Meta Faster R-CNN: Towards Accurate Few-Shot Object Detection with Attentive Feature Alignment

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Abstract
Few-shot object detection (FSOD) aims to detect objects using only a few examples. How to adapt state-of-the-art object detectors to the few-shot domain remains challenging. Object proposal is a key ingredient in modern object detectors. However, the quality of proposals generated for few-shot classes using existing methods is far worse than that of many-shot classes, e.g., missing boxes for few-shot classes due to misclassification or inaccurate spatial locations with respect to true objects. To address the noisy proposal problem, we propose a novel meta-learning based FSOD model by jointly optimizing the few-shot proposal generation and fine-grained few-shot proposal classification. To improve proposal generation for few-shot classes, we propose to learn a lightweight metric-learning based prototype matching network, instead of the conventional simple linear object/nonobject classifier, e.g., used in RPN. Our non-linear classifier with the feature fusion network could improve the discriminative prototype matching and the proposal recall for few-shot classes. To improve the fine-grained few-shot proposal classification, we propose a novel attentive feature alignment method to address the spatial misalignment between the noisy proposals and few-shot classes, thus improving the performance of few-shot object detection. Meanwhile we learn a separate Faster R-CNN detection head for many-shot base classes and show strong performance of maintaining base-classes knowledge. Our model achieves state-of-the-art performance on multiple FSOD benchmarks over most of the shots and metrics.

Introduction
Object detection is one of the most fundamental and challenging tasks in computer vision. Recent years have witnessed great progress in this field using deep learning techniques (Ren et al. 2015; Redmon et al. 2016; Liu et al. 2016; He et al. 2017; Tian et al. 2019). However, deep learning based object detection methods need a sufficient amount of human annotations for model training, which are expensive to collect and unavailable for rare categories. Given scarce training data, these models suffer from the risk of overfitting and poor generalization ability (Kang et al. 2019).

This has motivated research on few-shot object detection (FSOD) (Karlinovsky et al. 2019). Given a set of base classes with plenty of examples and another set of novel classes with only few examples, the goal is to transfer the knowledge learned from base classes to novel classes to assist in object detection for novel classes. How to learn few-shot object detectors both efficiently and effectively remains challenging.

Object proposal (Hosang et al. 2015) is a key ingredient in modern object detectors (Ren et al. 2015; Liu et al. 2016), which usually first generate a few potential object bounding boxes (a.k.a proposals) or dense anchor boxes and then convert object detection to a classification task1. Training the region proposal network (RPN (Ren et al. 2015)) and proposal classification network (Fast R-CNN (Girshick 2015)) using a large scale dataset have been demonstrated successful. However, as shown in Table 2, the quality of proposals for few-shot novel classes using existing methods are far worse than that of many-shot base classes. Specifically, the detector could miss some high IoU proposals for novel classes due to misclassification with very few examples. Moreover, the

1We omit the bounding box regression for simplicity
Figure 2: Our proposed object detection model for both many-shot base classes and few-shot novel classes. The detection of base and novel classes are decoupled into two branches with a shared feature extractor. For base classes, we follow the original Faster R-CNN detection pipeline. For novel classes, we propose a novel few-shot detector with a two-stage coarse-to-fine prototype matching network. Our method can improve the accuracy of few-shot object detection for novel classes, and also maintain high accuracy for base classes.

The spatial location of novel-class proposals usually do not tightly align with the true objects, and may contain only part of the objects, including large background areas, which makes the following few-shot proposal classification challenging.

To address the aforementioned issues, we propose a meta-learning based FSOD method consisting of two modules, in Figure 1. First, the Meta-RPN is proposed to generate category-specific proposals for few-shot novel classes both efficiently and effectively. Specifically, we use a lightweight non-linear matching network to measure the similarity between the dense sliding windows (a.k.a anchor boxes (Ren et al. 2015)) in the query image feature map and the few-shot novel classes, instead of the traditional simple linear object/nonobject classifier, e.g., used in RPN (Ren et al. 2015), thus improving the proposal recall for few-shot novel classes and easing the burden of the following fine-grained proposal classification. Second, the Meta-Classifier is proposed to measure the similarity between the noisy proposals and few-shot novel classes. Our key observation is that performing spatial alignment and focusing on corresponding foreground regions between the high-resolution proposal features and class prototypes (Snell, Swersky, and Zemel 2017) is crucial for few-shot proposal classification. To this end, we propose to estimate soft correspondences between each spatial position in the proposal features and class prototypes. Then based on the soft correspondences, we learn to perform spatial alignment between the two features and discover foreground regions. After that, a non-linear prototype matching network is learned to measure the similarity of the aligned features.

