Towards Few-Shot Open-Set Object Detection

Binyi Su, Hua Zhang, Zhong Zhou

Abstract—Open-set object detection (OSOD) aims to detect the known categories and identify unknown objects in a dynamic world, which has achieved significant attentions. However, previous approaches only consider this problem in data-abundant conditions. We seek a solution for few-shot open-set object detection (FSOSOD), which aims to quickly train a detector based on few samples while detecting all known classes and identifying unknown classes. The main challenge for this task is that few training samples tend to overfit on the known classes, and lead to poor open-set performance. We propose a new FSOSOD algorithm to tackle this issue, named FOOD, which contains a novel class dropout cosine classifier (CDCC) and a novel unknown decoupling learner (UDL). To prevent over-fitting, CDCC randomly inactivates parts of the normalized neurons for the logit prediction of all classes, and then decreases the co-adaptability between the class and its neighbors. Alongside, UDL decouples training the unknown class and enables the model to form a compact unknown decision boundary. Thus, the unknown objects can be identified with a confidence probability without any pseudo-unknown samples for training. We compare our method with several state-of-the-art OSOD methods in fewshot scenes and observe that our method improves the recall of unknown classes by 5%-9% across all shots in VOC-COCO dataset setting ¹.

Index Terms—Few-shot open-set object detection, over-fitting, class dropout cosine classifier, unknown decoupling learner.

I. Introduction

BJECT detection is a fundamental task in the field of computer vision, which aims to localize and recognize objects in an image. With the help of deep learning, object detection has achieved a remarkable progressing. However, existing object detection models [1], [2] are under a strong assumption that there exist enough samples for all the categories, which is time-consuming and expensive to annotate instances for the supervised training.

To alleviate this issue, few-shot object detection (FSOD) methods [3]–[12] are developed to reduce the data dependence of the CNN models. FSOD aims to train the detector based on few samples. Various approaches have presented significant improvements in FSOD problem. However, these methods hold a closed-set assumption, where the training and testing

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¹Code is available at https://github.com/binyisu/FSOSOD

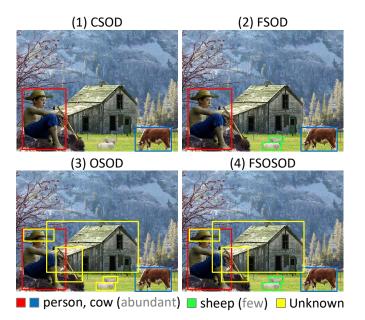


Fig. 1. The visualization of different tasks: closed-set object detection (CSOD), few-shot object detection (FSOD), open-set object detection (OSOD), and few-shot open-set object detection (FSOSOD). The CSOD task can only detect data-abundant classes in a close-set assumption, where the training and testing sets share the same classes. The FSOD task can detect data-hungary classes, while it holds a close-set assumption and cannot detect unknown objects. The OSOD task can detect unknown class, but it requires data-abundant classes for training. The FSOSOD task can detect the unknown objects and identify the known objects based on few training samples.

sets share the same classes. In the open-world situations, there are countless unknown classes, not included in the training set. These unknown objects can easily disrupt the rhythm of the close-set models, causing them to identify the unknown classes as known ones with a high confidence score [13].

In order to make the model better handle the open-set scenarios, open-set object detection (OSOD) [13], [14] has been constantly investigated, where the detector trained on the close-set datasets is asked to detect all known classes and identify unknown classes in the open-set conditions. These OSOD approaches leverage the good representation of the known classes with sufficient training samples to construct the unknown-class detector. However, open-set detectors suffer from a serious over-fitting problem [15] with rare training samples, which greatly degrades the performance of OSOD.

In this paper, we seek a solution for the unexplored fewshot open-set object detection (FSOSOD) problem. FSOSOD commits to training a detector using few samples while detecting all known and unknown objects. FSOSOD has enormous value in safety-centric applications such as autonomous driving and medical analysis. For example, in autonomous driving scenarios, the car needs to detect all known classes (including data-abundant base classes and data-hungry novel classes) and identify the unknown objects such as obstacles. The concept of FSOSOD is expressed in Fig. 1. FSOSOD could be viewed as an extension of the few-shot open-set recognition (FSOSR) [15]–[18]. However, our method is not to migrate the methods from FSOSR to FSOSOD. For example, the previous FSOSR studies adopt pseudo-unknown sample generation methods [16], [17] or prototype-based method [15], [18] to identify the unknown classes, however, our method is independent of the pseudo-unknown samples or the prototypes that denote the average feature of one class. Furthermore, the previous approaches for OSOD requires abundant known-class samples to train the detector, while this is invalid for FSOSOD task, which leads to serious overfitting problem. Therefore, how to solve the overfitting problem without affecting the performance of the known classes becomes our main intention.

We know that dropout [19] suppresses over-fitting by reducing the co-adaptation between neurons. Thus, we draw inspiration from the consensus that reduction of the co-adaptability between the class and its neighbors can effectively suppress over-fitting problem. We propose to identify the unknown classes by decoupling the interactions between the known classes and unknown classes from two aspects: 1) The optimization process for unknown classes does not consider interactions with the known classes, decoupling training it; 2) The classifier randomly inactivates parts of the normalized neurons for the prediction of class, and then decreases the co-adaptability between the class and its neighbors. Eventually, our method can identify the unknown classes without the performance degradation of the few-shot known classes.

