Leveraging Bottom-Up and Top-Down Attention for Few-Shot Object Detection

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Abstract—Few-shot object detection aims at detecting objects with few annotated examples, which remains a challenging research problem yet to be explored. Recent studies have shown the effectiveness of self-learned top-down attention mechanisms in object detection and other vision tasks. The top-down attention, however, is less effective at improving the performance of few-shot detectors. Due to the insufficient training data, object detectors cannot effectively generate attention maps for few-shot examples. To improve the performance and interpretability of few-shot object detectors, we propose an attentive few-shot object detection network (AttFDNet) that takes the advantages of both top-down and bottom-up attention. Being task-agnostic, the bottom-up attention serves as a prior that helps detect and localize naturally salient objects. We further address specific challenges in few-shot object detection by introducing two novel loss terms and a hybrid few-shot learning strategy. Experimental results and visualization demonstrate the complementary nature of the two types of attention and their roles in few-shot object detection. Codes are available at https://github.com/chenxy99/AttFDNet

Index Terms—Few-Shot Object Detection, Object Detection, Few-Shot Learning, Attention, Bottom-Up Attention, Top-Down Attention.

1 INTRODUCTION

Humans can learn novel knowledge from just one or two examples, which is a unique capability that modern artificial intelligence systems yet to develop. Recently, with their remarkable performance driven by large-scale datasets, deep neural networks (DNNs) have dominated the computer vision community. In many applications though, it is labor-intensive and sometimes impractical to collect a large amount of training data and annotations. In object detection, for example, annotating all the possible bounding boxes can be exhausting. Besides, domain-specific applications are generally costly in data collection due to the requirement of expertise.

Few-shot object detection is a trending research topic aiming at training object detectors that generalize well with a small amount of object annotations. Studies have shown that directly applying DNNs designed for big datasets to few-shot object detection tasks often leads to overfitting [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12]. Various learning strategies, such as meta-learning [4], [5], [6], [7] and transfer learning [1], [2], [3], have been explored to address this issue. Specifically, by combining some state-of-the-art methods gaining significant improvement in object detection, such studies [3], [9], [10] succeed to boosting the performance of few-shot object detection. More recently, any-shot object detector [11] proposes a realistic setting for the unseen and few-shot novel categories and weakly any-shot object detector [12] extend the former any-shot object detector with weakly supervision. However, under extremely few-shot situations, the very limited supervision is still insufficient for learning representative features of objects. Recent few-shot object detection studies [4], [5], [7] started to use the self-learned attention mechanism due to its effectiveness in many computer vision tasks. Attention often serves as a guidance to the most relevant spatial regions where models should assign a high priority when updating their parameters. However, because the learning of attention is dependent on top-down supervision, it could be difficult to train a generalizable attention model when only a small number of training samples are accessible. Therefore, with fewer training samples, the self-learned top-down attention tends to be less effective.

To address this challenge, we introduce an attentive few-shot object detection network (AttFDNet) by complementing the top-down attention with bottom-up attention learned from eye-tracking data. The bottom-up attention [13], [14], [15] also known as saliency, simulates where humans look without influences from tasks. It is directed towards interesting objects that naturally attract attention and can provide supplemental information for the detection of few-shot objects. It has been applied in different tasks, such as mobile robot vision navigation [16], [17], saliency detection [18], salient object detection [19], [20] and the prediction of where people look [21]. As shown in Fig. 1 by combining the top-down attention with bottom-up attention, the proposed object detector can successfully detect and localize few-shot object categories. Although top-down attention map is spread out, the saliency succeeds to capturing the object of interest and hence helps the detector effectively use the important feature to boost the final detection result. To support the learning of the proposed attention mechanism in few-shot object detection, we further propose two concentration losses and a hybrid few-shot learning strategy. The concentration losses allow the detector to boost its ability to discriminate different categories, while the hybrid learning strategy can provide a good initialization to prevent the model from overfitting. Quantitative results on the PASCAL VOC [22], [23] dataset show that incorporating bottom-up attention is able to significantly improve the few-shot object detection performance. With qualitative analysis, we further demonstrate the complementary roles of the bottom-up and top-down attention in few-shot object detection.

To sum up, we propose a novel AttFDNet for few-shot object detection.
Our contributions are four-fold: 1) we first leverage visual saliency maps as a bottom-up attention mechanism to complement the top-down attention that sometimes fail to capture objects of interest. 2) We propose the object concentration loss and background concentration loss to improve the intra-class agreements and avoid some hard negative anchors introduced to the calculation of the loss. 3) We also design a hybrid few-shot learning strategy that exploits the advantages of both transfer learning and meta-learning. 4) We provide a comprehensive qualitative analysis for the complementary characteristic of top-down attention and bottom-up attention.

We begin with a brief review of the related work in Section 2. Then, we introduce our AttFDNet in Section 3 which consists of the detailed designs of the object detector, the bottom-up and top-down attention mechanisms, and the objective functions. Next, in Section 4, we propose to modify the general one-stage object detector into the hybrid structure suitable for few-shot object detection to prevent from overfitting. In Section 5, we perform extensive experiments and show the corresponding quantitative and qualitative results followed by Section 6 concluding the paper.

