Cross-domain Few-shot Meta-learning Using Stacking

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Abstract. Cross-domain few-shot meta-learning (CDFSML) addresses learning problems where knowledge needs to be transferred from several source domains into an instance-scarce target domain with an explicitly different input distribution. Recently published CDFSML methods generally construct a “universal model” that combines knowledge of multiple source domains into one backbone feature extractor. This enables efficient inference but necessitates re-computation of the backbone whenever a new source domain is added. Moreover, state-of-the-art methods derive their universal model from a collection of backbones—normally one for each source domain—and the backbones may be constrained to have the same architecture as the universal model. We propose a CDFSML method that is inspired by the classic stacking approach to meta learning. It imposes no constraints on the backbones’ architecture or feature shape and does not incur the computational overhead of (re-)computing a universal model. Given a target-domain task, it fine-tunes each backbone independently, uses cross-validation to extract meta training data from the task’s instance-scarce support set, and learns a simple linear meta classifier from this data. We evaluate our stacking approach on the well-known Meta-Dataset benchmark, targeting image classification with convolutional neural networks, and show that it often yields substantially higher accuracy than competing methods.

Keywords: Cross-domain Few-shot Learning · Meta-learning · Stacking

1 Introduction

Cross-domain few-shot meta-learning (CDFSML) addresses the problem that state-of-the-art machine learning methods such as convolutional neural networks for image classification generally require a large amount of labelled training data to achieve high predictive accuracy when trained from scratch. In cross-domain few-shot learning (CDFSL), a learning algorithm is applied to a target domain for which only a few labelled training instances (the so-called “support set”)
are available. The aim is to nevertheless achieve high accuracy when predicting labels for never-before-seen instances of the target domain (the so-called “query set”). This can generally only be achieved by applying transfer learning: taking knowledge gleaned from one or several source domains where training data is plentiful and using this knowledge to inform learning in the target domain.

In CDFSL, the source domain(s) and the target domain are assumed to have explicitly different input distributions. This cross-domain setting is arguably more realistic than a scenario, frequently used in few-shot learning, where the support and query sets are mutually exclusive samples obtained from the same dataset. It also yields harder learning problems due to greater domain shift.

Meta-learning algorithms are the top performers in CDFSL benchmarks. In the CDFSL context, meta-learning algorithms are designed to learn how to most appropriately transfer knowledge from the source domain(s) to the target domain based on the information in the support set of a few-shot learning episode. This “meta-training” phase is followed by application of the learned model to the query set. Predictive performance is measured by accuracy on a labelled query set, enabling “meta-testing”. A majority of recently published CDFSL methods revolve around building a “universal model”, which is derived from a collection of backbones, with each backbone pretrained on one specific source domain. The universal-model paradigm is generally efficient at meta-test time, in the sense that only a single universal backbone is used, usually in conjunction with a simple robust classifier that turns extracted feature vectors into predictions. However, this paradigm has significant drawbacks in the meta-train phase, mainly in terms of flexibility and computational overhead. In order to be able to derive a universal model from a backbone collection, most methods need to constrain all backbones in the collection to the same architecture and/or feature shape as the intended universal model, rendering them inapplicable to heterogeneous backbone collections that are likely to occur in real-world practice. Moreover, these methods may require additional human-expert knowledge to function well. For example, given a source domain/backbone collection for image classification consisting of ImageNet [4] and several other “less comprehensive” source domains, recent methods are often tweaked to give the ImageNet backbone a greater effect than the other backbones on the universal model—usually achieved by biased sampling in the derivation process. Indeed, it is common for such methods to sample from ImageNet as frequently as all other source domains combined when deriving the universal model from a backbone collection. Assigning particular importance to ImageNet has been utilised to achieve good performance on benchmarks—which may include target domains such as CIFAR-10 that are quite similar in nature—but the usefulness of this bias in real-world applications can be questioned. Lastly, the process of deriving a universal model from a source domain/backbone collection is usually computationally expensive and non-incremental, which means it needs to be re-run if a source domain or its backbone is updated, or when a new source domain/backbone is added. Additionally, the derivation process normally requires access to source domain data,
which may not be available. Therefore, universal-model methods may not be practical in certain real-world CDFSML applications.

We propose an alternative CDFSML method that is based on stacking and does not exhibit these drawbacks. In the proposed approach, each source domain feature extractor in the collection of available backbone models is independently fine-tuned on the support set of the target domain task and saved at predetermined checkpoints throughout the fine-tuning process. To obtain data for meta-training, as in the classic stacking approach, the support set is split into $k$ sets of training and test splits using stratified $k$-fold cross-validation. For each set of train-test splits, a fresh copy of each backbone is fine-tuned on the training split, and its predictions of the test split instances at each checkpoint are cached as logits. After the process is complete on all $k$ folds, the cached logits of the $k$ test splits are combined, producing cross-validated logits for the entire support set. These are used to form training instances for a simple meta-classifier that assigns a trainable weight to each checkpoint of a source-domain-specific backbone, and produces a logit for each class as a weighted mean of the checkpoint-specific logits for the same class. The meta-classifier learns by minimising its loss given the support labels. After the meta-classifier is trained, when presented with a query-set instance for labelling, logits of the instance are computed by the backbones at their saved checkpoints, and the meta-classifier is used to aggregate the logits to produce a prediction.

