Abstract

Few-shot object detection aims to detect instances of specific categories in a query image with only a handful of support samples. Although this takes less effort than obtaining enough annotated images for supervised object detection, it results in a far inferior performance compared to the conventional object detection methods. In this paper, we propose a meta-learning-based approach that considers the unique characteristics of each support sample. Rather than simply averaging the information of the support samples to generate a single prototype per category, our method can better utilize the information of each support sample by treating each support sample as an individual prototype. Specifically, we introduce two types of attention mechanisms for aggregating the query and support feature maps. The first is to refine the information of few-shot samples by extracting shared information between the support samples through attention. Second, each support sample is used as a class code to leverage the information by comparing similarities between each support feature and query features. Our proposed method is complementary to the previous methods, making it easy to plug and play for further improvement. We have evaluated our method on PASCAL VOC and COCO benchmarks, and the results verify the effectiveness of our method. In particular, the advantages of our method are maximized when there is more diversity among support data.

1. Introduction

Multi-object detection is a classical computer vision task of recognizing and localizing the instances of specific objects categories from a given scene. In virtue of abundant images with bounding box annotations, object detection has experienced an enormous advancement with numerous deep learning-based approaches [28, 22, 25]. Notwithstanding its remarkable achievements, the methods still have difficulty in learning novel object categories when the number of labeled data samples is small [32, 18]. Few-shot learning problems address such issues, which is common in real-world cases. However, learning few-shot samples by empirical risk minimization in a supervised manner easily overfits and may result in poor generalization [2, 40].

To alleviate this problem, several approaches have been studied, and meta-learning is one of the most successful ones in the few-shot classification scenario. In the few-shot setting, the model is given a small number of labeled support data for training, and at the time of inference, an input query image is classified as one of the support categories. Metric-based classification frameworks [37, 44, 31, 16, 34], one of the popular meta-learning methods, firstly calculate the centroid of each support class called class prototype from the support data, and then classify the query by measuring the similarity of the prototype with the query.

Since a significant progress has been made in the literature of few-shot classification problems, the problem of few-shot learning for object detection (FSOD) has also been studied. One of the successful approaches for FSOD is to extend typical meta-learning approaches to FSOD. One of the key issues in this line of research is how to aggregate the class prototype with the query image [42, 14, 9, 43, 41]. Although there have been performance improvements of FSOD through previous methods based on meta-learning, previous aggregation methods have a couple of main problems. First, a handful of support data may be noisy and this can cause unexpected side effects. For example, instances of different categories may be close to one another or instances of the same class may differ in shape and perspective, which causes some samples to be far from intra-class samples in the feature space (Fig. 1 (a)). Therefore, if the information is not refined before averaging the support data, since it is a few-shot, the averaged prototype may be far from the centroid of the real distribution. Second, to our best knowledge, every method studied so far relies on class-wise single representative by averaging the information of...
the support data, which are compared with the query data (Fig. 1(b)). Instances in query images have large variations in size, perspective and even a possibility of occlusion. Furthermore, both the query and support images may have multiple instances with different categories close to each other. Therefore, rather than generating a single prototype per category that covers all the diversity and abolishing other information, it may be more advantageous to make better use of the information contained in the support data.

To resolve these problems, we propose a novel method (Fig. 1 (c)) consisting of two modules that aggregate the query and support data. First, we propose a method to refine the support information through an attention mechanism among support data before aggregating the query and support data. Second, rather than averaging the information of the support image, we use each support image as a prototype, which we call per-sample prototype. Through this method, we can better aggregate the diverse information of support data with queries.

We have applied the proposed method to two different architectures [9, 42] in different ways. Our method improves the average precision (AP) for new unseen classes on PASCAL VOC [7, 8] and COCO [21] benchmarks in both architectures. We also qualitatively verify that our method enhances the quality of the clusters available from support feature vectors of the same class via t-SNE [35].

