Unsupervised Meta-Learning for Few-Shot Image and Video Classification

Siavash Khodadadeh, Ladislau Bölöni
Dept. of Computer Science
University of Central Florida
siavash.khodadadeh@knights.ucf.edu, lboloni@cs.ucf.edu

Mubarak Shah
Center for Research in Computer Vision
University of Central Florida
shah@crcv.ucf.edu

November 30, 2018

Abstract

Few-shot or one-shot learning of classifiers for images or videos is an important next frontier in computer vision. The extreme paucity of training data means that the learning must start with a significant inductive bias towards the type of task to be learned. One way to acquire this is by meta-learning on tasks similar to the target task. However, if the meta-learning phase requires labeled data for a large number of tasks closely related to the target task, it not only increases the difficulty and cost, but also conceptually limits the approach to variations of well-understood domains.

In this paper, we propose UMTRA, an algorithm that performs meta-learning on an unlabeled dataset in an unsupervised fashion, without putting any constraint on the classifier network architecture. UMTRA uses statistical diversity properties and domain-specific augmentations to generate the training and validation data for a collection of synthetic tasks, \( \{T'_1, \ldots \} \). These tasks are then used in a meta-learning process. The only requirements towards the dataset are: sufficient size, diversity and number of classes, and relevance of the domain to the one in the target task. Exploiting this information, UMTRA generates synthetic training tasks for the meta-learning phase.

We evaluate UMTRA on few-shot and one-shot learning on both image and video domains. To the best of our knowledge, we are the first to evaluate meta-learning approaches on UCF-101. On the Omniglot and Mini-Imagenet few-shot learning benchmarks, UMTRA outperforms every tested approach based on unsupervised learning of representations, while alternating for the best performance with the recent CACTUs algorithm. We also evaluate our approach on the CelebA dataset which is unbalanced. Compared to supervised model-agnostic meta-learning approaches, UMTRA trades off some classification accuracy for a vast decrease in the number of labeled data needed. For instance, on the five-way one-shot classification on the Omniglot, we retain 85% of the accuracy of MAML, a recently proposed supervised meta-learning algorithm, while reducing the number of required labels from 24005 to 5.

Keywords
Deep Learning · Unsupervised Learning · Unsupevised Meta-Learning · Meta-Learning · Few-Shot Learning · Video Classification · Image Classification

1 Introduction

Meta learning or “learning-to-learn” approaches have been proposed in neural networks literature since the 1980s [1][2]. The general idea of these approaches is that the network is prepared through several auxiliary learning tasks \( T_1 \ldots T_n \), in a meta-learning phase in such a way that when the unseen task \( T_{n+1} \) is presented in the target learning phase, the network will be ready to learn it as efficiently as possible.

Recently proposed model-agnostic meta-learning approaches [3][4] can be applied to any differentiable network. When we use these approaches for classification tasks, the target learning phase consists of several gradient descent steps on a backpropagated supervised classification loss. These approaches have shown a remarkable ability to perform few or
even single-shot classification on the target task $T$, making the target learning phase extremely efficient, both from the point of view of training data as well as training time.

Unfortunately, these approaches require the auxiliary learning tasks $T_i$ to have the same supervised learning format as the target task. Acquiring labeled data for a large number of tasks is not only a problem of cost and convenience but also puts conceptual limits on the type of problems that can be solved through meta-learning. If we need to have labeled training data for tasks $T_1, \ldots, T_n$ in order to learn task $T_{n+1}$, this limits us to task types that are variations of tasks known and solved (at least by humans).

In this paper, we propose an algorithm called Unsupervised Meta-learning with Tasks constructed by Random sampling and Augmentation (UMTRA) that performs meta-learning on one-shot or few-shot classifiers in an unsupervised manner on an unlabeled dataset. Instead of starting from a collection of labeled tasks, $\{\ldots, T_i, \ldots\}$, UMTRA starts with a collection of unlabeled data $U = \{\ldots x_i, \ldots\}$. We have only a set of relatively easy-to-satisfy requirements towards $U$: its objects have to be drawn from the same distribution as the objects classified in the target task and it must have a set of classes significantly larger than the number of classes of the final classifier. Starting from this unlabeled dataset, UMTRA uses statistical diversity properties and domain specific augmentations to generate the training and validation data for a collection of synthetic tasks, $\{\ldots T'_i, \ldots\}$. These tasks are then used in a meta-learning process based on a modified classification variant of the MAML algorithm [3].

The contributions of this paper can be summarized as follows:

- We describe a novel algorithm that allows unsupervised, model-agnostic meta-learning for few-shot classification. To the best of our knowledge, the only similar work is the CACTUs algorithm posted as a preprint recently [5].
- On all the Omniglot and Mini-Imagenet few-shot learning benchmarks, UMTRA outperforms every tested approach based on unsupervised learning of representations, while alternating for the best performance with the CACTUs algorithm. It also achieves a significant percentage of the accuracy of the supervised MAML approach, while requiring vastly fewer labels. For instance, on five-way one-shot Omniglot classification, our approach retains 85\% of the classification accuracy of MAML while reducing the number of required labels from 24005 to 5.
- We demonstrate the ability to perform one-shot video classification using meta-learning (both supervised and unsupervised). We show that the algorithm outperforms pre-training based approaches, and works even when the meta-learning database (Kinetics) is different from the test database (UCF-101). To the best of our knowledge, this is the first work to show any type of meta-learning for video classification.

2 Related Work

Few-shot or one-shot learning of classifiers has significant practical applications. Unfortunately, the few-shot learning model is not a good fit to the traditional training approaches of deep neural networks, which work best with large amounts of data. In recent years, significant research targeted approaches to allow deep neural networks to work in few-shot learning settings. One possibility is to perform transfer learning, but it was found that the accuracy decreases if the target task diverges from the trained task. One solution to mitigate this is through the use of an adversarial loss [6].

