb{E}_{y_i \in C_u} [L_{ent}(p(x_i)) + L_{dis}]$$ (3)

where we do not deploy the diversity term for samples predicted as an unknown class since there is only one single unknown class. Although the entropy minimization plays a similar role as $L_{dis}$, which is already discussed in LPA, we empirically find it can help to balance the accuracy of known classes and unknown classes.

### 4 Experiments

#### 4.1 Datasets

**Open-set Single Domain Generalization.** For OS-SDG the model is trained on source data and evaluated on target data containing both known and unknown categories, but here domain shift exists between source and target domains. We use the following benchmarks just as CrossMatch [82]: 1) **Office31** [51] has 31 classes with 3 different domains: amazon (A), dslr (D) and webcam (W). The 10 classes shared by Office-31 and Caltech-256 [16] will be used as source categories. Then the last 11 classes in alphabetical order along with the 10 source categories will be used as target categories. Following CrossMatch, we only adopt A as the source domain, since D and W contain a relatively small amount of samples. 2) **Office-Home** [67] has 4 domains: Artistic (A), Clip Art (C), Product (P), and Real-World (R) with 65 categories. In alphabetic order, the first 15 classes are adopted as
Table 2: Accuracy (%) on **Office-31** dataset using ResNet-18 as backbone. **Open-set Single Domain Generalization** where $|C_s| = 10$, $|C_t| = 21$, $|C_s \cap C_t| = 10$. The second highest H score is underlined.

| Metric | ERM [20] +CM [82] | ADA [68] +CM [82] | MEADA [79] +CM [82] | **One Ring-S** |
|--------|--------------------|--------------------|----------------------|--------------|
| Acc    | 79.8               | 80.1               | **80.3**             | 80.5         |
| UNK    | 27.0               | 25.2               | 25.1                 | 41.1         |
| OS*    | 85.1               | 85.6               | **85.8**             | 85.9         |
| H      | 40.7               | 38.7               | 38.6                 | **54.7**     |

Source categories. And all classes are used as target categories. 3) **PACS** [26] has 4 domains: Art Paint, Cartoon, Sketch, and Photo. It has 7 categories. Of these, 4 classes (dog, elephant, giraffe, and guitar) will be used as source categories and all classes will be used as target categories. For Office-Home and PACS, the model will be trained on one domain and evaluated on all remaining domains.

**Source-free Univeral Domain Adaptation.** For SF-UNDA, the model is trained on the source domain first, then adapted to the target domain without access to any source data. Here both the source and target domains have their private categories and the target domain has some unknown categories. We evaluate our method on several benchmarks following the same setting as previous work in UNDA [76, 52, 53]: 1) **Office-31** shares 10 classes with Caltech-256 which will be used as the common categories. Then the next 10 classes in alphabetical order will be source private, and the remaining classes will be target private. 2) **Office-Home** The first 10 classes in alphabetical order are shared between domains, and the next 5 categories will be source private, and the remaining classes are target private. 3) **VisDA** (VisDA-C 2017) [48] The 6 classes out of 12 classes will be the shared categories, and source and target domain both have 3 private classes. 4) **DomainNet** [47] DomainNet is one of the largest domain adaptation benchmarks with around 0.6 million images. Following previous works, we will use 3 domains: Painting (P), Real (R), and Sketch (S). We will use the first 150 classes as shared categories, the next 50 classes are source private and the remaining 145 as target private. The number of source, target and shared categories is described in the title of each Table.

**Open-set Recognition.** We also evaluate on open-set recognition to further show the generalization ability of our method, where the model is trained on the source data and directly tested on the target data containing unknown classes. We use the following benchmarks to evaluate our method with the same setting as [65]: 1) **SVHN** [44] contains 10 street-view house numbers respectively. 2) **CIFAR10** [22] consists of natural images of 10 classes covering animals and vehicles. For these benchmarks, the model will be trained on 6 out of 10 categories and evaluated on the remaining 4 classes. 3) **CIFAR + N** [22] is an extension of CIFAR10. Here, methods are trained on 4 classes from CIFAR10 and evaluated on N classes from CIFAR100, where N is set to 10 or 50 classes. We will quantify open-set performance by AUROC for the OSR setting as previous methods did.

