AFD-Net: Adaptive Fully-Dual Network for Few-Shot Object Detection

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Abstract

Few-shot object detection (FSOD) aims at learning a detector that can fast adapt to previously unseen objects with scarce annotated examples, which is challenging and demanding. Existing methods solve this problem by performing subtasks of classification and localization utilizing a shared component (e.g., RoI head) in a detector, yet few of them take the preference difference in embedding space of two subtasks into consideration. In this paper, we carefully analyze the characteristics of FSOD and present that a general few-shot detector should consider the explicit decomposition of two subtasks, and leverage information from both of them for enhancing feature representations. To the end, we propose a simple yet effective Adaptive Fully-Dual Network (AFD-Net). Specifically, we extend Faster R-CNN by introducing Dual Query Encoder and Dual Attention Generator for separate feature extraction, and Dual Aggregator for separate model reweighting. Spontaneously, separate decision making is achieved with the R-CNN detector. Besides, for the acquisition of enhanced feature representations, we further introduce Adaptive Fusion Mechanism to adaptively perform feature fusion suitable for the specific subtask. Extensive experiments on PASCAL VOC and MS COCO in various settings show that, our method achieves new state-of-the-art performance by a large margin, demonstrating its effectiveness and generalization ability.

1. Introduction

Recent years have witnessed impressive advances of CNNs [17, 9, 18] in object detection [32, 30, 8, 14, 23, 29, 4, 13]. However, training general object detection models from scratch typically requires rich labeled data which is extremely expensive to obtain or even hard to collect, such as endangered animals. Thus, detectors significantly suffer a performance drop when training examples are inadequate [45]. On the contrary, humans exhibit a strong ability to address this issue; even a child can easily learn to recognize novel characteristics from only a few instances [34]. This triggers recent researches on few-shot learning (FSL). It is considered promising to enhance the generalization ability of deep networks from limited training examples [22, 37, 11, 25, 1]. Concretely, FSL aims at recognizing instances from novel classes given only a few annotated data per category in the inference stage, with the availability of abundant labeled training samples from base classes. However, most researches in few-shot learning community focus on image classification [21, 37, 35, 36, 12, 27], while far less progress has been made in the field of object detection [19, 44, 42], which is generally considered much more challenging due to the existence of an additional subtask, specifically, few-shot localization, besides the subtask of object recognition.

A trend to solve FSOD is to conjoin a reweighting module with a base object detector, e.g., Faster R-CNN [32]. Concretely, these few-shot detectors [44, 42] introduce an additional branch to extract discriminative features of support set from novel classes, and then use these class-attentive vectors to reweight RoI (Region-of-Interest) head shared for subsequent estimation of object categories and locations. However, classification and localization are two subtasks in FSOD. The former subtask focuses on providing a coarse location of the object via classification, while the
latter aims at estimating an accurate object state by a refined bounding box [43]. This leads to their distinct preferences towards feature representations. In other words, generated features suitable for classification are probably not suitable for bounding box regression. Meanwhile, these two sub-tasks are complementary [41], thus leveraging the information from unfocused tasks is crucial to enhance the representation ability of few-shot detectors.

Motivated by the abovementioned analysis, we present that a general few-shot detector should: 1) decompose the processing of classification and localization in FSOD with specific processing for the specific subtask, involving feature representations, model reweighting and decision making; 2) consider efficient feature fusion between two sub-tasks for effectively encoding both query image and support set, as shown in Fig. 1.

In this paper, we propose a novel framework for FSOD, namely Adaptive Fully-Dual Network (AFD-Net), as illustrated in Fig. 2. Specifically, we extend Faster R-CNN by introducing three modules, i.e., Dual Query Encoder (DQE), Dual Attention Generator (DAG), and Dual Aggregator (DA) for separate processing of two subtasks, together with Adaptive Fusion Mechanism (AFM) for the acquisition of enhanced feature representations. DQE and DAG are designed for separate feature representations in two sub-tasks. Query features are encoded by DQE into two groups of RoI vectors, where each group is obtained following the guidance of AFM and is used for a particular subtask. In parallel with DQE, DAG encodes support features into class-attentive vectors with the same scheme in feature representation. DA performs separate model reweighting using two aggregators, where each RoI vector from query features is aggregated with each class-attentive vector from support features in each aggregator assigned the specific subtask. Finally, a R-CNN detector is applied to estimate the object location and category respectively, realizing separate decision making, spontaneously.

