Comparing Transfer and Meta Learning Approaches on a Unified Few-Shot Classification Benchmark

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Abstract
Meta and transfer learning are two successful families of approaches to few-shot learning. Despite highly related goals, state-of-the-art advances in each family are measured largely in isolation of each other. As a result of diverging evaluation norms, a direct or thorough comparison of different approaches is challenging. To bridge this gap, we perform a cross-family study of the best transfer and meta learners on both a large-scale meta-learning benchmark (Meta-Dataset, MD), and a transfer learning benchmark (Visual Task Adaptation Benchmark, VTAB). We find that, on average, large-scale transfer methods (Big Transfer, BiT) outperform competing approaches on MD, even when trained only on ImageNet. In contrast, meta-learning approaches struggle to compete on VTAB when trained and validated on MD. However, BiT is not without limitations, and pushing for scale does not improve performance on highly out-of-distribution MD tasks. In performing this study, we reveal a number of discrepancies in evaluation norms and study some of these in light of the performance gap. We hope that this work facilitates sharing of insights from each community, and accelerates progress on few-shot learning.

1. Introduction
Few-shot learning — the ability to learn from a limited number of training examples — is a challenge that has received a lot of attention from the machine learning research community in the past few years (see Wang et al., 2020 for a recent survey). We do not yet have an algorithm that can match the human ability to acquire diverse new concepts from very few examples, rather than from orders of magnitude more training data (Lake et al., 2015). From a practical perspective, data collection and labeling is often time-consuming or expensive, and as a result, not all learning problems afford large quantities of training data.

Few-shot learning approaches can be grouped into two main categories: transfer learning and meta-learning. For transfer learning, a model is firstly pre-trained on an “upstream” dataset (e.g. ImageNet (Deng et al., 2009)), and later fine-tuned on different downstream tasks. Transfer learning approaches (Pan & Yang, 2009) are best exemplified when less downstream data is available. Typical downstream tasks have thousands or more training examples, but transfer may in principle be applied to few-shot classification.

Meta-learning may also be used to solve few-shot classification problems. Instead of relying on a hand-designed algorithm to transfer pre-trained representations to new tasks, meta-learning (i.e. “learning to learn”) attempts to discover a learning algorithm which yields good generalization (Schmidhuber, 1987; Hospedales et al., 2020). Meta-learning seeks an “algorithmic solution” to few shot learning, and does not place great emphasis on the data and architectures to train them. In contrast, transfer learning approaches tend to focus on learning representations using simple algorithms (supervised learning and fine-tuning), and focus more on the data source, architectures, and scale.

The existence of these different subfields, each with their standardized evaluation protocols, means that practical knowledge on how to learn from few labeled examples can sometimes be fragmented. Recent advances in transfer learning and meta-learning are not directly comparable if they are evaluated in different ways, which limits the adoption of best practices.

In order to bridge this gap, we use a few-shot classification evaluation protocol that can be adopted by both transfer learning and meta-learning to facilitate “apples-to-apples” comparisons between recent advances. To offer a low barrier of entry and leverage prior work, we combine the Visual

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We use this categorization for convenience and simplicity in writing. However we highlight that an alternative consideration could view meta-learning as belonging to transfer learning approaches, as they indeed can be used to model forms of transfer.
Task Adaptation Benchmark (VTAB) (Zhai et al., 2019) and Meta-Dataset (MD) (Triantafillou et al., 2020) — two comprehensive few-shot classification benchmarks recently introduced in the transfer learning and few-shot classification literature, respectively — into an evaluation protocol which we refer to as VTAB+MD. With this, we can verify whether advances in one field transfer across benchmarks, and can test overfitting to a particular benchmark. Our main contributions are:

1. We bring together two challenging transfer learning and few-shot classification benchmarks and perform a large-scale study on several competitive few-shot classification approaches from both research communities. We establish BiT-L (Kolesnikov et al., 2020) as SOTA on this unified evaluation protocol, and show that competitive approaches on the MD benchmark struggle to outperform transfer learning on VTAB.

2. We carefully study the impact of different aspects of the BiT model formulation (network scale, data, normalization layer choice, and resolution). Beyond showing aggregate benefits on MD learning episodes, coherent with observations in (Kolesnikov et al., 2020), we demonstrate that not all effects are consistent across all of MD’s sources of test tasks. In particular, we identify Omniglot and QuickDraw as two data sources for which BiT-L does no better than competing approaches despite being significantly larger both in terms of data and architecture size.