The proposed method is fully compatible with heterogeneous backbone collections, imposing no constraint on each backbone’s architecture, feature shape, or fine-tuning configuration. Additionally, our experiments show that the meta-classifier works well when initialised to assign equal weight to each backbone, requiring no pre-existing knowledge of a backbone’s significance to the target domain. Moreover, the proposed stacking-based approach does not require any source domain data, and does not require derivation of a universal model, as it uses the support set to directly fine-tune a backbone collection and train a meta-classifier. Hence, it does not incur the computational overhead associated with a derivation process that needs to be re-run in the event of a change in the backbone collection. In fact, within one target domain task, if a backbone is changed or added, only this backbone and the simple meta-classifier need to be fine-tuned or retrained; no new fine-tuning is required for the unchanged backbones as long as the cached logits from cross-validation are preserved.

We evaluate the stacking-based approach on the Meta-Dataset benchmark \[17\], which contains eight source domains and five target domains, and include five additional target domains: CropDisease, EuroSAT, ISIC, ChestX, and Food101 \[1\] \[6\]. We show that our stacking method significantly outperforms various recently published CDFSML methods on a number of target domains.

2 Related work

As our experiments are based on the Meta-Dataset framework for evaluating CDFSML methods, we review this benchmark first before discussing meta-
learning methods that we compare to in our experiments. We also briefly review other noteworthy methods in the literature.

2.1 Benchmark

The Meta-Dataset \cite{cofc} benchmark has multiple configurations; we describe the CDFSML configuration that we, as well as most recent publications in the field, use. It contains eight source domains: ILSVRC-2012 (ImageNet), Omniglot, Aircraft, CUB-200-2011 (Birds), Describable Textures, Quick Draw, Fungi, and VGG Flower. Recent work utilising Meta-Dataset \cite{cofc} has extended its original set of two target domains, Traffic Signs and MSCOCO, by adding three more: MNIST, CIFAR10, and CIFAR100. For an even more comprehensive evaluation, we add four target domains from the CDFSL benchmark in \cite{cofc}—CropDisease, EuroSAT, ISIC, and ChestX—but additionally also employ Food101 \cite{cofc}.

The Meta-Dataset framework splits each source domain into three partitions: training, validation, and test. The partitions are mutually exclusive in terms of their classes, with the training partition containing approximately 70% of source domain classes and the validation and test partitions containing approximately 15% of the classes each. The training and validation partitions are made available to the CDFSML method being evaluated. These methods generally use the training partition to pretrain the corresponding backbone model and the validation split to aid hyperparameter tuning. The test partition is reserved for the meta-test phase, to sample few-shot episodes for evaluation.

In contrast, the entire target domain data can be used for meta-testing. It is important to note that, by definition, only tasks sampled from target domains truly measure CDFSML performance. Using terminology that is common in this context, good performance on these domains indicates “strong generalisation”; good performance on tasks sampled from source domain test partitions can only indicate “weak generalisation”.

2.2 Methods included in the experimental comparison

Two recently published CDFSML methods that advanced the state-of-the-art on Meta-Dataset are Few-shot Learning with a Universal TEmplate (FLUTE) \cite{cofc} and Universal Representation Learning (URL) \cite{cofc}. We compare to these two methods in our experiments.

**Few-shot Learning with a Universal TEmplate.** Based on the FiLM approach \cite{cofc}, FLUTE trains a universal model on the source domains, employing the ResNet18 architecture \cite{cofc} widely used in CDFSML, but maintains a separate set of batch normalisation \cite{cofc} parameters for each domain. The ResNet “template” contains one set of convolutional weights shared across all source domains along with one set of batch normalisation weights for each source domain. FLUTE jointly trains the template on all source domains. At each training iteration, a random source domain is selected—with the previously discussed bias
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In forward propagation, the input batch flows through the shared convolutional layers and the specific set of batch normalisation layers corresponding to the selected source domain, and loss is computed by applying a cosine classifier \[2, 3\]. A nuance of FLUTE training is that back propagation is performed using a meta-batch of eight individual batches: the intention is to stabilise training by aggregating loss values across multiple domains.

When the template is trained, checkpoints are frequently saved. The final template is chosen as the checkpoint that yields best performance on the source domains’ validation partitions. To establish performance, few-shot episodes are sampled from these partitions. For each episode, feature vectors are extracted using the shared convolutional layers and the set of batch normalisation layers for the domain at hand. Accuracy is computed using a nearest-centroid classifier \[12, 15\] (as the aforementioned cosine classifiers is trained on different source domain classes and cannot be used). In our experiments, we use the checkpoint made available by the authors of FLUTE, which was obtained at iteration 610,000.

One more component produced by FLUTE’s, in a separate meta-training phase, is a blender network, which is a dataset classifier based on a permutation-invariant set encoder \[19\] followed by a linear layer. Given a batch of instances, the blender predicts, as a probability distribution, the source domain from which the batch is sampled. It is trained on batches sampled from the source domains’ training partitions, and the final blender model is chosen from the available checkpoints using batches from the validation partitions. Again, we use the checkpoint made available by the authors, which corresponds to iteration 14,000.

Given a few-shot episode at meta-test time, the blender uses the support set to produce a probability distribution. These probabilities in turn are used to form a linear combination of the source-domain-specific batch normalisation weights. Along with the shared convolutional weights from the template, this forms the initial set of parameters for the ResNet18 feature extractor, which is applied in conjunction with a nearest-centroid classifier. The model is then fine-tuned on the support set with only the batch normalisation parameters unfrozen. Hyperparameter tuning for FLUTE in \[16\] is performed using episodes sampled from source domain validation partitions: the Adam optimiser, a learning rate of 5e-3, and 6 iterations are chosen as the configuration for meta-testing.