A large class of approaches aim to enable few-shot learning by *meta-learning* - the general idea being that the meta-learning prepares the network to learn from the small amount of training data available in the few-shot learning setting. Note that meta-learning can be also used in other computer vision applications, such as fast adaptation for tracking in video [7]. The mechanisms through which meta-learning is implemented can be loosely classified in two groups. One class of approaches use a custom network architecture for encoding the information acquired during the meta-learning phase, for instance in fast weights [8], neural plasticity values [9], custom update rules [10], the state of temporal convolutions [11] or in the memory of an LSTM [12]. The advantage of this approach is that allows us to fine-tune the architecture for the efficient encoding of the meta-learning information. A disadvantage, however, is that it constrains the type of network architectures we can use; innovations in network architectures do not automatically transfer into the meta-learning approach. In a custom network architecture meta-learning model the target learning phase is not the customary network learning, as it needs to take advantage of the custom encoding.

A second, model-agnostic class of approaches aim to be usable for any differentiable network architecture. Examples of these algorithms are MAML [3] or Reptile [4], where the aim is to encode the meta-learning in the weights of the network, such that the network performs the target learning phase with efficient gradients. Approaches that customize the learning rates [13] during meta-training can also be grouped in this class. For this type of approaches, the target learning phase uses the well-established learning algorithms that would be used if learning from scratch (albeit it might use specific hyperparameter settings, such as higher learning rates). We need to point out, however, that the
meta-learning phase uses custom algorithms in these approaches as well (although they might use the standard learning algorithm in the inner loop, such as in the case of MAML). A recent work similar in spirit to ours is the CACTUs unsupervised meta-learning model described in [5].

3 The UMTRA algorithm

3.1 The few-shot classifier learning task

As the UMTRA algorithm is based on generating few-shot classifier learning tasks, we need to start with a careful definition of this problem. Let us consider the objective of classifying samples, \( x \), drawn from a domain, \( X \), into classes, \( y_i \in Y = \{C_1, \ldots, C_N\} \). Without loss of generality, we consider that the classes are encoded as one-hot vectors of dimensionality \( N \). We are interested in learning a classifier \( f_\theta \) that outputs a probability distribution over the classes. It is common to envision \( f \) as a deep neural network parameterized by \( \theta \), although this is not the only possible choice.

We package a certain supervised learning task, \( T \), of type \((N, K)\), that is with \( N \) classes of \( K \) training samples each, as follows: We sample the training data of the form \((x_i, y_i)\), where \( i = 1 \ldots N \times K \), \( x_i \in X \) and \( y_i \in Y \). We assume that there are exactly \( K \) samples for each possible \( y_i \). In the recent meta-learning literature, it is often assumed that the task \( T \) has \( K \) samples of each class for training and (separately), \( K \) samples for validation \((x^j_i, y^j_i)\).

The choices above, including the equal split between the training and validation samples, and the symmetry of the distribution of the training samples and the fact that we call it an N-way K-shot classification, although we have \( N \) times \( 2K \) data if we include the validation data, are conventions to which we will adhere for easier comparison on the experimental results.

For this task, a conveniently defined loss function is the cross-entropy loss over a particular dataset \( D \):

\[
\mathcal{L}(f_\phi) = - \sum_{x^{(j)}, y^{(j)} \sim D} y^{(j)} \log f_\phi(x^{(j)}) + (1 - y^{(j)}) \log(1 - f_\phi(x^{(j)})).
\]

Tasks defined as above are of practical importance, because there are many domains in which the acquisition of the supervised training data is costly. For instance, it is possible that both the samples \((x_i, y_i)\) can only be collected indirectly, from human activity. Alternatively, the input \( x_i \) can be provided by the algorithm, but a human needs to provide the \( y_i \) part. Due to the cost of acquiring the training data, we are specially interested in solving problems with small \( K \) sample values (e.g. \( K = 5 \) or even \( K = 1 \)).

3.2 Learning from scratch, transfer learning and supervised meta-learning

With these definitions, a baseline learning-from-scratch approach would proceed as follows. We are given a task \( T \). We start from a randomly initialized classifier \( f_{\phi_0} \), and update the value of \( \theta \) through some kind of learning algorithm, until the loss is minimized on the training data of the task \((K \) samples of each \( N \) classes\) or after a certain number of iterations. We evaluate the performance by calculating the loss on the validation data of the task. Unfortunately, the lower the value of \( K \), the lower the likelihood that a good classifier can be learned from scratch (that is, from a randomly initialized \( \theta \)). We need to start the learning process with a significant inductive bias which needs to be partially encoded in the classifier architecture and partially in its parameters \( \theta \).

A possible model is transfer learning, where the initialized \( \theta \) was acquired by learning on a different problem. In practice, our expectation is that the cost of training \( \theta \) has been already absorbed previously. This is the case, for instance of classifiers reusing ResNet or VGG networks trained on ImageNet. The way in which the transfer learning happened may be supervised or unsupervised. For transfer learning from models trained on ImageNet, this is, of course a supervised model. However, the general assumption here is that the learned \( \theta \) in fact conveys more about the domain \( X \) rather than the values \( Y \).

