Omni-Training for Data-Efficient Deep Learning

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Abstract
Learning a generalizable deep model from a few examples in a short time remains a major challenge of machine learning, which has impeded its wide deployment to many scenarios. While the unprecedented performance of deep learning models highly relies on large-scale labeled data, recent advances reveal that a properly pre-trained model endows an important property: transferability. A higher transferability of the learned representations indicates a better generalizability across domains of different distributions (domain transferability), or across tasks of different semantics (task transferability). Transferability has become the key to enable data-efficient deep learning, however, existing pre-training methods focus only on the domain transferability while meta-training methods only on the task transferability. This restricts their data-efficiency in downstream scenarios of diverging domains and tasks. A finding of this paper is that even a tight combination of pre-training and meta-training through a joint representation flow cannot achieve both kinds of transferability. This finding motivates the proposed Omni-Training framework towards data-efficient deep learning. Our first contribution is Omni-Net, a tri-flow architecture. Besides the joint representation flow, Omni-Net introduces two new parallel flows for pre-training and meta-training, respectively responsible for learning representations of domain transferability and task transferability. Omni-Net coordinates the parallel flows by routing their representations via the joint-flow, making each gain the other kind of transferability. Our second contribution is Omni-Loss, in which a mean-teacher regularization is imposed to both the pre-training and meta-training objectives, enabling the parallel flows to learn generalizable and stabilized representations. Omni-Training is a general framework that accommodates many existing pre-training and meta-training algorithms. A thorough evaluation on cross-task and cross-domain datasets in classification, regression and reinforcement learning problems shows that Omni-Training consistently and clearly outperforms the state-of-the-art deep learning methods.

Keywords: Data-efficient deep learning, Transfer learning, Meta-learning, Pre-training.

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1. Introduction

Deep learning (LeCun et al., 2015) has achieved the state-of-the-art performance in various machine learning tasks (He et al., 2016; Silver et al., 2016; Devlin et al., 2018; Adiwardana et al., 2020). However, most deep learning methods, in particular the foundation models (Bommasani et al., 2021), are “data hungry”, in that the success of these methods highly relies on large amount of labeled data. This clearly limits the application of deep learning to widespread domains, especially vertical domains with sparse data and insufficient annotations, such as personalized healthcare (Yu et al., 2019). In order to promote the grounding of deep learning models, data-efficient deep learning, which aims to learn various complex tasks from a few labeled data in a short time, has attracted enormous attention recently (Fei-Fei et al., 2006; Finn et al., 2017a; Wang et al., 2021b).

Human beings are equipped with the ability to efficiently learn new tasks by making use of previous experience and knowledge. In analogy to this, deep learning models can reuse the representations learned previously to help efficiently solve widespread downstream tasks. Recent advances have revealed that a properly pre-trained model endows an important property: transferability, and a higher transferability of the learned representations indicates a better generalizability to new scenarios, which reduces the amount of data required to learn new tasks in new domains. While there are many ways to achieve the goal of data-efficient deep learning, this paper focuses on the problem of learning transferable representations from pretext datasets to boost the data-efficiency in downstream tasks.

In general situations as illustrated by Figure 1, complex relationships between the pretext dataset and the new task hinder the downstream data-efficiency and challenge the transferability of learned representations. The two main challenges come from the different distributions across domains (distribution shift) and different semantics across tasks (task discrepancy). For example, in image classification, different domains may have different visual factors such as different styles, viewpoints, lighting, while different tasks may have different categories. In reinforcement learning, different domains have different physical factors in environments or agents such as embodiments, morphology, physics, while different tasks have different reward functions. In most cases, the two challenges, i.e. distribution shift and task discrepancy, entangle with each other, making data-efficient learning a very hard problem to date. Thus, a versatile algorithm should bridge these two gaps and learn representations with both domain transferability and task transferability, which respectively enable generalization across domains and tasks.

Two mainstream representation learning paradigms for data-efficient deep learning are pre-training and meta-training. In pre-training, we train a high capacity model for a pretext task on large-scale datasets (Devlin et al., 2018; Kolesnikov et al., 2020) and fine-tune the model on the target task (Radford et al., 2018). In meta-training, we train the model from diverse tasks and fast adapt the model to new tasks (Vinyals et al., 2016; Finn et al., 2017a; Snell et al., 2017). As evidenced by recent studies, neither paradigm can dominate in the widespread data-efficient learning scenarios (Chen et al., 2019a; Guo et al., 2020; Dumoulin et al., 2021). This is because data-efficient learning requires generalizing across both domains and tasks such that the training knowledge is transferred to boost the data efficiency in downstream context. Pre-training representations can generalize to widespread domains, since the pretext task is designed to be transferable across domains, but only pre-
training on a single pretext task makes it hard to fast adapt to many new tasks. In contrast, the diverse tasks equip meta-training with the ability to fast adapt across many tasks with extremely sparse data, but the meta-training tasks are usually drawn from a specific domain and thus the learned representations cannot generalize across domains.

In line with the understanding on pre-training and meta-training, we further study both paradigms with regard to the two transferability properties and reach a similar conclusion: pre-training methods are apt at the domain transferability while meta-training methods at the task transferability. We then take a step forward to exploit the collaboration between pre-training and meta-training and draw an important finding that neither a simple ensemble nor a tight combination can achieve both kinds of transferability. This finding motivates us to design a new Omni-Training framework towards data-efficient deep learning.

Omni-Training unifies pre-training and meta-training to learn deep representations with both domain transferability and task transferability. The first part is Omni-Net, a tri-flow architecture. Besides a joint-flow for shared representation learning, Omni-Net introduces two new parallel flows for pre-training and meta-training to yield representations of domain transferability and task transferability respectively. It further coordinates the parallel flows by routing their representations via the joint-flow, making each gain the other kind of transferability. The second part is Omni-Loss, which works in cooperation with the architecture for learning transferable representations. A mean-teacher regularization is imposed to both the pre-training and meta-training objectives, which enables the parallel flows to learn generalizable and stabilized representations. Omni-Training is a general framework that accommodates many existing pre-training and meta-training algorithms. A thorough evaluation on cross-task and cross-domain datasets in classification, regression and reinforcement learning problems shows that Omni-Training consistently and clearly outperforms the state-of-the-art deep learning methods.

We make in this work the following contributions towards data-efficient deep learning:

1. We envision the data-efficient deep learning problem, which aims to learn in complex domains and tasks with a few examples in a short time. It generalizes traditional few-shot learning (Fei-Fei et al., 2006) to more complex scenarios such as cross-domain
Table 1: Comparison of Omni-Training to pre-training and meta-training algorithms. Omni-Training achieves cross-domain and cross-task transferability simultaneously, empowering strong representations for data-efficient deep learning in a wide variety of learning settings.

| Method            | Transferability | Learning Setting |
|-------------------|-----------------|------------------|
|                  | Cross-Task | Cross-Domain | Classification | Regression | Reinforcement Learning |
| Baseline (2019a)  | ✗             | ✓               | ✓             | ✓           | ✓                      |
| MAML (2017a)      | ✓             | ✗               | ✓             | ✓           | ✓                      |
| ProtoNet (2017)   | ✓             | ✗               | ✓             | ✗           | ✗                      |
| Omni-Training     | ✓             | ✓               | ✓             | ✓           | ✓                      |

regression and reinforcement learning tasks. We find that domain transferability and task transferability are two key properties to enable data-efficient deep learning.

2. Through empirical study we find that pre-training approaches focus only on domain transferability while meta-training approaches only on task transferability. We further show that simple combinations of pre-training and meta-training cannot fully obtain both kinds of transferability, thereby impeding the data-efficiency of deep learning.

3. We propose a general Omni-Training framework to incorporate pre-training and meta-training for data-efficient deep learning. With the architecture design of Omni-Net and the objective design of Omni-Loss, the framework learns deep representations with both domain transferability and task transferability. It is able to accommodate many existing representation learning methods and exhibits wide applicability.

4. The Omni-Training framework is instantiated with implementations based on several well-known deep learning algorithms. Comprehensive experiments are conducted on a wide spectrum of cross-domain and cross-task datasets in classification, regression and reinforcement learning, and Omni-Training clearly outperforms existing methods.

2. Related Work

Data-efficient deep learning aims to make full use of every sample and address new tasks with a few labeled data (Fei-Fei et al., 2006; Wang et al., 2020; Yu, 2018). There are various ways to realize the goal of data-efficient deep learning, such as applying data augmentation techniques that make statistically efficient reuse of available data (Shorten and Khoshgoftaar, 2019), using semi-supervised learning techniques to guide the discriminative models towards unlabeled data (Chapelle et al., 2006; Grandvalet and Bengio, 2005), performing domain adaptation to utilize auxiliary data from related domains (Long et al., 2015, 2017, 2018; Ganin et al., 2016), etc. In this paper, we focus on representation learning algorithms towards data-efficiency, which aim to learn transferable representations from pretext data to reduce the data requirement of learning new tasks. We restrict our review to two mainstream categories of representation learning algorithms for data-efficient learning that achieve state-of-the-art performance: meta-training and pre-training.
2.1 Meta-Training

Meta-training addresses data-efficient deep learning by learning representations generalizable across many training tasks, which can be naturally adapted to new tasks (Schmidhuber, 1987; Naik and Mammone, 1992; Thrun and Pratt, 1998). Meta-training has been widely used in data-efficient learning for a variety of applications.

Data-efficient deep learning, in the special form of few-shot learning (Fei-Fei et al., 2006), is widely studied in the field of classification, especially image recognition, where a typical form is to learn from a few annotated data, i.e. the “N-way-K-shot” few-shot classification problems (Wang et al., 2020; Lu et al., 2020). Metric-based meta-learning methods are tailored for these classification problems, which learn an embedding space to form decision boundaries according to the embedding distances between samples (Koch et al., 2015; Vinyals et al., 2016; Snell et al., 2017; Sung et al., 2018; Allen et al., 2019). Recently, embedding functions are improved by stronger inductive bias such as graph networks (Garcia and Bruna, 2018), fine-grained attention maps (Hou et al., 2019), task-adaptive projections (Oreshkin et al., 2018; Yoon et al., 2019) and set-to-set functions (Ye et al., 2020). Metric-based meta-learning methods achieve superior performance in image recognition tasks. However, it is difficult to directly extend them to regression and reinforcement learning settings.

There are other meta-learning methods that are not restricted to the classification problem but can generalize to various applications, e.g., regression and reinforcement learning. Early works build meta-learners to learn how to update the model parameters and generalize the updating rules to new tasks (Bengio et al., 1990; Schmidhuber, 1992), which have been recently applied in deep learning to enable fast adaptation of deep networks (Andrychowicz et al., 2016; Ravi and Larochelle, 2017; Li et al., 2017). Such learning to learn paradigm is also demonstrated to work for regression (Andrychowicz et al., 2016; Li et al., 2017) and reinforcement learning (Xu et al., 2018; Houthooft et al., 2018). Several works equip networks with external or internal memory so that meta-knowledge can be effectively stored and queried for data-efficient adaptation to new tasks (Santoro et al., 2016; Munkhdalai and Yu, 2017; Mishra et al., 2018; Munkhdalai et al., 2018). The memory-augmented models are also applied to reinforcement learning to improve data-efficiency (Duan et al., 2016b; Wang et al., 2016; Mishra et al., 2018). These methods introduce additional parameters and storage costs or require a particular architecture of the learner for meta-learning.

Model agnostic meta-learning (MAML) introduces the gradient-based idea, which trains a good initialization of the deep network as the meta-knowledge such that a small number of gradient steps and interactions in the new environment can induce high generalization performance (Finn et al., 2017a). The idea is later improved by new architectures (Lee and Choi, 2018; Yao et al., 2019). Such gradient-based meta-training methods show strong performance in real robotics applications such as imitation learning (Duan et al., 2017; Finn et al., 2017b), locomotion (Frans et al., 2017), visual navigation (Jamal and Qi, 2019), and robot manipulation (Xie et al., 2018). They can also be extended to other applications such as regression and image classification by changing the architecture and training objective (Finn et al., 2017a; Rusu et al., 2019; Bertinetto et al., 2019; Lee et al., 2019).

