A Unified Framework for Attention-Based Few-Shot Object Detection

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Abstract

Few-Shot Object Detection (FSOD) is a rapidly growing field in computer vision. It consists in finding all occurrences of a given set of classes with only a few annotated examples for each class. Numerous methods have been proposed to address this challenge and most of them are based on attention mechanisms. However, the great variety of classic object detection frameworks and training strategies makes performance comparison between methods difficult. In particular, for attention-based FSOD methods, it is laborious to compare the impact of the different attention mechanisms on performance. This paper aims at filling this shortcoming. To do so, a flexible framework is proposed to allow the implementation of most of the attention techniques available in the literature. To properly introduce such a framework, a detailed review of the existing FSOD methods is firstly provided. Some different attention mechanisms are then reimplemented within the framework and compared with all other parameters fixed.

Keywords: Few-Shot Learning, Object Detection, Attention
1 Introduction

Few-Shot Object Detection (FSOD) is a challenging problem that aims to find all occurrences of a class in an image given only a few examples. Impressive progress has been made in object detection in the past decade, mostly because of deep convolutional networks (see e.g. [1, 2]). Current state-of-the-art performs high-quality detection, but it requires large annotated datasets and days of training to achieve that quality. Often, such requirements could not be met, and it is quite hard to achieve good performance for a specific task. The few-shot learning trend focuses specifically on this kind of use cases where data is scarce. Most few-shot approaches rely on a two-steps training strategy. First, the model is trained on a large dataset, slightly different from the desired task, to acquire general knowledge. Second, a fine-tuning step refines the model to learn the actual task. Of course, plenty of techniques have been introduced so that the fine-tuning does not disrupt base learning (see e.g. [3]). This has been extensively studied for classification in the past years. However, detection is a more challenging task than classification and has been only tackled recently from a few-shot perspective.

Current FSOD state-of-the-art is mainly based on attention mechanisms, which aim at extracting information about the task (i.e. semantic information about the classes that should be detected) from support examples. This information allows the network to condition the detection on the examples. It allows the network to adapt on the fly, provided with a few annotated images and a short fine-tuning step. A seminal work in this direction is presented in reference [4] which reweights features from the query image (i.e. the images in which the model performs the detection) with the features extracted from the support images. Plenty of methods based on the same idea have been introduced (see e.g. [5–8]). Although the attention mechanisms, deployed in most
FSOD methods, might differ from the original one proposed in [4], the main principle remains the same. Indeed, it combines information from the query image and the support set to detect only the objects annotated in the support.

The FSOD field is rapidly growing, and most new papers propose a novel attention technique. However, there are a lot of design choices that can be considered to address the FSOD problem. First, the detection framework (e.g. Faster R-CNN [1] or YOLO [2]) and its backbone (e.g. ResNet-50 or 101), then the different loss functions (e.g. L1, IoU, Focal Loss) to train each part of the network and finally all the hyperparameters that are tied to these methods (i.e. from the learning rate to the class splits for evaluation). All this makes the comparison between FSOD methods difficult. In this paper, the attention mechanism is considered as the heart of FSOD because it combines general features extracted from the input image and the conditioning features extracted from the support examples. Of course, it should be noted that not all works on FSOD are attention-based. Indeed, there exist some papers that use metric learning to solve FSOD (see e.g. [9–11]). Instead of combining query and support features, a generic embedding function is learned. The detection is then obtained from the comparison of the query and support embeddings. There are also approaches based only on fine-tuning. Although quite straightforward these methods generally do not perform as well as attention-based ones.

The main goal of this paper is to review a part of the attention-based FSOD methods and compare them fairly. To do so, a modular attention framework is proposed. It allows regrouping most attention-based methods under the same notations. Specifically, this framework is divided into three parts: spatial alignment, global attention, and fusion layer. This separation helps to easily implement the different mechanisms and facilitates the comparison.
Most importantly, this makes it possible to completely fix the other parameters and design choices without reimplementing each method. That way, a fair comparison of the performance of the different mechanisms can be obtained. The modular splitting also allows a deep understanding of what component of the attention is key for FSOD and gives insights to build better approaches. Moreover, to help the development of new techniques for FSOD and future comparisons, the code of the proposed framework will be made available\footnote{https://github.com/pierlj/aaf\_framework}. To our knowledge, there exist two papers that review FSOD methods [12, 13]. However, they focus on general FSOD while this work targets attention-based FSOD.

The rest of this paper is organized as follows. First, a review of existing methods for FSOD is conducted in Section 2. A formal description of the attention framework is then proposed in Section 3. Section 4 confirms the flexibility of the framework with a comparative analysis of some existing methods for FSOD. All these methods have been reimplemented through the proposed framework, achieving similar results to those reported in the original papers. Some insights about the key elements of the attention mechanisms are then provided. Section 5 concludes this paper.

