Few-Shot Classification on Unseen Domains by Learning Disparate Modulators

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Abstract

Although few-shot learning studies have advanced rapidly with the help of meta-learning, their practical applicability is still limited because most of them assumed that all meta-training and meta-testing examples came from the same domain. Leveraging meta-learning on multiple heterogeneous domains, we propose a few-shot classification method which adapts to novel domains as well as novel classes, which is believed to be more practical in the real world. To address this challenging problem, we start from building a pool of multiple embedding models. Inspired by multi-task learning techniques, we design each model to have its own per-layer modulator with a base network shared by others. This allows the pool to have representational diversity as a whole without losing beneficial domain-invariant features. Experimental results show that our framework can be utilized effectively for few-shot learning on unseen domains by learning to select the best model or averaging all models in the pool. Additionally, ours outperform previous methods in few-shot classification tasks on multiple seen domains.

1 Introduction

Few-shot learning aims to train models such as deep neural networks so that the models can quickly solve novel tasks or adapt to new environments with limited number of examples. In case of few-shot image classification, models are usually evaluated on a held-out test dataset which does not have any common class with the training dataset. This is the significant difference from conventional classification problems where training and test sets have the same class labels. In the real world, however, we often face harder problems in which novel tasks and new environments have dissimilar domains with previous ones. For example, training images are hand-written signatures, whereas test samples came from ID photos.

Little attention has been paid to this kind of cross-domain few-shot classification while many few-shot learning algorithms have been proposed and advanced rapidly. Task-specific adaptation improved the performance of few-shot classification as shown in [23, 40], but they have not taken into account tasks from multiple domains. Only a few recent studies have claimed a practical importance of this issue while proposing a more realistic benchmark dataset [37] or a partial solution under the assumption of availability of unlabeled data from the target domain [9].

In this study, we propose an algorithm to handle this challenging few-shot classification on a novel domain, under the assumption that labeled training datasets are from multiple domains other than the target one. Since it seems that a single parametric model is not good enough to represent a wide distribution of cross-domain novel tasks, we address this problem by constructing a disparate pool of embedding models expected to cover the potential cross-domain task distribution in a collective manner. This pool is built by training a base network shared by all models on every available domain, then learning one model-specific modulator for each domain adopting the scheme in multi-domain
We address this problem by building a pool of multiple embedding models which have their own
sharing as the number of available domains having minimal parameter overhead. At test time, we
make a prediction by simply averaging outputs from all models or selecting the best one picked by a
model selection network learned through cross-domain meta-learning.

Experimental results on a multi-domain dataset based on the Visual Decathlon [28] show that our
approaches outperform other well-known algorithms in few-shot classification on an unseen domain.
The proposed methods are also shown to be quite effective compared to other baselines when we are
given a few-shot classification task from one of the multiple seen domains but without any domain
identifier.

2 Methods

2.1 Problem formulation

We follow a common setting of few-shot classification in the meta-learning perspective [34, 38]. For a
N-way, K-shot classification task, an episode which consists of a support set \( S = \{ (x_i^s, y_i^s) \}_{i=1}^{NK} \) and
a query set \( Q = \{ (x_i^q, y_i^q) \}_{i=1}^{T} \) is sampled from a given dataset, where \( x_i^s, x_i^q, y_i^s \) and \( y_i^q \) represent
examples and their correct labels respectively and \( T \) is the number of query examples. Once a model
has been trained with respect to a number of randomly selected episodes at meta-training time, it is
expected to predict a correct label for an unlabeled query given a labeled support set even if this pair
came from classes which have never appeared during meta-training.

We solve a cross-domain few-shot classification task that requires generalization to unseen domains
in addition to unseen classes, where we presume that one domain corresponds to one dataset such as
ILSVRC12 (ImageNet12) [32] and CIFAR100 [10] in this study. While the conventional few-shot
classification setting assumes that the episodes in both meta-training and meta-testing belong to the
same domain, our setup makes the problem more practical but challenging because it requires that
episodes in meta-testing be sampled from a novel dataset which is not observed during meta-training.
We address this challenging problem by obtaining domain-level generalization through meta-learning
across multiple domains. Hence, we assume that we have multiple domains at meta-training time,
which we call source domains \( D_{S_1}, D_{S_2}, \ldots, D_{S_M} \), where \( M \) is the number of source domains. The
episodes in meta-testing come from a target domain \( D_T \) which does not overlap with source domains
(i.e., \( D_{S_i} \cap D_T = \emptyset \) for all \( i \)).