Universal Representation Learning

The URL approach first pretrains domain-specific ResNet18 backbones independently. Then, a separate ResNet18 feature extractor is trained to form a universal model by distillation. This is achieved by making it learn to match each domain-specific backbone’s output feature vectors and logits given instance batches sampled from the corresponding domain. To this end, the universal model contains pairs of auxiliary domain-specific components that each comprise i) a projection layer that transforms the universal extractor’s feature vector without altering its length (512 for a ResNet18 model)—this assists in matching the universal features to the ones extracted by
the corresponding backbone—and ii) a classifier layer trained to match the logits produced by the backbone.

In the experiments in [9], ImageNet data is given a greater presence in knowledge distillation through a larger batch size equivalent to the batch sizes of the other seven source domains combined. Checkpoints of the universal feature extractor are saved at predefined intervals during knowledge distillation. The final checkpoint is selected based on the accuracy of the universal feature extractor when combined with a nearest-centroid classifier, using few-shot episodes sampled from the source domains’ validation partitions. We use the officially available URL checkpoint in our evaluations.

After meta-training, the auxiliary components of the universal model are discarded, leaving only the feature extractor. At meta-test time, this extractor is frozen, and a newly initialised projection layer is trained on the support set. The transformed feature vectors are used to build a nearest-centroid classifier. The loss of this classifier is used to fine-tune the projection layer for 40 iterations with an Adadelta optimiser and a learning rate of 1 for the target domains. (A lower learning rate of 0.1 is used for the source domains.)

2.3 Other work on CDFSML

Selecting relevant features from a Universal Representation SUR [5] is an early CDFSML method that utilises independently pretrained feature extractor backbones directly for meta-testing. Each backbone is used to extract a set of feature vectors from the support set, with a trainable weight assigned to it. The feature vector sets are multiplied by their respective weights and concatenated to provide input to a nearest-centroid classifier. The weights are trained by optimising loss of the classifier on the support set. Overall, SUR is similar to URL in the meta-testing phase, as both make predictions with a nearest-centroid classifier and optimise parameters on the support set; the primary difference is that URL maintains a universal model while SUR uses the backbones directly.

Universal Representation Transformer URT [11] also assigns a weight to each source feature extractor during meta-testing. However, it utilises a universal model instead of direct optimisation on the support set to obtain the weights. URT trains an attention mechanism [18] for its universal model, which learns to assign appropriate weights to source feature extractors given a few-shot episode. The universal model is trained and has its hyperparameters selected using episodes sampled from the source domain’s training and validation partitions.

Task-Specific Adaptors TSA [10] is a very recent fine-tuning paradigm that is designed to be particularly suitable for CDFSML and shown to yield improved results when used in conjunction with URL, where it effectively adds trainable parallel matrix adaptors to the backbones’ architecture (in addition to the trainable projection layer used in the URL backbones). TSA is orthogonal to the stacking method introduced here. Due to the recency of its publication,
we were unable to evaluate the effect of TSA backbones in our setting. However, we conjecture that we can obtain performance improvements similar to those obtained when using these backbones in URL.

3 Stacking for cross-domain few-shot learning

We propose Feature Extractor Stacking (FES) for CDFSML, formulated as three phases: fine-tuning backbones to obtain checkpoints, cross-validation to produce meta-training data for a meta-learner, and meta-learning to create an ensemble from the checkpoints.

3.1 Fine-tuning

We use \( f_{\Phi_0}, f_{\Phi_1}, \ldots, f_{\Phi_{K-1}} \) to denote the collection of pre-trained feature extractors, where \( \Phi \) represents the extractor’s parameters and \( K \) is the number of source domains. The support set of a few-shot episode is denoted as \( S \) and the query set as \( Q \). \( S \) contains \( N \) instances belonging to \( C \) classes. We fine-tune each backbone independently on \( S \). As \( f_\theta \) is a feature extractor, a classifier \( g \) is attached to \( f_\theta \) to produce logits, and the resulting model is defined as \( h_\Psi = g \circ f_\theta \). \( \Psi \) is the combination of \( \Phi \) and the parameters in \( g \), and \( \Psi = \Phi \) if \( g \) is nonparametric. After a predetermined number of fine-tuning iterations, the state of \( h \) is denoted as \( h_\Psi^t \), and \( h_\Psi^t \) is saved as a checkpoint. Multiple checkpoints can be saved at different iterations of a fine-tuning process. In our results, we show it is beneficial to save checkpoints frequently. In the current version of FES, the meta-classifier treats every checkpoint independently, i.e., it does not consider whether two checkpoints \( h_{\Psi^t_0} \) and \( h_{\Psi^t_1} \) originate from the same un-fine-tuned model \( h_\Psi \) or two different ones. Therefore, for the ease of notation, we denote the collection of all checkpoints saved from all \( K \) backbones’ fine-tuning as a flattened list \( h_{\Psi^t_0}, h_{\Psi^t_1}, \ldots, h_{\Psi^t_{J-1}} \), where \( J \) is the total number of checkpoints.