## 2 Review of Existing Work on FSOD

This section reviews existing work on few-shot object detection. It begins with a summary of general object detection methods. Next, it presents the main principles of few-shot learning, and finally, it explains how these principles are applied to object detection in the scientific literature.
2.1 Overview of Object Detection Methods

Object detection, among other computer vision challenges, has made impressive progress with the rise of Convolutional Neural Networks (CNN). Some previous works, such as [14, 15], leverage CNNs to classify Region of Interest (RoI) generated by classical methods (e.g. selective search). However, these methods are slow and achieve relatively low performance. YOLO [2] and Faster R-CNN [1] have been the first fully convolutional approaches for object detection and are still the root of most recent work in this field. These two architectures are the most representative examples of the two kinds of detectors that exist: one-stage detectors with a trade-off on speed and two-stages detectors with a trade-off on accuracy. Plenty of improvements have been introduced over these methods. On the one hand, for one-stage detectors, Focal Loss [16] improves training balance between background and foreground. CenterNet [17] and CornerNet [18] propose new ways to predict boxes coordinates. FCOS [19] gets away from the concept of anchors boxes (a predefined set of boxes introduced both in YOLO and Faster R-CNN). On the other hand, two-stages detectors have been improved with pyramidal features extraction by [20], improving detection of objects of various sizes. Mask R-CNN [21] improves performance by adding an instance segmentation branch to Faster R-CNN. Recently, various works exploit self-attention mechanisms to increase detection quality. Dynamic Head combines three different types of attention, based on scale, location and current task [22]. Pushing even further, DETR [23] replaces the convolutional regressor and classifier with transformers.

2.2 Basic Concepts on Few-Shot Learning

Deep learning based methods achieve impressive results when provided with sufficient training data. However, it is often quite challenging to gather such a
dataset for a given use case. Hence, Few-Shot Learning (FSL) aims at learning tasks from only limited data. The main principle is to learn generic knowledge from large-scale training on a task similar to the actual problem. The model is then adapted to perform the final task from the scarce data available.

In FSL literature, a task is defined as $K$-shots, $N$-ways learning when the training set only contains $K$ examples for each of its $N$ classes. It is common to introduce the support and query sets for a given task. The support contains the available examples: $K$ images for each of the $N$ classes. It allows the network to adapt to the task by extracting relevant information from the examples. The query set contains images from the same classes and is used either for inference or training. For clarity, query and support images will refer to elements of the query and support sets respectively. Moreover, to assess the performance of FSL the set of classes is divided in base (or seen) and novel (or unseen) classes. Train and test classes can also be found in the literature. A large quantity of examples is available for base classes that serve during base training while for novel classes, only $K$ examples are available per class. Novel classes are presented to the network during fine-tuning and evaluation only. This allows assessing the generalization capabilities of the methods.

As summarized in Figure 1, FSL approaches can be classified as follows: fine-tuning, meta-learning, metric learning and attention-based. This classification could be refined as in [24] which offers a complete review of FSL.

**Fine-tuning** – This is the simplest way to tackle FSL. It consists in training the model on a large dataset with base classes examples only and then fine-tune it with a limited number of examples of the novel classes. While conceptually simple, these approaches prove to be effective. Nonetheless, they are often prone to catastrophic forgetting [3]: performance drops on base classes after
Fig. 1 Few-shot learning methods can be divided into 4 main categories: fine-tuning, meta-learning, attention-based learning and metric learning. Those are not completely separated, in particular, fine-tuning is part of the training strategy of many FSL methods. Episodic task training is also a widespread strategy for FSL.

fine-tuning. Plenty of tricks have been introduced to alleviate this issue. Fine-tuning on its own is not very powerful for FSL, but it is part of most other methods as their training strategy (see Figure 1).

**Meta-learning** – It attempts to learn models that can quickly adapt to a task. This is often performed by training two separate models: a meta-learner and a student (or learner). The meta-learner’s goal is to help the learner to train on new tasks. This can be achieved in different ways. For instance, in reference [25], a meta-learner that directly outputs weights updates for the student is proposed. Similarly, reference [26] proposes to only output initial weights for the learner. These techniques rely on a two-level optimization procedure. At the lower level, a task is selected (e.g. for classification: choosing a random subset of classes), and then the learner is trained for this task. At the higher level, the performance of the student is assessed on the current task and serves as a cost function for the meta-learner. This episodic training strategy improves adaptability to new tasks. However, these methods do not scale very well as the meta-learner often needs to be quite larger than the actual task learner.

**Metric Learning** – The goal of metric learning is to learn a generic embedding function from the base dataset, such that the embedding space is structured semantically, making it easier to distinguish between classes. To
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do so, a metric function is learned over the data manifold (or equivalently an embedding function that maps the data points into a Euclidean space). Input images are then classified according to the distance between their representations and the representations of the support examples in the embedding space. This has been introduced in the context of few-shot learning by Prototypical Networks [27]. Similarly, two separate networks can be trained to embed the support and query sets separately (e.g. [28]). Following these two methods, a series of improvements have been developed. For instance, in [29] a second network is trained to compute the similarity between prototypes and query embedding.