2.2 Building a pool of embedding function models

We address this problem by building a pool of multiple embedding models which have their own
representation space. It is expected that they can cover a distribution of potential target tasks as a
whole. When we are given a few-shot classification task at inference time, one of the models in this
pool can be chosen as the best fit for this particular task, or we can infer by combining outputs from
all models, which allows us to benefit from more relevant models to the given task.

Our approach is to build a base network shared by all constituent models as the first step, and then
train one model-specific modulator on every source domain on top of the base network, which is
inspired by the hard parameter sharing strategy whose effectiveness has been proved in the previous
multi-domain [29] and multi-task learning studies [31].

The full embedding model is denoted as \( f_e(\cdot; \theta, \alpha_i) \) where \( \theta \) represents a set of parameters for the
base network and each modulator indexed by \( i \) is parameterized by \( \alpha_i \) throughout the text. The
rationale behind this is to let our model pool have diversity, which is desirable for representing a wide
task distribution across potential target domains, while maintaining good representation capability
shared by various source domains.

In the first step, the base network is obtained by training a network for a large classification task
aggregating all classes from available source domains and removing the class-specific final linear
classifier following the standard feature extractor training procedure as shown in Figure 1(a). In the
next step, we train a modulator on each source domain \( D_{S_i} \) following the training procedure
of ProtoNet [34] by considering \( f_e(\cdot; \theta, \alpha_i) \) as the embedding network with \( \theta \) fixed (Figure 1(b))
through episodic training, known as the common and effective meta-learning strategy for few-shot
classification [4, 34, 58]. A modulator is combined with the base network at each layer in the form of
Algorithm 1 The overall learning procedure

Input: Training data from $D_S = \{D_{S_i}\}_{i=1}^M$, embedding networks $f_e(\cdot)$, a selection network $f_s(\cdot)$
Output: Learned parameters $\theta$, $\{\alpha_i\}_{i=1}^M$, $\phi$.

Step 1: Build a base network
1: Build one large classification dataset $(x_{agg}, y_{agg})$ by aggregating all classes from $D_S$.
2: Learn $\theta$ by optimizing $f_e(x; \theta, \alpha_0)$ for the aggregated dataset ($\alpha_0$: no modulation).

Step 2: Add modulators through intra-domain episodic training
1: while not converged do
2: Sample one domain $D_{S_i}$ from $D_S$, then sample one episode $(S, Q)$ from $D_{S_i}$.
3: Learn $\alpha_i$ by optimizing $f_e(x; \theta, \alpha_i)$ for $(S, Q)$ while keeping $\theta$ fixed.
4: end while

Step 3: Build a selection network through cross-domain episodic training
1: while not converged do
2: Sample one domain $D_{S_i}$ from $D_S$, then sample one episode $(S, Q)$ from $D_{S_i}$.
3: Get a task representation $z_{task}$ by averaging embedding vectors of $S$ from the base network.
4: Measure accuracies of $M + 1$ available embedding models $\{f_e(x; \theta, \alpha_i)\}_{i=0}^M$ for $(S, Q)$.
5: Set the best model index $y_{sel}$ to the index of the model with the highest accuracy.
6: Learn $\phi$ by training $f_s(z_{task}; \phi)$ so as to predict $y_{sel}$ for $(S, Q)$.
7: end while

1×1 convolution in parallel with the main 3×3 convolution operation or channel-wise linear transform following the main operation because per-layer modulation has been shown to be effective in many areas dealing with multiple domains [25, 29]. Finally, we add the base network to this pool also because all modulated models might affect unknown novel tasks negatively. The base network is considered to have the modulator parameterized by $\alpha_0$ which does not modulate the base network at all actually. The overall training procedure is summarized in Algorithm 1 including the step for learning a model selection network, which will be explained in the next subsection.