To this end, we propose a novel few-shot open-set object detector, named FOOD, which does not rely on the pseudo-unknown sample generation or prototype to identify the unknown objects. FOOD employs Faster R-CNN [1] as the base detector. We replace the original classifier with a novel class dropout cosine classifier (CDCC) and additionally plug a novel unknown decoupling learner (UDL). These two modules are cooperated with each other to solve the overfitting problem of FSOSOD. After good optimization, our model can achieve the best detection performance of all known and unknown classes than other state-of-the-art methods. Our contributions are threefold:

- To our best knowledge, we are the first to solve the challenging FSOSOD problem by decoupling training the unknown classes.
- We propose a novel FSOSOD algorithm with two welldesigned modules: CDDC and UDL, which could suppress the over-fitting problem caused by few training samples.
- We develop the first FSOSOD benchmark. We modify several state-of-the-art OSOD methods into FSOSOD methods. Compared with these methods, our FOOD improves the recall of unknown classes by 5%-9% across all shots in VOC-COCO dataset setting.

This paper is organized as follows: Section II shows an overview of the related works. Section III introduces the proposed method. Section IV presents the extensive experiments. Finally, Section V concludes the paper.

II. RELATED WORK

A. Few-Shot Object Detection

Since the conventional detectors based on the supervised learning require abundant annotated samples for training, fewshot object detection (FSOD) has received significant progresses recently [3]-[7], [10], [11], [20]-[23]. FSOD can be roughly divided into three types. 1) Meta learning-based methods. This type of works aims to learn the task-level knowledge that can be adapted to the new task with few support samples, such as FSRW [20], Meta-RCNN [21], FSOD [22], and Meta-DETR [23]. 2) Transfer-learning based approaches. This line of works adopts a simple two-stage fine-tuning strategy to train the detector, i.e., base-training and few-shot fine-tuning phases, which expects to transfer the general knowledge from the base-training stage to the few-shot fine-tuning stage, such as TFA [3], FSCE [4], and DeFRCN [10]. 3) Pseudo-sample generation approaches. This form of works views FSOD as a data imbalanced problem, they employ the data-augmentation technologies to generate the samples of few-shot classes and train the detector end-to-end, such as [11].

Although these FSOD methods focus on good detection performance under the close-set settings, the unknown detection capability is not guaranteed. We extend a sample FSOD method TFA [3] with various OSOD methods to identity unknown objects, and find that our method can better detect the unknown classes than other state-of-the-art methods.

B. Open-Set Object Detection

Open-set object detection (OSOD) methods intend to detect all known classes and identity the unknown classes, simultaneously. According to the generation of unknown samples, OSOD can be divided into three categories. 1) Virtual unknown samples synthesis. This type of methods synthesizes virtual unknown samples to train the unknown branch in the feature space [24] or image space [25]. 2) Select unknown samples from background. This kind of works selects the background boxes with high uncertainty scores as the unknown class to train the open-set detector, such as ORE [26], UC-OWOD [27], ROWOD [28], and OSODD [29]. 3) Select unknown samples from known classes. This form of works chooses the known boxes with high uncertainty scores as the unknown class to train the open-set detector, such as PROSER [30] and OpenDet [13]. Moreover, there exist several threshold-based methods. This type of works uses the energy or entropy of the predicted box as the uncertainty score, which is compared with a threshold to determine the known class and the unknown class, such as DS [14] and MCSSD [31].

The previous methods of OSOD need abundant samples of the known classes in training, which cannot be satisfied in few-shot conditions. The over-fitting problem caused by insufficient training data seriously decreases the detection performance of unknown objects. Inspired by dropout [19], reduction of the class dependence/interaction in optimization can efficiently suppress over-fitting issue, we propose a class dropout cosine classifier and an unknown decoupling learner to dilute dependencies between all known and unknown classes.

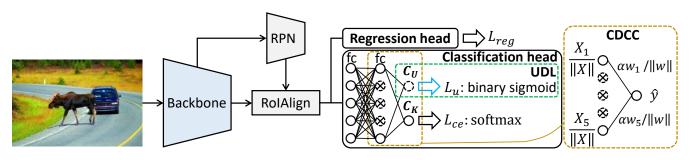


Fig. 2. The framework of our FOOD for few-shot open-set object detection. Compared to the standard Faster R-CNN, FOOD plugs a class dropout cosine classifier (CDCC) and an unknown decoupling learner (UDL). Our method is characterized by no pseudo-unknown sample generation, prototype-free, and threshold-free.

C. Few-Shot Open-Set Recognition

Few-shot open-set recognition (FSOSR) has fascinated scant attentions recently. However, to the best of our knowledge, few-shot open-set object detection is still not exploited. Here, we present several FSOSR works. PEELER [16] utilizes the pseudo-unseen class samples generated from seen classes to train the model. SnaTCHer [15] measures the distance between the query and the transformed prototype, then a distance threshold is set to identify the unseen classes. R3CBAM [17] leverages the outlier calibration network to recognize the objects in FSOSR scenes. SEMAN-G [18] learns a unseen prototype that automatically estimates a task-adaptive threshold for unseen recognition. Different from FSOSR, FSOSOD is a more challenging task, because except for known classes and unknown classes, FSOSOD also has a *background* class, which often confuses the detector.

III. PROPOSED METHOD

A. Problem Setup

We define the problem setup with reference to TFA [3] and OpenDet [13]. We are given an object detection dataset $D=\{(x,y),x\in\mathbf{X},y\in\mathbf{Y}\}$, where x denotes an input image and $y=\{(c_i,b_i)\}_{i=1}^I$ represents the objects with its class c and its box annotation b. The dataset D is divided into the training set D_{tr} and the testing set D_{te} . D_{tr} contains K known classes $C_K=C_B\cup C_N=\{1,...,K=B+N\}$, where $C_B=\{1,...,B\}$ expresses the B base classes with sufficient training samples, and $C_N=\{B+1,...,K\}$ denotes the N novel classes with M-shot support samples of each class. We test the detector in D_{te} that includes C_K known classes and C_U unknown classes. Duo to countless unknown categories, we merge all of them into one class $C_U=\{K+1\}$. Our goal is to employ the objects of known classes $D_{tr}^{C_K}$ to train a detector, which can be used to identify the known classes C_K , the background class C_{bg} , and the unknown class C_U .