Though meta-training empowers the deep representations with the ability to generalize across new tasks, a recent empirical study has revealed that meta-training representations cannot generalize across domains with distribution shift (Chen et al., 2019a). Tseng et al.
Shu et al. (2020) use feature-wise transformation layers to simulate various image feature distributions extracted from the training tasks in different domains. However, the domain transferability is still limited especially in domains with large distribution shift (Guo et al., 2020). Our method acquires the missing piece of domain transferability from pre-training, which does not require multiple pretext domains but achieves better cross-domain generalization ability.

2.2 Pre-Training

Another line of data-efficient deep learning methods is to learn deep representations by pre-training deep networks with a pretext task on the training datasets. With the prevalence of large-scale labeled datasets and the advanced computational infrastructure, deep networks with extremely big model capacity are trained for various applications such as computer vision (Szegedy et al., 2016; He et al., 2019; Kolesnikov et al., 2020) and natural language processing (Devlin et al., 2018; Radford et al., 2019). With such deep models, recent works re-take the pre-training and fine-tuning paradigm for data-efficient learning and demonstrate that fine-tuning high-capacity deep models pre-trained on large datasets achieves state-of-the-art performance in various applications with only a few labeled data (Brown et al., 2020; Cao et al., 2021; Zhu et al., 2020). Pre-training is also adopted in reinforcement learning to enable learning the policy for new environments with less interaction steps (Xie et al., 2021; Campos et al., 2021; Schwarzner et al., 2021). More advanced pre-training strategies also boost data-efficient learning performance, such as training an ensemble of models (Dvornik et al., 2019) and training with self-distillation (Tian et al., 2020).

There are methods towards the stage of fine-tuning on the new task. For example, some works reuse the representations to predict parameters of new categories (Qiao et al., 2018; Qi et al., 2018). Some works regularize the model of the new task from the aspects of parameters or representations to fully extract the knowledge of the pre-trained models (Xuhong et al., 2018; Li et al., 2019). Recent researches also proposed to explore relationships between the training and test datasets and mitigate negative transfer (Chen et al., 2019b; You et al., 2020). Cao et al. (2021) proposed an ease-in-ease-out fine-tuning method to enable transfer reinforcement learning across homotopy classes. These methods focus on different perspective of representation learning and are in parallel with this paper.

Pre-training approaches are simple and effective to improve data-efficiency in new scenarios, which show higher domain transferability and outperform sophisticated meta-training methods in the cross-domain setting (Chen et al., 2019a; Guo et al., 2020; Dumoulin et al., 2021). However, as the training stage only involves one pretext task, these methods cannot handle the rapid changes of semantics in new tasks (Finn et al., 2017a).

As summarized in Table 1, meta-training and pre-training are apt at task transferability and domain transferability respectively, and neither can dominate the other. A natural idea is to integrate two types of approaches to achieve both. Sun et al. (2019) simply chain the process of pre-training and meta-training, but such simple combination still lacks both kinds of transferability. In contrast, our Omni-Training framework features a flexible coordination between meta-training and pre-training to empower both kinds of transferability.
3. Background and Analysis

In this section, we first introduce the problem setting of data-efficient deep learning and its two key prerequisites: domain transferability and task transferability. Then we delve into two mainstream methods for data-efficient deep learning, pre-training and meta-training, each of which learns a representation to endow a specific kind of transferability and enable generalization to either new domains or new tasks, respectively.

3.1 Data-Efficient Deep Learning

There are different ways to improve the data-efficiency of deep learning models, such as the successful paradigm of “pre-training + fine-tuning” widely used to land AI technologies. Here we give a more concrete description of the problem we explore in this paper, characterized by generalizing to a set of new tasks in new domains with a few labeled examples. Our goal is to learn transferable representations on the training set capable of improving the data-efficiency of deep learning models for solving new tasks on the test set.

Definition 1 (Data-Efficient Deep Learning) This paradigm extends few-shot learning for classification to complex scenarios with regression and reinforcement learning tasks. At the training phase, our goal is to learn a feature representation \( F \) on the training set \( D_{\text{train}} \) of sufficient labeled examples, which enables solving new tasks from a few examples in a short time. At the testing phase, the learned representation \( F \) is evaluated on new tasks, either within domain or across domains — Each task comes with a test set \( D_{\text{test}} = \{S_{\text{test}}, Q_{\text{test}}\} \) partitioned into a support set \( S_{\text{test}} \) with a few labeled examples and a query set \( Q_{\text{test}} \) with many unlabeled examples to predict. The learned representation \( F \) should adapt fast to each new task through the support set and then yield accurate predictions on the query set.

This problem is closely related to topics such as few-shot learning (Vinyals et al., 2016), but with some important differences. Standard few-shot learning mainly considers the problem of adaptation to new tasks with different categories from the training dataset, with the assumption that they follow the same domain distribution. In the data-efficient learning setting, we relax this assumption and consider more general and challenging situations where both distribution shift and task discrepancy entangle between the training set and the new tasks. More importantly, existing few-shot learning scenario mainly focuses on the classification tasks, while we also explore to promote the data-efficiency in other widespread tasks such as regression and reinforcement learning.

The key to enable data-efficient deep learning in downstream tasks is the transferability of the representations, where the transferability can be subdivided into domain transferability and task transferability. We formally define the two types of transferability as follows.

Definition 2 (Transferability, Domain Transferability, and Task Transferability) Given input \( x \in X \) and output \( y \in Y \), denote the joint distribution as \( P(x, y) \) and the learning task as \( T : x \mapsto y \). Transferability characterizes the ability of reusing learned knowledge from an old system to boost a new system, in which the domain transferability measures the generalizability under train-test distribution shift, i.e., \( P_{\text{train}} \neq P_{\text{test}} \), and the task transferability measures the generalizability under train-test task discrepancy, i.e., \( T_{\text{train}} \neq T_{\text{test}} \).
In the general situation of data-efficient deep learning, complex relationships between the training dataset and the new tasks introduce both distribution shift and task discrepancy, which entangle with each other to make learning even more complicated. So we should learn representations with both domain transferability and task transferability to fully improve data-efficiency in downstream tasks.

Pre-training and meta-training have shown to be two effective paradigms for learning representations with domain transferability or task transferability respectively. In the next two subsections, we first introduce the background of these two mainstream representation learning approaches for data-efficient learning. Then we study them with regard to the two types of transferability, and take a step forward to explore the combination of these two types of training paradigms. This motivates the design of our Omni-Training framework.

3.2 Representation Learning via Pre-Training and Meta-Training

Pre-Training. In pre-training approaches, deep representations are often learned by supervised learning on a large-scale training dataset $\mathcal{D}_{\text{train}}$, which facilitate data-efficient learning for a variety of downstream tasks. We show a typical procedure of pre-training in
Figure 2. We use an abstract model composed of a feature extractor $F$ to generate the representation and a task-specific head $H$ to predict the output, which is applicable to various tasks. For example, $F$ is a convolutional network and $H$ is a classifier for a visual recognition task. During the training stage, the training set $D_{\text{train}}$ is viewed as samples from a joint distribution of inputs and labels: $P(x, y)$. Deep representation learning is conducted by optimizing $H$ and $F$ over the sampled mini-batches from the training distribution with the loss $\ell_{\text{pre}}$ tailored to the specific task or algorithm:

$$\left(\hat{H}, \hat{F}\right) = \arg\min_{(H,F)} \mathbb{E}_{(x,y) \sim P(x,y)} \ell_{\text{pre}}(y, H \circ F(x)).$$

(1)

In the testing stage, we transfer the pre-trained representations and models for data-efficient learning on the new task $D_{\text{test}} = \{S_{\text{test}}, Q_{\text{test}}\}$. The feature extractor $F$ is fine-tuned and a new task specific head $H_{\text{new}}$ handling the semantics in the new tasks is trained with the labeled data in the support set $S_{\text{test}}$ of the new task and applied on the query set $Q_{\text{test}}$.

**Meta-Training.** Meta-training is contrasted from pre-training in that the representations are learned to perform well across a set of tasks sampled from a task distribution constructed from the training set. Specifically, the training set $D_{\text{train}}$ is viewed as a distribution of tasks $T$. Each task mimics the testing situation, which contains a support set $S$ with only a few labeled samples and a query set $Q$ needing predictions. The meta-learner is optimized over episodes of tasks sampled from $T$. The feature extractor $F$ and the task-specific head $H$ are learned to efficiently solve each of the tasks conditioned on the support set $S$ with only a few samples, and updated by the performance evaluated on the query set $Q$:

$$\left(\hat{H}, \hat{F}\right) = \arg\min_{(H,F)} \mathbb{E}_{(S,Q) \sim P(T)} \mathbb{E}_{(x,y) \in Q} \ell_{\text{meta}}(y, H \circ F(x|S)),$$

(2)

where $\ell_{\text{meta}}$ is the loss of specific meta-training algorithms defined on each episode, e.g., the meta-objective in (Finn et al., 2017a). In the testing stage, the representations and models are fast adapted to the new task with its support set $S_{\text{test}}$ in a similar way as the training phase, and the adapted models can be used for predictions on the query set $Q_{\text{test}}$.

### 3.3 Transferability Assessment of Pre-Training and Meta-Training

**Transferability Assessment.** We empirically compare pre-training and meta-training in terms of task transferability and domain transferability. We evaluate two typical methods, **Baseline** (Chen et al., 2019a) as the pre-training method and **ProtoNet** (Snell et al., 2017) as the meta-training method. We first use two benchmarks mini-ImageNet and CUB and follow the protocol in Chen et al. (2019a). For each dataset, the model is trained on its training split, and tested on the left-out part with new categories. The test tasks are sampled from the test split with 1 or 5 examples per class in the support set. Note that we use test tasks from the same dataset to relieve the influence of distribution shift and mainly focus on task discrepancy. As shown in Figure 3a, the pre-training and meta-training methods perform comparably on mini-ImageNet-5 (5 examples per class). However, in the more extreme situation with 1 example per class, meta-training outperforms pre-training, where the boost becomes larger on CUB: a fine-grained dataset with small distribution shift between tasks. The result indicates higher task transferability of meta-training. Next,
Figure 3: (a) Task transferability of pre-training and meta-training representations in the cross-task setting; (b) Domain transferability of pre-training and meta-training representations in the cross-domain setting; (c) Accuracy of pre-training, meta-training and two combination strategies, Ensemble and Joint-Training on three benchmarks.

we explore the influence of distribution shift across domains. We train the model on the mini-ImageNet dataset, but evaluate it on different domains including CUB, Cars, Places and Plantae. As shown in Figure 3b, pre-training and meta-training have similar in-domain performance, but pre-training consistently outperforms meta-training in four cross-domain situations. This result indicates higher domain transferability of pre-training.

Our key finding is that pre-training representations have high domain transferability but low task transferability, while meta-training representations have high task transferability but low domain transferability. This explains the phenomena that both pre-training and meta-training may fail in some data-efficient learning scenarios (Finn et al., 2017a; Chen et al., 2019a; Triantafillou et al., 2020; Guo et al., 2020). In general situations, the new tasks hold complex relationships with the training set, present both challenges of distribution shift and task discrepancy, which entangle with each other. For example, in the in-domain experiment, there could still be distribution shift caused by different categories; In the cross-domain experiment, while distribution shift is the main challenge, task transferability is still required to adapt across different classes. Overall, we need to learn representations with both domain transferability and task transferability to fully enable data-efficient learning.

Combination Strategies. We propose two simple ways to combine pre-training and meta-training. One is to separately train two models with pre-training and meta-training, and use their ensemble for prediction, denoted as Ensemble. The other is to jointly train the model with both pre-training and meta-training losses, denoted as Joint-Training. We evaluate them on three data-efficient learning situations of mini-ImageNet, CUB, and transferring mini-ImageNet to CUB. As shown in Figure 3c, both combination strategies promote the performance in some cases, but the improvement is minor and inconsistent. The gain of Ensemble indicates that pre-training and meta-training representations endow complementary knowledge. However, this simple ensemble lacks the knowledge coordination between pre-training and meta-training. The improvement of Joint-Training shows the importance to extract shared knowledge between the two training paradigms, but this tight combination sacrifices the specific transferability held by each approach. Such a transferability dilemma motivates the proposed Omni-Training framework, which seeks to flexibly acquire both domain transferability and task transferability for data-efficient deep learning.
4. Omni-Training Framework

In this paper, we are interested in learning representations with both domain transferability and task transferability by incorporating pre-training and meta-training in a unified Omni-Training framework. As discussed and evaluated in Section 3.3, this goal is non-trivial to realize with simple combinations of these two training paradigms. Beyond the tight combination of joint-training, we have two key insights in designing the framework. Our first key insight is that the domain transferability of pre-training and the task transferability of meta-training should be preserved. Furthermore, there should be knowledge communication between the two types of training to enable them to complement each other. Our second key insight is that this non-trivial unification should be realized with the design in both network architectures and training algorithms. Note that we do not aim at newly designing a special method independent of existing architectures and algorithms, but seek to propose a general framework which can accommodate existing architectures for data-efficient learning.