2.3 Learning to select the best model through episodic training

One way to utilize the learned knowledge for few-shot classification tasks is to pick a model which fits best, i.e., a model with the highest classification accuracy for a given task. The classification
accuracy for each model can be calculated following the inference procedure introduced in Section 2.4. Once construction of the model pool has been done, we learn a model selection network which predicts the best model from all available models for a given task as shown in Figure 1(c). By training the selection network to choose the best model for a given task from diverse domains, we expect this ability to be generalized to a task of an unseen domain.

We adopt episodic training again across all source domains to train this selection network in this step. When an episode is randomly sampled from one of all available domains, a two-layer MLP classifier $f_s(\cdot; \phi)$ is trained in order to map a task representation $z_{\text{task}}$ to the index of the best model in the model pool as depicted in Figure 2. The task representation is obtained by passing all examples in the support set of the task through the base network and averaging all resulting embedding vectors. The index of the best model, which is the ground truth label for training the selection network is generated by measuring the classification accuracy of all models in the pool with the query set and picking one which has the highest accuracy. It is worth noting that the selection network can be also useful for few-shot classification on multiple seen domains, another practical extension of the standard few-shot learning, by finding the best model for a given task without requiring any domain identification of that task.

2.4 Inference with the pool

For a model $i$ in the pool and a query example $x^q$, let $d_i^y(x^q) = \| c_y - f_e(x^q; \theta, \alpha_i) \|^2$, where $c_y$ is the mean of all embedding vectors of support elements belonging to class $y$. Then, we interpret

$$p(y \mid x^q; i) = \text{softmax}(-d_i^y(x^q))$$

as a probability that $x^q$ belongs to class $y$. Once the best embedding model $b$ has been selected by $f_s(\cdot; \phi)$ for a given episode at meta-testing time, the prediction is done by finding $\text{argmin}_y d_b^y(x^q)$.

Another way to benefit from the model pool is to combine outputs from all available embedding models for inference. When a task is given, we collect output probabilities $p(y \mid x^q; i)$ to our target classes from all models. Then, we use a mean of these probabilities from all $M + 1$ models as our final prediction probability ($p_{\text{avg}}$) for the given task (Figure 1(d)) as follows

$$p(y \mid x^q)_{\text{avg}} = \frac{1}{M + 1} \sum_{i=0}^{M} p(y \mid x^q; i).$$

The sharing of the base network and the light modulator architecture can bring us a highly parameter-efficient averaging method. The averaging method based on the channel-wise transform incurs little parameter increase while keeping its accuracy higher than other methods in most cases as shown in the experimental results.

Optionally, we can perform further adaptation by appending a randomly initialized $N$-way linear layer $f_c(\cdot; \psi)$ to the embedding model at testing time and fine-tuning it for a given task following the observation in the recent study [39], where such fine-tuning is helpful for task-specific adaptation.
This enables us to infer the predicted class directly while replacing the above-mentioned comparison-based prediction. We apply this scheme to all feasible baseline methods as well as our methods (i.e., the selection of the best one or the averaging) because it has shown non-trivial performance improvement in most cases.

3 Experiments

We compare our method with multiple baseline models including strong state-of-the-art models in terms of the classification performance in unseen domains. Furthermore, we also analyze how the number of source domains affects the model performance. The results reveal that our model outperforms the baseline models not only in unseen domains but also in seen domains.

3.1 Setup

Datasets: We evaluate our methods using 8 datasets of Visual Decathlon [28] which consists of 10 image classification tasks of various visual domains, namely FGVC-Aircraft Benchmark [16], CIFAR100 [19], Daimler Mono Pedestrian Classification Benchmark (DMPCB) [19], Describable Texture Dataset (DTD) [2], German Traffic Sign Recognition Benchmark (GTSRB) [36], ILSVRC12 (ImageNet12) [32], Omniglot [11], Street View House Numbers (SVHN) [20], UCF101 [35], and Flowers102 [22]. After excluding DMPCB and SVHN which have too small number of classes to split, we employ customized splits (e.g., roughly 70% training, 15% validation, and 15% testing classes) for the remaining 8 datasets. Details about the dataset are given in the Supplementary. All results in this paper are produced by our implementation of the baseline models and the proposed methods.