The whole network, denoted as Meta Faster R-CNN, can be trained using meta-learning. After meta-training on the data-abundant base classes, our method can enroll few-shot novel classes incrementally without any training during meta-testing. Our meta-learning models achieve competitive results compared with the state-of-the-arts (SOTAs) fine-tuned on novel classes. With further fine-tuning, we can achieve SOTA accuracy on multiple FSOD benchmarks.

To enable base classes detection in our model, previous methods (Wang et al. 2020; Wu et al. 2020; Xiao and Marlet 2020; Yan et al. 2019) usually build a softmax based detector with both base and novel classes. We argue that the softmax detector is inflexible to add new classes because it always needs to fine-tune a new classifier. We also show in Table 6 that our few-shot detector is not suitable for base classes considering both running speed and detection accuracy. Considering both strengths and weaknesses of the two detectors, we propose to take advantage of the two detectors, by learning a separate Faster R-CNN detection head for base classes using the shared feature backbone, as shown in Figure 2. Experimental results demonstrate the effectiveness of our model for both base and novel classes.

Our contributions include: (1) We propose to learn a coarse-grained prototype matching network (Meta-RPN) with a metric-learning based non-linear classifier to generate class-specific proposals for novel classes with high recall. (2) We propose to learn a fine-grained prototype matching network (Meta-Classifier) with a spatial feature alignment and a foreground attention module to address the spatial misalignment issue between proposal features and class prototypes, which improves the overall detection accuracy. (3) Considering both strengths and weaknesses of the softmax based detector and our few-shot detector, we propose to take advantage of the two detectors to detect both base and novel classes by learning two detection heads. (4) We achieve SOTA results on multiple FSOD benchmarks.
Related Work

Object Detection. Recently, deep learning (Krizhevsky, Sutskever, and Hinton 2012; He et al. 2016) based methods have dominated the SOTA of object detection. They can be roughly grouped into proposal based methods (Ren et al. 2015; He et al. 2017; Han, Zhang, and Li 2017a, 2018) and proposal-free methods (Redmon et al. 2016; Liu et al. 2016; Han, Zhang, and Li 2017b; Tian et al. 2019). Our method belongs to the first kind as our goal is to push the limit of detection accuracy, which is still the top priority for FSOD.

Few-Shot Object Detection. Building on modern object detectors (e.g., Faster R-CNN (Ren et al. 2015)), existing works (Wang et al. 2020; Wu et al. 2020; Kang et al. 2019; Fan et al. 2020; Perez-Rua et al. 2020; Yan et al. 2019; Xiao and Marlet 2020; Hsieh et al. 2019; Osokin, Sumin, and Lomakin 2020; Wang, Ramanan, and Hebert 2019; Wu, Sahoo, and Hoi 2020; Han et al. 2021, 2022a,b) have explored adapting the current detection pipeline to the few-shot setting, including both proposal generation and proposal classification. For proposal generation, many current methods (Karlinsky et al. 2019; Wang et al. 2020) directly use the Region Proposal Network (RPN (Ren et al. 2015)) trained on base classes to generate proposals for novel classes. However, it could miss some high IoU boxes for novel classes as novel-classes boxes are regarded as background regions in RPN training over base classes. Fine-tuning RPN on novel classes (Wu et al. 2020; Xiao and Marlet 2020) could improve the performance, but the generalization ability to unseen classes is limited. Other methods (Kang et al. 2019; Hsieh et al. 2019; Fan et al. 2020) propose to modulate query image features with few-shot classes in order to generate category-specific proposals. However, the simple linear object/nonobject classification in RPNs often lacks the robustness in detecting high-quality proposals needed for FSOD. For proposal classification and bbox regression, few-shot learning methods (Vinyals et al. 2016; Snell, Swersky, and Zemel 2017; Sun et al. 2018; Finn, Abbeel, and Levine 2017; Girshick and Komodakis 2018; Ma et al. 2021; Huang et al. 2022; Ypsilantis et al. 2021), especially prototypical networks (Snell, Swersky, and Zemel 2017) are introduced to extract prototype representation for each class, and then classification can be performed by using a neural network to measure the similarity between proposal features and class prototypes (Sung et al. 2018; Koch, Zemel, and Salakhutdinov 2015). This has been demonstrated effective in FSOD. However, they ignore the spatial misalignment issue: similar semantic regions do not appear at the same spatial position between the noisy proposals and few-shot support images. Our proposed model with Meta-RPN and Meta-Classifier could alleviate the above-mentioned issues.