Meta-learning models have a different objective from the transfer learning - the objective is that the learning of the task \( T \) starts with an architecture that is especially good at learning such tasks. When we talk about an architecture this involves not only the starting parameters \( \theta_0 \) but also learning rates, update rules, memory content and other rules that might be considered. A frequently encountered setup is the following: We assume that we have access to a collection of tasks \( T_1 \ldots T_n \), drawn from a specific distribution of tasks. We meta-learn on these (supervised) tasks, and finally perform a task training on new task \( T \). Certain algorithms, such as MAML [3] use both the training and the validation data.
Algorithm 1: Unsupervised Meta-learning with Tasks constructed by Random sampling and Augmentation (UMTRA)

```
require : \( N \): class-count, \( N_{MB} \): meta-batch size, \( N_U \): no. of updates
require : \( U = \{ ...x_i,... \} \) unlabeled dataset
require : \( \alpha, \beta \): step size hyperparameters
require : \( A \): augmentation function
randomly initialize \( \theta \);
while not done do
  for \( i \) in \( 1 \ldots N_{MB} \) do
    Sample \( N \) data points \( x_1 \ldots x_N \) from \( U \);
    \( T_i \leftarrow \{ x_1 \ldots x_N \} \);
  end
  foreach \( T_i \) do
    Generate training set \( D_i = \{ (x_1, 1), \ldots (x_N, N) \} \);
    \( \theta_i' = \theta \);
    for \( j \) in \( 1 \ldots N_U \) do
      Evaluate \( \nabla_{\theta_j} \mathcal{L}_{T_i}(f_{\theta_j}) \);
      Compute adapted parameters with gradient descent: \( \theta_i' = \theta_i' - \alpha \nabla_{\theta_j} \mathcal{L}_{T_i}(f_{\theta_j}) \);
    end
    Generate validation set for the meta-update \( D_i' = \{ (A(x_1), 1), \ldots, (A(x_N), N) \} \)
  end
  Update \( \theta \leftarrow \theta - \beta \nabla_{\theta} \sum_{T_i} \mathcal{L}_{T_i}(f_{\theta_j}) \) using each \( D_i' \);
end
```

Whether it is worthwhile to perform meta-learning before few-shot classifier learning according to this model depends on two questions:

- What is the cost of acquiring the dataset for meta-training tasks \( T_1 \ldots T_n \)? If the cost of acquiring this dataset is higher than acquiring more training data for the target task \( T \), then we are better off by just acquiring training data for the task we are really interested in.

- How close the meta-training tasks \( T_1 \ldots T_n \) need to be to the target task \( T \)? One of the most compelling use case of few-shot learning is to perform classification in novel domains, where we either don’t have enough samples \( x \) or even humans might have difficulty assigning labels \( y \). If we need to create many closely-related labeled tasks, this would restrict us to variations of well known domains.

3.3 Unsupervised meta-learning for classification

Unsupervised meta-learning retains the goal of meta-learning by preparing a learning system for the rapid learning of the target task \( T \). However, instead of the collection of tasks \( T_1 \ldots T_n \) and their associated labeled training data, we only have an unlabeled dataset \( U = \{ ...x_i,... \} \), with samples drawn from the same distribution as the target task. We assume that every element of this dataset is associated with a natural class \( C_1 \ldots C_c \), \( \forall x_i \exists j \) such that \( x_i \in C_j \). We will assume that \( N \ll c \), that is, the number of natural classes in the unsupervised dataset is much higher than the number of classes in the target task. These requirements are much easier to satisfy than the construction of the tasks for supervised meta-learning - for instance, simply stripping the labels from datasets such as Omniglot and mini-ImageNet satisfies them.

The pseudo-code of the UMTRA algorithm is described in Algorithm 1. In the following, we describe the various parts of the algorithm in detail. In order to be able to run the UMTRA algorithm on unsupervised data, we need to create tasks \( T_i \) from the unsupervised data that can serve the same role as the meta-learning tasks serve in the full MAML algorithm. For such a task, we need to create both the training data \( D \) and the validation data \( D' \).

Creating the training data: In the original form of the MAML algorithm, the training data of the task \( T \) must have the form \( (x, y) \), and we need \( N \times K \) of them. The exact labels used during the meta-training step are not relevant, as they are discarded during the meta training phase. They can be thus replaced with artificial labels, by setting them \( y \in \{ 1, \ldots N \} \). It is however, important that the labels maintain class distinctions: if two data points have the same label, they should also have the same artificial labels, while if they have different labels, they should have different artificial labels.
The first difference between UMTRA and MAML is that during the meta-training phases we always perform one-shot learning, with $K = 1$. Note that during the target learning phase we can still set values of $K$ different from 1. The training data is created as the set $\mathcal{D}_i = \{(x_1, 1), \ldots (x_N, \bar{N})\}$, with $x_i$ sampled randomly from $\mathcal{U}$.

Let us see how this training data construction satisfy the class distinction conditions. The first condition is satisfied because there is only one sample for each label. The second condition is satisfied statistically by the fact that $N \ll c$. If the number of samples is significantly smaller than the number of classes, it is likely that all the samples will be drawn from different classes. If we assume that the samples are equally distributed among the classes, the probability that all samples are in a different class is $p \approx 1 - \frac{(N-2)! (N-1)!}{2^{N-2} (N-1)!}$. To illustrate this, the probability for 5-way classification on the Omniglot dataset used with each of the 1200 characters is a separate class ($c = 1200$, $N = 5$) is 99%. For Mini-ImageNet ($c = 64$), the probability is 81%, while for the full ImageNet it would be about 99%.

Creating the validation data: For the MAML approach, the validation data of the meta-training tasks is actually training data in the outer loop. It is thus required that we create a validation dataset $\mathcal{D}_i' = \{(x'_i, 1), \ldots (x'_N, \bar{N})\}$ for each task $\mathcal{T}_i$. Thus we need to create appropriate validation data for the synthetic task. A minimum requirement for the validation data would be to be correctly labeled in the given context. This means that the synthetic numerical label should map in both cases to the same class in the unlabeled dataset: $\exists! C$ such that $x_i, x'_i \in C$.