Attention-based Methods – Finally, there are methods similar to metric learning but which do not directly compare the query and support representations. Instead, the support representation is used to change the parameters of the model on the fly to adapt it to new tasks (i.e. new classes). The original idea has been proposed by [30]. A classification network is trained at the same time as a learnet whose purpose is to output some weights for the main network from the support images. That way, the network has dynamic weights and can adapt to new classes. Practically, the learnet is trained to output kernel weights adapted to the task from the support examples. This kernel is then plugged into the main detection network in a dynamic convolutional layer. This can be seen as an attention mechanism between a query image and support images, hence the Attention-based methods. Note that this is referred to as modulation in [12]. The query features are reweighted by the support features, with a channel-wise multiplication.

Usually, attention highlights features that are relevant to the task. In the case of self-attention (i.e. attention on the features themselves), this can be achieved by multiplying channel-wise a globally pooled feature vector with the
map itself, as proposed by [31]. It can also be with spatially distant features of the same image as in non-local neural networks [32] or Visual Transformers (ViT) [33]. But attention can also be computed with features coming from different images. In this case, features from external images are highlighted in the original map, this can be referred to as external or cross attention. This is particularly used for FSL to adapt query features to support examples. For instance, in Cross-transformers [34], the authors leverage transformer-like attention to spatially align the supports to the query. This makes the model more robust to intra-class variance and support choices.

2.3 Review of Few-Shot Object Detection Methods

Few-Shot Learning has been extensively studied in the light of classification tasks. For object detection however, the scientific literature is scarcer. This section aims to present some works proposed for FSOD and to compare them. They are divided into three different groups: transfer learning, metric learning, and attention-based learning. To our knowledge, there is no work completely based on meta-learning that tackles FSOD.

2.3.1 Fine-tuning

Low Shot Transfer Detector (LSTD) is a pioneer work on FSOD [35]. It proposes to first train a detector (Faster R-CNN) on a base dataset and then fine-tune it on a novel set containing only some examples of the novel classes. To prevent catastrophic forgetting, the authors introduced two regularization losses so that the network produces similar outputs for the base classes during fine-tuning. Closely related, reference [36] leverages the same idea without any additional loss. Instead, they choose to freeze all the network weights after base training except for the last classification and regressions layers. Reference
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[37] also proposes a basic fine-tuning strategy, but instead of freezing the network, they leverage a multiscale refinement branch, used only for training, to better guide the classification branch of the network. This way, a better balance between positive and negative samples is achieved, making base training and fine-tuning more efficient. Another method is proposed in [38] where two Faster R-CNN are trained: one on base classes and one on all classes (base and novel), as a fine-tuned version of the first one. Their main contribution is that both detectors are used together to output predictions. First, the objectness maps of base and novel detectors are combined so that the Region Proposal Network (RPN) outputs proposals both for base and novel classes. Next, the predictions of the base and novel heads are combined to get the bounding boxes for all classes. The authors also introduce a consistency loss so that the novel detector is encouraged to retain knowledge about base classes and alleviate catastrophic forgetting.

2.3.2 Metric Learning

For few-shot classification, metric-learning based methods are probably the most widespread. However, for detection, only a few works are based on this technique. RepMet [9] is one of the first, it consists in learning class representative vectors while training a modified Faster R-CNN detector. Closely related, [39] learns prototypes vectors as well as scale factors inside the CenterNet framework. These vectors are used in the classification head of the detector as class prototypes. The difference is that the vectors are learned through training and not simply computed from examples like in Prototypical Faster R-CNN [10]. The authors of this method proposed to embed a vanilla prototypical network into Faster R-CNN not only in the detection head but in the RPN as well. This prevents the RPN to specialize in base classes and output better proposals. Nevertheless, authors relate mitigated results with
this method. They hypothesize that computing prototypes from examples may not be the best detection strategy as the background is often dominant in the image, which can lead to biased prototypes and shortcut learning.

Reference [11] is halfway between RepMet and Prototypical Faster R-CNN. It computes the prototypes directly from the example but only in the second stage of the network. In addition, it leverages a contrastive supervised loss function to learn a semantically aware embedding space. These methods are all similar in how the class prototypes influence the classification of RoI. On the contrary, reference [40] uses the prototypes as reweighting vectors to enhance class-specific features of the embedded RoI. This is astride metric learning and attention-based methods, but it is presented from a metric learning perspective by its authors.

2.3.3 Attention-based

To address the shortcoming of metric learning-based methods, some works proposed attention-based techniques. The idea is to highlight relevant features for detection based either on the feature itself (self-attention) or the features of other instances (external attention). A seminal work in this field is [4], which trains a reweighting module along with a YOLO detector. The reweighting module outputs class-specific feature vectors through Global Pooling (GP) from the support set. These are then channel-wise multiplied with the query features extracted by the backbone (this operation is denoted $\text{CRW}$ for Class Re-Weighting in Table 1). Hence, class-specific query features are generated, and the detection head computes predictions for each class separately. Many works have been inspired by this idea. More generally, generating class-specific features and computing the detection separately is now standard in FSOD.

This has been used with different detection frameworks, for instance, references [8] and [41] are built upon Faster R-CNN and FCOS respectively. Other
authors proposed to leverage multi-scale reweighting vectors, such as in [5].