B. Baseline Setup

As shown in Fig. 2, Faster R-CNN [1] is adopted as the base detector that is composed of a backbone, a region proposal network (RPN), and an R-CNN. Compared with the standard Faster R-CNN, three tricks are utilized to improve the detector. (1) **Classification and regression decoupling**: The original R-CNN contains two shared fully connected (fc) layer and two

separate fc layers for classification and regression. In order to prevent the classification task from disturbing the regression task, the shared fc layers are replaced by two parallel fc layers. Simultaneously, the class-specific regression is changed to class-agnostic. For example, the standard output of the box predictor is $4\times(K+2)$, now we set it as 4, where K+2 denotes K known classes, 1 unknown class, and 1 background class. The above operations are utilized to decouple the classification and the regression, and then provide convenience to tackle the FSOSOD task.

- (2) **Two-stage fine-tuning strategy**: Following TFA [3], the training process consists of base training and few-shot fine-tuning stages. In the base training stage, we employ the abundant samples of base classes C_B to train the entire base detector, such as Faster R-CNN. Then, in few-shot fine-tuning stage, we first train the last linear layers of the base detector while freezing the other parameters of the model (linear probing [32]) on a small balanced training set consisting of both base and novel classes $(C_B + C_N)$, and then fine-tune all the parameters of the model (fine-tuning) in a soft-freezing way [10], which employs a scaled gradient to slowly update the parameters of backbone network to get the few-shot openset object detector.
- (3) Classifier placeholder: We can view the classifier placeholder [30] as the dummy class. In base training stage, we reserve dummy classifier placeholders for novel classes C_N and an unknown class C_U to augment the class number of close-set classifier. These placeholders reserved for novel classes will be filled in the few-shot fine-tuning stage. Overall, there are two advantages for predefined classifier placeholder: one is that the classifier placeholder omits the additional model surgery step [3], [10], which is used to augment the number of model categories from base training (base classes C_B) to few-shot fine-tuning (base classes C_B + novel classes C_N) for close-set classifier. This means that our method simplifies the training process for FSOD based on transfer learning. Another is that the dummy classifier for unknown class is necessary to optimize our proposed UDL branch, which can identify the unknown objects without relying on the unknown class samples for training.

C. Class Dropout Cosine Classifier

Few training samples lead to the serious over-fitting problem, thus the model cannot extract generalization features that can be used for the unknown object detection. The neuron dropout theory [19] has been employed to suppress overfitting issue. Dropout randomly drops some neurons during training, but there is no way to randomly drop them during prediction. This results in a large expected difference of the output between training and testing, and then causes unstable results. So we need to make the output expected value of training and testing as consistent as possible. As shown in Fig. 2, our CDCC dropouts the normalized input X/||X|| rather than X in cosine classifier, where $||\cdot||$ denotes the L2 norm. This makes the expected difference with and without dropout become bounded, and then the model is more stable.

Let us take an example: for R-CNN with a cosine classifier, $X \in \mathbb{R}^{N \times D}$ represents the input of last linear mapping to classes, where X includes N proposals with dimension D. When the retention probability of dropout is p, the input can be denoted as R*X/||X||, where $R \in \{0,1\}^{N \times D}$ is initialized with $R_{i,j} \sim \mathrm{Bernoulli}(p)$ and * represents elementwise product. The output could be expressed as

$$\widehat{y} = \alpha R * \frac{X}{||X||} \frac{w}{||w||},\tag{1}$$

where α denotes a positive scaling factor. If we set dropout ratio p, the expected value with dropout falls in $[-\alpha,\alpha]$, without dropout, it falls in [-p*a,p*a], thus the expected difference with and without dropout is $\mu_{diff}^{cos} \in [-(1+p)*a,(1+p)*a]$, which is boundary. For conventional output $\widehat{y}=Xw$, the expected difference with and without dropout is $\mu_{diff} \in [-\infty,+\infty]$. Compared with $\mu_{diff},\mu_{diff}^{cos}$ is bounded, that's means the output distribution with and without dropout is more consistent, resulting in more stable prediction results.

Next, we theoretically analyze why the CDCC can suppress over-fitting? Assuming a linear regression task, $y \in \mathbb{R}^N$ is the ground-truth label, the model tries to find a $w \in \mathbb{R}^D$ to minimizes

$$||y - \alpha \frac{X}{||X||} \frac{w}{||w||}||^2.$$
 (2)

We set $\bar{x}=X/||X||$ and $\bar{w}=w/||w||$. When the dropout is adopted, the objective function becomes

$$minimize \mathbb{E}_{R \sim \text{Bernoulli}(p)}[||y - \alpha R * \bar{x} \bar{w}||^{2}].$$
 (3)

This can reduce to

$$\underset{w}{minimize}||y - \alpha p \bar{x} \bar{w}||^{2} + \alpha^{2} p(1-p)||\tau \bar{w}||^{2}, \quad (4)$$

where $\tau = (diag(\bar{x}^T\bar{x}))^{1/2}$. We set $\widetilde{w} = \alpha p\bar{w}$, then

$$minimize_{xy} ||y - \overline{x}\widetilde{w}||^2 + \frac{(1-p)}{p} ||\tau \widetilde{w}||^2.$$
 (5)

Eq. 5 can be viewed as a ridge regression with a particular form for τ . If a particular data dimension changes a lot, the regularizer tries to compress its weight more [19], and then the over-fitting problem is alleviated through regularization. We can control the strength of the regularization by adjusting the dropout ratio p. For example, if we set p=1, the regularization term is 0, which means that it does not work. As p decreases, the regularization constant grows larger and the regularization effect becomes more pronounced.