2 RELATED WORK

With the fast development of deep learning, object detection has achieved significant success with a large amount annotation data. However, it is labor-intensive and sometimes difficult to collect such data and the corresponding annotations. The trending topic, few-shot learning has been developed and obtained remarkable performance in class recognition task. Furthermore, attention plays an important role in many different vision tasks and human eye-tracking data is beneficial for identifying the novel objects. We discuss these three main topics in this section.

Object detection is a classic computer vision task. Early methods formulate the object detection problem as the classification of a number of candidates sampled from sliding windows [24] or region proposals [25], [26]. Recently, many DNN-based object detectors have been proposed. Most of these detectors can be generally categorized as one-stage detectors or two-stage detectors. One-stage detectors, such as CenterNet [27], YOLO [28], [29], [30], SSD [31] and their variants [32], [33], simultaneously predict the bounding boxes and categories of objects. They are usually more efficient but less accurate. Differently, for the sake of high precision, two-stage detectors explicitly generate class-agnostic region proposals and further classify them into different object categories. R-CNN [34] and its corresponding variants [35], [36], [37] would fall into this category. Both approaches require intensive supervision to achieve favorable performance, so they are difficult to extend for novel objects with few examples.

Few-shot learning methods [38] have been widely applied in object recognition [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], with a focus of addressing the core issue of unreliable empirical risk minimizer. For object detection, a few different few-shot learning approaches have been proposed. The low-shot transfer detector (LSTD) [4] uses a regularized transfer learning framework to leverage object knowledge from source to target domains. Context-transformer [2] proposes to leverage the object knowledge from source-domain as a guidance and exploit contexts from the training images in the target-domain and hence distinguishes object confusion caused by annotation scarcity. Few-shot object detection [3] proposes to fine-tune the last layer of the two-stage object detector in the novel training stage with cosine similarity for the box classifier which achieves significant improvement. RepNet [49] replaces the standard linear classifier with a distance-based classifier to allow new few-shot categories to be learned on the fly. Recent research based on meta-learning [39] has also obtained remarkable performance [4], [5], [6], [7], [9], resulting in better generalization and faster deployment than transfer learning. Low-shot classification correction network (LSCN) [8] proposes classification refinement with four different parts (unified recognition, global receptive field, inter-class separation, and confidence calibration) to boost the performance of the overall classes. Apart from the use of meta-learning, opendeden centre net (ONCE) [9] built on the CenterNet [27], first proposes a new study of incremental few-shot object detection setting, where the new classes are registered incrementally without using the samples from base classes. Co-attention and co-excitation (CoAE) [10], uses the nonlocal operation [50] to explore the co-attention embodied in the query-target pair and the squeeze-and-co-excitation scheme [51] to emphasize the correlated feature channels to uncover the relevant proposals. Then it proposes a proposal ranking that the most relevant proposals to the query would appear in the top portion of the ranking list by a margin-based ranking algorithm. Any-shot object detection [11] proposes a realistic setting for the unseen and few-shot novel categories and trains them simultaneously in the same framework. The few-shot object detection is the special case of this framework. Furthermore, weakly-supervised any-shot object detection [12] introduces the weakly-supervision into the any-shot object detector. DID [52] proposes to address the continuous low-shot object detection problem, which is different from our aim and does not introduce any attention mechanism to the object detectors. Most of these methods are based on meta-learning that is known to be very sensitive to novel examples and may cause a performance drop on base categories. They also fail to work in extremely few-shot scenarios. To improve the detection performance for both base and novel categories, the proposed attentive few-shot object detector adopts a hybrid learning strategy with both transfer learning and imprinting.

Attention has been widely used in the design of neural networks for many vision tasks [53], [54], [55], [56]. The attention mechanism grants models the ability to focus on more important spatial locations or feature channels. It is noteworthy that even without the explicit supervision from human eye-tracking data, many attention models can learn where to focus simply by optimizing the task objectives. Supervised with a sufficient amount of annotations, the self-learned top-down attention can perform reasonably well in many vision tasks. Recent literature [50], [53] have exhaustively experimented the use of attention in object detection related tasks. The recently proposed few-shot object detectors [4], [5], [7] have also demonstrated the effectiveness of top-down attention. Specifically, YOLO-Low-Shot [4] and Meta R-CNN [5] both use a meta-model to produce reweighting attentive vectors for each specific category from the support set. They apply the attentive vectors on intermediate query features to obtain better detection results. Further, Fan et al. [7] propose an Attention-RPN that calculates the depth-wise cross correlation between support features and query features to improve the few-shot detection performance. While these studies learn attention in a top-down manner, the computed attention vectors or maps often fail to highlight the correct objects of interest, resulting in suboptimal model performance and lack of interpretability. In this work, we demonstrate that bottom-up attention could play
Fig. 1. In few-shot object detection, due to insufficient supervision, top-down attention learned from object annotations may fail to focus on objects of interest. (a) Input image with the ground-truth bounding box. (b) The top-down attention map. (c) The bottom-up attention map. (d) Detection result of the proposed method. It demonstrates the complementary characteristic of the top-down attention and bottom-up attention, where saliency can provide extra information to compensate the miss of information from top-down attention. We would discuss this characteristic in our qualitative analysis.