More sophisticated ways to combine information from query and support were also proposed. For instance, reference [42] trains three different heads that link, globally, locally, and patch-to-patch the features from the query and the support. Graph Neural Networks (GNN) can also combine the features and learn semantic relations between classes (see e.g. [43, 44]). Another way to combine query and support is to simply concatenate the features as in [22], but it requires that the features have the same spatial dimension.

\[ A_s(\phi_q, \phi_q) = \phi_q \phi_q^T \in \mathbb{R}^{m \times n} \]

\[ \tilde{\phi}_s = A_s^T \phi_s \in \mathbb{R}^{m \times d} \]

**Fig. 2** Spatial alignment between query and support feature maps. Similarity matrix is based on outer product between the maps. For sake of clarity, maps are reshaped as 2-D matrix where the first dimension controls the spatial position in the map: \( m \) positions for the query and \( n \) for the support. \( d \) is the number of channels. Similar colors mean that features are similar.

Another solution proposes to adjust the size of the features maps: spatial alignment. This consists in spatially reorganizing a feature map to match the other. For each location in the query map, the features from one support example (i.e. feature vectors at each location in the map) are linearly combined to produce a feature in the aligned support map (see Figure 2). This kind of alignment has been introduced in [32] for video classification. Feature alignment between successive frames improved overall performance by capturing long-range spatial dependencies. This idea has already been tested for FSL as mentioned in Section 2.2. Many choices can be made for the coefficients of the
linear combination, but often they are dynamically determined by computing the similarity between query and support features (in Table 1, all are referenced indifferently as \textit{QS Alignment} standing for query-support alignment). References \cite{45, 46} are based on this approach. Thus, the aligned maps can be easily combined and fed to the detection head. The combination is often performed through a non-learnable fusion layer composed of several point-wise operations and/or concatenation. In Table 1, these are denoted by their circle operator (e.g. $\oplus$ for addition), except for concatenation and the identity ($[\cdot, \cdot]$ and $\text{Id}$ respectively). In some cases, additional learnable modules are included to process the combination of query and support features before concatenation, this is denoted as \textit{learnable} in Table 1. The alignment mechanism can be associated with the global attention methods mentioned in the previous paragraph: reweighting features globally based on the support only, as in \cite{7} or the query and support similarity as in \cite{47} (\textit{Global Similarity Reweighting}). Alignment can also be carried out on the feature itself (i.e. without information from the support) as in \cite{48, 49}. The DETR framework is well suited for this kind of alignment mechanism as it is based on Visual Transformers. The few-shot variant of DETR, Meta-DETR described in \cite{48}, combines both self-attention and query-support alignment, achieving impressive performance. It first applies self-attention with a multi-head attention module and combines query and support features with a single-head module where query is taken as queries and support as keys and values.

Table 1 summarizes this literature analysis. The table is designed to compare attention mechanisms as this is the focus of this paper. Therefore, attention mechanisms are divided into three components that arise from the previous review: spatial alignment, global attention, and fusion layer. Methods without attention mechanism are also included in the Table to give a general overview of the methods available for FSOD.
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Table 1 Comparison of the FSOD methods from an attention perspective. This table separates the attention mechanisms into three components: spatial alignment, global attention, and fusion layer. Information about the original detection framework, the date of publication and the detection head is also included. All frameworks are working with multiscale features except for the one with the mention no FPN.

| Approach | Name               | Date  | Framework              | Alignment                  | Attention                  | Fusion                        |
|----------|--------------------|-------|------------------------|----------------------------|----------------------------|-------------------------------|
| AAF      | FRW [4]            | 2019  | YOLO (no FPN)          | None                       | GP + CRW                   | None                          |
|          | RSI [5]            | 2019  | YOLO                   | None                       | GP + CRW                   | None                          |
|          | ARMHD [42]         | 2020  | Faster R-CNN           | None                       | GP + CRW                   | None                          |
|          | VEOW [41]          | 2020  | Faster R-CNN           | None                       | GP + CRW                   | Pooling + Cat[⊕, ⊖, Id]       |
|          | WSAAN [43]         | 2020  | Faster R-CNN           | None                       | GP + GNN + CRW             | None                          |
|          | CACE [7]           | 2020  | Faster R-CNN           | None                       | GP + CRW                   | None                          |
|          | KT [44]            | 2020  | Faster R-CNN           | None                       | GP + GNN + CRW             | None                          |
|          | WOFT [8]           | 2021  | FCOS                   | None                       | GP + CRW                   | Pooling + Cat learnable       |
|          | FPDI [50]          | 2021  | Faster R-CNN           | Iterative Alignment via Optimization | CRW                      | None                          |
|          | MPRCN [47]         | 2021  | Faster R-CNN           | Rol Pooling + QS Alignment | Global Similarity RW       | Cat[⊕, Cat] learnable         |
|          | MDETR [48]         | 2021  | DETR (no FPN)          | Transformers-based Alignment | Transformers Self-Attention | None                          |
|          | DRL [51]           | 2021  | Faster R-CNN           | None                       | None                       | Pooling + Cat[⊕, ⊖, Id]       |
|          | DANA [46]          | 2021  | Faster R-CNN and RetinaNet | QS Alignment                | Background Attenuation      | Cat                           |
|          | SP [49]            | 2021  | Faster R-CNN           | Self-Alignment (query and support) | None                     | Cat                           |
|          | JCACKR [45]        | 2021  | YOLO                   | QS Alignment (higher order) | None                       | Cat                           |
|          | PNPDet [39]        | 2021  | Center Net (no FPN)    | None                       | CRW                        | None                          |
|          | UPE [40]           | 2021  | Faster R-CNN           | QS Alignment               | None                       | Id ⊕ Cat learnable            |
|          | RM [9]             | 2018  | Faster R-CNN           | None                       | None                       | None                          |
|          | FSCE [11]          | 2021  | Faster R-CNN           | None                       | None                       | None                          |
|          | PFRCN [10]         | 2021  | Faster R-CNN           | None                       | None                       | None                          |
|          | LSTD [36]          | 2018  | Faster R-CNN           | None                       | None                       | None                          |
|          | WOFG [38]          | 2020  | Faster R-CNN           | None                       | None                       | None                          |
|          | PFS [36]           | 2020  | Faster R-CNN           | None                       | None                       | None                          |
|          | MSPSR [37]         | 2021  | Faster R-CNN           | None                       | None                       | None                          |