In the original MAML model, these $x'_i$ values are labeled examples part of the supervised dataset. In our case, picking such $x'_i$ values is non-trivial, as we don’t have access to the actual class. Instead, we propose to create such a sample by augmenting the sample used in the training data using an augmentation function $x'_i = \mathcal{A}(x_i)$ which is a hyperparameter of the UMTRA algorithm. A requirement towards the augmentation function is to maintain class membership $x \in C \Rightarrow \mathcal{A}(x) \in C$. We should aim to construct the augmentation function to verify this property for the given dataset $\mathcal{U}$, based on what we know about the domain described by the dataset. However, as we do not have access to the classes, such a verification is not practically possible on a concrete dataset.

A domain independent choice for the augmentation function is the identity function $\mathcal{A} = \mathbb{I}$, that is, repeating the training data as validation data. While this would be an unsound practice for “validation” data understood in the usual sense, we need to point out that the validation data of the MAML inner loop is actually used as a training data in the outer loop. Thus the $\mathcal{A} = \mathbb{I}$ setting simply makes us use the same data in the (very different) updates in lines 12 and 16 of the Algorithm[1]. The advantage of the $\mathcal{A} = \mathbb{I}$ is that it is theoretically applicable to any dataset - be that images or videos, and it does not depend on the domain. The disadvantage is that this setting can lead to a sort of “meta-overfitting”. In traditional overfitting, we are overfitting to the training data – this is not an issue here, because we do not have the training data in the meta-learning phase. Instead, the danger is that the network will learn that the tasks are defined very narrowly. In some ways, the augmentation function is a way to complicate the tasks and force the network to learn better features.

Another choice for the augmentation function $\mathcal{A}$ is to apply some kind of domain-specific change to the images or videos. Examples of these include setting some of the pixel values to zero in the image (Figure[1]), or translating the pixels of the training image by some amount (eg. between -6 and 6).

The overall process of generating the training data from the unlabeled dataset in UMTRA and the differences from the supervised MAML approach is illustrated in Figure[2].

4 Experiments

4.1 UMTRA on the Omniglot dataset

Omniglot[14] is a dataset of handwritten characters frequently used to compare few-shot learning algorithms. It comprises 1623 characters from 50 different alphabets. Every character in Omniglot has 20 different instances each was written by a different person. To allow comparisons with other published results, in our experiments we follow...
Figure 2: The process of creation of the training and validation data of the meta-training task $T$. (top) Supervised MAML: We start from a dataset where the samples are labeled with their class. The training data is created by sampling $N$ distinct classes $C_{L_i}$, and choosing a random sample $x_i$ from each. The validation data is created by choosing a different sample $x'_i$ from the same class. (bottom) UMTRA: We start from a dataset of unlabeled data. The training data is created by randomly choosing $N$ samples $x_i$ from the dataset (and hoping that they are of different classes). The validation data is created by applying the augmentation function $A$ to each sample from the training data. For both MAML and UMTRA, artificial temporary labels 1, 2... $N$ are used.
the experimental protocol described in [15]: 1200 characters were used for training and 423 characters were used for testing.

UMTRA, like the supervised MAML algorithm is model-agnostic, that is, it does not impose conditions on the actual network architecture used in the learning. This does not, of course, mean that the algorithm performs identically for every network structure and dataset. In order to separate the performance of the architecture and the meta-learner, we run our experiments using an architecture originally proposed in [16]. This classifier uses four 3 x 3 convolutional modules with 64 filters each, followed by batch normalization [17], a ReLU nonlinearity and 2 x 2 max-pooling. On the resulting feature embedding, the classifier is implemented as a fully connected layer followed by a softmax layer.

The first question is what type of augmentation functions and hyperparameter settings we should use? UMTRA has a relatively large hyperparameter space that includes the augmentation function. As pointed out in a recent study involving performance comparisons in semi-supervised systems [18], excessive tuning of hyper-parameters can easily lead to an overestimation of the performance of an approach compared to simpler approaches. Thus, for the comparison in the reminder of this paper, we keep a relatively small budget for hyperparameter search: beyond basic sanity checks we only tested 5-10 hyperparameter combinations per dataset, without specializing them to the N or K parameters of the target task. Table 1 shows several choices for the augmentation function for the 5-way one-shot classification in Omniglot. Based on this table, in comparing with other approaches, we use an augmentation function consisting of randomly zeroed pixels and random shift.

As a note, based on the spread of the accuracies in Table 1, it is very likely that other choices of hyperparameters, possibly specialized to the N and K values may offer higher accuracy values. Depending on the needs of an application and the computational budget available, in practice it may be worthwhile to perform such a hyperparameter search step. This however, is beyond the scope of this paper.

The second consideration is what sort of baseline we should use when evaluating our approach on a few-shot learning task? Clearly, supervised meta-learning approaches such as an original MAML [3] are expected to outperform our approach, as they use a labeled training set. A simple baseline is to use the same network architecture being trained from scratch with only the final few-shot labeled set. If our algorithm takes advantage of the unsupervised training set U, as expected, it should outperform this baseline.

A more competitive comparison is against networks that are first trained to obtain a favorable embedding using unsupervised learning on U, with the resulting embedding used on the few-shot learning task. While it is not a meta-learning, we can train this model with the same target task training set as UMTRA. Similar to [5], we compare the following unsupervised pre-training approaches: ACAI [19], BiGAN [20], DeepCluster [21] and InfoGAN [22]. These up-to-date approaches cover a wide range of the recent advances in the area of unsupervised feature learning. Finally, we also compare against the CACTUs unsupervised meta-learning algorithm proposed in the [5], combined with MAML and ProtoNets [23].