Based on these two insights, the proposed Omni-Training framework includes an Omni-Net architecture and an Omni-Loss objective. Besides the joint representation flow for tight joint-training, the tri-flow architecture of Omni-Net introduces two new parallel flows for pre-training and meta-training, respectively responsible for learning specific representations of domain transferability and task transferability. It coordinates the parallel flows by routing their representations via the joint-flow, which promotes knowledge exchange between two flows and makes both representations gain the missing type of transferability. The Omni-Loss designs corresponding training objective for the tri-flow architecture and introduces a mean-teacher regularization to enhance stability and generalizability of the training process.

4.1 Omni-Net

We design the Omni-Net architecture for the proposed Omni-Training framework. As shown in Figure 4, Omni-Net is a tri-flow architecture constructed by stacking Omni-Layers for representation learning and Omni-Heads for output prediction.

**Omni-Layer.** We aim to simultaneously preserve the domain transferability of pre-training and the task transferability of meta-training, and promote knowledge communication between pre-training and meta-training. Thus, as shown in Figure 4, we design an Omni-Layer consisting of a main chunk layer $f_{\text{joint}}$ and two parallel branch layers $f_{\text{pre}}$ and $f_{\text{meta}}$. It enables three interdependent data flows with different network parameters. In the joint-flow, the training data only go through $f_{\text{joint}}$, which is jointly trained by pre-training and meta-training to extract common knowledge as well as to coordinate the two parallel flows for a better communication between them. Besides, the two parallel data flows for pre-training and meta-training are respectively responsible for maintaining domain transferability and task transferability. For pre-training, the data pass through both $f_{\text{joint}}$ and $f_{\text{pre}}$, and then these two outputs are added as the output of this Omni-Layer in the data flow. We denote this data flow as pre-flow. Similarly, for meta-training and its corresponding meta-flow, the output is derived by adding the outputs of $f_{\text{joint}}$ and $f_{\text{meta}}$. Overall, the transformation
function of the three parallel data flows in the $l$-th Omni-Layer can be summarized as:

$$x' = \begin{cases} 
  f_{\text{joint}}(x^{l-1}) + f_{\text{pre}}(x^{l-1}) & \text{in the pre-flow} \\
  f_{\text{joint}}(x^{l-1}) & \text{in the joint-flow} \\
  f_{\text{joint}}(x^{l-1}) + f_{\text{meta}}(x^{l-1}) & \text{in the meta-flow.} 
\end{cases}$$

(3)

This architecture can be transformed from the layers in existing backbones by copying their original layers as the main chunk layer $f_{\text{joint}}$ and add two similar branch layers $f_{\text{pre}}$ and $f_{\text{meta}}$. We design the two parallel branches as lightweight layers compared to the main chunk layer, which maintains parameter efficiency of the Omni-Training framework. For example, if $f_{\text{joint}}$ is a convolution layer with large kernels such as $7 \times 7$ or $3 \times 3$, $f_{\text{pre}}$ and $f_{\text{meta}}$ can be convolution layers with smaller kernels such as $1 \times 1$. Some existing architectures may introduce some additional special layers such as batch normalization and various activation functions. We let each data flow have its specific copy of these additional layers (denoted as $a_{\text{joint}}$, $a_{\text{pre}}$ and $a_{\text{meta}}$), which strengthens the specificity of the three data flows. We omit these additional layers in the equations for simplicity.

We stack the Omni-Layers to construct the backbone for Omni-Training, and the tri-flow in each layer expands to the entire data flows in the whole backbone. Specifically, we use $F_{\text{joint}}$ to denote the overall function of the joint-flow which stacks $f_{l_{\text{joint}}}$ in the backbone:

$$F_{\text{joint}} = f_{l_{\text{joint}}} \circ \cdots \circ f_{1_{\text{joint}}}.$$  

(4)

Further, we use $F_{\text{pre}}$ to denote the overall function of the stacked layers in the backbone that encodes the pre-flow, which enables knowledge routing by adding the joint-flow:

$$F_{\text{pre}} = (f_{l_{\text{pre}}} + f_{l_{\text{joint}}}) \circ \cdots \circ (f_{1_{\text{pre}}} + f_{1_{\text{joint}}}).$$

(5)

Similarly, we use $F_{\text{meta}}$ to denote the overall function of the stacked layers in the backbone that encodes the meta-flow, which enables knowledge routing by adding the joint-flow:

$$F_{\text{meta}} = (f_{l_{\text{meta}}} + f_{l_{\text{joint}}}) \circ \cdots \circ (f_{1_{\text{meta}}} + f_{1_{\text{joint}}}).$$

(6)

It is worth noting that such a stacked tri-flow encoding backbone benefits from many aspects. First, it is very parameter efficient, where the main chunk parameters are reused to encode different data flows and the architecture requires much fewer parameters than encoding these flows separately. Second, knowledge is softly shared between pre-training, meta-training, and joint-training by routing through the shared parameters in the architecture. Third, the Omni-Layer does not restrict on any specific architecture choices, but is generally applicable to various backbones in representation learning methods.

**Omni-Head.** The Omni-Head $H$ generates the final predictions of the three data flows with the representations extracted by the backbone. Specifically, $H$ consists of three heads: a joint-head $H_{\text{joint}}$, a pre-head $H_{\text{pre}}$ and a meta-head $H_{\text{meta}}$. Each head takes the corresponding data flow representations in the backbone as its input and outputs the prediction. Architectures of the three heads rely on the task, e.g., for classification problem, the heads can be classifiers with a single fully-connected layer. The separate outputs for the three data flows enable the use of different losses to train the three flows as introduced in Omni-Loss below. By chaining the backbone and the Omni-Head, we obtain the Omni-Net architecture.
Figure 4: The Omni-Training framework consists of three data flows: joint-flow (green), pre-flow (blue), and meta-flow (red), respectively responsible for joint-training, pre-training and meta-training. The Omni-Net consists of a backbone $F$ and an Omni-Head $H$, where $F$ is formed by stacking Omni-Layers and $H$ is comprised of three heads $H_{\text{joint}}$, $H_{\text{pre}}$ and $H_{\text{meta}}$ to generate the prediction for each flow. Each Omni-Layer has a main chunk layer $f_{\text{joint}}$ and two lightweight branch layers $f_{\text{pre}}$ and $f_{\text{meta}}$, followed by activation functions $a_{\text{joint}}$, $a_{\text{pre}}$, $a_{\text{meta}}$. The Omni-Loss consists of three losses respectively for joint-training $L_{\text{joint}}$, pre-training $J_{\text{pre}}$, and meta-training $J_{\text{meta}}$, which are computed on the corresponding head. We also propose a mean-teacher regularization for training pre-flow and meta-flow, which further boosts the stability of the training process and the generalizability of the model.

4.2 Omni-Loss

Based on the proposed architecture design of Omni-Net, we now describe the training loss, Omni-Loss, and the training process. The general idea is to train the parameters of each data flow with the corresponding pre-training or meta-training algorithm. We further take a step forward to enhance the stability and generalizability of the learned representations through special loss designs, by introducing a mean-teacher regularization.

**Joint-Training.** Joint-training is performed on the joint-flow with the losses of both pre-training and meta-training. In each iteration, we sample a standard mini-batch $B$ and a task episode $\{S, Q\}$ from the large-scale training set $D_{\text{train}}$. We add the pre-training loss with the mini-batch data and the meta-training loss with the sampled task on the output of the joint-head $H_{\text{joint}}$. The joint-training loss is derived as:

$$L_{\text{joint}} = \mathbb{E}_{B \sim \mathcal{P}(x,y)} \mathbb{E}_{(x,y) \in B} \ell_{\text{pre}}(y, H_{\text{joint}} \circ F_{\text{joint}}(x))$$

$$+ \mathbb{E}_{(S,Q) \sim \mathcal{P}(T)} \mathbb{E}_{(x,y) \in Q} \ell_{\text{meta}}(y, H_{\text{joint}} \circ F_{\text{joint}}(x|S)),$$

where $\ell_{\text{pre}}$ and $\ell_{\text{meta}}$ are the losses of pre-training and meta-training algorithms respectively. Though the joint-training extracts shared features between the two training paradigms,
such a brute-force combination is prone to negative knowledge transfer and fails to acquire representations with both domain transferability and task transferability simultaneously, as we have shown in Section 3.3. Thus, we further perform pre-training and meta-training on the two parallel data flows respectively to explicitly preserve domain transferability and task transferability.

**Pre-Training.** To specifically acquire strong domain transferability in the network, we perform pre-training on the pre-flow. In each iteration, we feed each sample \((x, y)\) from the mini-batch \(\mathcal{B}\) into the pre-flow of the Omni-Net, which maps the input with \(F_{\text{pre}}\), outputs the prediction with \(H_{\text{pre}}\), and finally leads to the pre-training loss on the pre-flow as follows:

\[
L_{\text{pre}} = \mathbb{E}_{B \sim \mathcal{P}(x,y)} \mathbb{E}_{(x,y) \in B} \ell_{\text{pre}}(y, H_{\text{pre}} \circ F_{\text{pre}}(x)),
\]

where \(\ell_{\text{pre}}\) is the loss of the pre-training algorithm, e.g., for the classification task, \(\ell_{\text{pre}}\) is the cross-entropy loss. Note that during training, the data batches exposed to the network change across iterations, which may encourage the model to focus more on the data in the current iteration and deteriorate its generalization across data in different iterations. But the representation should absorb knowledge from data of all iterations. Thus, we encourage our model to maintain stable when going through the changing batches during training.

Let \(\theta\) denote all the parameters in the backbone \(F\) and the Omni-Head \(H\), \(i\) denote the training steps, we keep the temporal ensemble of the network, i.e., an exponential moving average (EMA) of the model parameters \(\tilde{\theta}\), which is updated smoothly during training:

\[
\tilde{\theta}_i = \alpha \tilde{\theta}_{i-1} + (1 - \alpha)\theta_i.
\]

The EMA model serves as a mean-teacher to guide the training process of the Omni-Net. To fully grab the knowledge underlying the training dataset, in each iteration, the output of the current model is also encouraged to be consistent with the output of the EMA model.

We can derive this mean-teacher regularization for the pre-flow as:

\[
R_{\text{pre}} = \mathbb{E}_{B \sim \mathcal{P}(x,y)} \mathbb{E}_{(x,y) \in B} \ell_2(\tilde{H}_{\text{pre}} \circ \tilde{F}_{\text{pre}}(x), H_{\text{pre}} \circ F_{\text{pre}}(x)),
\]

where \(\tilde{F}_{\text{pre}}\) and \(\tilde{H}_{\text{pre}}\) denote the mapping functions of the pre-flow and pre-head in the EMA model with the temporal ensemble parameters of \(\tilde{\theta}\), and \(\ell_2\) is the squared loss. Overall, the mean-teacher regularized pre-training loss for the pre-flow is derived as follows,

\[
J_{\text{pre}} = L_{\text{pre}} + \lambda R_{\text{pre}},
\]

where \(\lambda\) is a hyper-parameter that controls the trade-off between the original pre-training loss and the mean-teacher regularization.