3 AAF Framework for Attention in FSOD

In Section 2.3.3, three main components of attention mechanisms for FSOD have been identified. To compare them without other interfering architecture choices, a unifying framework is proposed. The purpose of this framework is to provide a flexible environment to represent existing attention techniques. The three main components are: spatial alignment, global attention and fusion layer. Most attention-based FSOD methods rely on one or more of these components as shown in Table 1. Therefore, it seems convenient to provide a flexible unifying framework that can be used to implement these methods. The framework should take as input the features from the query image $\phi_q$ as well as the features extracted from every support images $\phi_c$ for $c \in C$. It outputs
The main principle of attention-based FSOD method is to extract features from the query and support images, and combine query and support features to create multiple query feature maps, each specialized for the detection of one class. These maps are then processed by the same detection head to make the actual predictions.

Class-specific query features $\bar{\phi}_c^q$ in which features relative to class $c$ are reinforced (see Figure 3). In order to match the three components of attention described above, the AAF (Alignment, Attention, Fusion) framework is also divided into three parts as shown in Figure 4. Each component is described below independently and examples of the possible design choices are given. Of course, this framework is presented from the perspective of object detection. However, it could be helpful for other kinds of few-shot tasks such as classification, instance segmentation, or image generation. As long as a task requires to condition the results on support examples, this framework could be applied.

### 3.1 Query Support Alignment

The alignment module denoted $\Lambda$, spatially aligns the features from the query and the support. It is unlikely that objects of the same class appear at the same position inside query and support images. Therefore, direct comparison between their respective feature maps will not produce a high response. This is commonly avoided by pooling the support map and using it as a class-specific reweighting vector. This trick loses the spatial information about the support object, which can be detrimental for the matching. Furthermore, in the case of
detection, it is likely that more than one object is visible in an image. Global pooling is even more detrimental in this case, as it can mix features from different objects. Instead, an alignment between query and support maps can be performed through attention. The idea is to re-organize one feature map in comparison to the other, so that similar features are spatially close in the maps. The alignment operator is defined as follows:

\[
\tilde{\phi}_q^1, ..., \tilde{\phi}_q^c, \tilde{\phi}_s^1, ..., \tilde{\phi}_s^c = \Lambda(\phi_q^1, \phi_s^1, ..., \phi_q^c, \phi_s^c)
\]

with

\[
\begin{align*}
\tilde{\phi}_q^i &= \lambda_q(\phi_q^i, \phi_s^i) \\
\tilde{\phi}_s^i &= \lambda_s(\phi_q^i, \phi_q^i)
\end{align*}
\]

(1)

where \(\lambda_q, \lambda_s\) are linear combinations of their first input: \(\lambda(\phi, \rho) = A(\phi, \rho)^T \phi\) and \(A \in \mathbb{R}^{m \times n}\) is an affinity matrix representing the similarity between local features from \(\phi \in \mathbb{R}^{m \times d}\) and \(\rho \in \mathbb{R}^{n \times d}\). The definition of the matrix \(A\) determines how features are aligned. This formulation is quite similar to the non-local blocks described in [32]. An example of such alignment is described in [52]. Transformers attention can be understood as an alignment of the values to match the queries-keys similarity. A major difference is that the same feature map is used for all inputs (query, key, and value) in visual transformers so that features are self-aligned.