Table 2 shows the results of the experiments. For the UMTRA approach we trained for 6000 meta-iterations for the 5-way, and 36,000 meta-iterations for the 20-way classifications. Our approach, with the proposed hyperparameter settings outperforms, with large margins, training from scratch and the approaches based on unsupervised representation learning. UMTRA also outperforms, with a smaller margin, the CACTUs approach on all metrics, and in combination with both MAML and ProtoNets.

As expected, the supervised meta-learning baselines perform better than UMTRA. To put this value in perspective, we need to take into consideration the vast difference in the number of labels needed for these approaches. In one-shot 5-way classification, UMTRA obtains a 77.80% accuracy with only 5 labels, while supervised MAML obtains 94.46%
Algorithm (N, K) & (5, 1) & (5, 5) & (20, 1) & (20, 5) \\
\hline
Training from scratch & 52.50 & 74.78 & 24.91 & 47.62 \\
BiGAN k_{nn}-nearest neighbors & 49.55 & 68.06 & 27.37 & 46.70 \\
BiGAN linear classifier & 48.28 & 68.72 & 27.80 & 45.82 \\
BiGAN MLP with dropout & 40.54 & 62.56 & 19.92 & 40.71 \\
BiGAN cluster matching & 43.96 & 58.62 & 21.54 & 31.06 \\
BiGAN CACTUs-MAML & 58.18 & 78.66 & 35.56 & 58.62 \\
BiGAN cluster matching & 54.74 & 71.69 & 33.40 & 50.62 \\
ACAI k_{nn}-nearest neighbors & 57.46 & 81.16 & 39.73 & 66.38 \\
ACAI linear classifier & 61.08 & 81.82 & 43.20 & 66.33 \\
ACAI MLP with dropout & 51.95 & 77.20 & 30.65 & 58.62 \\
ACAI cluster matching & 54.94 & 71.09 & 32.19 & 45.93 \\
ACAI CACTUs-MAML & 68.84 & 87.78 & 48.09 & 73.36 \\
ACAI CACTUs-ProtoNets & 68.12 & 83.58 & 47.75 & 66.27 \\
UMTRA (ours) & 77.80 & 92.74 & 62.20 & 77.50 \\
Supervised MAML (control) & 94.46 & 98.83 & 84.60 & 96.29 \\
Supervised ProtoNets (control) & 98.35 & 99.58 & 95.31 & 98.81 \\
\hline

Table 2: Accuracy in % of N-way K-shot (N,K) learning methods on the Omniglot dataset. The source of values, other than UMTRA is from [5].

Figure 3: Several augmentation functions used on Mini-Imagenet dataset. Auto Augment [25] applies augmentations from a learned policy based on combinations of translation, rotation, or shearing.

but requires 24005 labels. For 5-shot 5-way classification UMTRA obtains a 92.74% accuracy with only 25 labels, while supervised MAML obtains 98.83% with 24025.

4.2 UMTRA on the Mini-Imagenet dataset

The Mini-Imagenet dataset was introduced by [12] as a subset of the ImageNet dataset [24], suitable as a benchmark for few-shot learning algorithms. The dataset is limited to 100 classes, each with 600 images. We divide our dataset into train, validation and test subsets according to the experimental protocol proposed by [16]. The classifier network is similar to the one used in [3].

Since Mini-Imagenet is a dataset with larger images and more complex classes compared to Omniglot, we need to choose augmentation functions suitable to the model. We had investigated several simple choices involving random flips, shifts, rotation, and color changes. In addition to these hand-crafted algorithms, we also investigated the learned auto-augmentation method proposed in [25]. Table 3 shows the accuracy results for the tested augmentation functions. We found that auto-augmentation provided the best results, thus this approach was used in the reminder of the experiments.
Table 3: Exploration of several choices for the augmentation function hyperparameter on the Mini-Imagenet classification. For all cases, we use meta-batch size $N_{MB} = 4$ and number of updates $N_U = 5$.

| Augmentation Function $A$ | Accuracy % |
|---------------------------|------------|
| Training from scratch     | 24.17      |
| $A = \text{Shift} + \text{random flip}$ | 26.49     |
| $A = \text{Shift} + \text{random flip} + \text{randomly change to grayscale}$ | 30.16     |
| $A = \text{Shift} + \text{random flip} + \text{random rotation} + \text{color distortions}$ | 32.80     |
| $A = \text{Auto Augment}$ [25] | 35.09     |
| Supervised MAML           | 39.93      |
| Supervised MAML (control) | 46.81      |

Table 4: Accuracy in % of N-way K-shot (N,K) learning methods on the Mini-Imagenet dataset. The source of values, other than UMTRA and train from scratch is from [5].