Baselines: We adopt ResNet-18 architecture [7] as the backbone feature extractors for all baselines and our methods. The backbone network is trained on every class in all the source domains. We compare our methods with five baselines including popular few-shot learning methods and the model averaging method; Fine-tune, ProtoNet [34], FEAT [40], ProtoMAML [37], and Simple-Avg. Fine-tune model is a pre-trained feature extractor called base network in the previous section with an additional linear classifier which is further fine-tuned using the entire support examples at each episode for 100 epochs during the meta-testing. ProtoNet is a distance-based task-agnostic few-shot learning method which calculates the distance between each query and the prototype of each class. FEAT uses self-attention to transform task-agnostic embedding into task-specific embedding and ProtoMAML combines the simple inductive reasoning of the class from a very few examples in ProtoNet and the training procedure for task-adaptation in MAML [4]. Model averaging (Simple-Avg) is also considered as one of the baseline models. In this method, we train an embedding model independently on each source domain without sharing any parameters with others in the same way as ProtoNet. By including the base network, we get \((M + 1)\) embedding models, which is the same number of the models in the model pool of the proposed methods. The inference is done in the same way as our averaging method.

For the fair comparison with Fine-tune method, we adopt fine-tuning for other models, inspired by [39]. A linear classifier is placed on top of the feature extractor of the ProtoNet and the self attention module of the FEAT. During meta-testing, other parameters are fixed and the classifier is fine-tuned using the support examples for 100 iterations per episode. In case of FEAT, the classifier is trained for 100 epochs per query example not per episode because FEAT modulates a representation space for each query. Also, we adjusted the number of adaptation of the ProtoMAML to 100 for the better task-adaptation as done in [39].

Ours: We denote our few-shot classification method by selecting the best model as DoS (Domain-generalized method by Selection) and method by averaging all models in the pool as DoA (Domain-generalized method by Averaging). Also, DoS-Ch and DoA-Ch are the light versions of DoS and DoA using different types of modulation. Instead of the parallel modulation based on convolution \(1 \times 1\) used in DoS and DoA, DoS-Ch and DoA-Ch use channel-wise transform-based serial modulation, which uses significantly smaller number of parameters. The architectures of two modulators and their number of parameters are given in the Supplementary. For the meta-testing, a linear classifier is attached to the top of the modulated feature extractor and the classifier is fine-tuned for 100 epochs.
3.2 Results

3.2.1 Few-shot classification on unseen domains

We report few-shot classification results on unseen domains. Figure 3 shows the results of five baselines and our methods on unseen domain with 5-way 5-shot, 5-way 1-shot settings, respectively. For each specified target domain, we train all models using 7 other domains. Note that DoS outperforms all the baselines in general except the Fine-tune model on 1-shot 5-way setting, and DoA significantly outperforms all the baselines. It seems reasonable that DoA is more robust to unseen domains since it uses all the usable domain knowledge through averaging.

Although Simple-Avg requires 8 times more parameters than a single embedding model, it performs worse than almost all single model-based methods. On the other hand, our two averaging methods, DoA and DoA-Ch, outperform all other methods only with the increase of 76% and 0.5% in number of parameters.

These results imply that the channel-wise transform would be an effective and efficient modulation method only with negligible parameter overhead if the averaging method is being considered while the 1×1 convolution is preferred in the selection-based method.

3.2.2 Few-shot classification on seen domains

We also compare the methods on seen domains with the 5-way 5-shot setting. Each model is trained using examples from 7 domains (i.e., all domains except Flowers) and tested on each of the source domains.