Fig. 2. The network architecture of the proposed attentive few-shot object detector. First, we use the saliency model to generate the bottom-up attention for a given image. Then we send the image to the backbone, and use the generated bottom-up attention as well as the top-down attention through the backbone to provide a guidance of the specific spatial feature map. Last, we arrive to the six prediction heads to get the corresponding detection results related to the localization and category of an object. The backbone of the network is highlighted in blue, while the six prediction heads are highlighted in yellow.

The attentive few-shot object detector is composed of a one-stage object detection backbone and a number of prediction heads. In particular, the backbone network leverages both bottom-up and top-down attention for object detection. While the use of a self-learned top-down attention has been proven effective in conventional object detection tasks, in few-shot object detection, the performance of top-down attention is still limited with the insufficiency of training data and the misalignment with human visual attention. Thus, our method differentiates itself from the previous works by highlighting the importance of bottom-up attention in few-shot object detection. Although the network architecture is applicable to object detection in general, it is particularly useful in the few-shot context because of the complementary bottom-up attention mechanism that naturally detects regions of interest without requiring top-down supervision.

3 ATTENTIVE FEW-SHOT OBJECT DETECTION NETWORK

Training a few-shot object detector consists of two stages. In the base-training stage, a general object detector is trained on a large set of annotated images to detect a number of base categories. Next, in the novel-training stage, several novel object categories are added to the training data, each with only \( K \) annotations. The goal of few-shot object detection is to train a \( K \)-shot object detector by making use of the already trained base detector and the new data to detect all objects of the base and novel categories. In this section, we first focus on the general base-training stage and present the design of an attentive few-shot object detector. We will then introduce a novel concentration loss to address particular challenges in the novel-training stage.

3.1 One-Stage Object Detection

The proposed object detector flexibly integrates various kernels and dilated convolution layers into an SSD-style detector (see Fig. 2). It is composed of a visual encoder (i.e., VGG Net [57], [58]), two attention pathways (i.e., bottom-up attention and top-down attention), and six prediction heads that detect objects at different scales. Each detector head uses a convolutional layer to predict the bounding boxes, and another convolutional layer followed by a fully-connected layer to predict the object categories.

3.2 Bottom-Up and Top-Down Attention

An intrinsic challenge of few-shot object detection is that object detectors hardly find correct regions where the objects can be detected. The proposed attention pathways address this challenge by assigning different weights to the spatial locations, so that important features do not get ignored. As illustrated in Fig. 2, bottom-up attention and top-down attention detect important image regions in different ways. On the one hand, the detector can learn model attention by itself from the bounding box annotations, which has been commonly accepted by many studies due to its efficiency and effectiveness. On the other hand, bottom-up attention computed by a saliency prediction algorithm is not only interpretable but also applicable in a similar way to prioritize features. In the following, we introduce the design of top-down attention and then present
how bottom-up attention can be incorporated to further improve the detector’s performance.

On the one hand, the design of our top-down attention model is inspired by the global context (GC) block \([53]\), which benefits from the simplified nonlocal block \([50]\) and the squeeze-excitation (SE) block \([51]\). It is a lightweight network capturing long-range dependencies for the general representation of a scene effectively. To compute the top-down attention, we extract the \(C\)-dimensional feature maps \(y \in \mathbb{R}^{C \times H \times W}\) from the \(conv_4\_3\) layer, where \(y_{i,j} \in \mathbb{R}^C\) represents the local feature vector at the \(i,j\)-th pixel of the feature maps. The feature maps \(y\) is fed to a convolution layer \(W_k\) to compute a soft attention map
\[
h_{i,j} = \frac{e^{W_k y_{i,j}}}{\sum_{w=1}^{H} \sum_{m=1}^{W} e^{W_k y_{w,m}}}. \tag{1}
\]
The attention map \(h\) is used to model the spatial response from the top-down attention. It is multiplied with the feature maps \(y\) to compute the weighted global features to capture the long-range dependencies for the global representation of a scene:
\[
y' = y * h, \tag{2}
\]
where \(*\) represents the tensor multiplication. More specifically, we formulate the expression of \(y'\):
\[
y' = \sum_{i,j} y_{i,j} h_{i,j}.
\]
Hence \(y'\) models the global context of this specific feature map.

The global feature transform is specifically designed for the top-down attention to capture the channel-wise dependencies. As a lightweight attention block, it is easier to fine-tune with few training samples. Then, we put the weighted global features \(y'\) through a bottleneck transform that consists of a convolution layer \(W_{v1}\), a normalization layer (LN), a ReLU operation, and a convolution layer \(W_{v2}\), sequentially. An element-wise addition is used to fuse the bottleneck output with the original features in a residual form:
\[
z = y + W_{v2} \text{ReLU}(\text{LN}(W_{v1} y')). \tag{3}
\]

To further improve the object detection performance, we compute the saliency map of the input image \(x\), using a bottom-up attention model denoted as \(g(x; \varphi)\), where \(\varphi\) represents the parameters of this model. The computed saliency map is transformed and multiplied with the fused features \(z\) as
\[
z' = z \odot \ln(\epsilon + g(x; \varphi)), \tag{4}
\]
where \(\epsilon\) is a hyper-parameter, which is used to control the influence of the bottom-up attention and \(\odot\) represents the channel-wise multiplication.