Extensive experiments on two public datasets in various settings show that despite its simplicity, our method outperforms existing state-of-the-art approaches by a large margin, which demonstrates its effectiveness. To summarize, the main contributions of this paper are three-fold:

• We propose a simple yet effective framework for few-shot object detection. To the best of our knowledge, we are among the first to solve FSOD by decomposing the processing of classification and localization.

• We further introduce three modules, i.e., DQE, DAG and DA, to perform decomposition in multiple components of our network, along with AFM for enhanced feature representations.

• Our proposed method achieves a new state-of-the-art performance on multiple benchmarks.

2. Related Work

General Object Detection. Recent object detectors based on deep CNNs can be mainly divided into two steams, i.e., one-stage detectors and two-stage ones. R-CNN series [14, 13, 32, 16, 8, 23] belong to the first category, which generate region proposals [32] of potential objects in the first stage, and then perform category and bounding box estimation at the proposal-level. On the contrary, YOLO [29] and the variants [30, 24, 31, 3] dominate the one-stage steam. These methods use a single CNN to predict categories and locations of the objects directly, without explicitly generating proposals. These two branches of general object detectors unanimously depend on a huge amount of data with elaborate bounding box annotations. When training samples are limited, they struggle heavily.

Few-shot Learning. Few-shot learning refers to learning to learn general knowledge that can be easily transferred to new tasks with only a handful of annotated examples [22, 37, 1]. Few-shot classification has recently been widely investigated as a representative task of few-shot learning. Generally, solutions to this problem involve two groups: meta-learning based and fine-tuning based methods. The former can be further categorized into: 1) metric-learning based methods [21, 35, 36] that focus on the similarity of input images on the embedding space; 2) optimization-based ones [28, 11, 25], where a meta-learner is designed to simulate the optimization process for the fast adaptation to novel classes with limited samples; 3) model-based methods [2, 12, 39] that aim to estimate the network parameters for novel tasks with the help of a learned predictor. Fine-tuning based approaches [6, 7] demonstrate that simple fine-tuning techniques are crucial and effective towards few-shot learning. While substantial progress has been made in few-shot classification, the problem of few-shot object detection is relatively unsolved due to its complexity for the existence of additional localization task.

Few-shot Object Detection. There are several attempts to solve the problem of few-shot object detection. LSTD [5] applies transfer learning technique in object detection with limited examples and demonstrates its effectiveness. TFA [38] proposes that only fine-tuning the last layer of existing detectors is crucial and effective despite its simplicity. Metric learning widely explored in few-shot classification can be extended to few-shot object detection. For example, RepMet [20] scores the pair-wise similarity between embedded features of input query and support images. [10] incorporates attention mechanism into RPN (Region Proposal Network) and explicitly defines a multi-relation detector to suppress detection of the background. Recently, methods based on meta-learning have been a popular trend. FSRW [19] attaches a reweighting module with YOLOv2 [30] to adjust the full input image features using class-attentive vectors of support images,
3. Methodology

In this section, we first introduce the setup for few-shot object detection in Section 3.1. Then we elaborate on our proposed approach in Section 3.2. Finally, the detailed training procedure is provided in Section 3.3.

3.1. Problem Setup

As in previous work [19, 44, 42], we adopt the following few-shot object detection settings. In the training phase, we are provided with two training sets, i.e., a base set $D_{\text{base}}$ from base classes $C_{\text{base}}$ with abundant instances and a novel set $D_{\text{novel}}$ from novel classes $C_{\text{novel}}$ with only a few samples per category, where $C_{\text{base}}$ and $C_{\text{novel}}$ are non-overlapping, i.e., $C_{\text{base}} \cap C_{\text{novel}} = \emptyset$. For each sample $(x, y) \in D_{\text{base}} \cup D_{\text{novel}}$, $x = \{\text{obj}_i\}_{i=1}^N$ is an image containing $N$ objects, and $y = \{(\text{cls}_i, \text{box}_i)\}_{i=1}^N$ denotes $N$ categories $\{\text{cls}_i\}_{i=1}^N$ with each cls$_i \in C_{\text{base}} \cup C_{\text{novel}}$ and $N$ structured annotations $\{\text{box}_i\}_{i=1}^N$ of the $N$ objects in the image $x$. The aim of the few-shot object detector is to classify and locate objects from both novel and base classes in an image with only $K$ (usually less than 10) available instances per class in the phase of inference, with the help of transferable knowledge learned from abundant examples from base classes.