**Meta-Training.** Simultaneously, to specifically acquire task transferability in the network, in each iteration, we perform meta-training on the meta-flow with the sampled task episode \((\mathcal{S}, \mathcal{Q})\). Data in the support set \(\mathcal{S}\) are fed into the meta-flow to obtain the conditioned model. Then, each sample \((x, y)\) from the query set \(\mathcal{Q}\) passes through the meta-flow conditioned on the support set to derive the meta-training loss:

\[
L_{\text{meta}} = \mathbb{E}_{(\mathcal{S}, \mathcal{Q}) \sim \mathcal{P}(T)} \mathbb{E}_{(x,y) \in \mathcal{Q}} \ell_{\text{meta}}(y, H_{\text{meta}} \circ F_{\text{meta}}(x|\mathcal{S})),
\]

14
where \( \ell_{\text{meta}} \) denotes the loss for the meta-training algorithm, e.g., the meta-objective of the Model-Agnostic Meta-Learning (MAML) algorithm (Finn et al., 2017a). Similar to the pre-flow, we also impose the mean-teacher regularization for the meta-flow to encourage the model to be stable across the changing tasks sampled from task distribution \( \mathcal{P}(\mathcal{T}) \) during the training process and improve the generalizability of the meta-learned representations:

\[
R_{\text{meta}} = E_{(S,Q) \sim \mathcal{P}(\mathcal{T})} E_{(x,y) \in \mathcal{Q}} \ell_2(H_{\text{meta}} \circ \tilde{F}_{\text{meta}}(x|S), H_{\text{meta}} \circ F_{\text{meta}}(x|S)),
\]

where \( \tilde{F}_{\text{meta}} \) and \( H_{\text{meta}} \) denote the mapping functions of the meta-flow and meta-head in the EMA model, and \( \ell_2 \) is the squared loss. The training loss for the meta-flow includes the original meta-training loss and the proposed mean-teacher regularization:

\[
J_{\text{meta}} = L_{\text{meta}} + \lambda R_{\text{meta}},
\]

where \( \lambda \) is a hyper-parameter that controls the trade-off between the original meta-training loss and the mean-teacher regularization.

4.3 Overall Framework

Training. Taking all things together, we train the Omni-Net in an end-to-end way with the Omni-Loss to perform joint-training, pre-training and meta-training simultaneously:

\[
O_{\text{Omni}} = J_{\text{pre}} + J_{\text{meta}} + L_{\text{joint}}.
\]

With the cooperation of Omni-Net and Omni-Loss, our framework trains the two parallel flows to obtain both domain transferability and task transferability and coordinates the two parallel flows with by parameters to enable their knowledge communication, addressing both challenges of distribution shift and task discrepancy in data-efficient deep learning.

Inference. During the test time, we transfer knowledge learned from Omni-Training by reusing or fine-tuning the learned model and retraining a new Omni-Head for the new tasks on the labeled data in the support set \( S_{\text{test}} \). Since we focus on the representation learning stage but do not focus on the test time adaptation techniques, we train the new Omni-Head consisting of a new joint-head \( H_{\text{new}}^{\text{joint}} \), a new pre-head \( H_{\text{new}}^{\text{pre}} \) and a new meta-head \( H_{\text{new}}^{\text{meta}} \) following the corresponding algorithms we have used for pre-training and meta-training. Then for each test sample \( x \in \mathcal{Q}_{\text{test}} \), we predict \( x \) using one of the three heads or their ensemble based on the real application constraints. For example, if we need to deploy the model to a real-time prediction application, we only use the prediction of the meta-head for fast adaptation using only a few gradient updates. If there is no resource restriction, we can use the ensemble of all three heads for more accurate predictions.

5. Omni-Training Algorithms

In Section 4, we introduce the general framework of Omni-Training. In this section, we provide instantiations and implementations of the framework by specifying concrete algorithms. Due to the space quota, we only consider some mainstream pre-training and meta-training algorithms but the framework can generalize to a wider variety of algorithms.
5.1 Pre-Training Algorithms

Classification. The pre-training algorithm for classification is known as Baseline (Chen et al., 2019a) in the few-shot learning literature. To instantiate, $H_{\text{pre}}$ is a fully-connected classification layer with weights $[w_1, ..., w_K]$ and biases $[b_1, ..., b_K]$ for $K$ classes, $F_{\text{pre}}$ and $H_{\text{pre}}$ are pretrained on the training dataset $D_{\text{train}}$ by standard cross-entropy loss as $\ell_{\text{pre}}$:

$$\ell_{\text{pre}}(y, H_{\text{pre}} \circ F_{\text{pre}}(x)) = -\log \left( \frac{\exp(w_k^T F_{\text{pre}}(x))}{\sum_k \exp(w_k^T F_{\text{pre}}(x))} \right),$$

where $y$ is the class index of the ground-truth class label $y$ for $x$. The model is then fine-tuned on the support set $S_{\text{test}}$ for the new task with a new classification head $H_{\text{new}}$.

Regression. In the pre-training algorithm for regression, we use a fully-connected layer as the pre-head $H_{\text{pre}}$ to predict the output. Here the loss is defined as the squared error between the target value $y$ and the prediction, also known as the L2 loss:

$$\ell_{\text{pre}}(y, H_{\text{pre}} \circ F_{\text{pre}}(x)) = (H_{\text{pre}} \circ F_{\text{pre}}(x) - y)^2.$$

Reinforcement Learning. In the pre-training algorithm for reinforcement learning, we take the policy gradient in REINFORCE (Sutton et al., 2000). The Omni-Net serves as the parameterized policy $\pi = H_{\text{pre}} \circ F_{\text{pre}}$ and the head layer $H_{\text{pre}}$ is modeled as a fully-connected layer to predict the action given a state. Here the loss is defined as the expected return over the policy: $\ell_{\text{pre}}(H_{\text{pre}} \circ F_{\text{pre}}) = \mathbb{E}_{r \sim \pi} \left[ \sum_{t=0}^{\infty} r(s_t, a_t) \right]$. The gradient of the pre-training loss $\ell_{\text{pre}}$ with respect to the parameters $\theta$ of the policy $\pi$, i.e., the policy gradient, is defined as:

$$\nabla_{\theta} \ell_{\text{pre}}(H_{\text{pre}} \circ F_{\text{pre}}) = \sum_s p^\pi(s) \sum_a \nabla_{\theta} \pi(a|s) Q^\pi(s, a),$$

where $p^\pi(s)$ is discounted weighting of the probability of encountering states $s$ from the initial states and $Q^\pi$ is the Q-function with respect to $\pi$ (Sutton and Barto, 2018).

5.2 Meta-Training Algorithms

Model-Agnostic Meta-Learning (MAML). We first consider MAML, the algorithm of model-agnostic meta-learning (Finn et al., 2017a), which develops a gradient-based learning rule to rapidly adapt to new tasks with few data and gradient steps. At each iteration, we sample an episode of a support set $S$ and a query set $Q$, and optimize the MAML loss as

$$\ell_{\text{meta}}(y, H_{\text{meta}} \circ F_{\text{meta}}(x|S)) = \ell(y, H_{\text{meta}} \circ F_{\text{meta}}(x; \theta')),$$

for $(x, y) \in Q$ in the query set. Here $\theta$ is the parameters of $H_{\text{meta}}$ and $F_{\text{meta}}$ in the meta-flow, and $\theta' = \theta - \nabla_{\theta} \mathbb{E}_{(x,y) \in S} \ell(y, H_{\text{meta}} \circ F_{\text{meta}}(x; \theta))$ is the model parameters after a single gradient update on the support set $S$. MAML has few restrictions on the model architecture or the learning task, and can be widely used on various tasks such as regression, classification and reinforcement learning, simply by specifying an appropriate task-aware loss $\ell$.

Prototypical Networks. In the few-shot learning literature, one well-established meta-training algorithm is ProtoNet (Snell et al., 2017), which is specially designed for classification. Let $S_k$ denote the samples with the class index $k$ in a support set $S$ in the episode, the
prototype of this class \( c_k \) is the mean of the embedded data in \( S_k \):
\[
    c_k = \mathbb{E}_{(x,y) \in S_k} F_{\text{meta}}(x).
\]
A metric-based classifier predicts the probability distribution of each query point \( x \) based on its Euclidean distances \( d \) to the prototypes, which is penalized by a cross-entropy loss for classification:
\[
    \ell_{\text{meta}}(y, H_{\text{meta}} \circ F_{\text{meta}}(x|S)) = - \log \left( \frac{\exp(-d(F_{\text{meta}}(x), c_y))}{\sum_{k=1}^{K} \exp(-d(F_{\text{meta}}(x), c_k))} \right). \tag{20}
\]

When facing new classification tasks, the labeled data in the support set \( S_{\text{test}} \) are used to compute the prototypes of each new class. Then we can classify new samples in the query set \( Q_{\text{test}} \) by their nearest prototype.

We instantiate our framework by incorporating different pre-training and meta-training algorithms and introducing the specific loss formulations of \( \ell_{\text{pre}} \) and \( \ell_{\text{meta}} \) as well as some gradient update rules at each iteration if necessary (e.g. MAML). Our framework can be easily implemented by replacing the \( \ell_{\text{pre}} \) in Eq. (8) and the \( \ell_{\text{meta}} \) in Eq. (12) with the formulations of specific algorithms. Note that here we only showcase the implementations with several representative pre-training and meta-training methods, and Omni-Training can generally accommodate many different established algorithms for representation learning. In Section 6, we empirically show that our framework with different algorithms outperforms the original ones performing pre-training or meta-training separately or in a simple combination.

6. Experiments

We implement our Omni-Training framework with different representation learning algorithms and conduct comprehensive experiments on cross-task and cross-domain benchmarks in classification, regression and reinforcement learning for data-efficient learning. All codes and datasets will be available online at [https://github.com/thuml/Omni-Training](https://github.com/thuml/Omni-Training).

6.1 Classification

**Datasets.** We consider data-efficient classification problems with four datasets including in-domain datasets mini-ImageNet (Vinyals et al., 2016) and CUB-200-2011 (Wah et al., 2011), and cross-domain datasets mini-ImageNet→CUB and Multi-domain.

- **mini-ImageNet** is a subset of ILSVRC-12 dataset (Russakovsky et al., 2015) for generic object recognition. It contains 100 classes with 600 images per class selected from the full dataset. We use the same split introduced by (Ravi and Larochelle, 2017), which respectively splits 64/16/20 classes for the training/validation/testing set.

- **CUB-200-2011** is a fine-grained dataset of birds with a total of 200 classes and 11,788 images. We follow the protocol of (Hilliard et al., 2018) and split the dataset into 100/50/50 classes for training/validation/testing.

- **mini-ImageNet→CUB** is a cross-domain dataset. Following (Chen et al., 2019a), we use full mini-ImageNet dataset as the training set and split the CUB set as 50/50 classes for validation and testing.

- **Multi-domain** is another cross-domain dataset. We follow the split in (Tseng et al., 2020) and use the datasets of mini-ImageNet, CUB, Cars (Krause et al., 2013), Places (Zhou et al., 2017) and Plantae (Horn et al., 2018) as different domains. We explore two settings.
Table 2: The classification accuracy of the new tasks with 5 or 1 labeled samples per class on mini-ImageNet and CUB datasets, which forms the widely-evaluated cross-task setting.