As shown in Figure 4, our methods are also useful for another practical applications, few-shot classification on multiple seen domains, which has been rarely covered by previous few-shot learning studies. Our selection-based methods, DoS and DoS-Ch, outperform all other methods by a large margin. This implies that the learned model selector \( f_s \) is working properly, which is highly likely to select the modulator trained on the same domain as the given task even if any identification of that domain is not given at testing time. Our averaging methods also perform better than other baselines. However, both methods turn out to be less effective than the selection-based methods on multiple seen domains.
3.2.3 Few-shot classification on varying number of sources

We conduct experiments with the varying number of source domains. In many real-world cases, only small number of examples are available for the target domain whereas samples from the source domain are abundant. To evaluate our method in a more realistic setting, we first sort the datasets in a decreasing order of size, then select the 2, 4, and 6 largest datasets as source domains and test on other datasets.

As shown in Table 1, DoA outperforms other baselines in most of the cases. However, the results show that increasing the number of source domains does not impact the classification performance very much. When the UCF101 dataset is selected as a target domain, only Fine-tune and DoA improve consistently. Also, in case of the Aircraft-targeting experiments, the classification accuracies of all the methods except DoA drop when the number of source domains increases from 2 to 4.

4 Related works

Few-shot learning has been studied actively as an effective means for a better understanding of human learning or a practical learning method only requiring a small number of training examples [11][14]. Currently, meta-learning is one of the most popular techniques to solve the few-shot learning problems, which includes learning a task-invariant metric space [34][38], learning to optimize [1][27] or learning weight initialization [4][21]. A number of follow-up studies showed that the meta-learning-based methods could be improved further through additional task-specific adaptation on the learned metric space [6][23][26][33][40]. We adopt the similar architecture for task-specific adaptation as [23]. However, we perform the adaptation by combining pre-trained models or selecting the best one to cover the wide task distribution while the previous work did it through the learned parametric generator at meta-testing time. One comparative study performed an extensive analysis of well-known meta-learning-based few-shot learning methods [39].

Recent few-shot learning studies have tried to tackle challenging problems under more realistic assumptions. Some studies explored few-shot learning through semi-supervised [50] and unsupervised meta-learning [8]. In [8], the meta-learning-based method was proposed to deal with the few-shot learning with domain shifts between meta-training and meta-testing similarly to our setting. However, it differs from ours in that unlabelled examples of a target domain are required during its training time. More realistic benchmark was proposed for few-shot learning to overcome limitations of the current popular benchmarks including the lack of domain divergence [37]. Similar to our approach, a
We believe that there is still a large room for improvement in this challenging task. It would be one... unseen domains as well as unseen target domains. The results are averaged over 600 test episodes with 10 queries per class.

### Table 1: Few-shot classification accuracy of varying number of sources on the 5-way 5-shot setting.

| Sources | Target  | METHODS         | FINE-tune | ProtoNet | FEAT | ProtoMAML | DoS | DoA |
|---------|---------|------------------|----------|----------|------|-----------|-----|-----|
| C,I     | AIRCRAFT|                  | 38.65%   | 39.38%   | 36.71%| 35.37%    | 38.43%| 39.14%|
|         | DTD     |                  | 53.89%   | 55.27%   | 52.39%| 51.04%    | 54.80%| 57.15%|
|         | GTSRB   |                  | 70.01%   | 81.37%   | 77.67%| 81.25%    | 83.83%| 80.13%|
|         | OMNIGLOT|                  | 92.72%   | 92.62%   | 90.61%| 91.37%    | 93.11%| 94.00%|
|         | UCF101  |                  | 63.80%   | 63.25%   | 60.04%| 59.89%    | 63.67%| 66.28%|
|         | FLOWERS |                  | 79.28%   | 81.77%   | 78.86%| 80.50%    | 81.26%| 82.96%|
| Average |         |                  | 66.39%   | 68.94%   | 66.05%| 66.63%    | 69.18%| 69.94%|
| C,G,I,O | AIRCRAFT|                  | 38.12%   | 36.88%   | 35.11%| 34.96%    | 37.90%| 39.66%|
|         | DTD     |                  | 55.04%   | 49.96%   | 49.55%| 49.79%    | 55.85%| 56.73%|
|         | UCF101  |                  | 63.25%   | 56.53%   | 60.93%| 64.12%    | 64.32%| 67.58%|
|         | FLOWERS |                  | 79.88%   | 76.79%   | 77.67%| 81.40%    | 80.69%| 83.25%|
| Average |         |                  | 59.07%   | 55.04%   | 55.82%| 57.57%    | 59.69%| 61.81%|
| A,C,G,I,O,U | DTD           |                  | 53.60%   | 51.52%   | 51.86%| 50.94%    | 55.54%| 56.71%|
| A,C,G,I,O,U | FLOWERS       |                  | 80.80%   | 80.58%   | 79.70%| 79.40%    | 81.62%| 84.30%|
| Average |         |                  | 67.20%   | 66.05%   | 65.78%| 65.17%    | 68.58%| 70.51%|