| Algorithm / (N, K) | (5, 1) | (5, 5) | (5, 20) | (5, 50) |
|--------------------|--------|--------|---------|---------|
| Training from scratch | 24.17  | 32.90  | 38.66   | 40.87   |
| BiGAN $k_{nn}$-nearest neighbors | 25.56  | 31.10  | 37.31   | 43.60   |
| BiGAN linear classifier | 27.08  | 33.91  | 44.00   | 50.41   |
| BiGAN MLP with dropout | 22.91  | 29.06  | 40.06   | 48.36   |
| BiGAN cluster matching | 24.63  | 29.49  | 33.89   | 36.13   |
| BiGAN CACTUs MAML | 36.24  | 51.28  | 61.33   | 66.91   |
| BiGAN CACTUs ProtoNets | 36.62  | 50.16  | 59.56   | 63.27   |
| DeepCluster $k_{nn}$-nearest neighbors | 28.90  | 42.25  | 56.44   | 63.90   |
| DeepCluster linear classifier | 29.44  | 39.79  | 56.19   | 65.28   |
| DeepCluster MLP with dropout | 29.03  | 39.67  | 52.71   | 60.95   |
| DeepCluster cluster matching | 22.20  | 23.50  | 24.97   | 26.87   |
| DeepCluster CACTUs MAML | 39.90  | 53.97  | 63.84   | 69.64   |
| DeepCluster CACTUs ProtoNets | 39.18  | 53.36  | 61.54   | 63.55   |
| UMTRA (ours) | **39.93** | **50.73** | **61.11** | **67.15** |
| Supervised MAML (control) | 46.81  | 62.13  | 71.03   | 75.54   |
| Supervised ProtoNets (control) | 46.56  | 62.29  | 70.05   | 72.04   |

Table 4 lists the experimental results for few-shot classification learning on the Mini-Imagenet dataset. Similar to the Omniglot dataset, UMTRA performs better than learning from scratch and all the approaches that use unsupervised learning for representation learning. It performs weaker than supervised meta-learning approaches that use labeled data. Compared to the various combinations involving the CACTUs unsupervised meta-learning algorithm, UMTRA performs better on 5-way one-shot classification, while it is outperforming by the BiGAN-CACTUs-MAML combination on the other three techniques.

The results on Omniglot and Mini-Imagenet allow us to draw the preliminary conclusions that unsupervised meta-learning approaches like UMTRA and CACTUs, which generate meta tasks $T_i$ from the unsupervised training data tend to outperform other approaches for a given unsupervised training set $U$. UMTRA and CACTUs use different, orthogonal approaches for building $T$. UMTRA uses the statistical likelihood of picking different classes for the training data of $T_i$ in case of $K = 1$ and large number of classes, and an augmentation function $A$ for the validation data. CACTUs relies on an unsupervised clustering algorithm to provide a statistical likelihood of difference and sameness in the training and validation data of $T_i$. Except in the case of UMTRA with $A = 1$, both approaches require domain specific knowledge. The choice of the right augmentation function for UMTRA, the right clustering approach for CACTUs, and the other hyper-parameters (for both approaches) have a strong impact on the performance.

4.3 UMTRA for video action recognition

In this section, we show how the UMTRA can be applied to video action recognition, a domain significantly more complex and data intensive than the one used in the few-shot learning benchmarks such as Omniglot and Mini-Imagenet. To the best of our knowledge, we are the first to apply meta-learning to video action recognition. We perform our comparisons using one of the standard video action recognition datasets, UCF-101[26]. UCF-101 includes 101 action classes divided into five types: Human-Object Interaction, Body-Motion Only, Human Human Interaction, Playing
Musical Instruments and Sports. The dataset is composed of snippets of Youtube videos. Many videos have poor lighting, cluttered background and severe camera motion. As the classifier on which to apply the meta-learning process, we use a 3D convolution network, C3D [27].

Performing unsupervised meta-learning on video data, requires several adjustments to the UMTRA workflow, with regards to the initialization of the classifier, the split between meta-learning data and testing data, and the augmentation function.

First, networks of the complexity of C3D cannot be learned from scratch using the limited amount of data available in few-shot learning. In the video action recognition research, it is common practice to start with a network that had been pre-trained on a large dataset, such as Sports-1M dataset [28], an approach we also use in all our experiments.

Second, we make the choice to use two different datasets for the meta-learning phase (Kinetics [27, 29, 30]) and for the few-shot learning and evaluation (UCF-101 [26]). This gives us a larger dataset for training since Kinetics contains 400 action classes, but it introduces an additional challenge of domain-shift: the network is pre-trained on Sports-1M, meta-trained on Kinetics and few-shot trained on UCF-101. This approach, however, closely resembles the practical setup when we need to do few-shot learning on a novel domain. When using the Kinetics dataset for meta-learning, we limit it to 20 instances per class.

For the augmentation function $A$, working in the video domain opens a new possibility, of creating an augmented sample by choosing a temporally shifted video fragment from the same video. Figure 4 shows some samples of these augmentations. In our experiments, we have experimented both with UMTRA (using a Kinetics dataset stripped from labels), and supervised meta-learning (retaining the labels on Kinetics for the choice of the validation, but following the rest of the experimental protocol). This supervised meta-learning experiment is also significant because, to the best of our knowledge, meta-learning has never been applied to human action recognition from videos.

In our evaluation, we perform 30 different experiments. At each experiment we sample 5 classes from UCF-101, perform the one-shot learning, and evaluate the classifier on all the examples for the 5 classes from UCF-101. As the number of samples per class are not the same for all classes, in Table 5 we report both the accuracy and F1-score.

The results allow us to draw several conclusions. The relative accuracy ranking between training from scratch, pre-training and unsupervised meta-learning and supervised meta-learning remained unchanged. Supervised meta-learning had proven feasible for one-shot classifier training for video action recognition. UMTRA performs better than other approaches that use unsupervised data. Finally, we found that the domain shift from Kinetics to UCF-101 was successful.