3.2. Adaptive Fully-Dual Network

Our proposed framework decomposes the processing of few-shot classification and localization, as well as enhances feature representations. We adopt the widely used two-stage detector Faster R-CNN [32] as the base model, which first generates RoIs of potential objects, and then performs detection using a single RoI head. The overall architecture of our proposed network is demonstrated in Fig. 2. Concretely, we extend Faster R-CNN to a dual Siamese architecture suitable for the few-shot object detection scenario, where a query image is encoded by the upper Faster R-CNN branch, and the other branch for support set. Each branch further contains two paths, where each path performs a specific subtask. Query RoI vectors and class-attentive vectors of support set from two branches are then aggregated, achieving the reweighting of Faster R-CNN for the subsequent detection of novel instances. We introduce Dual Query Encoder (DQE) and Dual Attention Generator (DAG) for separate feature representations, and Dual Aggregator (DA) for separate model reweighting based on our proposed architecture. Furthermore, we present Adaptive Fusion Mechanism (AFM) to effectively encode both the query image and support set.

3.2.1 Dual Query Encoder

In two-stage object detectors, RPN is applied to generate class-agnostic RoIs. These RoIs are then utilized to perform object detection by a R-CNN detector. Instead of generating a single group of RoI vectors $\{r_i\}_{i=1}^n$ of the input query image $q$ by a single RoI head in previous work [44, 42],
we propose Dual Query Encoder (DQE) that generates two groups of RoI vectors \(\{r^t_i\}_{i=1}^n\) with \(t \in \{\text{cls}, \text{reg}\}\) of the input query image for subtasks of classification and bounding box regression respectively, guided by our observation that subtasks of classifying and locating objects in few-shot detection should be treated separately. In particular, DQE involves two parallel branches, where each branch encodes input query RoIs into RoI vectors for the specific task \(t\), as shown in Fig. 3. This procedure is formulated as below:

\[
\{r^t_i\}_{i=1}^n = E^t(\psi(\phi(q))), \ t \in \{\text{cls}, \text{reg}\} \tag{1}
\]

where \(q\) denotes input query image in Fig. 2, \(\phi(\cdot)\) denotes the backbone network of Faster R-CNN, \(\psi(\cdot)\) denotes the RoIAlign operation, \(E^t(\cdot)\) denotes feature extraction of the specific branch in DQE, \(t\) denotes the specific subtask, i.e., \(\text{cls}\) for classification and \(\text{reg}\) for bounding box regression, and \(n\) denotes the number of RoI vectors in each group.

We adopt a two-layer fully-connected (2-fc) encoder in regression branch and a convolution (conv) encoder in classification branch. Furthermore, we consider using the information from the unfocused branch to enhance the feature representations in each branch. Output task-specific RoI vectors from each branch are the weighted concatenation of fc features and conv features, where the weights can be adaptively adjusted according to the specific task and their values indicate the contributions of each group of RoI vectors to the integrated task-specific RoI vectors, which is the key philosophy of Adaptive Fusion Mechanism (AFM). Thus \(E^t(\cdot)\) in Eq. (1) can be rewritten as:

\[
E^t(\cdot) = [\lambda^t_{\text{conv}}E^t_{\text{conv}}(\cdot), \lambda^t_{\text{fc}}E^t_{\text{fc}}(\cdot)], \ t \in \{\text{cls}, \text{reg}\} \tag{2}
\]

where \(E^t_{\text{conv}}(\cdot)\) and \(E^t_{\text{fc}}(\cdot)\) denote conv encoder and fc encoder respectively for the specific subtask \(t \in \{\text{cls}, \text{reg}\}\), \(\lambda^t_{\text{conv}}\) and \(\lambda^t_{\text{fc}}\) denote the learnable weights of corresponding task-specific RoI vectors and are initialized to 1. \([\cdot, \cdot]\) denotes the depth-wise concatenation operation.

### 3.2.2 Dual Attention Generator

A popular scheme to solve FSOD is first encoding support set into class-attentive vectors, and then using them to reweight the base detector [19, 44, 42]. These vectors from support set can be regarded as the attentions of corresponding objects in the query image. The encoding process is performed by the support branch in Fig. 2. We further exploit this scheme, leading to our proposed Dual Attention Generator (DAG). DAG is designed in the same structure with DQE for the effectiveness of model reweighting, thus we omit its illustration for simplicity. It receives support set \(\{s^t_j\}_{j=1}^m\) from \(m\) categories as input and generates two groups of class-attentive vectors \(\{a^t_j\}_{j=1}^m\) with \(t \in \{\text{cls}, \text{reg}\}\) for two subtasks respectively:

\[
\{a^t_j\}_{j=1}^m = G^t\left(\varphi\left(\{s^t_j\}_{j=1}^m\right)\right), \ t \in \{\text{cls}, \text{reg}\} \tag{3}
\]

where \(\varphi(\cdot)\) denotes the backbone network in support branch sharing parameters with query branch in Fig. 2, \(G^t(\cdot)\) denotes the attention generation operation of the task-specific path in DAG for subtask \(t\).