As an example, Meta Faster R-CNN, described in [47], leverages an alignment module with an affinity matrix \(A(\phi, \rho) = \phi \rho^T\) which represents the similarity between each pair of spatial locations between query and support maps. Only the support features are aligned so that they match query features. This can be implemented in the framework with \(A_q(\phi, \rho) = I\) and \(A_s(\phi, \rho) = \phi \rho^T\) (see Example A in Figure 4).
3.2 Global Attention

The global attention module, denoted $\Gamma$, combines global information of the supports and the query. It highlights class-specific features and softens irrelevant information for the task. This operator is defined as follows:

$$
\hat{\phi}^1_q, ..., \hat{\phi}^c_q, \hat{\phi}^1_s, ..., \hat{\phi}^c_s = \Gamma(\tilde{\phi}^1_q, ..., \tilde{\phi}^c_q, \tilde{\phi}^1_s, ..., \tilde{\phi}^c_s) \text{ with } \begin{cases} 
\hat{\phi}^i_q &= \gamma_q(\tilde{\phi}^i_q, \tilde{\phi}^i_s) \\
\hat{\phi}^i_s &= \gamma_s(\tilde{\phi}^i_q, \tilde{\phi}^i_q)
\end{cases}, \tag{2}
$$

where $\gamma_q, \gamma_s$ combine the global information from their inputs and highlight features. This is generally done through channel-wise multiplication. In this way, class-specific features are highlighted, while features not relevant to the class are softened. This module formulation is meant to be flexible so that a wide variety of global attention mechanisms can fit into it. For instance, reference [4] pools the support maps with a global max pooling operation (GP) into a reweighting vector and reweights the query features channels with it: $\gamma(\phi, \rho) = \phi \oplus GP(\rho)$ (see Example B in Figure 4).

3.3 Fusion Layer

The purpose of the fusion component is to combine query and support maps. This is only applicable when the maps have the same spatial dimension. It is mostly used alongside with the alignment module, which does not combine the information from the support and the query but only reorganize the maps according to the other. In particular, when support and query maps do not have the same spatial dimension, aligning support to query can fix the size discrepancy. The fusion operator is defined as follows:

$$
\bar{\phi}^1_q, ..., \bar{\phi}^c_q = \Omega(\hat{\phi}^1_q, ..., \hat{\phi}^c_q, \hat{\phi}^1_s, ..., \hat{\phi}^c_s) \text{ with } \bar{\phi}^i_q = \omega(\hat{\phi}^i_q, \hat{\phi}^i_s), \tag{3}
$$
where $\omega$ is generally the concatenation of the results of multiple point-wise operators: $\omega(\phi, \rho) = \omega_1(\omega_2(\phi, \rho), \ldots, \omega_r(\phi, \rho))$ with $\omega_i \in \{\oplus, \odot, \ominus, [\cdot, \cdot], \ldots\}$.

An example of such fusion module is presented in [51] in which the query and support feature maps are element-wise multiplied, subtracted and then concatenated together: $\omega(\phi, \rho) = [\phi \odot \rho, \phi \ominus \rho]$ (see Example C in Figure 4). The point-wise operators can also contain small trainable models such as in [47], where small CNNs are applied after the point-wise operator, but before the concatenation: $\omega(\phi, \rho) = [\psi_{\text{dot}}(\phi \odot \rho), \psi_{\text{sub}}(\phi \ominus \rho), \psi_{\text{cat}}([\phi, \rho])]$.

The overall framework results in the successive application of the three components presented above:

$$
\tilde{\phi}^1_s, \ldots, \tilde{\phi}^c_s = \text{AAF}(\phi^1_q, \phi^1_s, \ldots, \phi^c_s) = (\Omega \circ \Gamma \circ \Lambda)(\phi^1_q, \phi^1_s, \ldots, \phi^c_s).
$$

Except for the fusion layer which must be applied last, spatial alignment and global attention can be applied in any order. In most cases, it will produce different results as they are probably not commutative. However, some FSOD methods (e.g. [46]) require applying global attention before spatial alignment, so the framework must be flexible enough to model this as well. The whole architecture of the AAF framework is illustrated in Figure 4, in which examples from the previous sections are also depicted.

4 Attention-based FSOD Comparison

In order to showcase the flexibility of the proposed AAF module, a comparison between multiple existing works is conducted. Some methods described in Section 2 are selected: FRW [4], WSAAN [43], DANA [46], MFRCN [47] and DRL [51] (see Table 1). These have been chosen because they represent well the variety of attention mechanisms available in the literature. FRW is based
Fig. 4 The Alignment Attention Fusion (AAF) module is composed of three components: spatial alignment $\Lambda$, global attention $\Gamma$ and a fusion layer $\Omega$. Examples for each module are depicted, these come from FSOD methods in the literature. Example A is presented in [47], Example B in [4] and Example C in [51].

on class-specific reweighting vectors, WSAAN has a more sophisticated global attention and computes reweighting vectors inside a graph structure. DANA and MFRCN leverage query-support alignment in a slightly different manner and DRL only uses a sophisticated fusion layer. Each of these methods has been reimplemented within the AAF framework. Of course, some details differ from the original implementations, but the purpose of this comparison is to evaluate only the attention mechanisms. In particular, the backbone and the training strategy (losses and episode tasks) may differ. The main comparison is done on Pascal VOC dataset [53] following the literature on FSOD. Some results are also provided on COCO dataset [54].