A: Aircraft, C: CIFAR100, G: GTSRB, I: ImageNet12, O: Omniglot, U: UCF101.

few suggestions combined multiple models to benefit from their diversity [3][15][24]. However, they formed an ensemble with multiple independent models while our models share a large part of the model with each other so that our method is more parameter-efficient.

Our research is also related to domain adaptation or generalization [5][13]. However, most of the researches about domain adaptation or generalization assume tasks with the same classes in both training and testing whereas our methods do not impose such limitations. Interestingly, some studies showed that the episodic training, the common few-shot learning technique, was useful for domain generalization [12][13]. The network architecture that we adopt is inspired by the parameter sharing strategies for multi-task learning [31] and multi-domain learning with domain-specific adaptation [29] because they have been known to lead to efficient parameterization and positive knowledge transfer between heterogeneous entities. Our selection method can be seen as a kind of the transfer learning based on the learned relationship similarly to [41].

## 5 Conclusion and future works

We propose a new few-shot classification method generalizing to unseen domains as well as unseen classes through cross-domain meta-learning. The core idea is to build the pool of embedding models, each of which is diversified by its own modulators with sharing most of parameters with others and make a prediction using this knowledge at testing time. Extensive experiments reveal that this approach is effective in few-shot classification on a novel domain compared to other existing algorithms. It also turns out to be quite useful for multi-domain few-shot classification, another practical extension of the standard single-domain few-shot learning.

We believe that there is still a large room for improvement in this challenging task. It would be one promising extension to find the optimal way to build the pool without being confined by the policy of one model per domain so that it can work even with a single source domain. Soft selection or weighted averaging can be also thought as one of future research directions because a single model or uniform averaging is less likely to be optimal. Even though our averaging methods incur small or negligible parameter overhead, they still require more computation than the single model-based methods at testing time, which also need improvement. We can also consider a more scalable extension to allow continual expansion of the pool only by training a modulator for an incoming source domain without re-training all existing models in the pool. In the perspective of applications, it seems interesting to try more radical generalization beyond vision domains. One example is knowledge sharing between the vision domain and the language domain similarly to what has been tried slightly in [17].
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Supplementary Materials

A Datasets

In our experiments, we use the Visual Decathlon dataset [28] which consists of 10 image classification tasks listed below:

- FGVC-Aircraft Benchmark (Aircraft, A) [16]
- CIFAR100 (CIFAR100, C) [10]
- Daimler Mono Pedestrian Classification Benchmark (DMPCB) [19]
- Describable Texture Dataset (DTD, D) [2]
- German Traffic Sign Recognition Benchmark (GTSRB, G) [36]
- ImageNet ILSVRC12 (ImageNet12, I) [32]
- Omniglot (Omniglot, O) [11]
- Street View House Numbers (SVHN) [20]
- UCF101 (UCF101, U) [35]
- Flowers102 (Flowers, F) [22]

The categories and the number of images of each domain are significantly different as well as the image size. All images have been resized isotropically to $72 \times 72$ pixels so that each image from various domains has the same size.

Daimler Mono Pedestrian Classification task has only 2 classes, pedestrian and non-pedestrian, therefore excluded from our experiments as we performed 5-way classification tasks. SVHN has 10 digit classes from 0 to 9, which were also considered to be inadequate and excluded from our experiments. To use Visual Decathlon dataset for multi-domain few-shot classification, we divide the examples into roughly 70% training, 15% validation, and 15% testing classes. For ILSVRC12, we follow the split of Triantafillou et al. [37] to adopt class hierarchy, and we use random class splits for other datasets. The number of classes at each split is shown in Table 2. We only use train and validation sets of the Visual Decathlon because the labels of the test set is not publicly available.