Finally, the attended features \(z'\) are used as the input to the next convolution layer of the object detection network and the remaining backbone is unchanged.

### 3.3 Objectives for Base and Novel Detectors

#### Base-training loss function.

The loss commonly used in object detection \([31]\), \([35]\) contains a smooth-\(L_1\) term for bounding box regression (i.e., \(L_{bbox}\)) and a multi-class cross entropy \(L_{cls}\) for object classification \([31]\), \([35]\). It can be denoted as
\[
L(\theta) = \frac{1}{N} \left( L_{cls}(\theta) + \alpha L_{bbox}(\theta) \right), \tag{5}
\]
where \(N\) is a default number of matched bounding boxes, and \(\alpha\) is the hyper-parameter that balances the weights of the two loss terms. In the base-training stage, the proposed object detector is trained using this general loss function.

#### Novel-training loss function.

In the novel-training stage, a number of challenges arise due to the limited number of training examples. To address these challenges, we design two concentration losses for few-shot object detection: the object-concentration loss and the background-concentration loss. They allow the object detector to better classify positive/negative anchors (i.e., bounding box candidates) in few-shot object detection. In brief, the object concentration loss helps the features corresponding to the same object get together.

1. **Object-concentration loss.**

   In few-shot object detection, the commonly used cross-entropy loss sometimes fails to distinguish similar categories (e.g., cats vs. dogs). The reason is that the number of samples is not enough for the fully-connected layer to learn more discriminative parameters and difficult to train the VGG \([57]\), \([58]\) and extra layers \([33]\) to encode more representative features for different categories. To better classify different few-shot object categories, we propose an object-concentration loss that maximizes the cosine similarity between positive anchors (i.e., those having a sufficiently large IoU with the ground-truth bounding box) of the same category. It pushes the features and their corresponding weights in the fully-connected layer closer to improve their intra-class agreements.

   The object-concentration loss measures the cosine similarity between the final convolutional layer features and the weights of the fully-connected layer. Specifically, we denote the feature of the prior anchors as \(f_i, 1 \leq i \leq N_{anchor}\), where \(N_{anchor}\) is the number of prior anchors in RFB \([33]\). We also denote the weights of the final fully-connected layer as \(w_j, j = 1, 2, \ldots, N_{cls}\), where \(N_{cls}\) is the number of categories. Both the features and the weights are normalized into unit vectors \([59]\). Next, we define an indicator function
\[
I_{i,j} = \begin{cases} 1 & \text{if } j \leq N_{anchor}, \frac{w_j^T f_i}{\|f_i\| \|w_j\|} \geq \theta, \\ 0 & \text{otherwise,} \end{cases}
\]
where \(\theta\) represents the \(i\)-th prior anchor belongs to the \(j\)-th category. The object-concentration loss for the positive anchors is denoted as
\[
L_{\text{conc}}^+ (\theta) = -\frac{\sum_{i=1}^{N_{anchor}} \sum_{j=1}^{N_{cls}} I_{i,j} w_j^T f_i}{\sum_{i=1}^{N_{anchor}} \sum_{j=1}^{N_{cls}} I_{i,j}}. \tag{6}
\]

2. **Background-concentration loss.**

   A unique challenge of few-shot object detection is the unavailability of complete annotations i.e., both the base and novel objects can remain unlabelled in the training images. On the one hand, novel objects (e.g., horse in Fig. [3]b) can be unlabeled in the base training set. On the other hand, base objects (e.g., person, dog, cat in Fig. [3]c) or objects of different novel categories (e.g., cow in Fig. [3]c) can also be unlabelled in the novel training set. In applications, there are two practical reasons of such incomplete annotations: (1) The two datasets are developed separately with different focuses. (2) Completely annotate the novel dataset may significantly increase the cost of data collection. Because of the incomplete annotations, with hard negative example mining \([31]\), the anchors corresponding to unlabelled objects are likely to be used as negative examples. Training a detector with such examples can lead to a catastrophic detection performance.

   To tackle this problem, we define a background-concentration loss to minimize the cosine similarity between the feature corresponding to the selected hard negative anchors and the weights for background in fully-connected layer. We represent the fully-connected layer weights corresponding to the background category as \(w_0\), and define a indicator function
\[
I_i = \begin{cases} 1 & 1 \leq i \leq N_{anchor} \text{ corresponds to the background category,} \\ 0 & \text{otherwise,} \end{cases}
\]
and the novel-training loss function can be written as
\[
L_{\text{conc}}^- (\theta) = -\frac{\sum_{i=1}^{N_{anchor}} I_i w_j^T f_i}{\sum_{i=1}^{N_{anchor}} I_i}.
\]

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The novel detector has additional parameters (red) for predicting novel categories. The parameters of the fully-connected layer for novel categories can be initialized from imprinting method [52], [59]. Specifically, following the incremental learning strategy [61], we set the knowledge distillation loss $L_{\text{dist}}(\theta)$ as the combination of the logits and the regression outputs between the base categories results from the base detector and the corresponding base categories results from the few-shot novel detector. Following [61], we use $L2$ loss for regression outputs as it demonstrates more stable training and performs better. The hyper-parameters $\alpha$, $\beta$, $\eta$, $\gamma$ determine the weights of the corresponding loss terms.