Our Approach

Task Definition

In few-shot object detection task, we have two disjoint sets of classes $C = C_{base} \cup C_{novel}$, including base classes $C_{base}$ and novel classes $C_{novel}$, and $C_{base} \cap C_{novel} = \emptyset$.

For the base classes, we have plenty of labeled training images $D = \{(I_i, y_i), I_i \in \mathcal{I}, y_i \in \mathcal{Y}\}$ with bounding box annotations, where $I$ is a training image, $y$ is the ground-truth labels for $I$. Specifically, $y = \{(c_i, box_i), c_i \in C_{base}, box_i = \{x_i, y_i, w_i, h_i\}\}^N_{i=1}$, containing $N$ bounding boxes in the image $I$ with both class label $c_i$ and box location $box_i$ for each bounding box.

For the novel classes, also known as support classes, we only have $K$-shot (e.g., $K = 1, 5, 10$) labeled samples for each class, also known as support images. Specifically, the support images for novel class $c \in C_{novel}$ is $S_c = \{(I'_i, box_i), I'_i \in \mathcal{I}, box_i = \{x_i, y_i, w_i, h_i\}\}^K_{i=1}$, where $I'_i$ is a training image, $box_i$ is the box location of the object with class label $c$.

The goal is to detect objects of novel classes using few-shot examples and also keep high accuracy for base classes.

The Model Architecture

The key idea of the meta-learning based FSOD is to learn how to match the few-shot classes with query images using the abundant training data of base classes, so that it can generalize to few-shot novel classes. Considering the difficulty of object detection with few-shot examples, we propose to learn the detection model via a coarse-to-fine manner following (Ren et al. 2015). Meanwhile, we learn a separate Faster R-CNN detection head for base classes using plenty of training samples. Our model mainly has the following four modules, as shown in Figure 2.

(1) Feature Extraction. We use a siamese network to extract features for both query images and the support images. Formally, given a query image $I_q \in \mathbb{R}^{H_q \times W_q \times 3}$, a deep feature backbone is used to extract CNN features $f_q = F(I_q) \in \mathbb{R}^{H \times W \times C}$, where $H$, $W$, $C$ are the height, width and channel dimension of the extracted features. Typically we use the output after $res4$ block in ResNet-50/101 (He et al. 2016) as our default image features.

For the support images, we first extend the original object bounding boxes with some surrounding context regions as the common practice in previous works (Fan et al. 2020; Kang et al. 2019; Yan et al. 2019; Xiao and Marlet 2020), and crop the corresponding object regions in the image. Then the cropped images are adjusted to the same size (Fan et al. 2020), and fed into the shared feature backbone to extract the CNN features $F'(I'_c)$ for each support image $I'_c$.

(2) Object Detection for Base Classes. On top of the feature extraction network, RPN is used to generate category-agnostic proposals of all base classes in the image. After that, for each proposal, an R-CNN classifier (Girshick 2015) is employed to produce softmax probabilities over all base classes $C_{base}$ plus a “background” class and bbox regression.

(3) Proposal Generation for Novel Classes. We aim to generate proposals for few-shot novel classes both efficiently and effectively. In Figure 3, similar to RPN, we attach a small subnetwork on top of $f_q$ to generate proposals centered at each spatial position of $f_q$. Specifically, a $3 \times 3$ conv and ReLU layer is used to extract features for multi-scale anchors centered at each spatial position. For each novel class, we take the averaged CNN features of the $K$-shot support images as the class prototype $f^c = \frac{1}{K} \sum_{i=1}^{K} F(I'_i), c \in C_{novel}$. Then in order to get the same feature size as the anchor boxes, we conduct spatial average pooling to get the pooled
where classifier in RPN, we propose to build a matrix is then used to compute proposal-aligned prototype.