4.1 AAF Framework Implementation Details

In order to make the comparison fair, some implementation details are kept fixed for all experiments. The backbone is a ResNet-50 with a 4-layers Feature Pyramid Network (FPN) on top [20]. It extracts features at 4 different levels, which should help the network to detect objects at multiple scales. As features are extracted at multiple levels, attention mechanisms are also implemented to work at different scales. This may differ from the original implementation, but most methods are designed to work at multiscale (see Table 1). The networks
are trained in an episodic manner. During each episode, a subset $\mathcal{C}_{ep} \subset \mathcal{C}$ of the classes is randomly sampled ($|\mathcal{C}_{ep}| = 5$). Only the annotations of these classes are shown to the networks. It means that the networks are not penalized for not detecting other classes. An episode is constituted of 100 images for each class, which constitutes a query set of 500 images. The base training is made of 1000 (3000 for COCO) of such episodes. With a batch size of 8, this corresponds to 60k (180k for COCO) iterations. The optimization is performed with SGD and a learning rate of $1 \times 10^{-3}$. The support set is composed of one example per class (i.e. one image with only one annotation) and a new support set is sampled at each iteration. Next, a fine-tuning stage occurs with a smaller learning rate ($1 \times 10^{-4}$). During this phase, test classes are added to the class selection. For these classes only $k$ examples are available ($k \in \{1, 3, 5, 10\}$). Hence, the query and support sets are both composed of $5k$ images. Images for base classes change between episodes while for test classes, they remained fixed. To keep the training comparable between multiple values of $k$, the number of episodes is adjusted so that the same number of weight updates is performed with each configuration. The selected methods are compared on Pascal VOC dataset, following the setup detailed in [4]. Training images are selected from VOC 2007 and 2012 train and validation set while the evaluation is performed on VOC 2007 test set. Five classes among the 20 available have been selected as test classes and have only been seen by the networks during the fine-tuning. For experiments on COCO, 20 classes are selected as test classes. As in the FSOD literature, these classes are the ones from Pascal VOC dataset. These details are often different from one method to another for FSOD. This makes the comparison cumbersome between different works. The purpose of this framework is to facilitate the implementation of new attention techniques while providing a fair way to compare them.
4.2 Results and Analysis on Pascal VOC

In Table 2, mean Average Precision (mAP) is reported for each of the selected methods from Section 4. mAP is computed with a 0.5 overlap threshold. For each method, the evaluation is split into base and novel classes. Results on base classes demonstrate the ability of the method to solve object detection with a large dataset available. This should be compared to the performance of vanilla FCOS on the same classes (0.68). While it is important to keep performance on base classes close to the baseline, the most important metric for FSOD is performance on novel classes. Evaluation on novel classes shows how well a method generalizes to unseen classes with limited data.

As mentioned in [12], two separate ways to evaluate the performance on novel classes exist in the FSOD literature. The first one, introduced by [4] samples only one fixed support set at test time (the same that is used during fine-tuning). The second one consists in repeating this process with multiple different support. The former is less reliable and often overestimates the generalization capabilities. The latter is a lot more time-consuming as it requires at least 30 different runs (i.e. fine-tuning and evaluation) to become steady. Results from Table 2 are computed using the quicker but less reliable method. However, the goal of this work is to provide a tool that helps to conduct a fair comparison between different FSOD techniques. Therefore, it must also adopt fair and reliable metrics. It is planned to perform more reliable comparisons as future work (i.e. repeating with different support sets and class splits).

From Table 2, one can observe, on base classes, a slight decrease in performance compared to FCOS baseline. This is expected, even if the network has seen a lot of examples of these classes during training, its predictions are still conditioned on a few examples, which can sometimes be misleading. On the other hand, performance on novel classes is significantly lower than the
Table 2 Performance comparison between five selected methods (see Section 4). All are reimplemented with the proposed AAF framework. Mean average precision is reported for each method on base and novel classes separately and for various numbers of shots (1, 3, 5 and 10). Bold values indicate the best performing method for each number of shots and for base/novel classes separately.

| # Shots | FRW [4] Base | Novel | WSAAN [43] Base | Novel | DANA [46] Base | Novel | MFRCN [47] Base | Novel | DRL [51] Base | Novel |
|---------|---------------|-------|-----------------|-------|----------------|-------|-----------------|-------|----------------|-------|
| 1       | 0.599         | 0.282 | 0.617           | 0.309 | 0.626          | 0.328 | 0.578           | 0.302 | 0.642          | 0.270 |
| 3       | 0.633         | 0.311 | 0.635           | 0.422 | 0.642          | 0.622 | 0.340           | 0.368 | 0.617          | 0.296 |
| 5       | 0.643         | 0.463 | 0.647           | 0.462 | 0.652          | 0.426 | 0.621           | 0.408 | 0.664          | 0.373 |
| 10      | 0.632         | 0.487 | 0.653           | 0.517 | 0.650          | 0.503 | 0.634           | 0.494 | 0.670          | 0.480 |

FCOS baseline (i.e. trained with plenty of examples), especially for low numbers of shots. The number of shots is crucial for performance on novel classes. The higher the number of shots, the better the network performs. In average, with 10 examples per class, the network achieves 0.2 higher mAP than with 1 example. More examples provide more precise and robust class representations, improving detection. The same phenomenon is observed with base classes with a smaller magnitude (+0.04 mAP from 1 to 10 shots). Figure 5 displays these trends clearly, both for base and novel classes. More detailed results are given in Figure 6 where the evolution of performance per class is plotted. From that, one can notice that performance varies greatly from a class to another. Classes that are the most difficult benefit the most from having more examples. This is true both for base and novel classes. In addition, the novel classes that are easier to detect are often quite similar to some base classes (e.g. cow is similar to horse and sheep), thus requiring fewer examples to achieve good detection.