3. We show that despite recent advances in cross-domain few-shot classification, meta-learning approaches still struggle to generalize to test tasks that are significantly outside of the training task distribution, as evidenced by their poor performance on VTAB with respect to comparable transfer learning implementations. We identify adaptability and scale as two promising avenues of future research to overcome these difficulties.

As evidenced by our results comparing transfer learning and meta-learning approaches on VTAB+MD, the collaboration across these fields that the benchmark affords is beneficial to both research communities, and we hope to facilitate the sharing of insights and accelerate progress on shared goal of learning from a limited number of examples.

2. Background and related Work

2.1. Transfer Learning

Transfer learning has long been used to exploit knowledge obtained on one task to improve performance on another, typically with less data. In the context of computer vision, the most popular form of transfer is to initialize a network with weights obtained by pre-training on ImageNet (Huh et al., 2016). More recently, transfer from larger datasets has been shown effective, including 100M Flickr images (Joulin et al., 2016; Li et al., 2017), JFT with 300M images (Sun et al., 2017), and 3.5B Instagram images (Mahajan et al., 2018). Most state-of-the-art methods on image classification benchmarks now use some form of transfer learning, and the best results are obtained by combining large-scale networks with large pre-training datasets (Kolesnikov et al., 2020; Xie et al., 2019; Dosovitskiy et al., 2020). Transfer learning has made a considerable impact in few-shot learning, most recently in in NLP (Brown et al., 2020) where very large models have proven successful for learning transfer with few datapoints. In computer vision, learning with few datapoints is, perhaps, more commonly addressed with semi-supervised learning (e.g. (Sohn et al., 2020)), however (Kolesnikov et al., 2020) show that large vision models transfer well to popular classification benchmarks (ImageNet, CIFAR, etc.) and VTAB-1k.

Several recent papers report that well-tuned transfer learning baselines are competitive with more complex few-shot classification approaches (Chen et al., 2019; Dhillon et al., 2020; Chen et al., 2020b; Tian et al., 2020). Our work adds to these observations by applying an established few-shot classification evaluation protocol (Meta-Dataset) to large scale (both in terms of data and capacity) transfer learners. Doing so highlights some limitations of episodic approaches in a new way, and also reveals where transfer learning falls short.

2.2. Episodic approaches to few-shot classification

Few-shot classification evaluation proceeds by sampling learning episodes from a test set of classes: first the test classes are subsampled into an $N$-way classification problem, then examples of the $N$ sampled test classes are subsampled and partitioned into a $k$-shot support set (used to fit the model on $k$ examples per class, for a total of $Nk$ support examples) and a query set (used to evaluate the model’s generalization performance on the learning episode). Meta-learning approaches to few-shot classification are usually trained in a way that mimics the evaluation conditions (called episodic training). Episodes are formed using a disjoint training set of classes and the meta-learner is trained in an end-to-end fashion by learning from the support set, evaluating on the query set, and backpropagating the loss through the learning procedure. This is hypothesized to be beneficial to performance on test episodes (Vinyals et al., 2016), and iconic gradient-based and metric-based meta-learning approaches such as MAML (Finn et al., 2017) or Prototypical Networks (Snell et al., 2017) (respectively) are trained episodically. The recent literature is rich in few-shot
classifiers, and an exhaustive survey is beyond the scope of this paper; see Wang et al. (2020) for an overview.

2.3. Benchmarks

Many visual classification benchmarks consist of single datasets, e.g. ImageNet (Deng et al., 2009), CIFAR (Krizhevsky, 2009), COCO (Lin et al., 2014), etc. However, benchmarks with multiple datasets are becoming more popular. The Visual Decathlon (Rebuffi et al., 2017) contains ten classification tasks, and focuses on multi-task learning. The Facebook AI SSL challenge contains various vision tasks (classification, detection, etc.) and targets linear transfer of self-supervised models.

Established episodic evaluation benchmarks range in scale and domain diversity from Omniglot (Lake et al., 2015) to mini-ImageNet (Vinyals et al., 2016), CIFAR-FS (Bertinetto et al., 2019), FC100 (Oreshkin et al., 2018), and tieredImageNet (Ren et al., 2018). Guo et al. (2020) propose a cross-domain few-shot classification evaluation protocol where learners are trained on mini-ImageNet and evaluated on episodes sampled from four distinct target domains.