Figure 4, we first establish soft correspondences between two
tial misalignment between proposals and class prototypes
accurate localization of proposals for novel classes, the
Meta-RPN, we use high-resolution features for fine-grained
matching thanks to the cascade design. However, due to the

Meta-RPN, we use high-resolution features for fine-grained

Different from using the spatially-pooled class prototypes in

To calculate the similarity of the generated propos-

Classes.

we first use a siamese network (includ-

tural misalignment between proposals and class prototypes
have a negative effect on the few-shot classification.

We propose an attention based feature alignment method

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and localize foreground regions. A non-linear classification
module is then followed to calculate the similarity score.

(a) Spatial Alignment Module. Formally, given a pair of input features \(f_p\) and \(\tilde{f}^c\), both feature maps have \(H' \times W'\) CNN grid features, each with a embedding dimension of \(\mathbb{R}^{C'}\). We compute the affinity matrix \(A \in \mathbb{R}^{H' \times W' \times H' \times W'}\), with each item the dot product of two embeddings,

\[
A(i, j) = f_p(i) \tilde{f}^c(j)^T
\]

where \(A(i, j)\) denotes the similarity of embeddings \(f_p(i)\) and \(\tilde{f}^c(j)\) at spatial location \(i\) and \(j\) of the proposal feature and class prototype respectively. Next is to calculate the proposal-aligned class prototype. The feature alignment is achieved by taking the weighted average of all CNN grid features in the prototype according to the dense semantic correspondence in the affinity matrix \(A\). An example is shown in Figure 4. We show the importance of the alignment direction in Table 4.

Formally, for a spatial location \(i \in \mathbb{R}^{H' \times W'}\) in \(f_p\), softmax normalization is performed over all spatial locations in \(\tilde{f}^c(j)\),

\[
A(i, j)' = \frac{\exp(A(i, j))}{\sum_k \exp(A(i, k))}
\]

Then, the proposal-aligned class prototype \(\tilde{f}^c\) at each spatial location \(i \in \mathbb{R}^{H' \times W'}\), can be calculated by aggregating the embeddings of all positions in class prototype \(\tilde{f}^c\) using the normalized similarity,

\[
\tilde{f}^c(i) = \sum_j A(i, j)' \tilde{f}^c(j)
\]

(b) Foreground Attention Module. As the proposals may contain undesired background regions, a foreground attention mask \(M \in \mathbb{R}^{H' \times W'}\) is generated to highlight the corresponding object regions. Formally, for each spatial location \(i\) in \(f_p\),
we summarize the similarity of \( f_p(i) \) to each spatial location in \( \tilde{f}^c \) using the affinity matrix \( A \). Then sigmoid function \( (\sigma) \) is applied to get the normalized probability,

\[
M(i) = \sigma(\sum_j A(i, j)) = \frac{1}{1 + \exp(-\sum_j A(i, j))}
\]  

(5)

where higher values in \( M \) indicate that the corresponding locations in \( f_p \) are more similar to that of the aligned prototype \( \tilde{f}^c \), and are more likely to be the same semantic parts. On the other hand, the background regions in the proposals can hardly find corresponding locations in the class prototypes with high similarity, leading to lower values in \( M \). Therefore we multiply the attention mask \( M \) with both \( \tilde{f}_p \) and \( \tilde{f}^c \) to focus on the corresponding foreground regions,

\[
\tilde{f} = M \odot \tilde{f}^c, \quad \tilde{f}_p = M \odot f_p
\]  

(6)

In addition, we further multiply the features \( \tilde{f}^c \) and \( \tilde{f}_p \) with learnable parameters \( \gamma_1 \) and \( \gamma_2 \) (both initialized as 0) and add back the input features for stable training,

\[
\tilde{f} = \gamma_1 \tilde{f}^c + \tilde{f}^a, \quad \tilde{f}_p = \gamma_2 \tilde{f}_p + f_p
\]  

(7)

(c) Non-linear Classification Module. To measure the similarity between the final features \( \tilde{f}^c \) and \( \tilde{f}_p \), we employ a feature fusion network to aggregate the two features with high-resolution,

\[
f = [\Psi_{Mult}(\tilde{f}^c \odot \tilde{f}_p), \Psi_{Sub}(\tilde{f}^c - \tilde{f}_p), \Psi_{Cat}[\tilde{f}^c, \tilde{f}_p]]
\]  

(8)

where \( \Psi_{Mult}, \Psi_{Sub} \) and \( \Psi_{Cat} \) are three similar CNN networks, each with 3 conv and ReLU layers for non-linear fusion. After that, a binary classification and bbox regression layer are followed for final detection.