This behavior is expected from any few-shot object detection method. Moreover, performance values are close to what is reported in the original papers. Of course, these are not the exact same values as many architectural choices differ from the proposed methods (e.g. backbone, classes splits, losses, etc.). Nevertheless, it confirms that the proposed AAF framework is flexible
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Fig. 5 Evolution of mAP<sub>0.5</sub> with the number of shots averaged on base and novel classes. Each line represents one of the reimplemented methods. Increasing the number of examples improve performance of the model. This improvement is larger for novel classes as the network has not been trained (apart from fine-tuning) to detect them.

Fig. 6 mAP<sub>0.5</sub> on Pascal VOC against the number of shots for each class and each method. Dashed lines represent average performance on all classes, either base classes(top row) or novel classes(bottom row).

enough to implement different attention mechanisms. Therefore, it is an appropriate tool to compare different methods and to find what are the most efficient operations to combine query and support information for FSOD.

DRL is arguably the simplest method among the five selected as it leverages only a fusion layer. It combines query features with the features of each support image through concatenation and point-wise operations, creating class-specific query features. It is therefore the closest to the regular FCOS functioning. This explains the very good performance (compared to the baseline) on base classes and lower mAP on novel classes. Regarding the other methods, FRW and WSAAN can be easily compared as both are based on global attention.
The only difference is how the class-specific vectors are computed. In FRW, they are globally pooled from the support feature map. However, WSAAN combines the same vector with query features in a GNN. This certainly provides more adaptive class-specific features yielding better results both on base and novel sets. The remaining methods, DANA and MFRCN both leverage spatial alignment. While it seems to bring quite an improvement for DANA over FRW or DRL, the gain is smaller for MFRCN. In both methods, spatial alignment is not used alone. It is combined with other attention mechanisms. In DANA, a Background Attenuation block (i.e. a global self-attention) is applied to the support features to highlight class-relevant features and soften background ones. In MFRCN, aligned features are reweighted with global vectors computed from the similarity matrix between query and support features. This last operation may be redundant as the similarity information is already embedded into the aligned features, whereas background attenuation could extract new information. To confirm this hypothesis, a specific ablation study on both of these methods is planned as future work.

From this comparison, one can conclude that both global attention and spatial alignment are beneficial for FSOD. However, these improvements may not always be compatible. Hence, the design of each component must be done carefully so that spatial alignment, global attention, and fusion work in unison.

4.3 Results and Analysis on COCO

Another set of experiments is conducted on COCO dataset. Only the two best-performing methods from Section 4.2 are selected and trained on COCO following the same experimental setup. The results are summarized in Table 3. The mAP value are reported following standards from Pascal VOC (mAP_{0.5} with one IoU threshold), and COCO (mAP_{0.5:0.95} with several thresholds).
Table 3  Performance comparison between the two best performing methods from Section 4.2 on COCO. mAP\textsubscript{0.5-0.95} (COCO mAP, with IoU thresholds ranging from 0.5 to 0.95) and mAP\textsubscript{0.5} values are reported in the table for base and novel classes separately and for different numbers of shots.

| # Shot | WSAAN [43] | DANA [46] |
|--------|------------|------------|
|        | mAP\textsubscript{0.5} | mAP\textsubscript{0.5-0.95} | mAP\textsubscript{0.5} | mAP\textsubscript{0.5-0.95} |
| 1      | 0.335 0.120 | 0.201 0.066 | 0.355 0.145 | 0.213 0.078 |
| 5      | 0.399 0.199 | 0.236 0.105 | 0.428 0.222 | 0.252 0.119 |
| 10     | 0.409 0.214 | 0.244 0.115 | 0.430 0.237 | 0.256 0.129 |
| 30     | 0.415 0.222 | 0.247 0.121 | 0.435 0.244 | 0.260 0.133 |

This is done for 1, 5, 10, and 30 shots. These results comfort the conclusion obtained on Pascal VOC: the framework is flexible enough to implement various FSOD techniques that achieve competitive results with state-of-the-art. As on Pascal VOC the networks achieve better detection with more shots. While more beneficial for novel classes, base classes also benefit significantly from a higher number of examples, unlike on Pascal VOC. WSAAN outperforms DANA on Pascal VOC but performs slightly worse on COCO.

5 Conclusion and Future Work

This paper introduces a modular framework that facilitates the implementation of different attention mechanisms for FSOD. Thanks to this, a fair comparison of the various techniques has been conducted. The experiments carried out in this work demonstrate the flexibility of the proposed framework and prove that it is convenient for comparing attention techniques. More comparisons are planned as future work, along with in-depth ablation studies and the design of new attention techniques for FSOD. To help the development of such methods and future comparisons, the code of the proposed AAF framework will be made available.

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