D. Unknown Decoupling Learner

Unknown decoupling learner (UDL) plays a decisive role to detect the unknown class, which provides a dummy unknown class for decoupling optimization, and then boosts the model to form a compact unknown decision boundary. The UDL does not depend on the pseudo-unknown samples generation method [16] to train the unknown class, because the data distribution of unknown class is more complex and changeable, the generated fake unknown samples often fail to simulate the real distribution of the unknown data. Inspired by the fact that known class data and unknown class data are often orthogonal [32], we propose to decouple optimize the unknown class without relying on the predictions of known classes. Thus, we select sigmoid function that deals with a single input value and does not care about the relationship of the overall input data to estimate the unknown probability:

$$p_u(z_{c_u}) = \frac{1}{1 + \exp(-\theta_u \cdot z_{c_u})},\tag{6}$$

where z_{c_u} represents the logit output for the unknown class c_u in the classification branch and θ_u is used to adjust the slope of the sigmoid function. Why do we choose the sigmoid function to compute the unknown probability p_u instead of softmax? If we select softmax, the objective function for classification branch becomes: $-logp_u - logp_* = -log(\exp(z_{c_u})/\sum_{c_i \in C} \exp(z_{c_i})) - log(\exp(z_{c_u})/\sum_{c_i \in C} \exp(z_{c_i}))$, where $C = C_K \cup C_U \cup C_{bg}$ expresses all known classes C_K , unknown class C_U and background C_{bg} . It is not hard to see that the optimization direction of the unknown class c_u and the ground-truth known classes c_* is conflict, which makes it difficult for the known classes to be converged. While the unknown probability product by the sigmoid function does not care about the logit outputs for other classes, we call it unknown decouple training, which can alleviate the above problem.

Therefore, the loss function of unknown class (unknown decoupling loss) is defined as follows:

$$L_u = -\frac{1}{N_{pos}} \sum_{i=1}^{N_{pos}} \log p_u(z_{i,c_u}) - \frac{1}{N_{neg}} \sum_{j=1}^{N_{neg}} \log p_u(z_{j,c_u}),$$
(7)

where N_{pos} and N_{neg} represent the number of positive samples (foreground of known classes) and the number of negative samples (background) respectively. Noting that the negative samples are necessary for loss optimization, because the model is also required to identify unknown class and background. How do we select the positive and negative samples to train the UDL branch? Energy score [24], [33] has been used to measure the uncertainty of the object. Here, we employ a conditional energy score to select the positive and negative samples. For a close-set object (x, b), the conditional energy score is defined as:

$$E(x,b)_{c_i \neq c_u} = -\log \sum_{c_i \neq c_u, c_i \in C} exp(z_{c_i}(x,b)),$$
 (8)

where $z_{c_i}(x, b)$ is the logit output for class c_i . Since there are no unknown class training samples, the term $exp(z_{c_u}(x, b))$ will become an interference term in the energy-based sampling

process. Thus, we discard it and select the top-k samples (proposals) ranked by the conditional energy score $E(x,b)_{c_i\neq c_u}$ to optimize the unknown decoupling loss L_u . Moreover, due to the imbalance of positive and negative samples, we pick positive and negative samples according to a certain proportion.

The dummy classifier of unknown class is equivalent to merging the binary sigmoid classifier of dummy unknown class into the softmax multi-classifier of known classes, which then synchronously identifies the specific class of the known and unknown objects. Instead of asynchronously distinguishing the unknown classes from the known class [14], [26], if it is not an unknown class, distinguish its specific class.

E. Overall Optimization

With the unknown decoupling loss L_u , the final loss function is defined as follows:

$$L = L_{RPN} + L_{reg} + L_{ce} + \lambda L_u, \tag{9}$$

where L_{RPN} is the RPN loss that consists of a binary cross entropy loss and a regression loss. L_{reg} denotes the smooth L1 loss for R-CNN. L_{ce} expresses the cross-entropy loss for R-CNN. λ is used to balance the proportion of the unknown decoupling loss L_u .

F. Inference

During inference, we normalize the logits of all classes (known classes, unknown class, and background) by the softmax function to get the classification score:

$$p_{c_j} = softmax(z_{c_j}) = \frac{exp(z_{c_j})}{\sum_{c_i \in C = C_K \cup C_U \cup C_{bg}} exp(z_{c_i})}.$$
 (10)

The specific class of the predicted box is $argmax(p_{c_i})$.

Why not select sigmoid to compute the probability of unknown class p_u ? If we choose sigmoid to compute p_u at test time, our method would become a threshold-based method to divide unknown class, which means we need set a threshold to identity unknown class. However, softmax is a threshold-free method during test, the class with the highest probability is the final predicted class of the box. Thus, we select it.

IV. EXPERIMENT

A. Experimental Setup

1) Datasets: We construct FSOSOD benchmarks using PASCAL VOC 2007+2012 [34] and MS COCO 2017 [35].

VOC10-5-5: the 20 classes of PASCAL VOC 2007+2012 are divided into 10 base classes C_B , 5 novel classes C_N , and 5 unknown classes C_U to evaluate the FSOSOD performance of our method. The novel classes have M=1, 2, 3, 5, 10, and 30 objects per class sampled from the training data of VOC 2007+2012. Here we select the test set of VOC07 for the few-shot open-set evaluation. In this paper, we define the above dataset division as the VOC10-5-5 setting. In details, $C_B=$ aeroplane, bicycle, bird, boat, bottle, bus, car, cat,

chair, cow $\}$, C_N ={diningtable, dog, horse, motorbike, person $\}$, C_U ={pottedplant, sheep, sofa, train, tvmonitor}={unknown}.