### 4 Hybrid Few-Shot Learning Strategy

Conventional few-shot learning methods are based on either transfer learning or meta-learning. In this work, we propose a hybrid few-shot learning strategy that exploits the advantages of both while resolving their problems. In particular, with the proposed network architecture, we first train a base object detector on a large dataset that provides sufficient annotations of base categories. In the novel-training stage, to make the best use of the knowledge learned by the base detector, we initialize the parameters of the novel object detector using parameters from the base object detector and an imprinting initialization method. The parameter initialization also allows the novel object detector to overcome overfitting incurred from the lack of training data.

As shown in Fig. 4, since the novel object detector is extended from the base object detector, the backbone (blue) and the prediction head layers corresponding to the base object categories (green) can be directly initialized with the parameters of the base object detector. However, given the new object categories added, the novel detector has additional parameters (red) for predicting the novel object categories and their bounding box positions. These additional parameters need to be initialized before novel-training.

We adopt two different strategies to initialize the convolutional layers for bounding box regression and the fully-connected layers for object classification. For the bounding box regression, since the convolutional layer is object-agnostic and only encodes information for detecting boundaries, we can directly copy the already learned parameters from the base object detector to the novel one. For the object classification, we initialize the final fully-connected layer following the imprinting method [52], [59]. Because the penultimate convolutional layer of the base object detector outputs discriminative features for different object categories, we can feed the novel images to the base object detector, and extract the features from its penultimate layer. After a normalization, we compute the average of these features for each novel category, and use the averaged feature vector as the weights of the fully-connected layer.

With this hybrid strategy, the novel object detector can be properly initialized, so that the novel learning will not overfit the support set and forget the base categories. It is fine-tuned on the support set containing all the novel data and a small portion
of samples from the base categories, until the object detection performance converges for all the base and novel categories.

5 EXPERIMENTS AND RESULTS

We conduct experiments and ablation studies to demonstrate the effectiveness of the proposed method. This section reports experimental details and results.

5.1 Dataset and Settings

The proposed few-shot object detector is trained and evaluated on the widely-used PASCAL VOC [22, 23] dataset. Following the common practice [29, 31, 35], we train our detector on the 2007 and 2012 training and validation sets, and use the 2007 test set for evaluation. Similar to the settings of YOLO-Low-Shot [4], Meta R-CNN [5] and MetaDet [6], we evaluate the trained detectors with three splits, each selecting 5 random novel categories and using the remaining 15 as the base categories. The three different novel class sets are (bird, bus, cow, mbike, sofa), (aero, bottle, cow, horse, sofa) and (boat, cat, mbike, sheep, sofa), respectively. All the annotations for the base categories are used in the base-training stage, while only K bounding boxes for each novel class and 3K bounding boxes for each base category are used in the novel-training stage [5]. The K-shot object detection is performed based on extremely few-shot cases K = (1, 2, 3) across all three base/novel splits.

We also evaluate our methods on MS COCO [62], the widely-accepted object detection benchmark. With 118k training images (train2017) and 5k validation images (val2017), MS COCO has a more diverse set of 80 categories compared with PASCAL VOC. In our experiments, we choose the same 20 categories as PASCAL VOC [22, 23], and use them and remaining 60 categories as the novel categories and base categories.

We further consider the cross-benchmark setting to transfer knowledge from COCO to PASCAL VOC. The few-shot object detector is trained with the 60 base categories of MS COCO and evaluated on the 20 novel categories of PASCAL VOC.

5.2 Implementation Details

The resolution of the input is 300 × 300 pixels following the RFB Net [33]. We adopt the Saliency Attentive Model (SAM) [63] to predict the bottom-up attention map. SAM was trained on the SALICON dataset [64] with all the parameters are frozen while training the object detector. We set the hyper-parameter α = 1 following the RFB Net [31, 33], and set γ = 1 following the common practice [61].

In the base-training phase, we use the Adam [65] optimizer with β1 = 0.9, β2 = 0.999 and L2 weight-decay 0.0005. The batch size is 64. The base object detector is trained for 150 epochs, using a step-wise learning rate decay: 4 × 10−4 by epoch 90, 4 × 10−5 by epoch 120, and 4 × 10−6 by epoch 140. Following the RFB Net [33], we also use the warmup strategy to stabilize the training.

In the novel-training stage, we use the SGD optimizer with momentum 0.9. The novel object detector is fine-tuned for 600 epochs, using a step-wise learning rate decay: 2 × 10−3 by epoch 250, 2 × 10−4 by epoch 400, and 2 × 10−5 by epoch 500.

5.3 Evaluation Results

PASCAL VOC. First, we present quantitative evaluations of the proposed method.