Our contributions can be summarized as follows:

- We show that refinements of the support feature maps induce useful information for aggregation through an attention mechanism.
- We propose a method that aggregates query and support features without using one prototype per class, which allows fully leveraging information of support data.
- We show that our method can be applied to various types of architectures, and yields meaningful performance improvement on the PASCAL VOC and COCO benchmarks compared to our baselines [9, 42].
- Through t-SNE and clustering experiments, we demonstrate that intra-class support features are well clustered by our method, learning robust classifiable features.

2. Related Work

Object Detection It is the task of detecting instances of a specific category in an image. There have been many studies [28, 26, 24] on supervised learning with large annotated image datasets. Also, several variant tasks have been studied. For example, weakly supervised object detection [15, 6] is the task of learning to detect only with weak annotations (e.g., image-level category) without bounding box annotation. Semi-supervised object detection [13, 32] is a task using both labeled and unlabeled data, and few-shot object detection, which we deal with in this paper, aims to detect instances of novel categories with few samples.

Object detectors are largely divided into single-stage and two-stage detectors. The single-stage detectors [22, 20] predict the object’s class and bounding box directly from the features from the feature extractor. The two-stage detectors [28, 3] detect objects in two steps: first, they generate class-agnostic candidate boxes using RPN (Region Proposal Network). Then, the candidate boxes are classified and the corresponding bounding boxes are regressed. In FSOD, both single-stage [4, 14] and two-stage methods [43, 39, 9, 42] have been studied. Following the majority trend, we devised our method that can be applied to two-stage detectors such as Faster R-CNN [28].

Meta-Learning Briefly speaking, it is a research topic to learn how to learn. There are several approaches of meta-learning, such as 1) gradient-based methods [10, 17] that learn to well-transfer the knowledge learned by several tasks to a new task and 2) model-based methods [23, 24] that aim to design structures that can generalize well, or utilize an external meta-learner or memory. 3) metric-based methods [31, 37, 27, 44] that perform non-parametric learning by comparing query sample with support samples and predicting the category of test data by comparing with train-
ing support samples. A typical strategy of applying metric-based learning to few-shot learning is to generate a single class prototype for each category by averaging features of support data belonging to the category. If networks learn sampled mini-batches called episodes through meta-learning, an episode will consist of sub-classes at each iteration. This episodic training strategy has been shown to generalize better on novel few-shot data because it naturally mimics the few-shot task. In this paper, instead of generating one prototype for each class, we propose an alternative method, generating per-sample prototypes, that makes better use of the information of the support data by treating each sample as a prototype.

### 3. Overall Architecture

Our method aims to find the novel instances in the query image by leveraging meta-learning. In the meta-learning scenario, we concentrate on two aspects of the pipeline: how to extract informative representation from support set $S$ and how to combine it with query features. To this end, we propose the Intra-Support Attention Module (ISAM) and the Query-Support Attention Module (QSAM), which can complement various frameworks in a plug-and-play manner and bring significant improvements in performance.

Figure 2 shows the overall architecture illustrating two baselines [9, 42] we used for FSOD. As shown in the figure, there are two candidate locations to apply the proposed aggregation modules. For different baselines [9] and [42], we designed similar aggregation methods composed of ISAM and QSAM and applied them at different locations as shown by [A] and [B] in Fig. 2.

Specifically, the overall architecture is based on the two-stage Faster R-CNN framework [28]. Backbone network receives a query image and $K$ samples from the support set of the same class and outputs $K + 1$ feature maps. The Region Proposal Network (RPN) proposes candidate boxes from the query feature map. Here, the input for the RPN depends on the baseline. In FewX [9], the aggregated query feature map is fed into RPN ([A] in Fig. 2). On the other hand, in FsDetView [42], the query feature map is fed directly into the RPN without aggregation. In both baselines, $N_{roi}$ query RoI features are aggregated with $K$ support RoI features. Then, RoI Head outputs box offsets and class confidences.