We use VTAB (1k example version) and Meta-Dataset as representative benchmarks for few-shot classification since they offer the largest domain variety in their respective communities. Furthermore, VTAB and Meta-Dataset have been used in the development of state-of-the-art transfer learning and meta-learning methods, respectively.

2.4. Related problems

Domain adaptation (Wang & Deng, 2018) addresses the problem setting where a large corpus of labeled data is available for a “source” domain, but the target application’s input distribution is different (e.g. natural images vs sketches). In supervised domain adaptation very few labeled samples are available from the “target” domain. In contrast to meta-learning, there is usually only one target domain and the class (label) distribution is usually assumed to be the same between the source and target domains.

Low-shot classification (Thrun, 1996) is interested in classification problems for which lots of training examples are available for a “base” set of classes and knowledge about “novel” classes is integrated incrementally and with a limited number of training examples.

While low-shot classification and domain adaptation are very relevant to real-world applications and are also important components of humans’ learning ability, for the purpose of this work we concentrate on few-shot classification problems for which the sets of training and test tasks do not overlap in terms of image classes.

2.5. Evaluated approaches

In this work we evaluate existing approaches from the transfer learning and meta-learning literature. The main transfer learning algorithm we consider is the recent Big Transfer (Kolesnikov et al., 2020). This algorithm attains near state-of-the-art performance on VTAB, as well as a number of other benchmark image classification datasets such as ImageNet (Deng et al., 2009), CIFAR-10/100 (Krizhevsky, 2009), Oxford-IIIT Pets (Parkhi et al., 2012), and Flowers-102 (Nilsback & Zisserman, 2008).

We also consider recent SOTA approaches on Meta-Dataset: SUR (Dvornik et al., 2020), which is trained on multiple training sources, and CrossTransformers (Doersch et al., 2020), which is trained only on ImageNet. We also include representatives of metric-based and gradient-based meta-learning approaches: Prototypical Networks (Snell et al., 2017) and ProtoMAML (Triantafillou et al., 2020), respectively.

Prototypical Networks (Snell et al., 2017) learn a representation (via episodic training) for which a Gaussian classifier with an identity covariance matrix performs well. For any given episode, the support embeddings of each class are averaged into prototypes, and the classifier logits are computed as the “query-embedding to prototype” Euclidean distances.

ProtoMAML (Triantafillou et al., 2020) is a variant of MAML (Finn et al., 2017) (also trained episodically) which initializes the output layer weights and biases in a way that is equivalent to Prototypical Network’s Gaussian classifier. During training, the optimization loop on the support set is unrolled, the query loss computed at the end is backpropagated through the optimization loop to update the trainable initialization parameters. Note that ProtoMAML uses the first-order variant of MAML, which ignores second-order derivatives to save on computation and memory.

SUR (Dvornik et al., 2020) trains separate feature extractors for each of MD’s training sources via supervised learning. To make a prediction for a test episode, the model constructs a representation by concatenating the modulated embeddings of each backbone and then optimizes the sigmoidal modulation coefficients (one per feature extractor) to minimize a nearest-centroid loss (computed using the cosine similarity) on the support set and its corresponding class centroids. Query examples are then classified based on their cosine similarity with these class centroids, in the modulated and concatenated embedding space.

CrossTransformers (Doersch et al., 2020) improves on centroid-based few-shot classification approaches by introducing a Transformer-based (Vaswani et al., 2017) component which replaces the feature extractor’s final global
pooling operation and whose purpose is to build class prototypes which are query-aligned and spatially aware. The paper also introduces an auxiliary self-supervised task which reformulates SimCLR (Chen et al., 2020a)’s contrastive instance discrimination task into an episodic learning problem (called SimCLR episodes).

**Big Transfer (BiT)** (Kolesnikov et al., 2020) consists of pre-trained weights and a transfer learning protocol. BiT models are based on ResNet-v2, except that batch normalization layers are replaced with group normalization, and weight standardization is applied. BiT models are pre-trained on datasets of different sizes: The ILSVRC-2012 ImageNet datasets (1.3M images) “BiT-S”, the full ImageNet-21k dataset (13M images) (Deng et al., 2009) “BiT-M”, or JFT-300M (300M images) (Sun et al., 2017) “BiT-L”.

**MD-Transfer** refers to the transfer learning baseline used in (Triantafillou et al., 2020). In contrast to BiT, it (1) uses the entire episode when calculating gradients,\(^5\) (2) uses batch normalization, (3) does validation on MD-v2 for model selection, (4) fine-tunes using the Adam optimizer, a constant learning rate of 0.01, and 100 parameter updates, and (5) uses a cosine classifier head. Note: (4) and (5) were selected based on the accuracy on MD-v2 validation episodes.