| Method                  | Backbone   | mini-ImageNet $K = 5$ | mini-ImageNet $K = 1$ | CUB $K = 5$ | CUB $K = 1$ |
|-------------------------|------------|-----------------------|-----------------------|-------------|-------------|
| MatchingNet (Vinyals et al., 2016) | ResNet-18 | 68.88 ± 0.69          | 52.91 ± 0.88          | 83.64 ± 0.60 | 72.36 ± 0.90 |
| ProtoNet (Snell et al., 2017)        | ResNet-18 | 73.68 ± 0.65          | 54.16 ± 0.82          | 87.42 ± 0.48 | 71.88 ± 0.91 |
| RelationNet (Sung et al., 2018)      | ResNet-18 | 69.83 ± 0.68          | 52.48 ± 0.86          | 87.25 ± 0.58 | 67.59 ± 1.02 |
| MAML (Finn et al., 2017a)           | ResNet-18 | 65.72 ± 0.77          | 49.61 ± 0.92          | 82.70 ± 0.65 | 69.96 ± 1.01 |
| TADAM (Oreshkin et al., 2018)        | ResNet-12 | 76.70 ± 0.30          | 58.50 ± 0.30          | –           | –           |
| GNN (Garcia and Bruna, 2018)         | ResNet-18 | 78.80 ± 0.78          | 57.40 ± 0.98          | 90.74 ± 0.57 | 78.52 ± 1.03 |
| LEO (Rusu et al., 2019)              | WRN28-10  | 77.59 ± 0.12          | 61.76 ± 0.08          | 78.27 ± 0.16 | 68.22 ± 0.22 |
| Baseline (Chen et al., 2019a)        | ResNet-18 | 74.27 ± 0.63          | 51.75 ± 0.80          | 82.85 ± 0.55 | 65.51 ± 0.87 |
| Baseline++ (Chen et al., 2019a)      | ResNet-18 | 75.68 ± 0.63          | 51.87 ± 0.77          | 83.58 ± 0.51 | 67.02 ± 0.90 |
| MTL (Sun et al., 2019)               | ResNet-12 | 75.50 ± 0.80          | 61.20 ± 1.80          | –           | –           |
| MetaOpt (Lee et al., 2019)           | ResNet-12 | 78.63 ± 0.36          | 62.64 ± 0.61          | 90.90 ± 0.23 | 80.23 ± 0.44 |
| TapNet (Yoon et al., 2019)           | ResNet-12 | 76.36 ± 0.10          | 61.65 ± 0.15          | –           | –           |
| Robust20 (Dvornik et al., 2019)      | ResNet-18 | 81.59 ± 0.42          | 63.95 ± 0.61          | 84.62 ± 0.44 | 69.47 ± 0.69 |
| CAN (Hou et al., 2019)               | ResNet-12 | 79.44 ± 0.34          | 63.85 ± 0.48          | –           | –           |
| RFS (Tian et al., 2020)              | ResNet-12 | 82.14 ± 0.43          | 64.82 ± 0.60          | –           | –           |
| Neg-Margin (Lin et al., 2020)        | ResNet-18 | 80.94 ± 0.59          | 62.33 ± 0.82          | 89.40 ± 0.40 | 72.66 ± 0.90 |
| PMM (Afrasiyabi et al., 2020)        | ResNet-18 | 77.76 ± 0.58          | 60.11 ± 0.73          | 86.01 ± 0.50 | 73.94 ± 1.10 |
| Multi-Task (Wang et al., 2021a)      | ResNet-12 | 77.72 ± 0.09          | 59.84 ± 0.22          | –           | –           |
| Meta-Maxup (Ni et al., 2021)         | ResNet-12 | 79.38 ± 0.24          | 62.81 ± 0.34          | –           | –           |
| Omni-TrainingProto              | ResNet-18 | 81.26 ± 0.57          | 64.31 ± 0.86          | 91.09 ± 0.38 | 81.18 ± 0.78 |
| Omni-TrainingProto              | ResNet-12 | 82.36 ± 0.54          | 66.62 ± 0.80          | 91.93 ± 0.38 | 82.94 ± 0.73 |
| Omni-TrainingGNN                | ResNet-18 | 87.14 ± 0.59          | 70.99 ± 0.97          | 95.96 ± 0.33 | 87.73 ± 0.78 |

The first setting is training the model on the mini-ImageNet domain and evaluating the model on other four domains. The second setting is the leave-one-out setting which selects one domain for evaluation and trains the model with all other domains.

**Implementation Details.** We use ResNet-18 in Chen et al. (2019a) and the more powerful ResNet-12 with dropblocks in Oreshkin et al. (2018) as the network backbone for mini-ImageNet, CUB-200-2011 and mini-ImageNet→CUB. Following Tseng et al. (2020), we use ResNet-10 on the Multi-domain dataset for a fair comparison. We refactor ResNet into a backbone for Omni-Training by transforming all convolution layers into Omni-Layers, where each Omni-Layer uses the 1 × 1 convolution layer as the lightweight branch layer.

We employ Baseline in Chen et al. (2019a) as the pre-training method and explore two powerful meta-training methods, ProtoNet (Snell et al., 2017) and GNN (Garcia and Bruna, 2018), denoted as Omni-TrainingProto and Omni-TrainingGNN respectively. In each iteration of the training stage, a mini-batch is sampled with the batch size of 64 for pre-training, and an episode of task is sampled for meta-training, with a support set containing 5 categories each having 5 labeled instances, and a query set containing the same categories with 16 instances per class. We apply standard data augmentation including random crop, left-right flip and color jitter to the training samples. We train our framework with 100 epochs for the mini-ImageNet, mini-ImageNet→CUB and Multi-domain datasets, and with 400 epochs for the CUB dataset. We use accuracy on the validation set to choose the best model for testing. In the test stage, we randomly sample 600 tasks from the testing set. Each task contains 5 unseen classes with $K = 5$ or $K = 1$ labeled samples per class as
Table 3: The classification accuracy of the new tasks with 5 or 1 labeled samples per class in the cross-domain setting, mini-ImageNet→CUB.

| Method            | Backbone | $K = 5$   | $K = 1$   |
|-------------------|----------|-----------|-----------|
| MatchingNet       | ResNet-18| 53.07 ± 0.74 | 38.78 ± 0.73 |
| ProtoNet (Snell et al., 2017) | ResNet-18 | 62.02 ± 0.70 | 40.67 ± 0.75 |
| RelationNet       | ResNet-18 | 57.71 ± 0.73 | 37.71 ± 0.69 |
| MAML (Finn et al., 2017a) | ResNet-18 | 51.34 ± 0.72 | 40.15 ± 0.65 |
| GNN (Garcia and Bruna, 2018) | ResNet-18 | 65.56 ± 0.87 | 43.65 ± 0.86 |
| Baseline (Chen et al., 2019a) | ResNet-18 | 65.57 ± 0.70 | 43.59 ± 0.74 |
| Baseline++ (Chen et al., 2019a) | ResNet-18 | 62.04 ± 0.76 | 44.14 ± 0.77 |
| Robust20 (Dvornik et al., 2019) | ResNet-18 | 65.04 ± 0.57 | –          |
| Neg-Margin (Liu et al., 2020) | ResNet-18 | 67.03 ± 0.76 | –          |
| PMM (Afrasiyabi et al., 2020) | ResNet-18 | 68.77 ± 0.90 | –          |
| Omni-Training Proto | ResNet-18 | 71.30 ± 0.71 | 50.42 ± 0.82 |
| Omni-Training Proto | ResNet-12 | 71.77 ± 0.71 | 52.38 ± 0.82 |
| Omni-Training GNN  | ResNet-18 | 75.83 ± 0.82 | 50.89 ± 0.91 |

The average accuracy as well as the 95% confidence intervals are reported. The hyper-parameter is chosen as $\lambda = 3.0$. We train the networks from scratch and use Adam optimizer (Kingma and Ba, 2014) with an initial learning rate of 0.001.

Results on Cross-Task Benchmarks. We first evaluate our method on the general dataset mini-ImageNet and the fine-grained dataset CUB. These two scenarios are considered as cross-task benchmarks, as the training and testing data are from the same domain. The results with $K = 5$ and $K = 1$ in the mini-ImageNet and CUB datasets are shown in Table 2. Omni-Training Proto outperforms Baseline and ProtoNet and Omni-Training GNN outperforms Baseline and GNN, especially in the extremely difficult scenarios with only 1 labeled instance, demonstrating that Omni-Training outperforms pre-training and meta-training alone. Note that although from the same dataset, there still exists distribution shift between the training and test sets caused by the split of different label sets. Our framework manages to incorporate pre-training and meta-training effectively to acquire both domain transferability and task transferability and thus achieves higher performance. We further report the performance of state-of-the-art algorithms for pre-training, meta-training and joint-training. Omni-Training outperforms all of them, including MTL (Sun et al., 2019) which combines pre-training and meta-training sequentially. This confirms that our architecture and loss design can better coordinate pre-training and meta-training.

Results on Cross-Domain Benchmarks. Next, we consider two more challenging cross-domain benchmarks, mini-imageNet→CUB and Multi-domain. Different from the cross-task benchmarks discussed above, in the cross-domain setting, the testing data are not only from different classes, but also from different domains, causing greater distribution shift between the training data and the testing data. As shown in Table 3, in mini-ImageNet→CUB, meta-training algorithms degrade due to the distribution shift while pre-training algorithms generalize better to the unseen domain. Omni-Training outperforms meta-training methods by a large margin, indicating the significance of domain transferability in the cross-domain
setting. Also, Omni-Training outperforms the pre-training Baseline, which reveals the equal importance of task transferability to fully enable data-efficient learning.

A more challenging benchmark is Multi-domain with more domains and larger distribution shift. Table 4 reports the results of the first setting where we train on the mini-ImageNet domain and test on other four domains. Table 5 reports the results of the second leave-one-out setting, where we choose one domain as the unseen test domain and train the model with all other domains. We can observe that methods with higher performance on the standard cross-task benchmarks can still achieve better results in the cross-domain setting, but the accuracy is limited by the distribution shift. We specially compare Omni-Training with Feature-Transformation (Tseng et al., 2020), which is a framework adopts domain generalization (Blanchard et al., 2011) into meta-training to obtain both domain transferability and task transferability. Among its implementations, FT-GNN achieves the best performance by incorporating a strong meta-training algorithm, GNN (Garcia and Bruna, 2018). When trained on mini-ImageNet, Omni-Training can still achieve comparable or better performance than FT-GNN with a simple meta-training algorithm such as ProtoNet. We also incorporate GNN into Omni-Training to form Omni-Training+GNN, which generally outperforms FT-GNN in all tasks, verifying the effectiveness of the proposed framework. Note that FT-GNN has the special design for domain generalization, which is tailored for the multi-domain training setting. But Omni-Training+GNN also achieves better performance on most cases, confirming that Omni-Training works generally well in different situations.

Table 4: The classification accuracy of the tasks from unseen domains with 5 or 1 labeled samples per class in the Multi-domain setting (trained with mini-ImageNet).

| Method           | CUB K = 5 | CUB K = 1 |Cars K = 5 |Cars K = 1 |Places K = 5 |Places K = 1 |Plantae K = 5 |Plantae K = 1 |
|------------------|-----------|-----------|-----------|-----------|-------------|-------------|--------------|--------------|
| MatchingNet (2016) | 51.37 ± 0.77 | 35.89 ± 0.51 | 38.99 ± 0.64 | 30.77 ± 0.47 | 63.16 ± 0.77 | 49.86 ± 0.79 | 46.53 ± 0.68 | 32.70 ± 0.60 |
| ProtoNet (2017)   | 57.64 ± 0.85 | 38.18 ± 0.76 | 42.84 ± 0.73 | 29.72 ± 0.59 | 68.86 ± 0.70 | 49.24 ± 0.81 | 47.41 ± 0.70 | 35.02 ± 0.63 |
| RelationNet (2018) | 57.77 ± 0.69 | 42.44 ± 0.77 | 37.33 ± 0.68 | 29.11 ± 0.60 | 63.32 ± 0.76 | 48.64 ± 0.85 | 44.00 ± 0.60 | 33.17 ± 0.64 |
| GNN (2018)        | 62.25 ± 0.65 | 45.69 ± 0.68 | 44.28 ± 0.63 | 31.79 ± 0.51 | 70.84 ± 0.65 | 53.10 ± 0.80 | 52.51 ± 0.59 | 35.60 ± 0.56 |
| FT-Matching (2020) | 55.23 ± 0.83 | 36.61 ± 0.53 | 41.24 ± 0.65 | 29.82 ± 0.44 | 64.55 ± 0.75 | 51.07 ± 0.68 | 41.69 ± 0.63 | 34.48 ± 0.50 |
| FT-Relation (2020) | 59.46 ± 0.71 | 44.07 ± 0.77 | 39.91 ± 0.69 | 28.63 ± 0.59 | 66.28 ± 0.72 | 50.68 ± 0.87 | 45.08 ± 0.59 | 33.14 ± 0.62 |
| FT-GNN (2020)     | 66.98 ± 0.68 | 47.47 ± 0.75 | 44.90 ± 0.64 | 31.61 ± 0.53 | 73.94 ± 0.67 | 55.77 ± 0.79 | 53.85 ± 0.62 | 35.95 ± 0.58 |

Table 5: The classification accuracy of the tasks from unseen domains with 5 or 1 labeled samples per class in the Multi-domain setting (trained with all other domains).