Note that both baselines [9, 42] generate a single prototype per class by averaging the support feature maps before aggregation at [A] for FewX and at [B] for FsDetView. Unlike the two baselines, our method performs aggregation by treating the support features as an individual prototype, i.e., per-sample prototype. The detailed per-sample aggregation procedures of ISAM and QSAM are introduced in Section 3.3 and Figure 3.
Figure 2. **Our overall Architecture** based on Faster R-CNN [28] to find instances of support category in the query image. [A] and [B] are aggregation procedure (Fig. 3) for the query feature and the support features. Baselines are FewX [9] and FsDetView [42], where FewX has both [A] and [B] operations, and in FsDetView, query features are directly fed into RPN without aggregation of [A] operation.

For implementation, ISAM is designed as the encoder of shallow Transformer [36, 38] composed of multi-head attention network consisting of the process of Eq. (1) and multi-layer perceptron with layer normalization [1].

**Query-Support Attention Module** aggregates the query feature and support feature maps through attention mechanism shown in Eq. (1). Here, \( K \) and \( V \) are assigned to the support feature vectors, and \( Q \) is assigned to the query feature vectors. The query feature vectors are generated in one of two processes: by flattening the query feature map in (a), i.e., \( q=HW \), or by concatenating query RoI feature vectors in (b), i.e., \( q=N_{roi} \). In other words, aggregation the query features and the support features are performed by dot-producting each query feature vector with all of the support feature vectors.

For implementation, QSAM is designed as the decoder of shallow Transformer which is also composed of multi-head attention network containing multi-layer perceptron blocks with layer normalization.
3.4. Training and Inference

Training Our framework is trained by two phases. First, the network is trained with abundant labeled base data \( D_b \) with base class \( C_b \). At this phase, the trained classes are \( C_b \), i.e., \( C_{train} = C_b \). Second, the network is finetuned with few-shot novel data \( D_n \) of novel classes \( C_n \). At this phase, the training is done on a balanced dataset composed of \( K \)-shot instances per class for both base data and novel data, i.e., \( C_{train} = C_b \cup C_n \). For both phases, the episodic training strategy is applied that each episode consists of \( N \)-way, \( K \)-shot support data and a query image. FewX \(^9\) are trained with 2-way, \( K \)-shot. Specifically, an episode consists of the following triplet: \((q_{c1}, s_{c1}, s_{c2})\) where class \( c1 \) and \( c2 \) are different classes sampled from \( C_{train} \), and \( q_{c3} \) indicates the query data containing instances of \( c1 \)-class. \( s_{c1} \) and \( s_{c2} \) indicate the 2-way, \( K \)-shot support data, i.e., \( |s_{c1}| = |s_{c2}| = K \). And for FsDetView \(^42\), an episode consists of a query image and all class of support data, i.e., \( |C_{train}| \)-way, \( K \)-shot.

Objective function The loss function of RPN’s foreground proposal and RoI Head’s detection outputs are Eq. \(^2\) where \( L_{rpn,loc} \) is the bounding box regression loss calculated as the smooth \( L_1 \) loss, and \( L_{rpn,cls} \) is the classification loss calculated as the cross-entropy loss. Note that the output of FewX is binary classification whether the query RoI feature vectors match or not with the support RoI feature vectors, and FsDetView is multi-class classification with the softmax function. \( L_{meta} \) is the cross-entropy loss used in FsDetView like Meta R-CNN \(^43\) for class features to be diverse for different classes.

\[
L = L_{rpn,loc} + L_{rpn,cls} + L_{det,loc} + L_{det,cls} + L_{meta} \tag{2}
\]

Inference The few-shot samples used in finetuning are used as the support data at the inference time. Therefore, all the support data are passed into the backbone network and ISAM once, and the output support feature vectors of ISAM and QSAM are stored for repeated use as multiple prototypes.