Each backbone’s fine-tuning configuration should be one that suits the model, and different backbones can use different configurations. The configuration includes hyperparameters such as the learning rate (and scheduling), number of fine-tuning iterations, optimiser, etc., as well as high-level parameters such as what classifier \( g \) to use or which parts of the model \( h_\Psi \) to freeze. A configuration should be determined with respect to the model’s architecture and pretraining, e.g., a FiLM network should have its convolutional layers frozen, leaving only the batch normalisation layers trainable. Our experimental setup section will explain the configurations we used, which should serve as a more detailed example.

3.2 Cross-validation

We apply stratified \( k \)-fold cross-validation to the support set \( S \), producing \( k \) sets of training/test splits \( (S_{\text{train}}^0, S_{\text{test}}^0), (S_{\text{train}}^1, S_{\text{test}}^1), \ldots, (S_{\text{train}}^{k-1}, S_{\text{test}}^{k-1}) \). Given a pair of \( (S_{\text{train}}, S_{\text{test}}) \) and a checkpoint \( h_\Psi^t \), we obtain an un-fine-tuned copy
of the checkpoint, i.e., \(h_\psi\), which can be assembled from \(f_\phi\) and \(g\) if \(g\)'s initialisation is deterministic, or needs to be a saved copy beforehand during fine-tuning if otherwise. We fine-tune \(h_\psi\) with the same configuration used to obtain \(h_\psi\), e.g., with the same optimiser, learning rate, number of iterations, etc., on \(S_{\text{train}}\), and the resulting model is denoted \(h_\psi_{\text{CV}}\). Logits \(L_{\text{CV}}\) are extracted from \(S_{\text{test}}\) with \(h_\psi_{\text{CV}}\), i.e., \(L_{\text{CV}} = h_\psi_{\text{CV}}(S_{\text{test}})\). Using this approach, the splits \((S_{\text{train}}^0, S_{\text{test}}^0), (S_{\text{train}}^1, S_{\text{test}}^1), \ldots, (S_{\text{train}}^{k-1}, S_{\text{test}}^{k-1})\) can be used to produce logits \(L_{\text{CV}}^0, L_{\text{CV}}^1, \ldots, L_{\text{CV}}^{k-1}\), and these can be combined into \(L_{\text{S}}^S\), i.e., logits for every support set instance extracted using cross-validation. \(L_{\text{S}}^S\) is a matrix of shape \(N \times C\), i.e., logits for \(C\) classes for \(N\) support instances.

Using the method above, support logits can be extracted for every checkpoint \(h_\psi_0', h_\psi_1', \ldots, h_\psi_{J-1}'\), producing \(L_{\text{CV}}^0, L_{\text{CV}}^1, \ldots, L_{\text{CV}}^{J-1}\), which can be stacked into a tensor \(L_{\text{S}}^S\) of shape \(N \times J \times C\). This tensor is used as training data for the meta-learner in our stacking-based approach.

### 3.3 Meta-learning

The parameters optimised by our meta-learner are structured as a weight array \(W\) of length \(J\), with \(W_j\) representing the \(j\)-th checkpoint’s weight. Given a meta-learning instance \(l\) of shape \(J \times C\), which contains logits for \(C\) classes extracted by \(J\) checkpoints, the meta-learner’s output logits \(l^W\) are obtained using a simple weighted average:

\[
l^W_c = \sum_{j=0}^{J-1} W_j \cdot l_{j,c},
\]

where \(c\) is one of the \(C\) classes. We compute the cross-entropy loss on the \(N\) support set instances based on the logits \(L^W\) and one-hot-encoded labels \(Y\), i.e.,

\[
- \sum_{n=0}^{N-1} Y_n \log(\text{softmax}(L_n^W)),
\]

which we minimise by training \(W\).

After training, \(W\) is used with Equation 1 to compute logits for a new query instance \(q\) using the logits \(L^q_j\) computed by the saved checkpoints \(h_\psi_0', h_\psi_1', \ldots, h_\psi_{j-1}'\). Then, a softmax function is used to obtain class probability estimates.

### 3.4 Convexity proof

We prove that optimising \(W\) on \(L^CV_j\) is a convex problem, by showing that the second derivative of every instance’s loss \(-y \cdot \log(\text{softmax}(l^W))\) is non-negative. Assuming \(c_y\) is the correct label among the \(C\) classes, the loss can be written as

\[
\ell = \log(\sum_{i=0}^{C-1} e^{l^W_{i,c_y}}) - l^W_{c_y}.
\]
Given any weight $w_j$ in the array $W$, and Equation 1, the first derivative is

$$\frac{d\ell}{dw_j} = \sum_{i=0}^{C-1} l_{j,c_i} e^{l_i^{W}} - l_{j,c_y}$$

The second derivative is

$$\frac{d^2\ell}{dw^2_j} = \sum_{i=0}^{C-1} (l_{j,c_i} e^{l_i^{W}})^2 - (\sum_{i=0}^{C-1} l_{j,c_i} e^{l_i^{W}})^2 \cdot \sum_{i=0}^{C-1} e^{l_i^{W}}$$

The denominator is clearly positive; we show that the numerator is non-negative.