VOC-COCO: we use 20 classes of PASCAL VOC 2007+2012 and 20 non-VOC classes in MS COCO 2017 as the close-set few-shot training data, where VOC servers as the base classes C_B and the 20 non-VOC classes of MS COCO are the few-shot splits of novel classes C_N . The novel classes have M=1, 2, 3, 5, 10, and 30 objects per class sampled from the training data of MS COCO. The remaining 40 classes of MS COCO are used as the unknown classes C_U . Meanwhile, we select the validation set of MS COCO for the few-shot open-set evaluation. In this paper, we define the above dataset division as the VOC-COCO setting. In details, C_B ={aeroplane, bicycle, bird, boat, bottle, bus, car, cat, chair, cow, diningtable, dog, horse, motorbike, person, pottedplant, sheep, sofa, train, tymonitor, $C_N = \{\text{truck, traffic}\}$ light, fire hydrant, stop sign, parking meter, bench, elephant, bear, zebra, giraffe, backpack, umbrella, handbag, tie, suitcase, microwave, oven, toaster, sink, refrigerator}, C_U ={frisbee, skis, snowboard, sports ball, kite, baseball bat, baseball glove, skateboard, surfboard, tennis racket, banana, apple, sandwich, orange, broccoli, carrot, hot dog, pizza, donut, cake, bed, toilet, laptop, mouse, remote, keyboard, cell phone, book, clock, vase, scissors, teddy bear, hair drier, toothbrush, wine glass, cup, fork, knife, spoon, bowl}={unknown}.

- 2) Evaluation Metrics: The mean average precision (mAP) of known classes (mAP_K) is chosen to evaluate the known object detection performance. mAP_B and mAP_N are used to measure the few-shot performance for base and novel classes, respectively. Finally, the average precision (AP_U) , precision (P_U) , and recall (R_U) are reported to evaluate the unknown object detection performance.
- 3) Implementation Details: Our base detector is Faster R-CNN and ResNet-50 with feature pyramid network (FPN) [36] is selected as the backbone. All models are trained using SGD optimizer with a mini-batch size of 16, a momentum of 0.9, and a weight decay of 0.0001. The learning rate of 0.02 is used in base training stage and 0.01 in few-shot fine-tuning stage. For CDCC, we set the scale factor $\alpha=20$ and the dropout ratio p=0.4. For UDL, we use a slope factor $\theta_u=0.09$ and $N_{pos}:N_{neg}=3:12$. In total loss, we set the trade-off factor $\lambda=1.0$. Note that both the base training stage and the few-shot fine-tuning stage need to optimize the UDL branch. Then we argue that the domain generalization knowledge learned by the base training stage between the known and unknown classes can be reserved for the few-shot fine-tuning stage. CDCC is only used in fine-tuning stage.
- 4) Baselines: We compare our proposed FOOD with several OSOD methods: OpenDet [13], DS [14], and PROSER [30] combined with TFA [3] for FSOSOD. We also present the FSOD results of TFA as a baseline to determine whether optimizing the dummy unknown class will reduce the performance of the known classes. Moreover, all methods employ the same ResNet-50 with FPN as the backbone for a fair comparison and we report the average results of 10 random runs for all comparison methods.

1-shot 2-shot VOC10-5-5 Backbone mAP_K mAP_B mAP_N AP_U P_U R_U mAP_K mAP_B mAP_N AP_U P_U R_U TFA [3] 45.31 63.71 8.50 0.00 0.00 0.00 46.48 62.55 14.34 0.00 0.00 0.00 DS [14]+TFA 43.82 62.11 7.22 1.90 7.61 23.99 46.28 63.20 12.44 2.08 8.20 24.56 PROSER [30]+TFA ResNet-50 8.49 30.95 42.70 13.56 31.53 41.64 58.22 3.26 5.60 57.27 3.42 5.35 OpenDet [13]+TFA 43 45 61.04 8 27 3 44 6.62 33 64 45 67 62.74 11.53 3.28 6.85 30.95 Our FOOD 43.97 61.48 8.95 4.26 3.58 43.72 45.85 61.37 14.80 4.61 3.51 45.52 3-shot 5-shot VOC10-5-5 P_U AP_U mAP_K mAP_N mAP_B P_U mAP_B AP_U mAP_K mAP_N R_U R_U TFA [3] 47.55 63.72 15.23 0.00 0.00 0.00 47.88 61.92 19.74 0.00 0.00 0.00 DS [14]+TFA 46.89 63.09 14.48 2.11 8.32 23.62 48.01 62.38 19.27 1.91 8.85 19.99 PROSER [30]+TFA 57.64 ResNet-50 43.30 57.30 3.23 32.30 45.12 20.08 3.56 15.16 5.32 5.34 32.68 OpenDet [13]+TFA 46.47 62.66 14.09 3.15 6.47 30.62 47.56 62.39 17.90 3.41 6.89 32.13 48.48 Our FOOD 64.30 16.83 4.50 3.54 44.52 50.18 63.72 23.10 4.63 3.51 45.65 10-shot 30-shot VOC10-5-5 mAP_K mAP_B mAP_N AP_U P_U R_U mAP_K mAP_B mAP_N AP_U P_U R_U 37.23 0.00 TFA [3] 51.10 63.56 26.19 0.00 0.00 0.00 56.20 65.68 0.00 0.00 9.95 DS [14]+TFA 48.01 62.38 25.66 1.91 8.85 19 99 56.60 36.96 1.90 18.02 66.27 PROSER [30]+TFA ResNet-50 48.35 59.96 25.13 3.59 5.16 32.61 53.93 62.96 35.86 3.46 4.76 33.93 OpenDet [13]+TFA 50.95 63.85 25.14 4.06 6.61 36.30 56.11 66.05 36.24 4.03 5.62 40.51

4.71

3.59

TABLE I THE GENERALIZED FEW-SHOT OPEN-SET OBJECT DETECTION RESULTS ON VOC10-5-5 dataset setting.