Similar to Dual Query Encoder, \(G^t(\cdot)\) in Eq. (3) can be rewritten as:

\[
G^t(\cdot) = \left[\lambda^t_{\text{conv}}G^t_{\text{conv}}(\cdot), \lambda^t_{\text{fc}}G^t_{\text{fc}}(\cdot)\right], \ t \in \{\text{cls}, \text{reg}\} \tag{4}
\]

where \(G^t_{\text{conv}}(\cdot)\) and \(G^t_{\text{fc}}(\cdot)\) denote conv and fc attention generators respectively for the specific subtask \(t\), \(\lambda^t_{\text{conv}}\) and \(\lambda^t_{\text{fc}}\) are shared with those in DQE, and the depth-wise concatenation \([\cdot, \cdot]\) here is also an adaptive-weighted operation.

### 3.2.3 Dual Aggregator

In this paper, besides separate feature representations for two subtasks, we decompose the processing of feature aggregation to realize separate model reweightings, leading to our Dual Aggregator (DA). DA consists of a classification aggregator and a bounding box regression aggregator in parallel. In each aggregator, each RoI vector of query features is aggregated with each class-attentive vector of support features following the scheme introduced in [42], as shown in Fig. 4, which can be formulated as:

\[
\{j^t_k\}_{k=1}^{n \times m} = A^t\left(\{r^t_i\}_{i=1}^n, \{a^t_j\}_{j=1}^m\right)
\]

\[
= \left\{[r^t_i \otimes a^t_j, r^t_i - a^t_j, r^t_i]_{k=1}^t\right\}_{i=1}^{n \times m}, \ t \in \{\text{cls}, \text{reg}\}, \ n \in \{1, 2, \ldots, m\} \tag{5}
\]

where \(\{f^t_k\}_{k=1}^{n \times m}\) denotes aggregated features from the aggregator assigned the specific subtask \(t\), \(A^t(\cdot, \cdot)\) denotes the aggregation of RoI vectors and class-attentive vectors for subtask \(t\), \(\otimes\) denotes the depth-wise multiplication.
The separate two groups of aggregated features \( \{ f_{k}^{n} \}_{k=1}^{m} \) with \( t \in \{ \text{cls}, \text{reg} \} \) are then provided to the classifier and regressor in R-CNN detector respectively, to obtain the estimated category and location. As the input features of the detector are divided into two groups distinct from prior methods, the decision making in our framework is decomposed as well.

3.3. Training Procedure

3.3.1 Training Phase

Following the common practice in [19, 44, 38, 42], we train our network in two phases. Base data \( D_{\text{base}} \) from base classes \( C_{\text{base}} \) with abundant samples per class are used to train the model in the first base training phase. Then the balanced base data \( D_{\text{base}} \) and novel data \( D_{\text{novel}} \) with only \( K \) samples per class are fed into the network in the second fine-tuning phase for the fast adaptation to novel classes.

3.3.2 Training Data Organization

In the training phase, distinct from general object detectors that applying an image \( x_{i} \) as the training mini-batch, our few-shot detector applies a task \( T_{i} \) as an input training data in the meta-learning paradigm [19, 44, 42]. Each input task \( T_{i} = S_{i} \cup Q_{i} \) is the union of a query set \( Q_{i} \) and a support set \( S_{i} \), where \( Q_{i} \) provided to query branch in Fig. 2 is a query image \( q_{i} \) containing objects from \( m \) classes \( C_{i} \subseteq C_{\text{base}} \cup C_{\text{novel}} \), and \( S_{i} \) for support branch contains \( m \) \( K \)-shot (\( K = 200 \)) in the base training phase and \( K = \{1, 2, 3, 5, 10\} \) in the fine-tuning phase) clusters \( \{ g_{p}^{m} \}_{p=1}^{m} \), where each cluster \( g_{p}^{m} \) includes \( K \) images \( \{ s_{i,j}^{p} \}_{j=1}^{K} \) in the category \( p \). Each support image \( s_{i,j}^{p} \) is depth-wise concatenated with a structured binary mask \( k_{j}^{p} \) (see the input support set in Fig. 2, only one object is considered when multiple objects are present within an image).