The Training Framework

Our training framework has the following three steps, 

 Meta-learning with base classes. We learn our Meta-RPN and Meta-Classifier using meta-training. In each training episode, we sample a few classes from base classes, each class with \( k \)-shot support images, to simulate the FSOD scenario for novel classes. Besides, we also sample a few query images with ground-truth boxes, and use binary cross-entropy loss and smooth \( L1 \) loss (Girshick 2015) for model training. To prevent the vast number of negative matching pairs from overwhelming the training loss, we keep a ratio of 1:3 for positive and negative matching pairs for balanced model training. After meta-training, the model can be directly applied to novel classes during meta-testing without any training.

 Learning the separate detection head for base classes. After meta-training, we fix the parameters of the backbone feature extractor, and learn the RPN and R-CNN module for base classes following (Ren et al. 2015).

 Fine-tuning with both base and novel classes. We only use base-classes dataset for training in the first two step. For fine-tuning, we sample a small balanced dataset (original images) of both base and novel classes following the common practice in previous works (Kang et al. 2019; Yan et al. 2019; Xiao and Marlet 2020; Fan et al. 2020; Wu et al. 2020; Wang et al. 2020). We make sure that the total number instances for each novel class is exactly \( k \)-shot in the sampled dataset, which are also used as the support set during testing.

 The key difference of meta-learning and fine-tuning is that, there is no training on novel classes in meta-learning. We only use the support set of novel classes to calculate prototypes during meta-testing. The support images are cropped from the original images using ground-truth annotations. While during fine-tuning, we use the original novel-classes images as query images to fine-tune our few-shot detector, including both the Meta-RPN and Meta-Classifier. The model performance for novel classes will improve when we gradually use more images for fine-tuning.

Experimental Results

Datasets

We use two widely-used FSOD benchmarks MSCOCO (Lin et al. 2014) and PASCAL VOC (Everingham et al. 2010) for model evaluation, and follow FSOD settings the same as previous works (Kang et al. 2019; Wang et al. 2020) by using the exact same few-shot images for fair comparison. More implementation details are included in the supplementary material.

Ablation Study

Effectiveness of our Meta-RPN. We compare three different proposal generation methods for novel classes (RPN, Attention-RPN (Fan et al. 2020), and our Meta-RPN) in Table 1 (b), (c) and (d) and Table 2. (1) The object/nonobject classifier in RPN, pretrained on base classes, do not generalize well to novel classes as only base-classes regions are regarded as true objects in training and it may miss some high IoU boxes for novel classes due to misclassification. Both proposal AR and detection AP of novel classes using RPN are much lower than the others. (2) Using class prototype to reweight query image features in Attention-RPN (Fan et al. 2020) can generate class-specific proposals and improve both proposal AR and detection AP. (3) By using a metric-learning based non-linear classifier with a lightweight feature fusion network, our Meta-RPN can perform better prototype matching compared with the simple linear object/nonobject classifier used in Attention-RPN (Fan et al. 2020). Our Meta-RPN consistently improves using different number of proposals, especially after fine-tuning. We use 100 proposals for each novel class by default.

Effectiveness of our Meta-Classifier. (1) We first show that using high-resolution features in our Meta-Classifier can achieve good results by comparing Table 1 (a) and (b). This is because fine-grained details could provide important clues when performing matching between two features. (2) Although using high-resolution feature maps improve matching performance, the large spatial misalignment between proposals and few-shot classes is harmful for matching due to the inaccurate proposal localization. Using our attentive feature alignment with both spatial alignment and foreground attention module, the performance can be improved consistently for most of the shots and metrics by comparing models in Table 1 (d), (e) and (f). (3) We show in Table 4 the importance...
The table shows the proposal average recall (AR) using the models in Table 1 with only meta-training and 10-shot meta-testing.