B. Results

Our FOOD

1) VOC10-5-5: In Table I, we compare our FOOD with several OSOD methods combined with TFA on VOC10-5-5 dataset setting. Our FOOD outperforms other methods across all shots on unknown AP_U and R_U . We achieve $0.65 \sim 1.35$ point improvement in AP_U over the best baseline and around $5.89 \sim 14.57$ point improvement in R_U . Simultaneously, our method outperforms other baselines on mAP_N of novel classes, which demonstrates its effectiveness for FSOSOD. However, in VOC10-5-5 settings, the detector may have seen unknown objects and treated them as background during training, which causes the evaluation bias for FSOSOD. To balance the above bias, we conduct experiments on VOC-COCO dataset setting, where the unknown classes are barely seen in training data.

53.23

65.54

28.60

2) VOC-COCO: In Table II, we carry out experiments on VOC-COCO dataset setting. Only look at the detection performance of the unknown class $(AP_U, P_U, \text{ and } R_U)$, our method presents the significant advantages, especially in recall R_U . For example, the highest recall 23.17% of the unknown class is obtained by our FOOD, which illustrates that our method has the better unknown object detection ability than other methods. Simultaneously, in extremely low shots (1, 2, 3, 5-shot) where the over-fitting problem is easier to occur than high shots (10, 30-shot), our method achieves 8.23%, 9.45%, 9.37%, and 8.53% recall R_U improvements than the other best method respectively, which demonstrates the effectiveness of our method in suppressing the over-fitting issue caused by few training samples.

Comparing to the baseline TFA on novel classes, the mAP_N of our method is similar to TFA. Meanwhile, the mAP_K and mAP_B of our method are higher than TFA, which verifies that our method not only improves the open-set detection performance of unknown class, but also slightly improves the performance of known classes $C_K = C_B \cup C_N$ for

close-set few-shot evaluation. Look at other methods, although DS+TFA, PROSER+TFA, and OpenDet+TFA achieve comparable close-set metrics $(mAP_K, mAP_B, \text{ and } mAP_N)$, the open-set performance is poor. Overall, the proposed FOOD surpasses other baselines and thus is of merit, the absolute mAP values indicate that there is still a lot of room for improvement for future works.

67.73

40.29

4.90

3.62

46,40

C. Ablation Studies

45.84

58.59

We conduct the comprehensive ablation studies on 10-shot setting of VOC-COCO dataset setting.

1) Effectiveness of different modules: We perform ablation studies on different modules (CDCC and UDL) in Table III, where the classical FSOD framework TFA [3] is used as the baseline. It can be seen that CDCC boosts the detection performance of the base classes (AP_B) and the novel classes (AP_N) simultaneously, which demonstrates the effectiveness of CDCC to alleviate the over-fitting problem. When exploring the influence of UDL, we find that the branch of UDL improves the detection ability for the close-set known classes in 10-shot setting. Simultaneously, UDL is a necessary condition for the unknown object detection in our FOOD. The best unknown detection result $AP_U = 3.27\%$ is obtained by the cooperation of two modules, although the detection performance of known classes is slightly degraded compared to UDL alone $(\downarrow 0.10\%)$, this is acceptable in terms of the overall results

2) Effectiveness of different fine-tuning methods: In Table IV, we carefully evaluate several fine-tuning methods to pick the most appropriate way. The linear-probing (LP) and fine-tuning (FT) [32] have been widely used in transfer learning to alleviate the over-fitting problem. Gradient decoupled layer (GDL) [10] is an auxiliary fine-tuning strategy, which conducts stop-gradient for RPN and scale-gradient (scale=0.001 in this paper) for RCNN. As a hard-freezing method, LP can

	TABLE II	
THE GENERALIZED FEW-SHOT OPE	N-SET OBJECT DETECTION RESULTS ON	VOC-COCO DATASET SETTING.

VOC-COCO	Backbone			1-shot						2-shot			
100-000	Dackbolle	$\mid mAP_K$	mAP_B	mAP_N	AP_U	P_U	R_U	mAP_K	mAP_B	mAP_N	AP_U	P_U	R_U
TFA [3]		15.77	29.03	2.50	0	0	0	15.82	28.01	3.63	0	0	0
DS [14]+TFA		15.47	28.84	2.11	0.48	11.53	3.57	16.28	29.36	3.21	0.51	11.46	3.77
PROSER [30]+TFA	ResNet-50	13.58	24.84	2.32	0.87	7.14	7.53	14.27	24.91	3.62	0.95	6.79	8.66
OpenDet [13]+TFA		16.01	29.72	2.29	0.86	7.20	7.24	16.39	29.52	3.27	0.96	6.84	8.97
Our FOOD		15.83	29.32	2.35	2.00	5.75	15.76	16.56	29.55	3.58	2.42	5.68	18.42
you gogo 3-shot					5-shot								
VOC-COCO		mAP_K	mAP_B	mAP_N	AP_U	P_U	R_U	mAP_K	mAP_B	mAP_N	AP_U	P_U	R_U
TFA [3]		16.55	28.27	4.81	0	0	0	17.13	27.71	6.56	0	0	0
DS [14]+TFA		16.93	29.38	4.49	0.54	12.47	3.95	17.10	27.91	6.30	0.57	14.15	3.86
PROSER [30]+TFA	ResNet-50	15.07	25.53	4.62	1.21	7.27	9.20	15.67	26.95	6.40	1.30	7.65	9.59
OpenDet [13]+TFA		16.82	29.11	4.55	1.16	7.39	9.56	17.16	27.75	6.56	1.48	7.84	11.49
Our FOOD		17.56	30.57	4.56	2.72	6.18	18.93	18.08	29.47	6.69	2.92	6.06	20.02
VOC-COCO				10-shot						30-shot			
VOC-COCO		mAP_K	mAP_B	mAP_N	AP_U	P_U	R_U	mAP_K	mAP_{B}	mAP_N	AP_U	P_U	R_U
TFA [3]		18.67	28.32	9.02	0	0	0	23.10	31.03	15.16	0	0	0
DS [14]+TFA		19.06	28.66	9.46	0.60	15.41	3.75	23.40	31.53	15.27	0.63	15.58	3.95
PROSER [30]+TFA	ResNet-50	17.00	25.24	8.75	1.36	7.87	10.06	21.44	28.58	14.30	1.52	7.31	12.06
OpenDet [13]+TFA		18.53	28.36	8.70	1.82	7.38	13.89	22.93	31.61	14.02	2.64	7.52	18.07
Our FOOD		20.17	30.67	9.48	3.27	6.48	21.48	23.90	33.32	14.47	3.80	6.68	23.17