4.2 Model Details and Evaluation

For all setting, we directly adopt the prediction of our **One Ring** model, without using any extra process for unknown category detection. To ensure fair comparison with previous methods, our method is based on the original code released by [65] (for OSR) and OVANet [53] (modified for OS-SDG and SF-UNDA). Details can be found in the submitted code.

For OSR and OS-SDG, we train our **One Ring** model on source with Eq. 1 and directly evaluate on the target. For SF-UNDA, after finishing source training with Eq. 1, we will adapt the source pretrained model to target domain without using source data. On the very large DomainNet under SF-UNDA setting we found that our method had difficulties converging. Therefore, we applied a two-phase training on the source data. In the first phase, we train with the standard CE loss. Then after convergence, we add the second CE loss for a few epochs. For all experiments under SF-UNDA setting, the **One Ring** classifier is fixed during target adaptation. When augmented with LPA [75], we set the hyperparameter $K$ in $\mathcal{L}_{dis}$ same as LPA, and $\beta$ in $\mathcal{L}_{div}$ as 1.

For OS-SDG, we will report average per-class accuracy over known categories ($\text{OS}^*$), unknown class accuracy (UNK) and harmonic mean (H) between $\text{OS}^*$ and UNK. For SF-UNDA, we will mainly report the harmonic mean, as all previous methods did, and also the average per-class accuracy over all categories (OS) on Office-31. Note for OS-SDG and SF-UNDA, the model is expected to have
Table 3: Accuracy (%) on Office-Home dataset using ResNet-18 as backbone. **Open-set Single Domain Generalization** where $|C_s| = 25$, $|C_t| = 65$, $|C_s \cap C_t| = 25$. The second highest H score is underlined.

|               | Artistic | Clipart | Product | Real World | Average |
|---------------|----------|---------|---------|------------|---------|
|               | OS* UNK  | H       | OS* UNK | H          | OS* UNK |
| ERM           | 68.4     | 20.5    | 31.1    | 66.8       | 24.7    |
| ERM+CM        | 66.5     | 48.6    | 52.9    | 64.8       | 42.0    |
| ADA           | 71.4     | 22.1    | 32.9    | 67.4       | 31.2    |
| ADA+CM        | 67.5     | 39.6    | 46.7    | 64.1       | 40.7    |
| MEADA         | 71.4     | 22.4    | 33.3    | 66.5       | 31.3    |
| MEADA+CM      | 66.6     | 45.3    | 52.3    | 64.3       | 37.8    |

**One Ring-S**
83.8 69.6 63.2 57.6 69.3 63.2 32.0 69.0 59.3 38.9 69.0 63.0 36.9 69.0 62.3

Table 4: Accuracy (%) on PACS dataset using ResNet-18 as backbone. **Open-set Single Domain Generalization** where $|C_s| = 4$, $|C_t| = 7$, $|C_s \cap C_t| = 4$. The second highest H score is underlined.

|               | Artistic | Cartoon | Sketch | Photo | Average |
|---------------|----------|---------|--------|-------|---------|
|               | OS* UNK  | H       | OS* UNK | H     | OS* UNK |
| ERM           | 68.8     | 24.6    | 38.9    | 59.5  | 33.1    |
| ERM+CM        | 68.7     | 44.6    | 44.9    | 62.3  | 43.2    |
| ADA           | 71.0     | 28.8    | 39.0    | 62.1  | 33.8    |
| ADA+CM        | 72.0     | 40.0    | 42.4    | 64.4  | 49.1    |
| MEADA         | 70.9     | 28.7    | 38.9    | 62.1  | 33.6    |
| MEADA+CM      | 70.5     | 33.4    | 41.9    | 63.8  | 53.7    |