3.3.3 Loss Function

We optimize our network in both training phases using the same loss function introduced in [44]:

\[
L = L_{\text{Faster R-CNN}} + L_{\text{meta}}
\]

where \( L_{\text{Faster R-CNN}} \) denotes the loss function of base detector Faster R-CNN, involving the RPN loss, and classification loss together with bounding box regression loss for the decision making. \( L_{\text{meta}} \) denotes a meta loss aiming at encouraging attention features of support set to distinguish with each other.

Since our proposed DAG and DQE are in a dual architecture, \( L_{\text{meta}} \) in this paper is a sum of two components for classification and regression respectively. Thus the loss function in Eq. (6) can be precisely written as:

\[
L = L_{\text{Faster R-CNN}} + L_{\text{meta-cls}} + L_{\text{meta-reg}}
\]

where \( L_{\text{meta-cls}} \) and \( L_{\text{meta-reg}} \) denote the meta losses for classification and regression subtasks, respectively.

4. Experiments

In this section, we evaluate the effectiveness of our proposed few-shot object detector. We first introduce the experimental settings in Section 4.1. Then we present comparison results with recent SOTAs on multiple benchmarks in Section 4.2, and analyze the performance of information fusion in Section 4.3. Finally, we provide relative ablations to obtain a comprehensive understanding of our method in Section 4.4.

4.1. Experimental Settings

**Benchmarks.** We evaluate our method on general object detection benchmarks, i.e., PASCAL VOC 2007, 2012 and MS COCO, in few-shot detection settings. As for PASCAL VOC, we follow the common practice in previous work [19, 44, 38, 42] and use train/val sets of VOC 07 and 12 for training while the test set of VOC 07 for testing. This benchmark covers 20 object categories, where 15 of them are regarded as base classes for the base training phase and the remaining 5 categories with only \( K \) (\( K = \{1, 2, 3, 5, 10\} \)) samples per class are considered as novel classes for few-shot fine-tuning phase. For the fair quantitative comparison, we adopt the same three class splits provided in [19]. For the evaluation protocol, we use mean Average Precision (mAP) of novel objects and the Intersection of Union (IoU) is set as 0.5 (AP\(_{50}\)). Another benchmark we evaluate on is MS COCO, which has 80k train images and 40k validation images, covering 80 classes. Among them, we denote the 20 classes overlapped with PASCAL VOC as novel classes with \( K \) (\( K = \{10, 30\} \)) samples per category and the rest 60 classes as base classes. We use 5k images from validation set for evaluation with the standard COCO-style evaluation metrics [24, 31] and the rest for training. To compare empirically, on both datasets, we evaluate on novel classes over 10 repeated runs and report the average performance.

**Baselines.** In our experiments, we compare our approach with two groups of baselines: meta-learning based methods, i.e., FSRW [19], MetaDet [40], Meta R-CNN [44], FSOD [10], and FSDetView [42] along with transfer learning based methods, which can be further divided into: 1) attempts focusing on domain transfer, e.g., LSTD [5]; 2) jointly training base detectors with base and novel objects without fine-tuning, denoted as YOLO/FRCN-joint [19, 44]; 3) first training base detectors with base objects and fine-tuning the entire model using novel objects with conditional iterations, denoted as YOLO/FRCN-ft [19, 44]; 4) training detectors in the same way as YOLO/FRCN-ft in the first phase yet fine-tuning the entire model until convergence, denoted as YOLO/FRCN-
### Table 1. Few-shot detection performance ($AP_{50}$) for novel categories on PASCAL VOC dataset. We evaluate baselines on three different novel sets. Our approach consistently outperforms other baselines by a large margin. RED/BLUE indicate SOTA/the second best. Reported results are averaged over multiple repeated runs.