| #Proposals† | RPN | Attention-RPN† | Our Meta-RPN |
|-------------|-----|----------------|--------------|
| Meta-training the model on base classes, and meta-testing on novel classes |
| 10          | 7.8 | 18.0           | 18.3         |
| 100         | 20.5| 32.7           | 33.2         |
| 1000        | 35.0| 44.1           | 44.9         |
| Fine-tuning the model on novel classes, and testing on novel classes |
| 10          | 9.2 | 18.7           | 18.9         |
| 100         | 22.9| 33.2           | 33.8         |
| 1000        | 37.4| 44.7           | 45.8         |

Base classes: AR@10=27.6, AR@100=43.3, AR@1000=51.0

Table 2: Proposal average recall (AR) using the models in Table 1 (b), (c) and (d), with 10-shot meta-testing and 10-shot fine-tuning. † The number of proposals generated for each novel class. ‡ (Fan et al. 2020).

Effectiveness of our non-linear feature fusion network. As shown in Table 3, we perform ablation study of our proposed feature fusion network in both Meta-RPN and Meta-Classifier. We can find that using simple element-wise fusion operations especially the Mult subnetwork shows good results, which is widely used in previous work (Kang et al. 2019; Yan et al. 2019; Xiao and Marlet 2020; Fan et al. 2020). Directly using the Cat subnetwork does not achieve good results in both Meta-RPN and Meta-Classifier. This is because the Cat subnetwork attempts to learn complex fusion between the two features, which is not easy for training and generalization. When combining all three subnetworks together, it could ease the training of the Cat subnetwork and learn complementary fusion beyond the Mul and Sub subnetworks.

**Effectiveness of both meta-learning and fine-tuning.** We show the comparison of meta-training and fine-tuning in Table 1 (f) and (h) for ResNet-50, and in Table 1 (g) and (i) for ResNet-101. We can find that using fine-tuning, the performance improves for large shot settings (e.g., 10/30 shot). However, for extremely few-shot setting (e.g., 2 shot), the performance could hardly improve because fine-tuning is prone to overfitting using very few examples.

We would like to highlight the advantage of our meta-learning method. (1) **Efficient for adaptation to novel classes.** After meta-training on base classes, there is no further training during meta-testing. To enroll novel classes, we only need to calculate their prototype representations via net-
Table 5: Few-shot object detection performance (AP50) on the PASCAL VOC dataset. We use ResNet-101 following most of the previous works. † Our reimplementation results.

| Method                                      | Venue | Novel Set 1 | Novel Set 2 | Novel Set 3 |
|---------------------------------------------|-------|-------------|-------------|-------------|
|                                             |       | 1 2 3 5 10  | 1 2 3 5 10  | 1 2 3 5 10  |
| FSRW (Kang et al. 2019)                     | ICCV 2019 | 14.8 15.5 26.7 33.9 47.2 | 15.7 15.3 22.7 30.1 40.5 | 21.3 25.6 28.4 42.8 45.9 |
| MetaDet (Wang, Ramanan, and Hebert 2019)    | ICCV 2019 | 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 (Yan et al. 2019)                | ICCV 2019 | 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 (Wang et al. 2020)                | ICML 2020 | 36.8 29.1 43.6 55.7 57.0 | 18.2 29.0 33.4 35.5 39.0 | 27.7 33.6 42.5 48.7 50.2 |
| TFA w/ cos (Wang et al. 2020)               | ICML 2020 | 39.8 36.1 44.7 55.7 56.0 | 23.5 26.9 34.1 35.1 39.1 | 30.8 34.8 42.8 49.5 49.8 |
| Xiao et al. (Xiao and Marlet 2020)          | ECCV 2020 | 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 |
| MPSR (Wu et al. 2020)                       | ECCV 2020 | 41.7 42.5 51.4 55.2 61.8 | 24.4 29.3 39.2 39.9 47.8 | 35.6 41.8 42.3 48.0 49.7 |
| Fan et al. (Fan et al. 2020)†               | CVPR 2020 | 37.8 43.6 51.6 56.5 58.6 | 22.5 30.6 40.7 43.1 47.6 | 31.0 37.9 43.7 51.3 49.8 |
| SRR-FSD (Zhu et al. 2021)                   | CVPR 2021 | 47.8 50.5 51.3 55.2 56.8 | 32.5 35.3 39.1 40.8 43.8 | 40.1 41.5 44.3 46.9 46.4 |
| TFA + Halluc (Zhang and Wang 2021)          | CVPR 2021 | 45.1 44.0 44.7 55.0 55.9 | 23.2 27.5 35.1 34.9 39.0 | 30.5 35.1 41.4 49.0 49.3 |
| CoRPNs + Halluc (Zhang and Wang 2021)       | CVPR 2021 | 47.0 44.9 46.5 54.7 54.7 | 26.3 31.8 37.4 37.4 41.2 | 40.4 42.1 43.3 51.4 49.6 |
| FSCE (Sun et al. 2021)                      | CVPR 2021 | 44.2 43.8 51.4 61.9 63.4 | 27.3 29.5 43.5 44.2 50.2 | 37.2 41.9 47.5 54.6 58.5 |
| Meta Faster R-CNN (Ours)                    | This work | 43.0 54.5 60.6 66.1 65.4 | 27.7 35.5 46.1 47.8 51.4 | 40.6 46.4 53.4 59.9 58.6 |