### 4.4 UMTRA on the CelebA dataset

In this series of experiments we evaluate our algorithm on the CelebA large scale face dataset [31]. Each subject has a different number of face images. This makes the unlabeled dataset $U$ also unbalanced, a less favorable but possibly more realistic scenario. The evaluation is done on 600 different tasks, on faces whose identities were never seen during
Table 5: Accuracy and F1-Score for a 5-way, one-shot classifier trained and evaluated on classes sampled from UCF-101. All training (even for “training from scratch”), employ a C3D network pre-trained on Sports-1M. For all approaches, none of the UCF-101 classes was seen during pre- or meta-learning.

| Algorithm | Test Accuracy / F1-Score |
|-----------|--------------------------|
| Training from scratch | 29.30 / 20.48 |
| Pre-trained on Kinetics | 45.51 / 42.49 |
| UMTRA on unlabeled Kinetics (ours) | 60.33 / 58.47 |
| Supervised MAML on Kinetics | 71.08 / 69.44 |

Table 6: Comparison between our method and supervised meta learning on CelebA dataset.

| Algorithm (N, K) | (5, 1) | (5, 5) | (5, 10) |
|-----------------|-------|-------|--------|
| Training from scratch | 26.86 | 39.65 | 50.61 |
| UMTRA (ours) | **33.43** | **50.19** | **58.84** |
| Supervised MAML | 72.26 | 84.90 | 88.26 |

the meta-learning phase. The augmentation function was auto augment which gave the best results for Mini-Imagenet. Figure 5 compares a sampled task generated by UMTRA with one of the sampled tasks generated by supervised MAML. The comparison between UMTRA, training from scratch and supervised MAML is shown in Table 6. The results confirm the trend that UMTRA outperforms learning from scratch, but performs worse than supervised learning.

5 Conclusions

In this paper, we described the UMTRA algorithm for few-shot and one-shot learning of classifiers for images and videos. UMTRA performs meta-learning on an unlabeled dataset in an unsupervised fashion, without putting any constraint on the classifier network architecture. Experimental studies, over a number of different image and video classification databases show that UMTRA enables one-shot and few-shot learning over both few-shot learning image benchmarks (Omniglot, Mini-Imagenet) and video activity recognition dataset (UCF-101), as well as over an unbalanced image dataset (CelebA). UMTRA outperformed learning-from-scratch approaches and approaches based on unsupervised representation learning. In experiments where results were available for both algorithms, it alternated in obtained by best result with CACTUs, a recently proposed approach that takes a different approach to unsupervised meta-learning. For all experiments, UMTRA performed worse than the equivalent supervised meta-learning approach - but requiring several orders of magnitude less labeled data.

An important theme of future research is the choice of hyperparameters. Both meta-learning, and the task construction methods involved in unsupervised meta-learning approaches introduce additional hyperparameters whose choice can have a significant effect on performance. Our experiments were performed with only a minimal effort budget for

Figure 5: Visualization of 5-way classification tasks generated by UMTRA (Left) and MAML (Right) on CelebA faces. Top: Task’s training images. Bottom: Task’s validation images.
hyperparameter optimization. Finding approaches that can reduce the number of hyperparameters, or allow their automatic choice can further improve the overall performance and cost-benefit ratio of the approach.

Acknowledgement

This work had been supported in part by the National Science Foundation under grant numbers IIS-1409823 and IIS-1741431. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.
References

[1] Jürgen Schmidhuber. *Evolutionary principles in self-referential learning, or on learning how to learn: the meta-meta-... hook*. PhD thesis, Technische Universität München, 1987.

[2] Yoshua Bengio, Samy Bengio, and Jocelyn Cloutier. *Learning a synaptic learning rule*. Université de Montréal, Département d’informatique et de recherche opérationnelle, 1990.

[3] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. *Proc. of Int’l Conf. on Machine Learning (ICML)*, 2017.

[4] Alex Nichol and John Schulman. Reptile: a scalable metalearning algorithm. *arXiv preprint arXiv:1803.02999*, 2018.

[5] Kyle Hsu, Sergey Levine, and Chelsea Finn. Unsupervised learning via meta-learning. *arXiv preprint arXiv:1810.02334*, 2018.

[6] Zelun Luo, Yuliang Zou, Judy Hoffman, and Li Fei-Fei. Label efficient learning of transferable representations across domains and tasks. In *Proc. of Advances in Neural Information Processing Systems (NIPS)*, pages 165–177, 2017.

[7] Eunbyung Park and Alexander C Berg. Meta-tracker: Fast and robust online adaptation for visual object trackers. *arXiv preprint arXiv:1801.03049*, 2018.

[8] Jimmy Ba, Geoffrey E Hinton, Volodymyr Mnih, Joel Z Leibo, and Catalin Ionescu. Using fast weights to attend to the recent past. In *Proc. of Advances in Neural Information Processing Systems (NIPS)*, pages 4331–4339, 2016.

[9] Thomas Miconi, Jeff Clune, and Kenneth O Stanley. Differentiable plasticity: training plastic neural networks with backpropagation. *arXiv preprint arXiv:1804.02464*, 2018.

[10] Luke Metz, Niru Maheswaranathan, Brian Cheung, and Jascha Sohl-Dickstein. Learning unsupervised learning rules. *arXiv preprint arXiv:1804.00222*, 2018.

[11] Nikhil Mishra, Mostafa Rohaninejad, Xi Chen, and Pieter Abbeel. A simple neural attentive meta-learner. *arXiv preprint arXiv:1707.03141*, 2018.

[12] Sachin Ravi and Hugo Larochelle. Optimization as a model for few-shot learning. *Proc. of Int’l Conf. on Learning Representations (ICLR)*, 2016.

[13] Franziska Meier, Daniel Kappler, and Stefan Schaal. Online learning of a memory for learning rates. In *Proc. of IEEE Int’l Conf. on Robotics and Automation (ICRA)*, pages 2425–2432, 2018.

[14] Brenden Lake, Ruslan Salakhutdinov, Jason Gross, and Joshua Tenenbaum. One shot learning of simple visual concepts. In *Proc. of the Annual Meeting of the Cognitive Science Society*, volume 33, 2011.