Table 2: The details of datasets used in our experiments.

| DATASET   | # DATA | # CLASSES | Splits |
|-----------|--------|-----------|--------|
| AIRCRAFT  | 6667   | 100       | Train 15 | Val 15 | Test 15 |
| CIFAR100  | 50000  | 100       | 70      | 15     | 15     |
| DTD       | 3760   | 47        | 32      | 7      | 8      |
| GTSRB     | 39209  | 43        | 30      | 6      | 7      |
| IMAGENET12| 1281167| 1000      | 712     | 158    | 130    |
| OMNIGLOT  | 25968  | 1623      | 1136    | 243    | 244    |
| UCF101    | 9537   | 101       | 70      | 15     | 16     |
| FLOWERS   | 2040   | 102       | 70      | 16     | 16     |

B Architectures

Figure 5 shows the architecture of the embedding network $f_e(\cdot; \theta, \alpha)$, which processes an input image and produces a 512-dimensional embedding vector. The embedding network is based on the ResNet-18 architecture [2], which consists of one convolutional layer with 64 $7 \times 7$ filters followed by 4 macro blocks, each having 64-128-256-512 $3 \times 3$ filters. Figure 5(a) and Figure 5(b) depict how the base network is modulated by the convolution $1 \times 1$ modulator and the channel-wise transform modulator, respectively. These modulators are placed within each residual block of the macro blocks, same as the previous works in [29] and [25].
Table 3: The comparison of the number of parameters for convolution $1 \times 1$ and channel-wise transform modulators. This is the case when the number of source domains is 7.

|                      | Convolution 1x1 | Channel-wise transform |
|----------------------|-----------------|------------------------|
| Modulators $\{\alpha_i\}_{i=1}^{7}$ | $8,571,136$     | $53,760$               |
| Embedding function network $\theta$ | $11,176,512$     | $11,176,512$           |
| Selection network $\phi$ | $66,696$       | $66,696$               |
| Sum                   | $19,814,344$     | $11,296,968$           |

The number of parameters for two modulators are shown in Table 3. The values on the first row are the number of modulator parameters that are additionally applied to the embedding network. Note that the channel-wise transform modulator has much fewer number of parameters than the convolution $1 \times 1$ modulator. In particular, the channel-wise transform modulator has negligible number of parameters compared to that of embedding network, which is ResNet-18. The convolution $1 \times 1$ modulator increases the number of total parameters by 76% whereas the channel-wise transform modulator increases the number of parameters only by 0.5%.

The selection network $f_s(\cdot; \phi)$ is a two-layered MLP (multi-layer perceptron) network, which receives an embedding vector produced by the embedding network as an input and performs the best model index prediction. Two layers are a linear layer of $512 \times 128$ and a linear layer of $128 \times (M+1)$, where $M$ is the number of source domains.

C Training details

The hyperparameters including the learning rate are selected by grid search in the unseen domain experiments. And we used the same hyperparameters in the seen domain cases. We tested the models on validation data examples of the source domains, making sure that no information of the target domain are used during the training. The selected hyperparameters therefore are not guaranteed to be optimal in the test domain, however, this makes the experiments more suitable for the purpose of this study.

For FEAT and ProtoMAML, Adam optimizer is used for training and the learning rate and weight decay are set to be 0.0001. Other models are also trained using Adam optimizer with the learning rate 0.001, but additional decaying nor parameter regularization method was used. All models are trained
for 200 epochs and the best models which produce the highest validation accuracy are chosen for testing.

D Additional experimental results

D.1 Without Fine-tuning

As an ablation study, ProtoNet, FEAT, and our models are tested without additional linear classifiers \( f_c(\cdot; \psi) \). The number of parameter update steps in ProtoMAML is reduced to 3, which is not enough to have the models fine-tuned. Tables 4 and 5 show the results tested on unseen and seen domains, respectively. We can see that accuracy drops in almost all cases compared to corresponding fine-tuned cases whose results are in our main paper, but our models generally do better than other baselines in any experimental settings.