| Method / Shots | Novel Set 1 | Novel Set 2 | Novel Set 3 |
|----------------|-------------|-------------|-------------|
|                | 1 2 3 5 10  | 1 2 3 5 10  | 1 2 3 5 10  |
| YOLO-joint [19]| 0.0 0.0 1.8 1.8 1.8 | 0.0 0.1 0.0 1.8 0.0 | 1.8 1.8 1.8 3.6 3.9 |
| FRCN-joint [44]| 2.7 3.1 4.3 11.8 29.0 | 1.9 2.6 8.1 9.9 12.6 | 5.2 7.5 6.4 6.4 6.4 |
| FRCN-ft [44]   | 11.9 16.4 29.0 36.9 36.9 | 5.9 8.5 23.4 29.1 28.8 | 5.0 9.6 18.1 30.8 43.4 |
| FRCN-ft-full [44]| 13.8 19.6 32.8 41.5 45.6 | 7.9 15.3 26.2 31.6 39.1 | 9.8 11.3 19.1 35.0 45.1 |
| LSTD [5]       | 8.2 1.0 12.4 29.1 38.5 | 11.4 3.8 5.0 15.7 31.0 | 12.6 8.5 15.0 27.3 36.3 |
| FSRW [19]      | 14.8 15.5 26.7 33.9 47.2 | 15.7 15.2 22.7 30.1 40.5 | 21.3 25.6 28.4 42.8 45.9 |
| MetaDet [40]   | 18.9 20.6 30.2 36.8 49.6 | 21.8 23.1 27.8 31.7 43.0 | 20.6 23.9 29.4 43.9 44.1 |
| Meta R-CNN [44]| 19.9 25.5 35.0 45.7 51.5 | 10.4 19.4 29.6 34.8 45.4 | 14.3 18.2 27.5 41.2 48.1 |
| TFA w/ fc [38]| 22.9 34.5 40.4 46.7 52.0 | 16.9 26.4 30.5 34.6 39.7 | 15.7 27.2 34.7 40.8 44.6 |
| TFA w/ cos [38]| 25.3 36.4 42.1 47.9 52.8 | 18.3 27.5 30.9 34.1 39.5 | 17.9 27.2 34.3 40.8 45.6 |
| FSDetView [42] | 24.2 35.3 42.2 49.1 57.4 | 21.6 24.6 31.9 37.0 45.7 | 21.2 30.0 37.2 43.8 49.6 |
| Ours           | 33.1 39.6 51.6 55.3 60.7 | 24.7 29.2 40.4 44.6 48.4 | 27.1 35.0 43.1 48.4 53.6 |

### Table 2. Few-shot detection performance ($AP_{50}$) for base and novel categories on Novel Set 1 of PASCAL VOC dataset. Our approach outperforms other baselines on novel classes and has a strong generalization ability. RED/BLUE indicate SOTA/the second best.

| Shots | Method       | Base $AP_{50}$ | Novel $AP_{50}$ |
|-------|--------------|----------------|-----------------|
| 3     | LSTD [5]     | 66.3           | 12.4            |
|       | FSRW [19]    | 64.8           | 26.7            |
|       | Meta R-CNN [44] | 64.8       | 35.0            |
|       | TFA w/ cos [38] | 77.3           | 42.1            |
|       | FSDetView [42] | -              | 42.2            |
|       | Ours         | 67.9           | 51.6            |
| 10    | LSTD [5]     | 66.3           | 38.5            |
|       | FSRW [19]    | 63.6           | 47.2            |
|       | Meta R-CNN [44] | 67.9       | 51.5            |
|       | TFA w/ cos [38] | 77.5           | 52.8            |
|       | FSDetView [42] | -              | 57.4            |
|       | Ours         | 70.6           | 60.7            |

**4.2. Comparison Results**

**PASCAL VOC.** Our evaluation results are presented in Table 1. The comparison experiments cover few-shot object detection scenarios in five setups ($K = \{1, 2, 3, 5, 10\}$) across three base/novel set splits. As can be observed, our method outperforms recent state-of-the-art baselines by a large margin and obtains the best performance in all 15 cases. We notice that in the majority of cases, the improvements are much larger than the gap among previous approaches, which indicates the strong generalization ability of our model. Surprisingly, although the existence of high variance of support data in the extreme few-shot setup ($K = 1$), we obtain large improvements (+7.8% in the first split and +5.8% in the third split), showing the robustness of our method in tough scenarios. Besides, in the robust 10-shot setup, the improvements (+3.3% in the first split, +2.7% in the second split and +4% in the third split) are lower than those in other setups. This can be explained by that, as the number of instances per novel class increases, the sample variance decreases and the detection performance stabilizes.