4. Experiments

4.1. Dataset

We evaluate our method on PASCAL VOC \(^7\) \(^8\) and MS COCO \(^21\) benchmarks. We follow the experimental setup of previous works \(^43\) \(^14\) \(^39\) \(^42\). For VOC experiments, our network is trained using PASCAL VOC 07+12 trainval dataset and tested on VOC 07 test dataset. The 20 classes are divided into 15 base classes and 5 novel classes and evaluated with three different splits. The number of shots is set to \( K \in \{1, 2, 3, 5, 10\} \). For 10-shot and 30-shot experiments on MS COCO, of the total 80 classes of COCO, the 20 classes overlapping with those of VOC are set as novel classes. As in TFA \(^39\), it is assumed that \( K \)-shot base data can be used when finetuning with \( K \)-shot novel data. Because the performance can vary depending on the few-shot sample configuration, we distinguished between the experiments in fixed support samples and the experiments in which random sampling is performed multiple times.

4.2. Implementation detail

The query images are resized to short size 600 and the maximum long side is set to 1000. The support images are resized to 320x320 for FewX and 224x224 for FsDetView. We use Resnet-101 \(^11\) for the VOC experiment and Resnet-50 for the COCO experiment as the weight-shared backbone network except the first convolution layer of FsDetView. Because input support data for FsDetView have 4 channels that consists of 3 rgb channels and 1 channel for the binary mask of ground truth bounding box, FsDetView has a 3-channel convolution layer for the query image and a 4-channel convolution layer for the support data. The backbone networks are pretrained on Imagenet-1k \(^29\). The learnable parameters of batchnorm \(^2\) trained on imagenet 1k are frozen at both base training and finetuning for both baselines. Learning schedulings are the same for both FewX and FsDetView including the optimizer, learning rate, batch size and training/finetuning iterations. Unless otherwise noted, the numbers of support samples \( K \) during base training of FewX, FewX+Ours, FsDetView and FsDetView+Ours are set to 10, 10, 1 and 1\(^1\) respectively.

ISAM and QSAM are implemented by utilizing the encoder and the decoder of the Transformer \(^56\), respectively. Both are set to have 2-heads, 2-layers with layer normalization, and ReLU is used as an activation function. The dropout rate of Transformer is 0.1. And the hidden dimensions of the Transformer are set to 256.

4.3. Analysis for ISAM and QSAM

We applied our method to FsDetView \(^42\) and analyzed how the performance changes on PASCAL VOC by two experiments: ablation study of ISAM and QSAM (Table 1), and the effect of the number of per-class samples \( K \) during base training (Table 2). All experiments in Table 1 and Table 2 were conducted 30 times to calculate the means and standard deviations.

Ablation study Table 1 shows the average precision at IoU=0.50 (Intersection over Union) of the novel classes with or without ISAM and QSAM on PASCAL VOC07 test dataset. It can be seen that it is effective to refine support features by paying attention to other support features through ISAM. In addition, it can be seen that aggregation with the support features as they are through QSAM is more

\(^1\) The \( K \) during base training of FewX and FsDetView without ours followed the official code.
Table 1. Ablation study on Novel set 1 of VOC07 test dataset. At base training, 3 support images per class are used.

| method                      | K=1          | K=2          | K=3          | K=5          | K=10         |
|-----------------------------|--------------|--------------|--------------|--------------|-------------|
| FsDetView                   | 23.8 ± 6.0   | 35.9 ± 6.1   | 42.1 ± 4.3   | 48.7 ± 3.4   | 56.9 ± 2.9  |
| FsDetView+ISAM              | 24.0 ± 6.1   | 35.6 ± 5.2   | 44.0 ± 4.6   | 50.0 ± 4.0   | 57.9 ± 3.1  |
| FsDetView+QSAM              | 23.9 ± 6.9   | 35.9 ± 5.5   | 43.9 ± 4.9   | 50.5 ± 3.9   | 58.1 ± 3.0  |
| FsDetView+ISAM+QSAM         | 24.3 ± 6.2   | 36.5 ± 5.3   | 44.9 ± 4.3   | 52.0 ± 3.8   | 59.2 ± 2.6  |

Table 2. Ablation study with changes of K during base training on Novel set 1 of VOC07 test dataset.