D.2 Comparative analysis about the averaging methods

As an effort for better understanding the averaging methods, we investigate how each model in the pool contributes to the final prediction. Figures 6(a) and 6(b) show how many correct predictions are made by each model with the Simple-Avg and our DoA methods respectively given 50 queries per episode for 40 episodes.

The measured numbers show that the individual models of our DoA perform better than those in the Simple-Avg, which explains the higher performance of the proposed method partly. Additionally, we can observe that major contributors (i.e., the models with higher accuracy) tend to change every episode in our DoA whereas only two models seem to play dominant roles regardless of the given episode. This implies that our method for constructing the model pool provides the averaging model with more beneficial diversity.

Table 4: 5-way 5-shot classification accuracy on unseen domains without fine-tuning. Each model is trained with all datasets except the target dataset. The results are averaged over 600 test episodes with 10 queries per class.

| SOURCES \ TARGET | METHODS          |
|------------------|------------------|
|                  | Fine-tune | ProtoNet | FEAT | ProtoMAML | DoS  | DoA     |
| ALL \ A AIRCRAFT | 36.40%    | 35.42%   | 33.30% | 32.87%    | 34.73% | 36.93%  |
| ALL \ C CIFAR100 | 53.26%    | 55.17%   | 52.60% | 58.01%    | 55.79% | 58.30%  |
| ALL \ D DTD     | 55.18%    | 51.03%   | 50.37% | 45.46%    | 54.11% | 54.88%  |
| ALL \ G GTSRB   | 78.01%    | 76.33%   | 75.79% | 78.81%    | 77.03% | 77.36%  |
| ALL \ I IMAGE12 | 34.81%    | 32.90%   | 33.50% | 36.46%    | 34.34% | 34.36%  |
| ALL \ O OMNIGLOT| 92.69%    | 92.64%   | 91.99% | 83.80%    | 93.68% | 94.95%  |
| ALL \ U UCF101  | 62.16%    | 59.74%   | 58.54% | 58.40%    | 62.04% | 65.93%  |
| ALL \ F FLOWERS | 81.00%    | 79.42%   | 80.82% | 69.47%    | 81.85% | 82.71%  |
| AVERAGE         | 61.69%    | 60.33%   | 59.62% | 57.91%    | 61.70% | 63.19%  |
Table 5: 5-way 5-shot classification accuracy on seen domains without fine-tuning. Each model is trained with 7 specified domains and tested on each of the source domains. The results are averaged over 600 test episodes with 10 queries per class.

| METHODS       | SOURCES | TARGET       | FINE-TUNE | ProtoNet | FEAT | ProtoMAML | DoS | DoA     |
|---------------|---------|--------------|-----------|----------|------|-----------|-----|---------|
|               | A,C,D,G,I,O,U | AIRCRAFT    | 41.31%    | 52.00%   | 50.39%| **63.72%**| 62.57%| 47.28%  |
|               |         | CIFAR100     | 54.20%    | 58.52%   | 59.63%| 61.79%    | **71.58%**| 65.58%  |
|               |         | DTD          | 55.98%    | 54.32%   | 52.47%| 43.96%    | **58.73%**| 58.15%  |
|               |         | GTSRB        | 77.87%    | 88.23%   | 90.08%| 95.67%    | **97.03%**| 83.56%  |
|               |         | ImageNet12   | 56.29%    | 53.41%   | 49.70%| 48.18%    | 55.91%| **57.76%**|
|               |         | Omniglot     | 94.51%    | 95.70%   | 92.58%| **99.21%**| 98.96%| 96.88%  |
|               |         | UCF101       | 65.29%    | 66.74%   | 65.64%| 60.94%    | **72.11%**| 71.19%  |

| AVERAGE       |         |              | 63.63%    | 66.99%   | 65.78%| 67.64%    | **73.84%**| 68.63%  |

![Figure 6: Contributions of individual models in model averaging methods.](image)

(a) Simple averaging (Simple-Avg)

(b) Proposed averaging (DoA)