Taking evaluation performance on base classes into consideration, we provide detailed results on the first base/novel split in Table 2. We can find that on base classes, recent fine-tuning based approach TFA [38] leads the per-
Table 3. Few-shot detection performance for novel categories on MS COCO dataset. Our approach achieves an significant improvement over other baselines. RED/BLUE indicate SOTA/the second best. Reported results are averaged over multiple repeated runs.

| Shots | Method             | Average Precision 0.5:0.95 | Average Precision 0.5 | Average Precision 0.75 | Average Precision S | Average Precision M | Average Precision L | Average Recall 1 | Average Recall 10 | Average Recall 100 |
|-------|--------------------|-----------------------------|------------------------|------------------------|---------------------|---------------------|---------------------|------------------|------------------|------------------|
| 10    | LSTD [5]           | 3.2                         | 8.1                    | 2.1                    | 0.9                 | 2.0                 | 6.5                 | 7.8              | 10.4            | 10.4             |
|       | FSRW [19]          | 5.6                         | 12.3                   | 4.6                    | 0.9                 | 3.5                 | 10.5                | 10.1             | 14.3            | 14.4             |
|       | MetaDet [40]       | 7.1                         | 14.6                   | 6.1                    | 1.0                 | 4.1                 | 12.2                | 11.9             | 15.1            | 15.5             |
|       | Meta R-CNN [44]    | 8.7                         | 19.1                   | 6.6                    | 2.3                 | 7.7                 | 14.0                | 12.6             | 17.8            | 17.9             |
|       | TFA w/ fc [38]     | 9.1                         | 17.3                   | 8.5                    | -                   | -                   | -                   | -                | -                | -                |
|       | TFA w/ cos [38]    | 9.1                         | 17.1                   | 8.8                    | -                   | -                   | -                   | -                | -                | -                |
|       | FSOD [10]          | 11.1                        | 20.4                   | 10.6                   | -                   | -                   | -                   | -                | -                | -                |
|       | FSDetView [42]     | 12.5                        | 27.3                   | 9.8                    | 2.5                 | 13.8                | 19.9                | 20.0             | 25.5            | 25.7             |
|       | Ours               | 16.9                        | 32.8                   | 15.8                   | 4.9                 | 18.5                | 27.1                | 23.9             | 30.8            | 31.1             |

| Shots | Method             | Average Precision 0.5:0.95 | Average Precision 0.5 | Average Precision 0.75 | Average Precision S | Average Precision M | Average Precision L | Average Recall 1 | Average Recall 10 | Average Recall 100 |
|-------|--------------------|-----------------------------|------------------------|------------------------|---------------------|---------------------|---------------------|------------------|------------------|------------------|
| 30    | LSTD [5]           | 6.7                         | 15.8                   | 5.1                    | 0.4                 | 2.9                 | 12.3                | 10.9             | 14.3            | 14.3             |
|       | FSRW [19]          | 9.1                         | 19.0                   | 7.6                    | 0.8                 | 4.9                 | 16.8                | 13.2             | 17.7            | 17.8             |
|       | MetaDet [40]       | 11.3                        | 21.7                   | 8.1                    | 1.1                 | 6.2                 | 17.3                | 14.5             | 18.9            | 19.2             |
|       | Meta R-CNN [44]    | 12.4                        | 25.3                   | 10.8                   | 2.8                 | 11.6                | 19.0                | 15.0             | 21.4            | 21.7             |
|       | TFA w/ fc [38]     | 12.0                        | 22.2                   | 11.8                   | -                   | -                   | -                   | -                | -                | -                |
|       | TFA w/ cos [38]    | 12.1                        | 22.0                   | 12.0                   | -                   | -                   | -                   | -                | -                | -                |
|       | FSOD [10]          | -                           | -                      | -                      | -                   | -                   | -                   | -                | -                | -                |
|       | FSDetView [42]     | 14.7                        | 30.6                   | 12.2                   | 3.2                 | 15.2                | 23.8                | 22.0             | 28.2            | 28.4             |
|       | Ours               | 18.6                        | 35.0                   | 17.9                   | 5.6                 | 19.8                | 29.2                | 25.5             | 33.0            | 33.3             |

Figure 5. Performance visualization of our proposed Adaptive Fusion Mechanism. We plot values of four learnable weights, i.e., $\lambda_{\text{conv}}^{\text{cls}}, \lambda_{\text{fc}}^{\text{cls}}, \lambda_{\text{conv}}^{\text{reg}},$ and $\lambda_{\text{fc}}^{\text{reg}}$ against number of training iterations on: (a) PASCAL VOC in the first split, (b) MS COCO, in the base training phase. $\text{cls-conv}, \text{cls-fc}, \text{reg-conv}, \text{reg-fc}$ indicate $\lambda_{\text{conv}}^{\text{cls}}, \lambda_{\text{fc}}^{\text{cls}}, \lambda_{\text{conv}}^{\text{reg}},$ and $\lambda_{\text{fc}}^{\text{reg}}$, respectively.

$i \in \{\text{conv, fc}\}, j \in \{\text{cls, reg}\}$ indicates that extractor $i$ dominates the subtask $j$ in feature extraction.