| Method           | CUB K = 5 | CUB K = 1 |Cars K = 5 |Cars K = 1 |Places K = 5 |Places K = 1 |Plantae K = 5 |Plantae K = 1 |
|------------------|-----------|-----------|-----------|-----------|-------------|-------------|--------------|--------------|
| MatchingNet (2016) | 51.92 ± 0.80 | 37.90 ± 0.55 | 38.87 ± 0.51 | 28.96 ± 0.45 | 61.82 ± 0.57 | 49.03 ± 0.65 | 47.29 ± 0.51 | 33.21 ± 0.51 |
| ProtoNet (2017)   | 59.26 ± 0.89 | 39.31 ± 0.72 | 43.66 ± 0.68 | 29.52 ± 0.54 | 68.03 ± 0.61 | 47.96 ± 0.77 | 45.39 ± 0.72 | 35.40 ± 0.68 |
| RelationNet (2018) | 62.13 ± 0.74 | 44.33 ± 0.59 | 40.64 ± 0.54 | 29.53 ± 0.45 | 64.34 ± 0.57 | 47.76 ± 0.63 | 46.29 ± 0.56 | 33.76 ± 0.52 |
| GNN (2018)        | 69.26 ± 0.68 | 49.46 ± 0.73 | 48.91 ± 0.67 | 32.95 ± 0.56 | 72.59 ± 0.67 | 51.39 ± 0.80 | 58.36 ± 0.68 | 37.15 ± 0.60 |
| FT-Matching (2020) | 61.41 ± 0.57 | 43.29 ± 0.59 | 43.08 ± 0.55 | 30.62 ± 0.48 | 64.99 ± 0.59 | 52.54 ± 0.67 | 48.32 ± 0.57 | 35.12 ± 0.54 |
| FT-Relation (2020) | 64.59 ± 0.54 | 48.38 ± 0.63 | 43.44 ± 0.59 | 32.21 ± 0.51 | 67.35 ± 0.54 | 50.74 ± 0.66 | 50.39 ± 0.52 | 35.00 ± 0.52 |
| FT-GNN (2020)     | 73.11 ± 0.68 | 51.51 ± 0.80 | 49.88 ± 0.67 | 34.12 ± 0.63 | 77.05 ± 0.65 | 56.31 ± 0.80 | 58.84 ± 0.66 | 42.09 ± 0.68 |

Omni-Training+Proto 65.17 ± 0.75 | 45.83 ± 0.78 | 51.19 ± 0.71 | 34.82 ± 0.70 | 74.16 ± 0.69 | 55.73 ± 0.89 | 57.88 ± 0.69 | 38.54 ± 0.71 |

Omni-Training+GNN 70.24 ± 0.82 | 49.51 ± 0.96 | 48.99 ± 0.83 | 35.31 ± 0.78 | 79.61 ± 0.81 | 61.74 ± 1.05 | 60.08 ± 0.84 | 40.52 ± 0.81 |
6.2 Regression

Datasets. For the data-efficient regression problem, we conduct experiments on a sinusoid dataset following Finn et al. (2017a). Specifically, the regression problem is defined to predict the output \( y \) on a sine wave given the input \( x \). Thus, the input and output both have a dimensionality of 1. We define a task as regressing a sine wave with a particular amplitude and phase from some labeled data and consider a continuous task distribution in which the amplitude varies within \([0.1, 5.0]\) and the phase varies within \([0, 2\pi]\). The input datapoint \( x \) is sampled uniformly from \([-5.0, 5.0]\) for all tasks. The training dataset \( D_{\text{train}} \) contains a large number of sampled sine waves and each test task \( \{S_{\text{test}}, Q_{\text{test}}\} \) is an unseen sinusoid with a few labeled datapoints in \( S_{\text{test}} \) and other points which need prediction in \( Q_{\text{test}} \). The goal is to train a regression model on \( D_{\text{train}} \) to predict the outputs of the datapoints in the query set \( Q_{\text{test}} \) after adaptation with a few labeled data in \( S_{\text{test}} \).

Implementation Details. We implement our method by taking the mean-squared error, \( \text{i.e.} \) the L2 loss between the predictions and ground-truth values of the sampled training datapoints as the training loss. We use Baseline (Chen et al., 2019a) for pre-training and use MAML (Finn et al., 2017a) for meta-training. We employ a backbone with 2 fully-connected layers of size 64 with the activation function of Tanh. We construct a backbone of two Omni-Layers of size 64 in each flow for Omni-Training. We adopt a training set \( D_{\text{train}} \) with 30000 randomly sampled tasks and each task is a sine wave with 50 labeled datapoints. We then enable data-efficient regression on a new sine wave with a support set of \( K = \{5, 10, 20\} \) labeled examples and test the adapted model on points in \( Q_{\text{test}} \) of the wave. We train the model on \( D_{\text{train}} \) and fine-tune it on the \( K \) labeled examples for the new sine wave with an SGD optimizer. The learning rate for the inner loop is 0.02 and that for parameter update is initialized as 0.01, which decrease linearly during training.

![Figure 5: The mean squared error (log scale) of different training methods with different gradient steps and different support set sizes K for data-efficient regression.](image)

Results. We sample 100 new tasks for test and report the mean squared error on the sine wave after fine-tuning the trained model on its \( K \) labeled points with different gradient steps from 1 to 10, where each gradient step uses all these labeled examples for parameter update. As shown in Figure 5, Baseline generally performs worse than MAML. The tasks change rapidly during the training and test stages in this problem and task transferability is important, which is missing for pre-training methods. With different numbers of labeled
data and of gradient steps, Omni-Training consistently improves upon the meta-training method, which shows the efficacy of Omni-Training for regression tasks.

We further conduct a case study and show the typical sine waves recovered by pre-training, meta-training and Omni-Training with $K = 5$ labeled samples and with 1 or 10 gradient steps in Figure 6. We also show the ground-truth sine wave and the labeled points in the support set. We observe that MAML and Omni-Training quickly regress closed to the ground-truth curve, while the process is much slower for Baseline. However, compared with MAML, the recovered curve of Baseline maintains smooth, which is an important common property in the sinusoid distribution. Omni-Training also maintains a smoother curve, which simultaneously fits these datapoints quickly and preserves the domain transferability of sine waves. This explains the improvements brought by the Omni-Training framework.

![Figure 6](image)

Figure 6: The recovered sine wave of pre-training (Baseline), meta-training (MAML) and Omni-Training. The models are updated using 5 sampled points with 1 or 10 gradient steps.

### 6.3 Reinforcement Learning

**Environments.** To evaluate Omni-Training in reinforcement learning problems, we construct several sets of tasks based on two simulated continuous control environments: **2D Navigation** and **Locomotion** in the rllab benchmark suite (Duan et al., 2016a).

![Figure 7](image)

Figure 7: Illustration of the 2D navigation (left) and the locomotion (right) environments.

As shown in Figure 7, in the 2D Navigation environment, the goal of the agent is to move to a target position in 2D. The state space is the 2D location and the action space is the 2D velocity, where the action is clipped to be in the range of $[-0.1, 0.1]$. The reward is the negative squared distance to the goal, and the episodes terminate when the agent is
within 0.01 of the goal or at the horizon of $H = 100$. We construct a task of 2D navigation by randomly sampling a goal position from a unit square.

In the more complex high-dimensional Locomotion environment, we adopt the agent in the Mujoco HalfCheetah environment (Todorov et al., 2012). We follow the state and action space in the original HalfCheetah environment. We create two different sets of tasks for evaluation. The first set of tasks aim to run at a particular velocity. The reward is the negative absolute value between the current velocity of the cheetah agent and a goal velocity, which is chosen uniformly at random between 0.0 and 2.0 for different tasks. The second set of tasks aim to run in a particular direction. The reward is the magnitude of the velocity in either the forward or backward direction, which is randomly chosen for different tasks. The horizons of both sets of tasks are set as $H = 200$.

**Implementation Details.** In both the 2D navigation and the Locomotion environments, we adopt the policy as a neural network with two fully-connected layers of 64 hidden units and use the Tanh function as the activation function. We train the policy with the REINFORCE algorithm (Williams, 1992) using 20 trajectories per gradient step. We use the standard linear feature baseline proposed by Duan et al. (2016a), which is fitted separately at each iteration for each sampled task in the batch. During the training stage, we train the model with 500 iterations. In each iteration, 20 different tasks are sampled for the 2D navigation environment and 40 tasks are sampled for Locomotion, where 20 trajectories are sampled for each task. During the test stage for data-efficient reinforcement learning, we randomly sample 2000 new tasks for evaluation. Each task consists of trajectories with rewards as the support set. We use 20 trajectories from each task for each gradient step and use 1 to 4 gradient steps for adaptation to new tasks. We use 20 trajectories as the query set to compute the final testing reward of each task. We also use Baseline (Chen et al., 2019a) as the pre-training method and MAML (Finn et al., 2017a) as the meta-training method. In each iteration of meta-training, the policy is first trained using a single gradient step on the support trajectories with the inner loop step size 0.1, and then meta-updated on the query trajectories with the outer loop step size 0.03.

![Graphs showing average expected return for different tasks](image)

(a) 2D Navigation  (b) Locomotion-Velocity  (c) Locomotion-Direction

Figure 8: Average expected return of the tasks in the 2D Navigation environment and the two sets of tasks in the Locomotion environment for reinforcement learning.

**Results.** The results of the three sets of reinforcement learning tasks in the two environments are shown in Figure 8. The higher performance of MAML over Baseline within limited
gradient steps demonstrates that task discrepancy becomes the main challenge for transferability in these scenarios. Omni-Training outperforms both Baseline and MAML with large margins in the 2D Navigation environment, which demonstrates that the learned representations with both domain and task transferability can boost the generalization performance in this case. In the Locomotion environment, the performance gap between MAML and Baseline becomes larger, indicating more complex cross-task situations. Omni-Training still improves upon MAML in the velocity tasks. In the direction tasks, the pre-training method fails to generalize across these complex tasks with limited trajectories and updates, thereby performing similarly to the random initialization. In this extreme case, Omni-Training still performs comparably with MAML, without being negatively influenced. These results have proved the generalization ability of Omni-Training in a variety of complex situations.

7. Analysis

We further empirically analyze and understand our proposed framework. Without specification, we use the ResNet-18 as the backbone. We use the Baseline in Chen et al. (2019a) as the pre-training method and the ProtoNet (Snell et al., 2017) as the meta-training method.

7.1 Fine-grained Comparison with Baselines

Comparison with Simple Combinations. We compare Omni-Training with two simple combinations of pre-training and meta-training discussed in Section 3.3, i.e. the ensemble of the two models trained separately (Ensemble) and joint-training with the losses of the two training paradigms (Joint-Training). We evaluate on the classification dataset mini-ImageNet→CUB and the sinusoid regression dataset. We use $K = 5$ and $K = 1$ labeled samples in the support set in classification and use $K = 5$ and $K = 10$ labeled points with 2 gradient steps of parameter update in regression. As shown in Figure 9a and 9b, Ensemble and Joint-Training do not always improve upon pre-training and meta-training, and the performance gain is minor. Omni-Training instead outperforms all the compared methods consistently, which demonstrates that the proposed Omni-Net with a tri-flow architecture
and the Omni-Loss designs provide a better solution to acquire both domain transferability and task transferability from pre-training and meta-training.

**Extension to Other Algorithms.** Despite the competitive performance on various benchmarks, we also want to demonstrate that different data-efficient learning algorithms can benefit from the Omni-Training framework. We extend Omni-Training to more data-efficient algorithms. Since most pre-training algorithms adopt the similar pre-training and fine-tuning process, we mainly investigate the varieties of meta-training algorithms including MatchingNet (Vinyals et al., 2016), MAML (Finn et al., 2017a) and RelationNet (Sung et al., 2018). We conduct experiments in the mini-ImageNet dataset since some algorithms cannot deal with the regression problem. As shown in Figure 9c, Omni-Training with different algorithms significantly outperforms the corresponding baselines. This demonstrates that our framework can generally accommodate different data-efficient learning algorithms.