[15] Adam Santoro, Sergey Bartunov, Matthew Botvinick, Daan Wierstra, and Timothy Lillicrap. Meta-learning with memory-augmented neural networks. In *Proc. of Int’l Conf. on Machine Learning (ICML)*, pages 1842–1850, 2016.

[16] Oriol Vinyals, Charles Blundell, Tim Lillicrap, and Daan Wierstra. Matching networks for one shot learning. In *Proc. of Advances in Neural Information Processing Systems (NIPS)*, pages 3630–3638, 2016.

[17] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*, 2015.

[18] Avital Oliver, Augustus Odena, Colin Raffel, Ekin D Cubuk, and Ian J Goodfellow. Realistic evaluation of deep semi-supervised learning algorithms. *arXiv preprint arXiv:1804.09170*, 2018.

[19] David Berthelot, Colin Raffel, Aurko Roy, and Ian Goodfellow. Understanding and improving interpolation in autoencoders via an adversarial regularizer. *arXiv preprint arXiv:1807.07543*, 2018.

[20] Jeff Donahue, Philipp Krähenbühl, and Trevor Darrell. Adversarial feature learning. *arXiv preprint arXiv:1605.09782*, 2016.
[21] Mathilde Caron, Piotr Bojanowski, Armand Joulin, and Matthijs Douze. Deep clustering for unsupervised learning of visual features. arXiv preprint arXiv:1807.05520, 2018.

[22] Xi Chen, Yan Duan, Rein Houthooft, John Schulman, Ilya Sutskever, and Pieter Abbeel. InfoGAN: Interpretable representation learning by information maximizing generative adversarial nets. In Proc. of Advances in Neural Information Processing Systems (NIPS), pages 2172–2180, 2016.

[23] Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In Proc. of Advances in Neural Information Processing Systems (NIPS), pages 4077–4087, 2017.

[24] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), pages 248–255. IEEE, 2009.

[25] Ekin D Cubuk, Barret Zoph, Dandelion Mane, Vijay Vasudevan, and Quoc V Le. Autoaugment: Learning augmentation policies from data. arXiv preprint arXiv:1805.09501, 2018.

[26] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. UCF101: A dataset of 101 human actions classes from videos in the wild. arXiv preprint arXiv:1212.0402, 2012.

[27] Du Tran, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. Learning spatiotemporal features with 3d convolutional networks. In Proc. of the IEEE Int’l Conf. on Computer Vision (ICCV), pages 4489–4497, 2015.

[28] Andrej Karpathy, George Toderici, Sanketh Shetty, Thomas Leung, Rahul Sukthankar, and Li Fei-Fei. Large-scale video classification with convolutional neural networks. In Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), pages 1725–1732, 2014.

[29] Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. Caffe: Convolutional architecture for fast feature embedding. In Proc. of the 22nd ACM Int’l Conf. on Multimedia, pages 675–678. ACM, 2014.

[30] Andrej Karpathy, George Toderici, Sanketh Shetty, Thomas Leung, Rahul Sukthankar, and Li Fei-Fei. Large-scale video classification with convolutional neural networks. In CVPR, 2014.

[31] Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep learning face attributes in the wild. In Proc. of Int’l Conf. on Computer Vision (ICCV), 2015.
Supplementary Material

Evolution of accuracy during training

In these series of experiments we study the evolution of the accuracy obtained after a specific number of gradient training steps during the target learning phase. The results for Omniglot are shown in Figure 6 (with K=1), while those for Mini-Imagenet in Figure 7 with K values of 1, 5 and 20. For both datasets, we compare learning from scratch, UMTRA and supervised MAML. As expected, both MAML and UMTRA reach their accuracy plateau very quickly during target training, while learning from scratch takes a larger number of training steps. Further training does not appear to provide any benefit for either approach. The results are averaged among 1000 tasks.

An interesting phenomena happens with $K = 5$ and $K = 20$ values for Mini-Imagenet: the accuracy curve of UMTRA dips after the first iteration, and it takes several iterations to recover. We conjecture that this is a result of the fact that UMTRA sets $K = 1$ during meta-learning, thus the resulting network is best optimized to learn from one sample per class.

![Figure 6: The accuracy curves during the target training task on the Omniglot dataset for $K = 1$. The band around lines denotes a 95% confidence interval.](image)

Feature Representations

To compare generalization of training from scratch, UMTRA and supervised MAML, we visualize the activations of the last hidden layer of the network on Omniglot dataset by t-SNE. We compare all of the methods on the same target training task which is constructed by sampling five characters from test data and selecting one image from each character class randomly. Each character has 20 different instances. Figure 8 shows the t-SNE visualization of raw pixel values of these 100 images. Instances which are sampled for the one-shot learning task are connected to each other by dotted lines. Figure 9 shows the visualization of the last hidden layer activations for the same task. UMTRA as well as MAML can adapt quickly to a feature space which has a better generalization than training from scratch.
Figure 7: The accuracy curves during the target training task on the Mini-Imagenet dataset. Accuracy curves are shown for $K = 1$ (Top), $K = 5$ (Middle), and $K = 20$ (Bottom). The band around lines denotes a 95% confidence interval.

Figure 8: t-SNE on the Omniglot raw pixel values.
Figure 9: Visualization of the last hidden layer activation values by t-SNE on the Omniglot dataset before target task training (Left), and after target task training (Right). Visualized features are shown for training from scratch (Top), UMTRA (Middle), and MAML (Bottom). Each class is shown by a different color and shape. From each class one instance is used for target task training. Training instances are denoted by larger and lighter symbols and are connected to each other by dotted lines.