In this section, we discuss the performance of Adaptive Fusion Mechanism. We introduce four learnable weights, i.e., $\lambda_{\text{conv}}^{\text{cls}}, \lambda_{\text{fc}}^{\text{cls}}, \lambda_{\text{conv}}^{\text{reg}},$ and $\lambda_{\text{fc}}^{\text{reg}}$ in Eq. (2) and Eq. (4), to control the contributions of encoded conv and fc feature components from two paths to the fused output features in DQE and DAG shown in Fig. 3. Obviously, larger $\lambda_i^j$ with

**MS COCO.** We show the evaluation of 20 novel classes on MS COCO in 10/30-shot setups and report the standard COCO-style metrics in Table 3. Obviously, our approach significantly outperforms recent SOTAs in all setups, despite the complexity and a huge amount of data in MS COCO, verifying its effectiveness and robustness. Note that our method performs much better in detection of small objects compared with other SOTAs, indicating that our proposed network indeed enhances feature representations and obtains high-quality image information.

**4.3. Feature Fusion Analysis**

In this section, we discuss the performance of Adaptive Fusion Mechanism. We introduce four learnable weights, $i.e., \lambda_{\text{conv}}^{\text{cls}}, \lambda_{\text{fc}}^{\text{cls}}, \lambda_{\text{conv}}^{\text{reg}},$ and $\lambda_{\text{fc}}^{\text{reg}}$ in Eq. (2) and Eq. (4), to control the contributions of encoded conv and fc feature components from two paths to the fused output features in DQE and DAG shown in Fig. 3. Obviously, larger $\lambda_i^j$ with
In this section, we conduct relative ablations in 3/10-shot scenarios on the first base/novel split of PASCAL VOC. Results in all experiments are obtained by averaging over multiple random runs.

**Effect of fusion.** To examine the effectiveness of Adaptive Fusion Mechanism in Dual Query Encoder and Dual Attention Generator, we compare the performance of various feature fusion combinations and report $AP_{50}$ of novel classes in 10-shot setup, as shown in Table 4, where $j \in \{cls, reg\}$, $i \in \{conv, fc\}$ in the header represents applying extractor $i$ in subtask $j$. The existence of two extractors within a branch indicates that the information fusion is applied (e.g., the regression branch in Fig.3 can be represented by “reg-fc & reg-conv”). In Ablation 1-4, we adopt only one extractor in each branch without feature fusion. Among these four experiments, “cls-conv & reg-fc” achieves the best performance, while “cls-fc & reg-conv” performs the worst, indicating that conv extractor prefers classification and fc extractor is more suitable for bounding box regression in the first split on PASCAL VOC dataset. This is consistent with the observations in Section 4.3. In Ablation 5-7, feature fusion is adopted in only one branch and boost the detection performance, suggesting that leveraging information from unfocused tasks is essential in each sub-task. Applying feature fusion in both branches shown in

**Effect of meta loss.** In our approach, we further divide meta loss $L_{meta}$ introduced in [44] into task-specific meta losses, i.e., $L_{meta-cls}$ for classification and $L_{meta-reg}$ for bounding box regression. Similarly, we evaluate the effect of meta losses in Table 5. Obviously, both of the introduced $L_{meta-cls}$ and $L_{meta-reg}$ can indeed improve the performance on novel classes in $K$-shot setups. Besides, they provide similar contributions individually in robust 10-shot setup, while $L_{meta-reg}$ outperforms in relatively extreme (3-shot) scenario in comparison with $L_{meta-cls}$, probably suggesting that bounding box regression matters more when performing more strict few-shot object detection. Interestingly, the existence of meta losses almost have no positive influence on the detection of base classes. We believe the reason is that the few-shot detector has already been able to detect objects from base classes after base training phase with abundant annotations, despite the lack of meta losses.

**5. Conclusion and Future Work**

This work targets the problem of few-shot object detection. We carefully analyzed the characteristics of FSOD and presented that a general few-shot detector should: 1) explicitly decompose the processing of classification and localization; 2) fuse information from both subtasks for enhanced feature representations. Based on our observations, we proposed Adaptive Fully-Dual Network that performs two subtasks separately, involving feature representations, module reweighting, and decision making. For the acquisition of enhanced features, we proposed a novel Adaptive Fusion Mechanism. Despite its simplicity, our approach achieved significant performance on multiple benchmarks, demonstrating its effectiveness and generalization ability. It is worth noting that, our proposed framework and feature fusion mechanism are general, thus can be potentially applied into other two-stage or even one-stage models.
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