We rename $i$ into $a$ and $b$. The minuend becomes $\sum_{a=0}^{C-1} l_{j,c_a} e^{l_{a}^{W}}$, and the subtrahend becomes $\sum_{b=0}^{C-1} l_{j,c_b} e^{l_{b}^{W}}$, transforming the subtraction into

$$\sum_{a=0}^{C-1} \sum_{b=0}^{C-1} (l_{j,c_a} e^{l_{a}^{W}} - l_{j,c_b} l_{j,c_b}) \cdot e^{(l_{a}^{W} + l_{b}^{W})}.$$ 

$e^{(l_{a}^{W} + l_{b}^{W})}$ is always positive. When $a = b$, we have $l_{j,c_a} e^{l_{a}^{W}} - l_{j,c_b} l_{j,c_b} = 0$. Any off-diagonal pair $(a,b)$ in the $C \times C$ matrix can be paired up with its opposite $(b,a)$. The sum of each pair is

$$(l_{j,c_a} - l_{j,c_b}) \cdot e^{(l_{a}^{W} + l_{b}^{W})} + (l_{j,c_b} - l_{j,c_b} l_{j,c_b}) \cdot e^{(l_{a}^{W} + l_{b}^{W})}$$

$$= (l_{j,c_a} - l_{j,c_b}) \cdot e^{(l_{a}^{W} + l_{b}^{W})} + (l_{j,c_b} - l_{j,c_b} l_{j,c_b}) \cdot e^{(l_{a}^{W} + l_{b}^{W})}$$

Therefore, the sum of every pair is non-negative, and the pair sum is positive if $l_{j,c_a} \neq l_{j,c_b}$.

In conclusion, the second derivative of the loss $\ell$ is non-negative, and it is positive as long as $\exists a, b \in L_j^{CV}: a \neq b$. Therefore, the problem of optimising $W$ on $L_j^{CV}$ is convex.

### 3.5 Handling single-instance classes

Meta-Dataset’s sampling scheme sometimes produces support sets where classes have only one instance, which interferes with the initialisation of classifiers during cross-validation. During cross-validation, if the only instance belonging to a single-instance class is partitioned into the test split $S_{\text{test}}$, then the training split $S_{\text{train}}$ will have no instance in that class for classifier initialisation, i.e., its
centroid cannot be computed. To solve this issue, the problematic classes need to have their centroids set to null vectors, i.e., filled with zeros, and corresponding instances in the test split need to be removed as they will not lead to logits useful to meta-learning.

However, if classes are effectively removed from the extracted logits $L^{CV}_J$, the meta-learner $W$ will not have a complete picture of the support set (even though it is still able to function as normal because it only learns a weight for each checkpoint instead of any statistical knowledge specific to individual classes). To compensate for $W$’s missing training instances, we include a new meta-learner $W_K$, containing a weight for each of un-fine-tuned $K$ models $h_{\Psi_0}, h_{\Psi_1}, ..., h_{\Psi_{K-1}}$. To differentiate the two meta-learners, $W$ will be referred to as $W_J$ hereon. Each $h_{\Psi}$ is used to extract logits from the entire support set $S$, and logits extracted by all un-fine-tuned models are stacked into $L^K_J$, which is then used to train $W_K$. Then $W_K$ and $W_J$ are converted into the same space representing the union of \{h_{\Psi_0}, h_{\Psi_1}, ..., h_{\Psi_{K-1}}\} and \{h_{\Psi_0}', h_{\Psi_1}', ..., h_{\Psi_{J-1}}'\}, by padding their weight arrays with zeros for the checkpoints that they lack respectively. (Usually the $J$ checkpoints already contain the $K$ un-fine-tuned ones, and only $W_K$ needs to be padded.) The weights are scaled to be consistent, i.e., $W_K = \max(\text{abs}(W_K))$ and $W_J = \max(\text{abs}(W_J))$. A blending factor is defined as $b = \frac{\text{single-instance-class count}}{\text{all class count}}$, and the two meta-learners are blended into one $W_U = b \cdot W_K + (1-b) \cdot W_J$. $W_U$ can then be utilised as $W_J$ for instance classification. In the extreme case of a one-shot episode, i.e., every class contains a single instance, $b = 1$ and $W_U = W_K$, as cross-validation cannot be performed.

4 Experimental setup

To facilitate comparison with FLUTE and URL, we use saved models provided by official repositories of these methods in our stacking-based method, and fine-tuning configurations specified in the corresponding articles. The download for FLUTE contains a FiLM ResNet18 model with one set of convolutional weights and eight sets of batch normalisation weights, which can be converted into eight standalone ResNet18 models that have identical convolutional weights. URL contains a “universal” ResNet18 model produced by distilling knowledge from eight source domain feature extractors, and we use URL’s universal model directly as a feature extractor. Therefore, we have nine extractors available.

When fine-tuning each FLUTE feature extractor, we keep the convolutional layers frozen, and use FLUTE’s choice of the Adam optimiser and a learning rate of 5e-3. We attach a cosine classifier to the end of each FLUTE feature extractor, and the classifier’s weight matrix is initialised with the centroids of support set feature vectors extracted by the feature extractor before fine-tuning.

When fine-tuning the URL feature extractor, we keep the entire extractor frozen, and apply a trainable projection with a weight matrix of shape 512 x 512 (initialised as an identity matrix) to the extractor’s output. We use URL’s choice
of an Adadelta optimiser and a learning rate of 0.1 for the source domains and 1 for the target domains. Logits are produced from projected feature vectors using a nearest-centroid classifier. URL scales its logits by a factor of 10 in its training, which need to be scaled back by 0.1 at logit extraction time to be consistent with FLUTE’s logits.