### 3. Unifying VTAB and Meta-Dataset

We start by describing VTAB and Meta-Dataset, both of which evaluate on tasks with limited training data. Note that each benchmark use slightly different terminology. The tasks that can be used for learning prior to evaluation are referred to as upstream tasks in VTAB and training tasks in MD. Similarly, tasks on which evaluation performance is reported are referred to as downstream and test tasks by VTAB and MD, respectively. Since each test task itself contains training and test examples, MD refers to these as support and query sets. To avoid confusion, when appropriate, we will prefer MD’s nomenclature

VTAB features 19 evaluation tasks which can be grouped into “natural”, “structured”, and “specialized” sets of tasks. Each task corresponds to an existing classification problem (e.g. CIFAR100) or one converted into classification (e.g. DMLab). For the VTAB-1k variant (that we use in VTAB+MD), the support set is constructed by taking the original problem’s training set and randomly subsampling 1000 examples. The performance on the task is then measured as the average accuracy on a query set which consists of the original problem’s entire test set. VTAB allows a model to be trained or validated on any dataset except the 19 evaluation tasks, and it does not provide validation tasks.

Meta-Dataset features 10 test “sources” (i.e. existing classification problems) from which learning episodes are formed by 1) selecting a source, 2) randomly subsampling classes, and 3) randomly subsampling examples within the selected classes that are assigned either to the support set or query set. Performance is measured as the query accuracy averaged over many (typically 600) test episodes and aggregated across the 10 test sources. Training and validation sources are also provided, some of which intersect with the 10 test sources. For intersecting sources, the classes are partitioned into training, validation, and test set classes so that the validation and test classes are never seen during training. Meta-Dataset also features several datasets whose classes are never sampled during training or validation, in order to measure out-of-distribution (OOD) performance.

Conceptually, VTAB and Meta-Dataset can be combined by either treating the 19 VTAB evaluation tasks as 19 test episodes (albeit with a larger-than-usual support and query set), or treating every Meta-Dataset test episode as a evaluation task and grouping the tasks into 10 additional sets of tasks. This makes it easy for approaches that already evaluate on Meta-Dataset or VTAB to extend their evaluation to VTAB+MD.

In combining VTAB and Meta-Dataset into VTAB+MD, we have to resolve certain task/source collisions. This also provides an opportunity of improving on design choices previously made for VTAB and Meta-Dataset. In order to disambiguate between the original VTAB and MD formulations and their VTAB+MD-adapted counterparts, we refer to the VTAB+MD ones as VTAB-v2 and MD-v2, respectively.

We make the following changes:

- VTAB does not provide a validation set of tasks; we therefore propose to use Meta-Dataset’s validation episodes for that purpose.
- Meta-Dataset partitions ImageNet classes into training, validation, and test sets of classes, which makes it awkward to leverage pre-trained ImageNet initializations; we therefore choose to treat ImageNet as a training-only source in MD-v2.
- Finally, VTAB’s Flowers102 and DTD tasks are scattered into training, validation, and test classes in Meta-Dataset, which we resolve by entirely removing Flowers as a MD-v2 source and removing DTD as a VTAB-v2 task, respectively.

We report both aggregated and per-dataset accuracies for VTAB+MD. Aggregated reporting consists of the average query accuracy for episodes of all MD-v2 test sources and the average test accuracy for all VTAB-v2 tasks, which

\(^5\)When data augmentation is used, resulting images are not re-sampled for different batches. In contrast BiT uses a fixed batch size of 512 images, which can include two different augmented versions of the same image.
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is further decomposed into “natural”, “specialized”, and “structured” task averages (Figure 1). Detailed reporting breaks down the accuracies into their individual MD-v2 sources and VTAB-v2 tasks; we provide detailed reporting figures and tables in the Appendix.

We allow the use of the following data for upstream training or meta-training:

1. All of the ImageNet training set.
2. The training sets of classes of the Omniglot, Aircraft, CU Birds, DTD, QuickDraw, and Fungi datasets as defined by MD-v2.
3. Any dataset whose images do not overlap with VTAB+MD’s evaluation images.

The use of any subset of the above choices therefore ensures no overlap with data used by test tasks. For example, the use of choices 1 and 2 above will be referred to as all MD-v2 sources in our experiments.