Comparison with baseline. To demonstrate the advantages of the introduced approach, we compare two variants of our method with a baseline method. The baseline, namely RFB-ft-full, takes a two-phase training strategy to directly fine-tune the top-down attention-based RFB object detector [33]. It first uses the base categories to train the detector, and then uses the combination of the base categories and novel categories to fine-tune the detector until it fully converges. The two variants of our method use different saliency models as bottom-up attention. AttFDNet (BU′+TD) uses the BMS [66] saliency model and AttFDNet (BU+TD) uses the SAM [63] saliency model. Both of them utilize the proposed concentration losses and the hybrid learning strategy. Compared with the baseline (RFB-ft-full), AttFDNet (BU+TD) improves the performance significantly (e.g., +135% for 1-shot on Split 2 and +160% for 2-shot on Split 3). The improvements may come from multiple components of our proposed methods (i.e., the use of bottom-up attention, concentration losses and the hybrid learning strategy). Between SAM and BMS saliency models, the two detectors’ performances are similar. The AttFDNet (BU+TD) model is also significantly better than the RFB-ft-full baseline. It demonstrates the robustness and generalizability of the proposed method. It also suggests that the performance gain is not from the external training on the SALICON dataset, since the BMS model is not data-driven.

Comparison with the state of the art. The results of our proposed AttFDNet (BU+TD) is also compared with four state-of-the-art few-shot object detectors, LSTD [1], YOLO-Low-Shot [4], Meta R-CNN [5] and MetaDet [6]. For a fair comparison, we use the same data sampling method as Meta R-CNN [5] does. As shown in Table 2, the AttFDNet (BU+TD) outperforms LSTD (YOLO)-full [1] in all the 9 cases (e.g., +217% for 2-shot on Split 1; +242% for 2-shot on Split 3), YOLO-Low-Shot [4] in 8 out of the 9 cases (e.g., +100% for 1-shot on Split 1; +35% for 2-shot on Split 2), the Meta R-CNN [5] in 8 out of the 9 cases (e.g., +54% for 1-shot on Split 2 and +60% for 2-shot on Split 3) and the MetaDet [6] in 6 out of the 9 cases (e.g., +69% for 2-shot on Split 1; +22% for 2-shot on Split 3). These improvements demonstrate the effectiveness of the proposed method in few-shot object detection. Notably, with a relatively low-resolution input (i.e., 300 × 300 pixels), our method is also more cost-efficient than YOLO-Low-Shot (416 × 416 pixels) and Meta R-CNN (800 × 600 pixels).

Table 2 presents the detailed evaluation results. In general, the proposed AttFDNet (BU+TD) or AttFDNet (BU′+TD) achieves a high overall mean average precision (mAP, averaged over all base and novel categories) on both splits. It is noteworthy that all the few-shot object detectors trained with the novel categories have decreased APs on the base categories, compared with their base detectors. However, the proposed AttFDNet (BU+TD) considerably outperforms the state-of-the-art and RFB-ft-full on base categories. Such results suggest that the bottom-up attention mechanism and hybrid training strategy effectively keep the performance of base categories from catastrophic forgetting. They also suggest that the hybrid training strategy alleviates the negative impacts from the random selection of the support set. So without sacrificing the detection performance on base categories, the proposed AttFDNet (BU+TD) and AttFDNet (BU′+TD) effectively
learn novel category features to improve its performance on the novel categories.

**MS COCO.** We evaluate 10-shot and 30-shot scenarios on the MS COCO benchmark with the standard metrics AP, AP₅₀, and AP₇₅. The evaluation results on the novel categories are presented in Table 3. Our AttFDNet (BU+TD) is consistently better than RFB-ft-full (e.g., +41.8% AP₇₅ for 10-shot), suggesting that few-shot object detectors can gain benefits from the introduced top-down and bottom-up attention. Our proposed AttFDNet (BU+TD) outperforms LSTD (YOLO)-full [1] (e.g., +561.9% AP₇₅ for 10-shot), YOLO-Low-Shot [4] (e.g., +202.2% AP₇₅ for 10-shot) and MetaDet [6] (e.g., +127.9% AP₇₅ for 10-shot) in all the cases. It also outperforms the Meta R-CNN [5] in 5 out of 6 cases (e.g., +110.6% AP₇₅ for 10-shot). These significant performance improvements demonstrate that our AttFDNet (BU+TD) can achieve better bounding box regression and object category classification. Our AttFDNet (BU+TD) performs better than the baseline and state-of-the-art approaches.

**MS COCO to PASCAL VOC.** We evaluate our method with 10-shot data of each categories from PASCAL. The mAP of AttFDNet (BU+TD) is 33.9%, while the proposed AttFDNet (BU+TD) achieves 40.3% mAP. Compared with LSTD (YOLO)-full [1] 29.0%, YOLO-Low-Shot [4] 32.3% mAP and Meta R-CNN [5] 37.4% mAP. The performance of the baseline (RFB-ft-full) is 28.9% mAP. It suggests that bottom-up attention can also provide extra information to boost the object detection performance across different benchmarks.