![Comparison of Each Flow with Baselines.](image)

**Comparison of Each Flow with Baselines.** We investigate whether the coordination of pre-training and meta-training with the shared parameters in our tri-flow architecture can improve the performance of pre-training and meta-training. Figure 10a reports the training losses and validation accuracies of the pre-flow in Omni-Training and pre-training algorithm Baseline (Chen et al., 2019a) alone, while Figure 10b reports the results of the meta-flow in Omni-Training and the meta-training algorithm ProtoNet (Snell et al., 2017). The experiments are conducted in the CUB dataset with $K = 5$. The pre-flow and the meta-flow in Omni-Training reach lower losses and higher accuracies than the baselines trained independently. Even though the pre-flow and Baseline achieve nearly the same training loss, the pre-flow achieves much higher validation accuracy than Baseline. This shows that the knowledge communication enables pre-flow to obtain part of task transferability and meta-flow to obtain part of domain transferability to improve their performance.

We also compare the transferability of the pre-training method and the pre-flow on the mini-ImageNet and mini-ImageNet→CUB datasets. As shown in Figure 10c, the pre-flow also outperforms pre-training in various situations. We further investigate fine-tuning the representations with 1/10 gradient steps. The performance of the pre-training model drops a lot with limited updates, but the pre-flow still performs well and comparably with the
pre-training model updated 10 more times. This reveals that the pre-flow also acquires task transferability to fast adapt across tasks. These results demonstrate that Omni-Training coordinates the two parallel flows and makes each gain the other kind of transferability.

| Input   | Pre-Train | Meta-Train | Pre-Flow | Meta-Flow | Joint Flow |
|---------|-----------|------------|----------|-----------|------------|
| Solar   | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) |
| Dish    | ![Image](image6.png) | ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) | ![Image](image10.png) |
| School  | ![Image](image11.png) | ![Image](image12.png) | ![Image](image13.png) | ![Image](image14.png) | ![Image](image15.png) |
| Bus     | ![Image](image16.png) | ![Image](image17.png) | ![Image](image18.png) | ![Image](image19.png) | ![Image](image20.png) |
| Tree    | ![Image](image21.png) | ![Image](image22.png) | ![Image](image23.png) | ![Image](image24.png) | ![Image](image25.png) |
| House   | ![Image](image26.png) | ![Image](image27.png) | ![Image](image28.png) | ![Image](image29.png) | ![Image](image30.png) |
| Auklet  | ![Image](image31.png) | ![Image](image32.png) | ![Image](image33.png) | ![Image](image34.png) | ![Image](image35.png) |

Figure 11: Comparison of different spatial attentions revealed in the representations of the pre-training model, the meta-training model and the three data flows in Omni-Training.

**Comparison of Attention Maps.** We compare the spatial attention in different representations learned by pre-training, meta-training and the three data flows in Omni-Training. From Figure 11, we observe that pre-training representations focus on a broad area containing the objects as well as some noisy context, which fully grab the domain knowledge but lack some concentration on the important information to discriminate different categories. On the contrary, the meta-training representations focus on a very small area with very concise information, which is easy to generalize across tasks quickly but also easy to make mistakes when the attending area deviates only a little from the objects. Such deviation is more likely to occur with the domain shift. Such attention heatmaps are consistent with our analyses before that pre-training learns representations with higher domain transferability while meta-training learns representations with higher task transferability.

Switching to Omni-Training, the pre-flow focuses on a more concise area only including the whole object while ignoring the noisy context. The meta-flow focuses on a broader area to grab more knowledge in the whole domain and increase the tolerance of mistakes. This observation demonstrates that there is knowledge transfer between pre-flow and meta-flow, which coordinates these two flows and improves them with the other kind of transferability. The joint-flow shows a different attention map from the pre-flow and the meta-flow. This also demonstrates that the three flows in the Omni-Training framework focus on different areas on the input space and form a more comprehensive understanding of the datapoints.
7.2 Framework Analysis

**Backbone Modification.** We investigate the influence of the number of Omni-Layers of the backbone. Since ResNet-18 is composed of 8 Res-Blocks, we attempt to keep the first \( n \) Res-Blocks unchanged and transform the rest \( 8 - n \) blocks into Omni-Layers. The first index of the block with Omni-Layers is \( n + 1 \). We train the models with these modified backbones. We report classification results with \( K = 5 \) in the CUB dataset (Figure 12a) and the mini-ImageNet→CUB dataset (Figure 12b). When the index of the first block with Omni-Layers is 1, which means the whole backbone is changed into Omni-Net, the model performs best. As the index increases, which means more preceding layers are completely shared between different flows as done in Multi-Task Learning, the accuracy drops sharply. This reveals the efficacy of the Omni-Layers on learning the three flows to coordinate pre-training and meta-training. Omni-Net is a general-purpose backbone for data-efficient learning.

**Parameter Sensitivity.** We analyze the sensitivity of the loss trade-off hyper-parameter \( \lambda \). We report the accuracy on the mini-ImageNet dataset with \( K = 1 \) and on the cross-domain mini-ImageNet→CUB dataset with \( K = 5 \) in Figure 12c. We observe that the model performs well in a range of parameters: \([1.0, 3.0]\). However, the performance degrades when setting \( \lambda = 0 \), i.e., removing the mean-teacher regularization. In general, we use the same hyper-parameter: \( \lambda = 3.0 \) for the different tasks in our experiments to avoid over-tuning it.

**Ablation Study of Losses.** We conduct an ablation study by using different combinations of losses in the Omni-Training framework. For the losses of \( L_{\text{pre}}, L_{\text{meta}} \) and \( L_{\text{joint}} \), if we do not use any of the three losses, we will not use the corresponding branch for inference. We report results on mini-ImageNet, CUB and mini-ImageNet→CUB datasets with \( K = 5 \) in Table 6. We observe that all of the loss functions in the tri-flow design including the mean-teacher regularization contribute to the improvement of the Omni-Training framework.

**Influence of the Model Size.** In Omni-Net, we use lightweight \( 1 \times 1 \) convolution layers for the parallel branches. Although the number of parameters does not increase significantly (from 11.17M to 13.98M if we use ResNet-18), there is still a concern that the performance gain of Omni-Training may come from the increase in the model size. Thus, we add the same
parameters as these additional $1 \times 1$ convolution layers to the original ResNet-18 backbone, and denote it as ResNet-18*. Though having the same number of parameters, ResNet-18* is different from our Omni-Training backbone because it does not have different data flows inside respectively for pre-training and meta-training, and is only trained with one learning paradigm. We train ProtoNet (Snell et al., 2017) with the ResNet-18* backbone (denoted as ProtoNet*) and report the accuracy with the support set size $K = 5$ in Table 7.

**Table 7: Ablation study on the model size.**

| Method      | #Params  | ImageNet | CUB   | ImageNet→CUB |
|-------------|----------|----------|-------|--------------|
| ProtoNet    | 11.17M   | 73.68    | 87.42 | 62.02        |
| ProtoNet*   | 13.98M   | 73.44    | 87.81 | 61.27        |
| Omni-Training | 13.98M  | 81.26    | 91.09 | 71.30        |

Despite having more parameters, ProtoNet* does not show obvious improvement over ProtoNet. This indicates that simply increasing the model complexity does not ensure better performance. Omni-Training has comparable parameters with ProtoNet*, but outperforms ProtoNet* with a large margin. This reveals that the main reason that improves the performance is not increasing the model size, but coordinating pre-training and meta-training to learn deep representations with both domain transferability and task transferability.

**8. Conclusion**

This paper focuses on learning transferable representations for data-efficient deep learning, which enables the model to fast generalize to new domains and tasks with a few examples. We pinpoint that domain transferability and task transferability are the key factors to data-efficiency in downstream tasks. We empirically show that pre-training and meta-training methods and simple combinations of them cannot obtain both domain transferability and task transferability, so we propose Omni-Training to learn representations with both types of transferability. With the tri-flow Omni-Net architecture, the model preserves the specific transferability of pre-training and meta-training and coordinates these flows by routing their representations via the joint-flow, making each gain the other kind of transferability. We design an Omni-Loss to learn the three flows and impose a mean-teacher regularization to en-
able the parallel flows to learn generalizable and stabilized representations. Omni-Training is a general framework that accommodates various existing pre-training and meta-training algorithms. Thorough evaluation on cross-task and cross-domain datasets in classification, regression and reinforcement learning problems shows that Omni-Training consistently and clearly outperforms the state-of-the-art deep learning methods for data-efficient learning.

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References

Daniel Adiwardana, Minh-Thang Luong, David R So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, et al. Towards a human-like open-domain chatbot. arXiv preprint, 2020.

Arman Afrasiyabi, Jean-François Lalonde, and Christian Gagné. Persistent mixture model networks for few-shot image classification. arXiv preprint, 2020.

Kelsey Allen, Evan Shelhamer, Hanul Shin, and Joshua Tenenbaum. Infinite mixture prototypes for few-shot learning. In ICML, pages 232–241, 2019.

Marcin Andrychowicz, Misha Denil, Sergio Gomez, Matthew W Hoffman, David Pfau, Tom Schaul, Brendan Shillingford, and Nando De Freitas. Learning to learn by gradient descent by gradient descent. In NeurIPS, pages 3981–3989, 2016.

Yoshua Bengio, Samy Bengio, and Jocelyn Cloutier. Learning a synaptic learning rule: Université de montréal. Département d’informatique et de recherche opérationnelle, 1990.

Luca Bertinetto, Joao F Henriques, Philip Torr, and Andrea Vedaldi. Meta-learning with differentiable closed-form solvers. In ICLR, 2019.

Gilles Blanchard, Gyemin Lee, and Clayton Scott. Generalizing from several related classification tasks to a new unlabeled sample. In NeurIPS, pages 2178–2186, 2011.

Rishi Bommasani, Percy Liang, et al. On the opportunities and risks of foundation models. arXiv preprint, 2021.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In NeurIPS, pages 1877–1901, 2020.
Víctor Campos, Pablo Sprechmann, Steven Stenberg Hansen, Andre Barreto, Steven Kap-
turowski, Alex Vitvitskyi, Adria Puigdomenech Badia, and Charles Blundell. Beyond
fine-tuning: Transferring behavior in reinforcement learning. In ICML Workshop on
Unsupervised Reinforcement Learning, 2021.

Zhangjie Cao, Minae Kwon, and Dorsa Sadigh. Transfer reinforcement learning across
homotopy classes. IEEE Robotics and Automation Letters, 6(2):2706–2713, 2021.

Olivier Chapelle, Bernhard Schölkopf, and Alexander Zien. Semi-supervised Learning. Mit
Press, 2006.

Wei-Yu Chen, Yen-Cheng Liu, Zsolt Kira, Yu-Chiang Frank Wang, and Jia-Bin Huang. A
closer look at few-shot classification. In ICLR, 2019a.

Xinyang Chen, Sinan Wang, Bo Fu, Mingsheng Long, and Jianmin Wang. Catastrophic
forgetting meets negative transfer: Batch spectral shrinkage for safe transfer learning. In
NeurIPS, 2019b.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training
of deep bidirectional transformers for language understanding. arXiv preprint, 2018.

Yan Duan, Xi Chen, Rein Houthooft, John Schulman, and Pieter Abbeel. Benchmarking
deep reinforcement learning for continuous control. In ICML, pages 1329–1338, 2016a.

Yan Duan, John Schulman, Xi Chen, Peter L Bartlett, Ilya Sutskever, and Pieter Abbeel.
Rl2: Fast reinforcement learning via slow reinforcement learning. arXiv preprint, 2016b.

Yan Duan, Marcin Andrychowicz, Bradly C Stadie, Jonathan Ho, Jonas Schneider, Ilya
Sutskever, Pieter Abbeel, and Wojciech Zaremba. One-shot imitation learning. In
NeurIPS, 2017.

Vincent Dumoulin, Neil Houlsby, Utku Evci, Xiaohua Zhai, Ross Goroshin, Sylvain Gelly,
and Hugo Larochelle. Comparing transfer and meta learning approaches on a unified
few-shot classification benchmark. arXiv preprint, 2021.

Nikita Dvornik, Julien Mairal, and Cordelia Schmid. Diversity with cooperation: Ensemble
methods for few-shot classification. In ICCV, pages 3722–3730, 2019.

Li Fei-Fei, Rob Fergus, and Pietro Perona. One-shot learning of object categories. TPAMI,
28(4):594–611, 2006.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast
adaptation of deep networks. In ICML, pages 1126–1135, 2017a.

Chelsea Finn, Tianhe Yu, Tianhao Zhang, Pieter Abbeel, and Sergey Levine. One-shot
visual imitation learning via meta-learning. In CoRL, pages 357–368, 2017b.