4. Experiments

We begin by evaluating all approaches on VTAB+MD, following closely the prescriptions in their respective papers, in an effort to answer the question: How would current approaches fare in a direct comparison?

Practices differ between transfer learning and few-shot classification evaluation. Few-shot classification benchmarks tend to standardize around a restricted set of input resolutions (84 × 84, 126 × 126) and network architectures (four-layer CNN, ResNet-18, etc.). Episodic training also imposes restrictions on input resolution and network capacity, since the batch size is determined by an episode’s ways and shots and the support set cannot be trivially sharded into independent batches and distributed across multiple accelerators. This is especially true for large-scale benchmarks such as Meta-Dataset, where support sets can contain up to 500 examples. This makes it difficult to scale up meta-learners; one notable effort is the CrossTransformer model, which trains a ResNet-34 architecture on 224 × 224 inputs using a customized multi-GPU implementation. Transfer learning benchmarks on the other hand typically train at 224 × 224 (and may evaluate at even higher resolution), and routinely use network architectures in the ResNet-50 scale and beyond. We summarize some of these high level details and differences here:

- For BiT we use the ResNet-101x3 architecture trained on JFT (“BiT-L-R101x3”).6 This model is trained and evaluated at 224 × 224. While increasing resolution during transfer is recommended (Touvron et al., 2019), we match the pre-training and test resolutions to match the other methods.
- In accordance with the practice established in Meta-Dataset, MD-Transfer, ProtoMAML, and ProtoNets are initialized from a ResNet-18 classifier trained on ImageNet at 126 × 126. They are then further trained (episodically for ProtoMAML and ProtoNets) on either ImageNet or all MD-v2 training sources.
- CTX (CrossTransformers) trains a ResNet-34 architecture from scratch on 224 × 224 ImageNet episodes as well as SimCLR episodes.
- SUR reuses the 84 × 84 ResNet-18 backbones provided by the paper authors, with two key differences: (1) we re-train the ImageNet backbone using the entire ImageNet dataset using the recommended hyperparameters, and (2) we remove the Flowers backbone, since Flowers is an evaluation task in VTAB+MD.

Additional implementation details are provided in the Appendix. The differences in performance will undoubtedly be influenced by design decisions informed by each approach’s original evaluation setting, which we investigate through ablations on BiT-L (subsection 4.2).

All non-BiT learning approaches and baselines considered in this work perform model selection on MD-v2 validation episodes using Triantafillou et al. (2020)’s hyperparameter search space (detailed in the Appendix, along with the best values found).

For BiT, we follow hyperparameter selection strategies similar to previous works. For MD-v2 we use the transfer heuristic suggested in Kolesnikov et al. (2020): 500 steps of SGD with learning rate 0.003, momentum 0.9. However, instead of the recommended task-dependent image resolutions, we use a fixed resolution of 224 × 224 since other methods all use constant resolution. For VTAB-v2, we use the same optimizer but with a small hyperparameter sweep suggested in Zhai et al. (2019) over the product of \{2.5k, 10k\} steps and learning rate \{0.01, 0.001\}. We train on the VTAB recommended 800 training example splits, select the single hyperparameter with the best average performance across tasks on the 200 example validation splits, and evaluate that setting on the test sets. Therefore, for each of VTAB and MD, each model uses a single set of hyperparameters for all tasks.

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6The BiT paper also presents an even larger ResNet-152x4, however we limit to the ResNet-101x3 to speed up experiments which run on many episodes, and it R101x3 large enough to demonstrate the effect of scale.
Figure 1. VTAB-v2 and MD-v2 aggregated accuracies for approaches trained only on ImageNet (left) or larger-scale datasets (right). BiT-L (ResNet-101x3) emerges as SOTA, both in the ImageNet-only setting and when using larger-scale datasets.

Figure 2. Despite identical network architectures (ResNet-18) and input resolutions (126 x 126), transfer learner implementations from the transfer learning (BiT-ResNet-18) or few-shot classification (MD-Transfer) communities exhibit different performance profiles.

Figure 3. Scaling up the resolution and network capacity contributes to BiT’s success on MD-v2, but not across all test sources. For Omniglot and QuickDraw a higher resolution decreases performance for larger-capacity networks. All models are trained on ImageNet. CTX accuracies are shown for reference.