### 5.4 Qualitative Analysis

Next, we compare qualitative results between the AttFDNets with and without bottom-up attention. As shown in Fig. 5, without the bottom-up attention, the baseline detector AttFDNet (TD) either fails to detect the objects or easily overfit the support set. Differently, with an off-the-shelf saliency model (i.e., SAM), our AttFDNet (BU+TD) can significantly improve the object detection performance on base and novel categories. Bottom-up attention can (a) help object detectors remember previously acquired knowledge, (b) classify object categories more accurately, (c) avoid missed classification, (d) reduce ambiguous results, and (e) improve the precision of bounding box localization. These improvements are mostly due to the complementary nature of bottom-up attention and top-down attention. A comparative analysis on the PASCAL VOC 2007 test set shows week correlations between the bottom-up and top-down attention maps (Pearson’s r = 0.208, Spearman’s ρ = 0.205), suggesting that the two attention mechanisms highlight different regions of interest. Fig. 6 further demonstrate the complementary nature of the two attention mechanisms. We summarize three typical scenarios where the two attention mechanisms complement each other:

**Scenario 1:** Bottom-up attention can successfully capture the objects of interest. In this scenario, compared with top-down attention, bottom-up attention plays an important role by placing a high priority on the salient regions related to the object to detect. As shown in the Fig. 5a,b, the bottom-up attention itself can result in correct object detection (i.e., *bird* and *boat*), while top-down attention...
TABLE 3
Few-shot detection performance on MS COCO 2017 validation set for novel categories. We compare the state-of-the-art methods with baseline (RFB-ft-full) and AttFDNet (BU+TD: bottom-up (BMS) and top-down, BU+TD: bottom-up (SAM) and top-down) under 10-shot and 30-shot scenarios of novel categories.

| Method                | 10-shot |           |           | 30-shot |           |           |
|-----------------------|---------|-----------|-----------|---------|-----------|-----------|
|                       | AP      | AP_{50}   | AP_{75}   | AP      | AP_{50}   | AP_{75}   |
| LSTD (YOLO)-full [1]  | 3.2     | 8.1       | 2.1       | 6.7     | 15.8      | 5.1       |
| YOLO-Low-Shot [4]     | 5.6     | 12.3      | 4.6       | 9.1     | 19.0      | 7.6       |
| Meta R-CNN [5]        | 8.7     | 19.1      | 6.6       | 12.4    | 25.3      | 10.8      |
| MetaDet [6]           | 7.1     | 14.6      | 6.1       | 11.3    | 21.7      | 8.1       |
| RFB-ft-full           | 9.2     | 13.9      | 9.8       | 12.0    | 18.6      | 13.0      |
| AttFDNet (BU+TD)      | 9.5     | 15.4      | 10.0      | 12.0    | 19.8      | 12.1      |
| AttFDNet (BU+TD)      | 12.9    | 19.5      | 13.9      | 16.3    | 24.6      | 17.3      |

Fig. 5. Qualitative results of 2-shot object detection. Detected objects are annotated in green.

attention either fails to have a clearly focused region or attends to similar regions as bottom-up attention.

Scenario II: Bottom-up attention may sometimes focus only on a part of an object (e.g., Fig. [c]), or highlight some but not all objects of interests (e.g., Fig. [d]). Under such circumstances, top-down attention can focus on different regions/objects that bottom-up attention misses. For example, in Fig. [c], bottom-up attention only highlights the upper part of the person and a small part of the mbike. Therefore, the top-down attention plays an important role in detecting the entire bounding box of the person and the mbike. In addition, in Fig. [d], we can observe that bottom-up attention highlights the person and bus, but not the car. The top-down attention, on the other hand, is directed to the car and the bus but misses the person. As a result, the object detector jointly considers the different regions highlighted by the bottom-up and top-down attention maps, to detect all the three objects.

Scenario III: There are also cases where top-down attention can play a more important role in detecting objects of interest. For example, as shown in Fig. [e], due to the complexity of the scene and the relatively small object region (i.e., the cow walking on the bank), the bottom-up attention not only highlights the cow, but also the background. In this case, the object detector relies on top-down attention to exclude a large area of irrelevant regions and pay more attention to the more related regions.

We also demonstrate the effectiveness of our proposed AttFDNet (BU+TD) by comparing the qualitative results between AttFDNet (BU+TD) and one of the state-of-the-art methods Meta R-CNN [5]. As shown in Fig. [f] AttFDNet (BU+TD) predicts the object categories more accurately and positions the bounding boxes more precisely. Specifically, we observe four typical benefits from the incorporation of bottom-up attention: (1) Object categories are classified more accurately (e.g., cow in Fig. [f] and bus in Fig. [g]). (2) Bounding box localization is more precise (e.g., motorbike in Fig. [f]). (3) The detector better remembers previously acquired knowledge (e.g., sofa in Fig. [f]). (4) The number of ambiguous results is reduced (e.g., bird in Fig. [f]). These observations suggest that bottom-up attention can highlight the globally salient features so that the detector can better detect and recognize such regions, leading to the improved performances.

In sum, the qualitative examples suggest that bottom-up attention and top-down attention localize different regions of interest in a complementary manner, which jointly improves the detection performance.

5.5 Ablation Studies
We present results of comprehensive ablation studies to analyze the effects of various components. All ablation studies are conducted on the PASCAL VOC 2007 test set for the 2-shot scenario on the second and third splits.

Effects of the backbone. First, we compare the performances of two backbone networks (i.e., VGG [57], [58] and ResNet-101 [67]) on detecting base and novel object categories. Table 4 shows that VGG outperforms the ResNet-101 model on both base and novel categories. The bottom-up attention consistently improves the performance of few-shot object detectors despite the different backbones used.
Fig. 6. Top-down attention and bottom-up attention are complementary. From left to right: images with detected objects annotated in green from the results of our AttFDNet (BU+TD), images overlaid with bottom-up attention maps and top-down attention maps, respectively.