Kevin Frans, Jonathan Ho, Xi Chen, Pieter Abbeel, and John Schulman. Meta learning
shared hierarchies. arXiv preprint, 2017.
Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky. Domain-adversarial training of neural networks. *JMLR*, 17(1):2096–2030, 2016.

Victor Garcia and Joan Bruna. Few-shot learning with graph neural networks. In *ICLR*, 2018.

Yves Grandvalet and Yoshua Bengio. Semi-supervised learning by entropy minimization. In *NeurIPS*, 2005.

Yunhui Guo, Noel C Codella, Leonid Karlinsky, James V Codella, John R Smith, Kate Saenko, Tajana Rosing, and Rogerio Feris. A broader study of cross-domain few-shot learning. In *ECCV*, pages 124–141, 2020.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, pages 770–778, 2016.

Kaiming He, Ross Girshick, and Piotr Dollár. Rethinking imagenet pre-training. In *ICCV*, pages 4918–4927, 2019.

Nathan Hilliard, Lawrence Phillips, Scott Howland, Artём Yankov, Courtney D Corley, and Nathan O Hodas. Few-shot learning with metric-agnostic conditional embeddings. *arXiv preprint*, 2018.

Grant Van Horn, Oisin Mac Aodha, Yang Song, Yin Cui, Chen Sun, Alexander Shepard, Hartwig Adam, Pietro Perona, and Serge J. Belongie. The inaturalist species classification and detection dataset. In *CVPR*, pages 8769–8778, 2018.

Ruibing Hou, Hong Chang, MA Bingpeng, Shiguang Shan, and Xilin Chen. Cross attention network for few-shot classification. In *NeurIPS*, pages 4005–4016, 2019.

Rein Houthooft, Richard Y Chen, Phillip Isola, Bradly C Stadie, Filip Wolski, Jonathan Ho, and Pieter Abbeel. Evolved policy gradients. *arXiv preprint*, 2018.

Muhammad Abdullah Jamal and Guo-Jun Qi. Task agnostic meta-learning for few-shot learning. In *CVPR*, pages 11719–11727, 2019.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint*, 2014.

Gregory Koch, Richard Zemel, Ruslan Salakhutdinov, et al. Siamese neural networks for one-shot image recognition. In *ICML deep learning workshop*, 2015.

Alexander Kolesnikov, Lucas Beyer, Xiaohua Zhai, Joan Puigcerver, Jessica Yung, Sylvain Gelly, and Neil Houlsby. Big transfer (bit): General visual representation learning. In *ECCV*, pages 491–507, 2020.

Jonathan Krause, Michael Stark, Jia Deng, and Li Fei-Fei. 3d object representations for fine-grained categorization. In *ICCV*, pages 554–561, 2013.
Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *Nature*, 521(7553):436–444, 2015.

Kwonjoon Lee, Subhransu Maji, Avinash Ravichandran, and Stefano Soatto. Meta-learning with differentiable convex optimization. In *CVPR*, pages 10657–10665, 2019.

Yoonho Lee and Seungjin Choi. Gradient-based meta-learning with learned layerwise metric and subspace. In *ICML*, pages 2927–2936, 2018.

Xingjian Li, Haoyi Xiong, Hanchao Wang, Yuxuan Rao, Liping Liu, Zeyu Chen, and Jun Huan. Delta: Deep learning transfer using feature map with attention for convolutional networks. In *ICLR*, 2019.

Zhenguo Li, Fengwei Zhou, Fei Chen, and Hang Li. Meta-sgd: Learning to learn quickly for few-shot learning. *arXiv preprint*, 2017.

Bin Liu, Yue Cao, Yutong Lin, Qi Li, Zheng Zhang, Mingsheng Long, and Han Hu. Negative margin matters: Understanding margin in few-shot classification. In *ECCV*, pages 438–455, 2020.

Mingsheng Long, Yue Cao, Jianmin Wang, and Michael Jordan. Learning transferable features with deep adaptation networks. In *ICML*, pages 97–105, 2015.

Mingsheng Long, Han Zhu, Jianmin Wang, and Michael I. Jordan. Deep transfer learning with joint adaptation networks. In *ICML*, pages 2208–2217, 2017.

Mingsheng Long, ZHANGJIE CAO, Jianmin Wang, and Michael I Jordan. Conditional adversarial domain adaptation. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, *NeurIPS*, 2018.

Jiang Lu, Pinghua Gong, Jieping Ye, and Changshui Zhang. Learning from very few samples: A survey. *arXiv preprint*, 2020.

Nikhil Mishra, Mostafa Rohaninejad, Xi Chen, and Pieter Abbeel. A simple neural attentive meta-learner. In *ICLR*, 2018.

Tsendsuren Munkhdalai and Hong Yu. Meta networks. In *ICML*, pages 2554–2563, 2017.

Tsendsuren Munkhdalai, Xingdi Yuan, Soroush Mehr, and Adam Trischler. Rapid adaptation with conditionally shifted neurons. In *ICML*, pages 3664–3673, 2018.

Devang K Naik and Richard J Mammone. Meta-neural networks that learn by learning. In *IJCNN*, pages 437–442, 1992.

Renkun Ni, Micah Goldblum, Amr Sharaf, Kezhi Kong, and Tom Goldstein. Data augmentation for meta-learning. In *ICML*, pages 8152–8161, 2021.

Boris Oreshkin, Pau Rodríguez López, and Alexandre Lacoste. Tadam: Task dependent adaptive metric for improved few-shot learning. In *NeurIPS*, pages 721–731, 2018.
Hang Qi, Matthew Brown, and David G Lowe. Low-shot learning with imprinted weights. In CVPR, pages 5822–5830, 2018.

Siyuan Qiao, Chenxi Liu, Wei Shen, and Alan L Yuille. Few-shot image recognition by predicting parameters from activations. In CVPR, pages 7229–7238, 2018.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. OpenAI blog, 2018.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9, 2019.

Sachin Ravi and Hugo Larochelle. Optimization as a model for few-shot learning. In ICLR, 2017.

Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. IJCV, 115(3):211–252, 2015.

Andrei A Rusu, Dushyant Rao, Jakub Sygnowski, Oriol Vinyals, Razvan Pascanu, Simon Osindero, and Raia Hadsell. Meta-learning with latent embedding optimization. In ICLR, 2019.

Adam Santoro, Sergey Bartunov, Matthew Botvinick, Daan Wierstra, and Timothy Lillicrap. Meta-learning with memory-augmented neural networks. In ICML, pages 1842–1850, 2016.

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

Jürgen Schmidhuber. Learning to control fast-weight memories: An alternative to dynamic recurrent networks. Neural Computation, 4(1):131–139, 1992.

Max Schwarzer, Nitarshan Rajkumar, Michael Noukhovitch, Ankesh Anand, Laurent Charlin, Devon Hjelm, Philip Bachman, and Aaron Courville. Pretraining representations for data-efficient reinforcement learning. arXiv preprint, 2021.

Connor Shorten and Taghi M Khoshgoftaar. A survey on image data augmentation for deep learning. Journal of Big Data, 6(1):1–48, 2019.

David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. nature, 529(7587):484–489, 2016.

Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In NeurIPS, pages 4077–4087, 2017.

Qianru Sun, Yaoyao Liu, Tat-Seng Chua, and Bernt Schiele. Meta-transfer learning for few-shot learning. In CVPR, pages 403–412, 2019.
Flood Sung, Yongxin Yang, Li Zhang, Tao Xiang, Philip HS Torr, and Timothy M Hospedales. Learning to compare: Relation network for few-shot learning. In CVPR, pages 1199–1208, 2018.

Richard S. Sutton and Andrew G. Barto. Reinforcement Learning: An Introduction. The MIT Press, 2018.

Richard S Sutton, David A McAllester, Satinder P Singh, and Yishay Mansour. Policy gradient methods for reinforcement learning with function approximation. In NeurIPS, pages 1057–1063, 2000.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In CVPR, pages 2818–2826, 2016.

Sebastian Thrun and Lorien Pratt. Learning to learn. Springer Science & Business Media, 1998.

Yonglong Tian, Yue Wang, Dilip Krishnan, Joshua B Tenenbaum, and Phillip Isola. Rethinking few-shot image classification: a good embedding is all you need? In ECCV, pages 266–282, 2020.

Emanuel Todorov, Tom Erez, and Yuval Tassa. Mujoco: A physics engine for model-based control. In IROS, pages 5026–5033, 2012.

Eleni Triantafillou, Tyler Zhu, Vincent Dumoulin, Pascal Lamblin, Utku Evci, Kelvin Xu, Ross Goroshin, Carles Gelada, Kevin Swersky, Pierre-Antoine Manzagol, and Hugo Larochelle. Meta-dataset: A dataset of datasets for learning to learn from few examples. In ICLR, 2020.

Hung-Yu Tseng, Hsin-Ying Lee, Jia-Bin Huang, and Ming-Hsuan Yang. Cross-domain few-shot classification via learned feature-wise transformation. In ICLR, 2020.

Oriol Vinyals, Charles Blundell, Timothy Lillicrap, Daan Wierstra, et al. Matching networks for one shot learning. In NeurIPS, pages 3630–3638, 2016.

Catherine Wah, Steve Branson, Peter Welinder, Pietro Perona, and Serge Belongie. The caltech-ucsd birds-200-2011 dataset. 2011.

Haoxiang Wang, Han Zhao, and Bo Li. Bridging multi-task learning and meta-learning: Towards efficient training and effective adaptation. In ICML, 2021a.

Jane X Wang, Zeb Kurth-Nelson, Dhruva Tirumala, Hubert Soyer, Joel Z Leibo, Remi Munos, Charles Blundell, Dharshan Kumaran, and Matt Botvinick. Learning to reinforcement learn. arXiv preprint, 2016.

Ximei Wang, Jinghan Gao, Mingsheng Long, and Jianmin Wang. Self-tuning for data-efficient deep learning. In ICML, pages 10738–10748, 2021b.

Yaqing Wang, Quanming Yao, James T Kwok, and Lionel M Ni. Generalizing from a few examples: A survey on few-shot learning. ACM Computing Surveys, 53(3):1–34, 2020.
Ronald J Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine learning*, 8(3):229–256, 1992.

Annie Xie, Avi Singh, Sergey Levine, and Chelsea Finn. Few-shot goal inference for visuomotor learning and planning. In *CoRL*, pages 40–52, 2018.

Tengyang Xie, Nan Jiang, Huan Wang, Caiming Xiong, and Yu Bai. Policy finetuning: Bridging sample-efficient offline and online reinforcement learning. *arXiv preprint*, 2021.

Zhongwen Xu, Hado van Hasselt, and David Silver. Meta-gradient reinforcement learning. *arXiv preprint*, 2018.

LI Xuhong, Yves Grandvalet, and Franck Davoine. Explicit inductive bias for transfer learning with convolutional networks. In *ICML*, 2018.

Huaxiu Yao, Ying Wei, Junzhou Huang, and Zhenhui Li. Hierarchically structured meta-learning. In *ICML*, pages 7045–7054, 2019.

Han-Jia Ye, Hexiang Hu, De-Chuan Zhan, and Fei Sha. Few-shot learning via embedding adaptation with set-to-set functions. In *CVPR*, 2020.

Sung Whan Yoon, Jun Seo, and Jaekyun Moon. Tapnet: Neural network augmented with task-adaptive projection for few-shot learning. In *ICML*, pages 7115–7123, 2019.

Kaichao You, Zhi Kou, Mingsheng Long, and Jianmin Wang. Co-tuning for transfer learning. In *NeurIPS*, 2020.

Chao Yu, Jiming Liu, and Shamim Nemati. Reinforcement learning in healthcare: A survey. *arXiv preprint*, 2019.

Yang Yu. Towards sample efficient reinforcement learning. In *IJCAI*, pages 5739–5743, 2018.

Bolei Zhou, Agata Lapedriza, Aditya Khosla, Aude Oliva, and Antonio Torralba. Places: A 10 million image database for scene recognition. *TPAMI*, 40(6):1452–1464, 2017.

Zhuangdi Zhu, Kaixiang Lin, and Jiayu Zhou. Transfer learning in deep reinforcement learning: A survey. *arXiv preprint*, 2020.