TABLE III
THE ABLATION STUDY OF DIFFERENT MODULES.

CDCC	UDL	$\mid mAP_K$	mAP_B	mAP_N	AP_U	P_U	R_U
Baseline	e (TFA)	18.67	28.32	9.02	0	0	0
/	,	19.20 20.27	28.97 30.96	9.44 9.58	0 2.35	0 6.59	0 16.69
✓	✓	20.27	30.67	9.48	3.27	6.48	21.48

TABLE IV
THE ABLATION STUDY OF DIFFERENT FINE-TUNING METHODS.

Fine-tuning methods	mAP_K	mAP_B	mAP_N	AP_U	P_U	R_U
LP	19.89	30.55	9.22	3.14	6.57	20.91
FT	15.31	20.59	10.03	0.78	9.10	5.17
FT+GDL	20.10	30.42	9.78	3.20	6.51	21.30
LP-FT	19.87	30.35	9.39	3.22	6.45	21.33
LP-FT+GDL	20.17	30.67	9.48	3.27	6.48	21.48

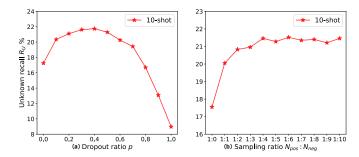


Fig. 3. Effect of different dropout ratios p and sampling ratios $N_{pos}:N_{neg}$ on 10-shot VOC-COCO dataset setting.

preserve the general knowledge of base training stage, thus it achieves a competitive detection result in Table IV. However, FT fine-tunes the entire model to fit the few-shot close-set training data, it gradually forgets the base classes and destroys the general knowledge during few-shot fine-tuning stage, thus

we can see that compared FT with LP, the results of the base classes degrade 9.96%, and the unknown class descends 2.36%. The advantage of FT is the better performance of novel classes mAP_N than other approaches. LP-FT exploiting the advantage of LP and FT achieves a compromise result.

Comparing with FT, FT+GDL achieves better results in mAP_K and AP_U . This indicates that GDL reserves the general knowledge by gradient decoupling training, which uses a scale-gradient to slowly update the parameters of backbone network. We view the GDL as a soft-freezing method, which enables the backbone to slowly fit the close-set data while retaining the ability to extract the generalization features. GDL improves the performance of close-set object detection and achieves a competitive unknown object detection performance. Based on above analysis, we adopt a hard-soft combination approach (LP-FT+GDL), which first trains the last linear layers of the model while freezing other parameters. And then we fine-tunes all the model via a soft-freezing way. As illustrated in Table IV, LP-FT+GDL outperforms other approaches in terms of mAP_K , mAP_B , AP_U , and R_U , which evidently verifies its effectiveness.

- 3) Effectiveness of different sampling methods: The sampling rules of positive and negative samples to train the UDL branch are as follows:
 - Min max-probability [13]: the samples are sorted in ascending order by the maximum predicted value across all classes, and top-k samples are chosen.
 - $Min(z_{c_u})$: the samples are sorted in ascending order by the unknown probability, and top-k samples are chosen.
 - $Max(E(x,b)_{c_i \neq c_u})$: the samples are sorted in descending order by the conditional energy score. The lager the energy, the higher the uncertainty of the sample [24]. We select top-k samples for optimization.

As presented in Table V, the conditional energy-based sampling method $Max(E(x,b)_{c_i\neq c_n})$ outperforms other meth-

 $\label{thm:table v} TABLE\ V$ The ablation study on different sampling methods.

Simpling methods	$\mid mAP_K$	mAP_B	mAP_N	AP_U	P_U	R_U
$\begin{array}{c} \hline Min\ max\text{-}probability\ [13] \\ Min(z_{c_u}) \\ Max(E(x,b)) \\ Max(E(x,b)_{c_i \neq c_u}) \\ \end{array}$	19.85	30.30	9.30	3.05	6.38	20.80
	19.53	29.39	9.66	2.73	7.04	17.55
	19.94	30.57	9.31	3.08	6.42	20.89
	20.17	30.67	9.48	3.27	6.48	21.48

TABLE VI
THE ABLATION STUDY OF DIFFERENT BACKBONES.