Fig. 7. Qualitative examples of 2-shot object detection results on PASCAL VOC. We compare our proposed AttFDNet (BU+TD) with Meta R-CNN [5]. Detected bounding boxes are shown in green.

For simplification, we use VGG backbone in all the other experiments since such one-stage detectors SSD [31] and RFB [33] also use VGG backbone.

**Effects of the hyper-parameters.** With a grid search, we optimize the hyper-parameters $\beta$ and $\eta$ that control the weights of the proposed object-concentration loss and background-concentration loss. Table 6 shows that the introduction of concentration loss terms can improve the performance of few-shot detection on the novel categories. It is also noteworthy that improving the performance of the novel categories could decrease the performance on the base categories. Based on it, we chose $\beta = 2$ and $\eta = 0.4$ as the hyper-parameters for all the experiments, as they result in the highest overall mAP. Furthermore, we analyze the 2-shot scenario for split 2 in the test set. The cosine similarity between the features of the ground truth prior anchors and their corresponding weights of the final fully-connected layer is increased from 0.452 to 0.573 compared with the elimination of the object-concentration loss, which demonstrates that object-concentration loss can improve the intra-class agreement of features.

We further conduct ablation studies on the selection of the hyper-parameter $\epsilon$ that controls the smoothness of the bottom-up attention when it is integrated into the model. A larger $\epsilon$ indicates a more smooth integration and hence assigns similar weights for salient/non-salient regions of the feature map. When $\epsilon$ is too large, the proposed AttFDNet (BU+TD) would degrade to AttFDNet (TD), since the model cannot fully utilize the information from the bottom-up attention to boost the few-shot object detection in this case. A smaller $\epsilon$ indicates a sharper integration, which means that we assign more weights to the salient regions than the non-salient regions. When $\epsilon$ is too small, we would assign an approximately zero weight (even when $\epsilon = 1$, this weight would become 0) for non-salient regions to generate the feature map, which will
The ablation study (TD: top-down only, BU+TD: bottom-up and top-down) of network backbones VGG [57, 58] and ResNet-101 [67] for the 2-shot scenario.

| # Split | Backbone | Attention | Base mAP | Novel mAP | All mAP |
|---------|----------|-----------|----------|-----------|---------|
| 2       | VGG      | TD        | 69.2     | 17.6      | 56.3    |
|         |          | BU+TD     | 70.0     | 20.7      | 57.7    |
|         | ResNet-101 | TD       | 67.2     | 18.4      | 55.0    |
|         |          | BU+TD     | 66.5     | 21.2      | 55.2    |

We investigate the effectiveness of the proposed distillation. Table 6 shows the performance among different parameter settings. On the one hand, a large \( \gamma \) indicates more attention would be paid on the performance of the base categories and hence ignores the performance of the novel categories. When \( \gamma \) is too large (e.g., \( \gamma = 1.0 \)), the proposed AttFDNet (BU+TD) would focus on the performance of the base categories, while the performance of novel categories would degrade as indicated in Table 6. On the other hand, a small \( \gamma \) means that the network would focus on the performance of the novel categories. Due to the few-shot object detection scenario, it would be easy to overfit the novel training dataset. More severely, it would also be harmful to the learned feature representation of the different aspects of the object and hence lead to the degradation of the overall performance. When \( \gamma \) is too small (e.g., \( \gamma = 0.0 \)), the proposed AttFDNet (BU+TD) would focus on the performance of the novel categories. It leads to a catastrophic forgetting on the base categories and losses the learned feature representation as indicated in Table 6.

**Effects of the different modules.** We investigate the effectiveness of the proposed modules. Compared AttFDNet (TD) with AttFDNet (BU’+TD) and AttFDNet (BU+TD), we observe that the bottom-up attention can provide extra information to improve the performance. The improvement of the use of SAM and BMS also demonstrate the robustness of our proposed bottom-up attention. We can also observe that all AttFDNet models (TD, BU’+TD and BU+TD) significantly outperform the baseline (RFB-ft-full). Next, we discuss the three loss terms introduced in Equation (5). AttFDNet (BU+TD) w/o distillation represents the ablation of distillation module from our AttFDNet (BU+TD), while AttFDNet (BU+TD) w/o bk means the ablation of background concentration loss from our AttFDNet (BU+TD). Furthermore, AttFDNet (BU+TD) w/o (bk+obj) is the ablation of background concentration loss and object concentration loss from our AttFDNet (BU+TD). Without the distillation loss, the performance of the base mAP degrades significantly, which means that distillation loss can play an important role in remembering the previous detection tasks. We can also observe that the concentration loss can still help to boost the performance of base and novel categories.

### 6 Conclusion

In this paper, we have introduced a novel attentive few-shot object detector that incorporates bottom-up and top-down attention for detecting novel object categories with extremely few training samples. Learning from human attention data, bottom-up attention provides prior knowledge about salient regions and plays a different role from the top-down attention learned from the object annotations. To address specific challenges in few-shot object detection, we also propose a hybrid few-shot learning strategy and two concentration loss terms. The proposed detector achieve state-of-the-art performances in extremely few-shot scenarios, demonstrating the significant and complementary roles of the two attention mechanisms. Future efforts will be focused on...
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