| method                      | base train K | Average precision at IoU=0.5 |
|-----------------------------|--------------|-----------------------------|
| FsDetView                   | 1            | 23.8 ± 6.5                  |
|                            | 3            | 23.8 ± 6.0                  |
|                            | 10           | 23.2 ± 5.7                  |
| FsDetView+ISAM+QSAM         | 1            | 24.7 ± 6.5                  |
|                            | 3            | 24.3 ± 6.2                  |
|                            | 10           | 24.1 ± 5.9                  |

The number of shots K during base training Table 2 shows the AP50 results of the novel classes on PASCAL VOC07 test dataset according to the change of K during base training. Our performances are generally higher, but the more similar the K for base training and the K for finetuning, the higher the performance. When FsDetView is trained by base data with ours at K = 1, ISAM did not learn how to pay attention to support features, and QSAM did not learn how to aggregate multiple prototypes together. Even if ISAM and QSAM learn their roles when finetuning, the performances were lower than those of K = 3 or 10 when base training. In addition, the higher the number of shots during base training, the lower the standard deviations.

4.4. Clustering of support feature vectors

**t-SNE** Our hypothesis is that collected natural images can be far from class prototypes. Hence, it is better that support features are refined into shared information through ISAM by paying attention to other support features. Figure 4 is the t-SNE results of the novel classes on COCO 30-shot to verify the hypothesis. As in (a) and (b) of the figure, some features exist close to others despite the categories are different. In these cases, the data are noisy; for example, there are instances of several categories together in RGB images (a), (b). However, as can be seen in (c), ISAM makes clustering better for support features by paying attention to other support features. Some points are misclustered in all of (a), (b), and (c) when there are ambiguities in RGB images, such as multiple categories, occlusions, or partial appearances.

**Distance from class centroid** We evaluated quantitatively whether each support feature vector, which we plotted on t-SNE, is actually closest to the corresponding class mean (single prototype) calculated by 30-shots on the novel support data of COCO 30-shot. The accuracy was evaluated by measuring L1-distance with class means. The accuracies of Baseline, before ISAM and after ISAM are 75.2%, 77.8% and 97.8%, respectively.

4.5. Comparison with state-of-the-art

We applied our method to two baselines [9, 42] and compared it with other methods on PASCAL VOC and COCO benchmarks. Note that the base models are trained by base data with K=10 for our method with FewX and K=3 for ours with FsDetView, as mentioned in implementation details (Sec. 4.2). Both models are finetuned from each base model and are evaluated on novel classes.

**PASCAL VOC** Table 3 shows the AP50 results of the novel classes on PASCAL VOC07 test dataset. We evaluated Ours with FewX [9] with the same few-shot samples as MetaYOLO [14] and TFA [39], and there are significant performance improvements compared to the baseline. However, as shown in Table 1, the variance of performance is large. Therefore, we evaluated ours with FsDetView [42] by averaging 30 times of random samplings of few-shot samples. Likewise, significant performance improvements are found in FsDetView [42].

**MS COCO** Table 4 summarizes the results for novel classes on MS COCO dataset, and we report the standard
5. Future work

Aggregation with spatial information of support data
As the support feature vectors were abstracted, spatial information of the vectors disappeared. Therefore, it is worth noting that the attention mechanism operates to reflect spatial information of support images. In other words, when ISAM refines the support data, it is helpful to pay attention to each other without the support feature maps being pooled by global average pooling. Similarly, when QSAM aggregates the query with the support, it is helpful to aggregate with spatial information of support feature maps rather than that of support feature vectors.

Toward class scalable detector
We evaluate Ours with FewX trained only on the base data of COCO dataset without finetuning on the novel data. The novel 20-class AP is 7.1 (+0.9 point increase compared to baseline) even though the novel data were not finetuned. Because the current framework based on metric-based meta-learning has the form of $P(\text{box}|\text{query image}, \text{support images})$. If the networks learn how to match given support images with the query image well, detection can be performed without finetuning the novel classes. If this characteristic is well utilized, it may be more advantageous to detect many unknown classes in the same domain or to perform it incrementally.