FLUTE fine-tunes a model for 6 iterations during meta-test while URL fine-tunes for 40. We fine-tune all extractors for 40 iterations and save a checkpoint after each iteration, in addition to one checkpoint saved for the un-fine-tuned model, i.e., a total of 41 checkpoints per model.

Our experiments indicate that stratified 2-fold cross-validation is sufficient in the stacking approach and increasing the number of folds does not lead to significantly different results. Therefore, we use 2-fold cross-validation, which is computationally cheaper than having more folds. Due to the convexity of the meta-learning problem, we use an LBFGS optimiser to train the meta-learner, applying its default hyperparameters in the PyTorch library, except that we utilise its line search function. The meta-learner’s weight matrix is initialised with a small constant, i.e., 1/41 so that the initial weights of all checkpoints for each backbone sum up to 1.

5 Results

We present our experimental results here. In order to eliminate the randomness in Meta-Dataset’s sampling, which has been observed to cause accuracy fluctuations of up to 3% between different runs, 600 test episodes were sampled from each domain and cached, so that all methods presented below are evaluated on exactly the same FSL tasks. We first compare our stacking method with recently published CDFSML methods, and then conduct ablation studies to analyse the effect of fine-tuning length and checkpoint frequency.

5.1 Performance on the extended Meta-Dataset

We evaluate FES in three different settings: with all nine available backbones (FES full), with the eight FLUTE backbones (FES FLUTE), and with the single URL backbone (FES URL). We compare performance to that of FLUTE and URL. We also include a FES baseline without cross-validation, where the meta-learner contains 9 weight values, one for each backbone after 40 iterations of fine-tuning. The baseline uses the fine-tuned models to extract training logits for the meta-learner directly from the support set instead of utilising cross-validation. The evaluation results are given in Table 1 showing the methods’ accuracy on the eight weak generalisation domains and the ten strong generalisation domains, as well as accuracy averaged over both, the two groups and all datasets. Values in Tables 1, 2, and 3 represent query set accuracy averaged over 600 episodes with a 95% confidence interval.

FES full exhibits the best strong generalisation and overall performance out of the six methods, while being less accurate in weak generalisation domains
Table 1. Performance of FES in three different settings, compared with URL and FLUTE, as well as a baseline without cross-validation

| Dataset       | URL     | FLUTE    | FES_URL  | FES_FLUTE | FES_full | Baseline |
|---------------|---------|----------|----------|-----------|----------|----------|
| ilsvrc2012    | 57.0±1.0| 51.1±1.1 | 56.7±1.1 | 52.9±1.1  | 56.0±1.1 | 50.5±1.1 |
| omniglot      | 94.1±0.4| 93.6±0.5 | 93.9±0.5 | 91.1±0.7  | 92.1±0.6 | 91.4±0.6 |
| aircraft      | 88.5±0.5| 87.6±0.6 | 88.4±0.5 | 86.5±0.8  | 89.0±0.6 | 83.9±0.8 |
| cu_birds      | 80.4±0.7| 78.9±0.8 | 80.4±0.8 | 78.5±0.9  | 81.3±0.8 | 75.7±0.9 |
| dtd           | 76.5±0.7| 69.0±0.8 | 76.2±0.8 | 72.7±0.9  | 75.0±0.9 | 74.0±0.8 |
| quickdraw      | 82.2±0.6| 79.2±0.7 | 82.4±0.6 | 78.8±0.7  | 81.8±0.6 | 71.9±0.9 |
| fungi         | 68.1±1.0| 57.9±1.1 | 67.7±1.0 | 55.3±1.2  | 65.7±1.1 | 43.2±1.1 |
| vgg_flower    | 92.3±0.5| 92.0±0.6 | 92.1±0.6 | 91.9±0.6  | 92.6±0.6 | 92.2±0.6 |
| traffic_sign  | 62.7±1.2| 58.1±1.1 | 62.6±1.2 | 75.6±1.2  | 76.3±1.1 | 70.5±1.2 |
| mscoco        | 54.5±1.0| 50.0±1.0 | 54.6±1.1 | 50.1±1.1  | 54.2±1.1 | 45.9±1.2 |
| mnist         | 94.5±0.4| 96.0±0.3 | 94.2±0.6 | 96.7±0.4  | 96.8±0.4 | 97.4±0.3 |
| cifar10       | 71.8±0.7| 78.8±0.7 | 70.4±0.9 | 78.5±0.9  | 79.0±0.9 | 78.4±0.9 |
| cifar100      | 63.0±1.0| 67.8±0.9 | 62.7±1.0 | 70.1±1.0  | 71.2±1.0 | 68.5±1.0 |
| CropDisease   | 80.6±0.8| 77.9±0.8 | 80.2±0.8 | 85.2±0.8  | 86.0±0.7 | 80.6±0.9 |
| EuroSAT       | 86.1±0.6| 81.8±0.6 | 85.4±0.7 | 87.0±0.8  | 87.7±0.7 | 87.6±0.6 |
| ISIC          | 46.0±0.8| 46.4±0.9 | 41.3±1.0 | 43.0±0.9  | 44.0±1.0 | 38.4±0.9 |
| ChestX        | 29.2±0.6| 28.5±0.6 | 23.2±0.7 | 26.2±0.6  | 26.5±0.6 | 27.2±0.5 |
| Food101       | 52.3±1.1| 46.0±1.1 | 52.9±1.1 | 49.7±1.2  | 53.8±1.1 | 45.5±1.2 |
| Average WG    | 79.87   | 76.18    | 79.71    | 75.95     | 79.20    | 72.85    |
| Average SG    | 64.06   | 63.12    | 62.74    | 66.21     | 67.54    | 64.00    |
| Average all   | 71.08   | 68.93    | 70.28    | 70.54     | 72.72    | 67.93    |

than URL. While FES_URL generally performs worse than URL, FES_FLUTE performs better than FLUTE in the target domains. We speculate that FES benefits more from a diverse backbone collection than a single powerful backbone. Note that FLUTE and URL trained their respective backbones with the same source domain datasets, and FES_FLUTE generalises better than FES_URL. This speculation is further supported by the fact that FES_full performs better than both FES_FLUTE and FES_URL, as FES_full has the most diverse backbone collection.