**One Ring-S**
57.3 38.4 46.0 36.0 50.3 53.0 25.9 86.6 39.8 35.7 22.1 27.1 43.7 49.4 41.5

Table 5: Accuracy (%) on Office-31 and VisDA dataset using ResNet-50. **Universal Domain Adaptation** where for Office-31: $|C_s| = 20$, $|C_t| = 21$, $|C_s \cap C_t| = 10$; and for VisDA: $|C_s| = 9$, $|C_t| = 9$, $|C_s \cap C_t| = 6$. The second highest H score is underlined. SF indicates whether source-free.

| Office-31     | SF | A2C | A2P | A2R | C2A | C2P | C2R | P2A | P2C | P2R | R2A | R2C | R2P | Avg | VisIA |
|---------------|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| OSBP          | X  | 66.1| 50.2| 73.6| 55.3| 85.6| 57.2| 72.9| 51.1| 47.4| 49.8| 60.5| 50.2| 67.7| 52.3| 27.3 |
| UAN           | X  | 85.6| 58.6| 94.8| 70.6| 98.0| 71.4| 86.5| 59.7| 85.5| 60.1| 85.1| 60.3| 89.2| 63.5| 30.5 |
| ROS           | X  | -   | 71.3| -   | 94.6| -   | 95.3| -   | 71.4| -   | 81.0| -   | 81.2| -   | 82.1 | -    |
| CMU           | X  | 86.7| 67.3| 96.7| 79.3| 98.0| 80.4| 89.1| 68.1| 88.4| 71.4| 88.6| 72.2| 91.1| 73.1 | 34.6 |
| DCC           | X  | 91.7| 78.5| 94.5| 79.3| 96.2| 88.6| 93.7| 88.5| 90.4| 70.2| 92.0| 75.9| 93.1| 80.2 | 43.0 |
| OVNan         | X  | -   | 79.4| -   | 95.4| -   | 94.3| -   | 85.8| -   | 80.1| -   | 84.0| -   | 86.5 | 53.1 |

**One Ring-S**
89.8 67.9 92.5 910.5 96.5 89.4 81.9 74.9 64.8 74.8 69.7 78.8 79.1 79.4 35.2 |
**One Ring**
87.8 88.3 94.7 95.2 97.5 96.0 86.6 85.7 82.0 85.8 81.0 84.7 86.8 88.5 60.7 |
**One Ring+**
85.3 85.4 94.0 94.2 97.0 93.6 88.4 86.1 88.9 90.7 87.3 84.0 90.2 89.0 66.1 |

Table 6: H-score (%) on Office-Home dataset using ResNet-50 as backbone. **Universal Domain Adaptation** where $|C_s| = 15$, $|C_t| = 60$, $|C_s \cap C_t| = 10$. The second highest H score is underlined. SF indicates whether source-free.

|            | SF | A2C | A2P | A2R | C2A | C2P | C2R | P2A | P2C | P2R | R2A | R2C | R2P | Avg | Ave |
|------------|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| OSBP       | X  | 39.6| 45.1| 46.2| 45.7| 45.2| 46.8| 45.3| 40.5| 45.8| 45.1| 41.6| 46.9| 44.5 |
| UAN        | X  | 51.6| 51.7| 54.3| 61.7| 57.6| 61.9| 50.4| 47.6| 61.5| 62.9| 52.6| 65.2| 56.6 |
| CMU        | X  | 56.0| 56.9| 59.1| 66.9| 64.2| 67.8| 54.7| 51.0| 66.3| 68.2| 57.8| 69.7| 61.6 |
| DCC        | X  | 58.0| 54.1| 58.0| 74.6| 70.6| 77.5| 64.3| 73.6| 74.9| 81.0| 75.1| 80.4| 70.2 |
| OVNan      | X  | 62.8| 75.6| 78.6| 70.7| 68.8| 75.0| 71.3| 58.6| 80.5| 76.1| 64.1| 78.9| 71.8 |

**One Ring-S**
55.7 72.4 79.6 64.6 65.3 74.6 65.9 51.5 77.9 72.1 57.8 75.0 67.7 |
**One Ring**
63.3 72.4 81.0 68.8 67.2 74.6 73.3 60.8 80.9 78.1 63.9 76.7 71.8 |
**One Ring+**
69.5 81.4 87.9 73.2 77.9 82.4 81.5 68.6 88.1 81.1 70.5 85.7 79.0 |