Table 6: Base classes evaluation results on MSCOCO using ResNet-101. We compare our final model with the pre-trained base model using the softmax classifier, TFA (Wang et al. 2020) 30-shot fine-tuning, and 2/10/30-shot meta-testing using the few-shot model in Table 1 (g).

| Model                                      | AP  | Accuracy AP50 | Speed (limg) |
|--------------------------------------------|-----|----------------|--------------|
| Base model                                 | 39.2 | 59.3 42.8      | 0.21s        |
| TFA (Wang et al. 2020)                     | 35.8 | 55.5 39.4      | 0.21s        |
| 2-shot meta-testing                        | 18.5 | 29.4 19.8      | 2.1s         |
| 10-shot meta-testing                       | 21.4 | 33.6 23.1      | 2.1s         |
| 30-shot meta-testing                       | 22.7 | 35.3 24.7      | 2.1s         |

Figure 5: Visualization of the affinity matrix for feature alignment.
Table 7: Few-shot object detection performance on the MSCOCO dataset. We use ResNet-101 following most of the previous works. †Our reimplementation results using the exact same few-shot training instances as (Kang et al. 2019; Wang et al. 2020).
‡The authors report these results at https://github.com/YoungXIAO13/FewShotDetection.

Figure 6: Failure cases on COCO dataset. Detection score threshold is 0.5. Left: Missing detection of small objects ‘Person’. Right: Misclassification of the ‘Boat’. Future work could improve multi-scale object detection and introduce image context information for detection.

The limitation of the softmax based detector is the inflexibility to add new classes to the system, because they need to fine-tune a new softmax based detector with new classes. Our method addresses this problem by decoupling the detection of base and novel classes into two detection heads, and learning a class-agnostic FSOD for novel classes.

Comparison with State-of-the-arts
We compare our final model with the state-of-the-arts on two FSOD benchmarks in Table 5 and 7 respectively. (1) Most of the previous works only report fine-tuning results. We demonstrate that our meta-learning-only model improves significantly compared with the strong baseline model (Fan et al. 2020), and outperforms or at least attains comparable results compared with other SOTAs using fine-tuning, especially in extremely few-shot setting (e.g., 1/2-shot), where fine-tuning is not effective. (2) We achieve SOTA performance in most of the shots and metrics of the two FSOD benchmarks. The exception is that SRR-FSD (Zhu et al. 2021) and Halluc (Zhang and Wang 2021) have better performance on voc split1&2 1-shot setting due to the introduction of linguistic semantic knowledge and image hallucination, which is complementary to our model. Moreover, our meta-learning-only model shows better results in the more challenging MSCOCO 1/2-shot settings. (3) We show the failure cases in Figure 6. More results can be found in the supplementary material.

Conclusion
We propose a novel meta-learning based few-shot object detection model in this paper. Our model consists of the following two modules to tackle with the low quality of proposals for few-shot classes. First, a lightweight coarse-grained prototype matching network is proposed to generate proposals for few-shot classes in an efficient and effective manner. Then, a fine-grained prototype matching network with attentive feature alignment is proposed to address the spatial misalignment between the noisy proposals and few-shot classes. Experiments on multiple FSOD benchmarks demonstrate the effectiveness of our approach.

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