5.2 Fine-tuning iterations

We perform an ablation study by limiting the number of fine-tuning iterations for FES. Table 2 shows the performance of FES_full when the number of fine-tuning iterations is limited to 10, 20, 30, and when all 40 iterations are performed. A checkpoint is saved after every iteration, in addition to the initial un-fine-tuned checkpoint, e.g., fine-tuning for 10 iterations creates 11 checkpoints for each backbone.

Fine-tuning for 40 iterations is overall the best performing configuration, as it is significantly better than its fewer-iteration alternatives on datasets such as Traffic Signs and Crop Disease. When it is worse, the difference is always within the 95% confidence interval. FES_full still shows clear signs of improvement on
the Traffic Signs dataset at 40 iterations, and it may achieve even higher accuracy if fine-tuned for more iterations. Results in Table 2 show that FES benefits from more fine-tuning when some backbones need more iterations to converge to a good solution. On the other hand, FES is able to adjust its weights so that it is not affected by checkpoints over-fitted from too much fine-tuning, as more fine-tuning iterations never harm performance significantly.

### 5.3 Checkpoint frequency

We perform another ablation study by limiting the number of checkpoints saved over 40 iterations. Table 3 shows the performance of FES\textsubscript{full} when one checkpoint is saved per 1, 5, 10, 20, and 40 iterations, in addition to the un-fine-tuned checkpoint, leading to a total of 41, 9, 5, 3, and 2 checkpoints respectively. We include one more setting where only one checkpoint at iteration 40 is saved for each backbone, without the un-fine-tuned checkpoint.

There is no checkpoint frequency setting that is best in every scenario. However, in many case, the differences appear statistically insignificant. Nevertheless, to achieve good performance on target domains such as Traffic Signs, where FES significantly outperforms FLUTE and URL, as shown in Table 1, saving more checkpoints is preferable. Indeed, important checkpoints may be situated in the middle of the fine-tuning process, and saving frequently ensures that they are available to the meta-learner. Practical applications of FES should save checkpoints as frequently as it is feasible.

The “1 ckpt” column in Table 3 forms a good comparison with the “Baseline” column in Table 1 as both of them have access to the same nine model check-

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**Table 2.** FES\textsubscript{full} performance when fine-tuning for 10, 20, 30, or all 40 iterations

| Dataset       | 10\_iter | 20\_iter | 30\_iter | 40\_iter |
|---------------|----------|----------|----------|----------|
| ilsvrc\textsubscript{2012} | 56.0±1.1 | 56.0±1.1 | 56.0±1.1 | 56.0±1.1 |
| omniglot      | 92.2±0.6 | 92.2±0.6 | 92.2±0.6 | 92.1±0.6 |
| aircraft      | 89.0±0.6 | 89.0±0.6 | 89.0±0.6 | 89.0±0.6 |
| cu\_birds     | 81.7±0.8 | 81.7±0.8 | 81.5±0.8 | 81.3±0.8 |
| dtd           | 75.2±0.8 | 75.0±0.9 | 75.2±0.9 | 75.0±0.9 |
| quickdraw     | 81.7±0.6 | 81.7±0.6 | 81.8±0.6 | 81.8±0.6 |
| fungi         | 65.5±1.1 | 65.6±1.1 | 65.7±1.1 | 65.7±1.1 |
| vgg\_flower   | 92.8±0.6 | 92.5±0.6 | 92.6±0.6 | 92.6±0.6 |
| traffic\_sign | 68.6±1.2 | 70.7±1.2 | 73.8±1.1 | 76.3±1.1 |
| mscoco        | 53.9±1.1 | 54.0±1.1 | 54.1±1.1 | 54.2±1.1 |
| mnist         | 96.5±0.4 | 96.6±0.4 | 96.8±0.4 | 96.8±0.4 |
| cifar10       | 79.4±0.9 | 79.2±0.9 | 79.2±0.9 | 79.0±0.9 |
| cifar100      | 70.9±0.9 | 71.0±0.9 | 71.1±1.0 | 71.2±1.0 |
| CropDisease   | 83.9±0.7 | 84.5±0.7 | 85.3±0.7 | 86.0±0.7 |
| Euro\_SAT     | 86.8±0.7 | 87.3±0.7 | 87.6±0.7 | 87.7±0.7 |
| ISIC          | 43.2±0.9 | 43.1±0.9 | 43.6±1.0 | 44.0±1.0 |
| Chest\_X      | 25.7±0.5 | 26.2±0.6 | 26.6±0.6 | 26.5±0.6 |
| Food101       | 53.7±1.1 | 53.8±1.1 | 53.8±1.1 | 53.8±1.1 |
Table 3. FES full performance given different numbers of checkpoints saved over 40 fine-tuning iterations