High performance on both known and unknown accuracy, which should result in a high harmonic mean (H). As pointed out by **ROS** [2], OS is not a reasonable evaluation metric and can be quite high even when `UNK` is 0, since $OS = \frac{|C_s|}{|C_s|+1} \times OS + \frac{1}{|C_s|+1} \times UNK$. For OSR, we will report AUROC to quantify the open class detection performance. All results are the average of three random runs, except for OSR which we only run once under 5 different splitting. In the following tables, we will denote our model trained with only source data as **One Ring-S**, model after target adaptation as **One Ring**, and model augmented with LPA after target adaptation as **One Ring+**.
Table 7: H-score (%) on DomainNet using ResNet-50 as backbone. **Universal Domain adaptation** where $|C_s| = 200$, $|C_t| = 295$, $|C_s \cap C_t| = 150$. The second highest H score is underlined. **SF** indicates whether source-free.

| Method         | SF | P2R | R2P | P2S | S2P | R2S | S2R | Avg |
|----------------|----|-----|-----|-----|-----|-----|-----|-----|
| OSBP [55]      | x  | 33.6| 33.0| 30.6| 30.5| 30.6| 33.7| 32.0|
| DANCE [52]     | x  | 21.0| 47.3| 37.0| 27.7| 46.7| 21.0| 33.5|
| UAN [76]       | x  | 41.9| 43.6| 39.1| 38.9| 38.7| 43.7| 41.0|
| CMU [15]       | x  | 50.8| 52.2| 45.1| 44.8| 45.6| 51.0| 48.3|
| DCC [30]       | x  | 56.9| 50.3| 43.7| 44.9| 43.3| 56.2| 49.2|
| OVNet [53]     | x  | 56.0| 51.7| 47.1| 47.4| 44.9| 57.2| 50.7|
| **One Ring-S** |    | 59.1| 42.9| 43.8| 35.5| 39.5| 52.9| 45.6|
| **One Ring**   | ✓  | 57.9| 52.0| 46.5| 49.6| 44.1| 57.8| 51.3|

Table 8: Results of **Open-set Recognition** task. All results indicate the area under the Receiver-Operator curve (AUROC) averaged over five ‘known/unknown’ class splits. All methods are augmented with improved optimization strategies from [65]. Results are taken from [65].

| Method     | SVHN | CIFAR10 | CIFAR + 10 | CIFAR + 50 |
|------------|------|---------|------------|------------|
| OSRCI [43] | 89.9 | 87.2    | 91.1       | 90.3       |
| (ARPL + CS) [5] | 96.8 | 93.9    | 98.1       | 96.7       |
| MSP [65]   | 96.0 | 90.1    | 95.6       | 94.0       |
| MLS [65]   | 97.1 | 93.6    | 97.9       | 96.5       |
| **One Ring-S** | 97.3 | 93.7    | 97.8       | 96.2       |

### 4.3 Quantitative results

**Open-set Single Domain Generalization.** In Tab. 2-4, we show the results of our source model One Ring-S on Office-31, Office-Home and PACS. ERM [20], ADA [68] and MEADA [79] are methods originally designed for typical domain generalization, CrossMatch (CM) [82] is plugged into these methods which empower them with the ability to detect unknown classes in the target domain. Note that CrossMatch demands several extra modules, such as $|C_s|$ binary classifiers and unknown sample generation, and entropy-based unknown rejection with a manually set threshold is used to decide whether the sample is unknown. While our One Ring-S is elegantly simple, the results show it has significantly better results compared to CM. Note, we have no module specifically for DG in One Ring-S. The fact that One Ring-S has better performance proves the efficacy of our method.