Backbones	$\mid mAP_K$	mAP_B	mAP_N	AP_U	P_U	R_U
ResNet-50	20.17	30.67	9.48	3.27	6.48	21.48
ResNet-101	20.84	31.48	10.00	3.32	6.02	22.37
Swin-T	25.64	40.49	10.80	3.41	6.13	22.93

ods, which demonstrates its effectiveness for positive and negative sample selection. Furthermore, the absence of unknown training samples causes unknown class c_u to become a distractor, thus the results of Max(E(x,b)) is worse than our $Max(E(x,b)_{c_i\neq c_u})$. Simultaneously, we can see that these energy-based sampling methods (Max(E(x,b)) and $Max(E(x,b)_{c_i\neq c_u}))$ perform better than other methods, which proves that the energy score is an excellent uncertainty metric for the positive and negative sample selection in the optimization of UDL branch.

- 4) Dropout ratio and sampling ratio: Fig. 3 presents the visualization of different dropout ratios and sampling ratios on 10-shot VOC-COCO dataset setting. We fix the ratio of positive and negative samples 1:4 to explore different dropout ratios. As presented in Fig. 3(a), when the dropout ratio is set to 0.4, the unknown recall R_U arrives at 22.74%, which is higher than other settings. Subsequently, we fix p=0.4 to iterate over different sampling ratios. As can be seen from the Fig. 3(b), starting from a sampling ratio of 1:4, the value of unknown recall begins to be stabilize. Sampling ratio of 1:6 seems to perform best but our usual default value of 1:4 is close to optimal. Moreover, if the negative samples do not participate in the optimization of UDL branch, the unknown detection performance drops significantly.
- 5) Effectiveness of different backbones: We use ResNet-101 [37] and swin transformer (Swin-T) [38] as backbones in Table VI, and then compare them with ResNet-50. ResNet-101 tends to perform better than ResNet-50, which presents that our method benefits from the deeper backbone. While employing a more powerful transformer-based backbone (Swin-T), our proposed method achieves additional improvements.
- 6) Does the unknown-class placeholder hurt the accuracy of few-shot object detection?: No. As illustrated in the first and third rows of Table III, when UDL branch introduces the unknown-class placeholder into the baseline TFA, the performances of novel classes have achieved 0.56% improvements, which proves that dummy placeholder of the unknown class does not hurt the detection performance for the few-shot novel classes.
- 7) Weight averaging: As shown in Fig. 4, the performance trends of base classes AP_B and unknown classes AP_U are conflict with novel classes AP_N in fine-tuning stage of our

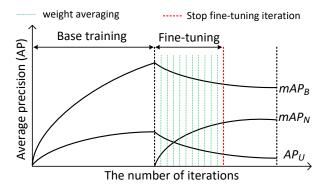


Fig. 4. The relationship between iteration and performance metric $(mAP_B, mAP_N, \text{ and } AP_U)$ for our FSOSOD method. We are hard to select a proper stop fine-tuning iteration to balance the performance of base classes, novel classes, and unknown class.

TABLE VII
THE PERFORMANCE OF WEIGHT AVERAGING.

VOC-COCO	mAP_K	mAP_{B}	mAP_N	AP_U	P_U	R_U
Our FOOD	20.17	30.67	9.48	3.27	6.48	21.48
Our FOOD+WA [39]	23.32	37.89	8.76	4.13	6.82	24.87

FSOSOD method. Therefore, it is difficult for us to choose a suitable stop fine-tuning iteration that can make the base, novel and unknown classes perform best. Motivated by weight averaging (WA) [39] that is a simple ensemble method, but it achieves the state-of-the-art performance in domain generation [40]–[42]. We present WA to approximate the optimal model. The WA is defined as:

$$\theta_{WA}(L_{D_{tr}}) = \frac{1}{H} \sum_{h=1}^{H} \theta_h, \tag{11}$$

where $\{\theta_h\}_{h=1}^H$ represents the weights of dense sampling in a single run (model sampling step 100 iterations). WA uses the idea of ensemble learning to balance the representation bias between base, novel, and unknown classes. As illustrated in Table VII, when incorporating with WA, the evaluation metrics $(mAP_K, mAP_B, \text{ and } AP_U)$ of FOOD achieve evidently improvements, which demonstrates its effectiveness. However, the drawback is that WA decreases the performance of novel classes mAP_N . The main reason is that WA hurts its performance through poor weight integration in low fine-tuning iterations. However, if you want to improve the detection performance of base classes and unknown class at the expense of little performance for novel classes, WA is a good choice for FSOSOD.

D. Visualization

We provide qualitative visualizations of the detected unknown objects on 10-shot VOC-COCO dataset setting in Fig. 5. We can observe that the baseline model easily recognizes unknown objects as known classes and cannot detect unknown objects frequently. Comparing to the baseline, our method can detect unknown objects, but it is easy to identify known objects as unknown especially for the few-shot novel classes. As shown in the red box of Fig. 5, several giraffes (novel class)



Fig. 5. The visualization results of open-set object detection in few-shot scenes (10-shot). Red box is the failure case.

are misidentified as the unknown class. Simultaneously, this phenomenon can also be seen from the quantitative analysis that our method shows slightly low unknown precision P_U , as illustrated in Table II. We view this situation as a limitation for the dummy class-based method, which needs to be further researched in the future.

V. CONCLUSION

In this paper, we propose a new task named few-shot openset object detection (FSOSOD) and build the first benchmark. To tackle the challenging FSOSOD task, we propose a simple method incorporating several tricks in Faster R-CNN with two novel modules: class dropout cosine classifier (CDCC) and unknown decoupling learner (UDL). The CDCC is developed to decrease the co-adaptability between the class and its neighboring classes during training process. Alongside, the UDL branch is employed to detect unknown objects in fewshot scenes without depending on the class prototype and pseudo samples. Comparing with other OSOD methods in fewshot scenes, our method achieves the state-of-the-art results on different shots settings of VOC10-5-5 and VOC-COCO.

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