6. Conclusion

There are studies on the Few-Shot Object Detection framework based on meta-learning that detects instances of support category in a query image. Based on this framework, we propose the Intra-Support Attention Module (ISAM) and Query-Support Attention Module (QSAM) applicable to various methods. ISAM performs an attention mechanism between support features of the same class to refine the information that may be noisy, and QSAM aggregates the query features and the support features by per-sample prototypes, not a single prototype per class for using unabridged information of support data. Better feature maps for detecting unseen novel classes in $K$-shot support data are generated through these two modules. We demonstrate the effectiveness of the proposed modules in that the support feature vectors are clustered when collected support samples are somewhat far from the prototype. And the performances are improved when the attention vectors were refined and aggregated as per-sample prototypes.
### Table 4. AP and AR of novel classes on MS COCO minival.

| method                  | backbone | image size | AP  | AR   |
|-------------------------|----------|------------|-----|------|
|                         |          |            | AP50:95 | AP50 | AP75 | 1    | 10   | 100  |
|                          |          |            |       |      |      |      |      |      |
| MetaYOLO [14]           | Darknet19 | 416x416    | 5.6  | 12.3 | 4.6  | 10.1 | 14.3 | 14.4 |
| MetaDet [41]            | VGG16    | -          | 7.1  | 14.6 | 6.1  | 11.9 | 15.1 | 15.5 |
| TFA w/ fc * [39]        | R101FPN  | short800   | 9.1  | 17.3 | 8.8  | -1   | -1   | -1   |
| TFA w/ cos * [39]       | R101FPN  | short800   | 9.1  | 17.3 | 8.8  | -1   | -1   | -1   |
| Meta R-CNN [43]         | R50      | short600   | 5.6  | 12.3 | 4.6  | 10.1 | 14.3 | 14.4 |
| FewX †                   | R50      | short600   | 9.1  | 17.3 | 8.8  | -1   | -1   | -1   |
| FewX+Ours †             | R50      | short600   | 9.1  | 17.3 | 8.8  | -1   | -1   | -1   |
| FsDetView †             | R50      | short600   | 12.5 | 27.3 | 9.8  | 20.0 | 25.5 | 25.7 |
| FsDetView+Ours †        | R50      | short600   | 10.6 | 25.5 | 6.3  | 18.1 | 23.8 | 23.9 |
|                         |          |            |       |      |      |      |      |      |
|                          |          |            |       |      |      |      |      |      |
| MetaYOLO [14]           | Darknet19 | 416x416    | 9.1  | 19.0 | 7.6  | 13.2 | 17.7 | 17.8 |
| MetaDet [41]            | VGG16    | -          | 11.3 | 21.7 | 8.1  | 14.5 | 18.9 | 19.2 |
| TFA w/ fc * [39]        | R101FPN  | short800   | 13.4 | 24.7 | 13.2 | -1   | -1   | -1   |
| TFA w/ cos * [39]       | R101FPN  | short800   | 13.7 | 24.9 | 13.4 | -1   | -1   | -1   |
| Meta R-CNN [43]         | R50      | short600   | 12.4 | 25.3 | 10.8 | 15.0 | 21.4 | 21.7 |
| FewX †                   | R50      | short600   | 13.8 | 25.8 | 13.5 | 20.8 | 30.8 | 31.0 |
| FewX+Ours †             | R50      | short600   | 15.3 | 29.3 | 14.5 | 21.2 | 31.7 | 32.1 |
| FsDetView †             | R50      | short600   | 12.0 | 22.2 | 11.8 | -1   | -1   | -1   |
| FsDetView+Ours †        | R50      | short600   | 12.1 | 22.0 | 12.0 | -1   | -1   | -1   |

* † marks method based on finetuning.

Table 3. AP50 on VOC2007 test dataset. The first four rows are based on YOLOv2 [26], and the rest are based on Faster R-CNN [28] with/without FPN [19] or DCN [5]. Methods with * marks are based on finetuning and the others are based on meta-learning. † indicates the re-implemented version using the official code. ‡ marks mean multiple-run results. Red/Blue texts indicate the first/second best on multiple-run results.
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