**Source-free Universal Domain Adaptation** In Tab. 5-7, we show the results under universal DA setting where **SF** column indicates whether source-free. Note that our method does not need source data during target adaptation. As shown in the tables, our source model (One Ring-S) already achieves decent H performance. The simple One Ring with only entropy minimization already outperforms all other methods on all 4 benchmarks, adding LPA [75] into method as shown in Eq. 3 (One Ring+) can further improve the results significantly, leading to 0.5%, 5.4% and 7.2% improvement on Office-31, VisDA and Office-Home respectively, and it surpasses the current state-of-the-art OVANet by by 2.5%, 7.2% and 13% on Office-31, Office-Home and VisDA respectively.

**Open-set Recognition.** Even though in this paper our focus is on open-set recognition under domain shift, we also include results for OSR (which does not include any domain shift) in Tab. 8. All

![Figure 2: (Left) H value of our source model and entropy based rejection on A2C of Office-Home. t-SNE visualization of features with either only source known categories (Middle) or also with 10 source extra unknown categories (Right) from source model on Artistic of Office-Home, where the cross is the class prototype. The red denotes known classes while other for unknown class.](image-url)
methods in the table use the same training tricks to improve the source performance including learning rate decay, warmup, label smoothing and more data augmentations, which are proposed in [65]. Note OSRCI [43] and ARPL+CS [5] are complex methods which either need to generate open-set samples or learn extra reciprocal points. The results show that our source model One Ring-S can work quite well on OSR task without any extra learning process, indicating good generalization ability. It is important to observe that we do not have any hyperparameter.

4.4 Analysis

**Compare One Ring with entropy based unknown rejection.** We also show the results with entropy based unknown rejection, where a sample is predicted as unknown if the entropy (maximal normalized) of the prediction (with normal classifier head) is higher than a manually set threshold. Fig. 2 (left) shows the H value of source pretrained model on A2C task of Office-Home under universal DA setting, where the x axis denotes the threshold. Our source model gets better results without any extra effort.

![Figure 3: H value of open-partial domain adaptation on Office-Home. We vary the number of unknown classes as shown in the x axis. Results for other methods are copied from Ovanet [53].](image)

**Trade-off between 2 CE losses.** In this paper, we show results where the two CE losses have equal weight, and hence our method does not have any hyperparameter. However, in Eq. 1 we can also multiply a weight factor to the standard CE loss as a trade-off. Intuitively, a smaller factor to the standard CE loss gives more weight to unknown-class recognition and vice versa. The results under OS-SDG setting in Fig. 4 verify this, where the x axis denotes the weight factor multiplied to the standard CE loss. As can be seen, this trade-off can be used to further improve results. However, for the sake of simplicity, and given the already good results, we choose not to optimize this parameter.

**Visualization of features and class prototypes.** In Fig. 2 (Middle), we visualize the source features and class prototypes (weights of One Ring classifier) from source model with t-SNE. The prototype of the unknown category is in the corner with no source features around it. In Fig. 2 (Right), we further visualize 10 extra unknown classes. It shows that those features of unknown categories will not cluster around any of the known classes, but they are close to the unknown prototype. This implies that the One Ring model can efficiently distinguish known and unknown categories.

**Importance of weight in entropy minimization.** We ablate the weights (\(\frac{1}{n_k}, \frac{1}{n_u}\)) in entropy minimization in Eq. 2. The OS*, UNK and H on R2C (Office-Home) without weights are 19.2/97.8/32.1, while with the weights they are 57.8/71.6/63.9, showing the weights are important to balance known and unknown samples.

**Robustness to amount of unknown categories.** In Fig. 3 we compare our One Ring method to ROS [2] and Ovanet [53] under UNDA with different amount of unknown categories from target domain. The results show that our method is robust to the amount of unknown categories.
5 Conclusion

In this paper, we first introduce a simple method with the proposed One Ring classifier head, it possesses strong ability to detect unknown categories from target data even no matter without or with domain shift after training with two simple cross entropy losses. Then, we further adapt the model to the target domain which contains unknown categories, with only weighted entropy minimization and no access to source data. In the experiment, we show that our method achieves good performance on open-set recognition, open-set single domain generalization and source-free universal domain adaptation, which proves the effectiveness of our method.

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