| Dataset       | 41ckpt | 9ckpt | 5ckpt | 3ckpt | 2ckpt | 1ckpt |
|---------------|--------|-------|-------|-------|-------|-------|
| ilsvrc2012    | 56.0±1.1 | 56.1±1.1 | 56.2±1.1 | 56.5±1.1 | 57.0±1.1 | 57.3±1.1 |
| omniglot      | 92.1±0.6 | 92.1±0.6 | 92.0±0.6 | 92.1±0.6 | 92.2±0.6 | 92.7±0.6 |
| aircraft      | 89.0±0.6 | 88.9±0.6 | 88.7±0.7 | 88.9±0.7 | 89.3±0.7 | 89.7±0.7 |
| cu_birds      | 81.3±0.8 | 81.1±0.8 | 81.1±0.8 | 81.3±0.8 | 81.7±0.8 | 81.8±0.8 |
| dtd           | 75.0±0.9 | 75.2±0.9 | 75.3±0.9 | 75.5±0.9 | 76.1±0.9 | 76.9±0.8 |
| quickdraw     | 81.8±0.6 | 81.8±0.6 | 81.8±0.6 | 82.0±0.6 | 82.0±0.6 | 82.1±0.6 |
| fungi         | 65.7±1.1 | 65.5±1.2 | 65.3±1.2 | 65.3±1.2 | 65.3±1.2 | 64.9±1.2 |
| vgg_flower    | 92.6±0.6 | 92.7±0.6 | 92.7±0.6 | 92.9±0.6 | 92.9±0.5 | 93.2±0.5 |
| traffic_sign  | 76.3±1.1 | **76.6±1.1** | 76.4±1.1 | 75.9±1.1 | 71.2±1.1 | 72.5±1.1 |
| mscoco        | **54.2±1.1** | 54.0±1.1 | 53.6±1.1 | 53.6±1.1 | 53.5±1.1 | 53.0±1.1 |
| mnist         | 96.8±0.4 | 96.8±0.4 | 96.8±0.4 | 96.9±0.4 | 96.8±0.4 | **97.2±0.3** |
| cifar10       | 79.0±0.9 | 78.9±0.9 | 78.7±0.9 | 78.9±0.9 | 79.4±0.9 | **79.8±0.8** |
| cifar100      | **71.2±1.0** | **71.2±0.9** | 71.1±1.0 | **71.2±0.9** | **71.2±0.9** | 70.9±1.0 |
| CropDisease   | 86.0±0.7 | **86.2±0.7** | 85.9±0.7 | 85.9±0.7 | 84.4±0.7 | 84.4±0.7 |
| EuroSAT       | 87.7±0.7 | 87.7±0.7 | 87.7±0.7 | 87.8±0.7 | 87.7±0.7 | **88.3±0.7** |
| ISIC          | 44.0±1.0 | 43.4±0.9 | 43.7±0.9 | 43.9±0.9 | **45.2±0.9** | 43.4±0.9 |
| ChestX        | 26.5±0.6 | 26.7±0.6 | 26.6±0.6 | 26.8±0.6 | **28.4±0.6** | **28.4±0.6** |
| Food101       | **53.8±1.1** | **53.8±1.1** | 53.7±1.1 | 53.7±1.1 | 53.7±1.1 | 53.7±1.1 |

points at the end of 40 iteration, with the difference being that “1ckpt” uses cross-validation to produce training data for the meta-learner while “Baseline” does not. The method with cross-validation outperforms the method without it on almost every dataset in the benchmark, which indicates that cross-validation is a vital part of FES, as it avoids over-fitting caused by data reuse.

5.4 Weight heat maps

We include heat maps of the FES weights averaged over 600 episodes on the Traffic Signs and MNIST datasets, as shown in Figures 1 and 2.

For Traffic Signs, the ILSVRC-2012 extractor is assigned high positive weights at the beginning of fine-tuning, and most models are assigned positive weights at the end of fine-tuning, especially so for the Describable Textures extractor. On the other hand, for MNIST, the Omniglot extractor is assigned the highest positive weights at the end of fine-tuning. The URL model is never assigned strongly negative weights for either dataset, presumably due to it being a “universal model”.

6 Future work

Given the experiments conducted and results presented in this work, we can see the following future research tasks:

1. integrating TSA into FES as a fine-tuning method;
implementing detection and selection mechanisms to terminate unhelpful backbones and configurations early in fine-tuning to make FES more efficient; conversely, allowing relevant backbones to fine-tune for as long as they need to converge to their optimum; and 
4. determining checkpoint saving frequency dynamically based on episode attributes such as support set size.

7 Conclusion

We present the stacking-based CDFSML method FES, which creates checkpoints from fine-tuning independent backbones with different configurations on the support set, uses cross-validation to avoid over-fitting from support data reuse, and trains a simple meta-learner to appropriately weight the checkpoints. FES achieves highly competitive results on the Meta-Dataset benchmark. When given the same backbones, FES achieves better results on a number of target domains than recently published universal-model methods. FES also has important advantages that makes it more applicable in real-world scenarios:

1. It can work with out-of-the-box heterogeneous backbone collections and does not require source domain data at the meta-level.
2. It is change friendly: when the backbone collection is updated, there is no change-related computational overhead at the meta-level.
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