4.1. Comparison of selected approaches

BiT-L achieves SOTA BiT-L (trained on ImageNet/JFT) emerges as the overall best-performing approach on VTAB+MD, outperforming other approaches by at least 3.5/7.8% and 10.4/14.4% on MD-v2 and VTAB-v2, respectively (Figure 1; see the Appendix for tables summarizing the contents of all figures presented in the main text). This is consistent with existing few-shot classification work which shows that “baseline” transfer learners benefit from scaling up the input architecture (Chen et al., 2019) and the upstream dataset (Dhillon et al., 2020). As reported by Kolesnikov et al. (2020) on standard transfer datasets (CIFAR-10, Oxford Pets, etc.), increasing network capacity even further does not appear to show clear signs of overfitting on tasks for which there is little training data available; our results show that the observation also holds on MD-v2, whose learning episode sampling procedure allows for even smaller data regimes. This highlights one of the disadvantages that episodic approaches face: scaling them up is a significantly harder engineering challenge. This doesn’t preclude the possibility that other approaches trained on JFT using a ResNet-101x3 network architecture would perform as well as (or even better than) BiT-L, but it is a hypothetical setting that is out of reach for most of the existing implementations. In the Appendix we make a first attempt to scale up SUR’s backbones to ResNet-50 trained on 224 x 224 images. This yields an overall 5% improvement on VTAB-v2, but a marginal improvement on MD-v2 (< 1%).

Meta-learning performance suffers on VTAB-v2 In contrast to BiT, Figure 1 shows that meta-learning approaches struggle to compete with transfer learning on VTAB-v2. MD-Transfer outperforms MD-v2’s meta-learning champions (CTX, SUR), with the exception of CTX on VTAB-v2’s natural tasks. A scaled-down ResNet-18 variant of BiT trained on 126 x 126 inputs (yellow column) consistently outperforms CTX and SUR. This is consistent with Chen et al. (2019)’s observation that meta-learning approaches may be competitive on tasks derived from classes similar to those used in training but struggle with cross-dataset generalization. This is especially noticeable for SUR, which underperforms CTX on VTAB-v2 despite having been trained on more datasets. This represents an oppor-
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Figure 4. The scale of the upstream task contributes to BiT-L’s success on MD-v2, but not necessarily monotonically and not across all test sources. On Traffic Sign, performance decreases with the scale of the upstream task. All models are trained with 224 × 224 inputs. CTX and SUR accuracies are shown for reference.

Figure 5. The presence of test image duplicates in JFT is not a contributing factor to BiT-L’s success on MD-v2, but the presence of aircraft-, bird-, and fungi-related classes does play a role for their respective test sources, as evidenced by the drop in performance when removing those classes from JFT. All models are trained with 224 × 224 inputs.

tunity to apply existing cross-domain few-shot classification approaches (Tseng et al., 2020; Sun et al., 2020; Phoo & Hariharan, 2020; Liu et al., 2020; Cai & Shen, 2020) at scale.

ProtoMAML is competitive with transfer learning on the specialized VTAB-v2 tasks, but less so on the other splits. The adaptation protocol for both ProtoMAML is very similar to fine-tuning used by transfer learning. The main differences are in the trained initial weights, and the hyperparameter selection strategy. ProtoMAML weights are first initialized by ImageNet weights used for the MD-Transfer baseline. However, during meta-training ProtoMAML uses very few adaptation steps, and it uses similarly few during adaptation (see Appendix for details). As a result it seems that limiting the ability for the model to adapt, even when the episodes are small, outweighs the refined initialization weights.

Large-scale transfer is not always a silver bullet Examining a per-source performance breakdown for MD-v2 reveals a more nuanced picture: whereas BiT-L outperforms other approaches on Birds, Textures, and MSCOCO, it underperforms competing approaches on Omniglot and QuickDraw despite being significantly larger (Figure 4). On those sources, the benefits of meta-learning — and more generally of incorporating inductive biases informed by knowledge of the test distribution of tasks — appear clearer. SUR performs well on Omniglot and QuickDraw, most likely because some of its backbones were trained on classes similar to those used to form test episodes. CTX, which is only trained on ImageNet classes, outperforms BiT-L trained on JFT, even in the face of a significant capacity and data disadvantage. This shows that while success cases of large-scale transfer learning have been recently highlighted (Kolesnikov et al., 2020; Dosovitskiy et al., 2020), its failure cases should be examined and tackled as well, and that recent approaches to few-shot classification can offer insights in that regard.

4.2. Deconstructing BiT-L’s success on MD-v2

The BiT paper (Kolesnikov et al., 2020) established that large-scale transfer learning performs well on few-shot classification tasks, including VTAB-1k evaluation tasks, and benefits from both larger network architectures and upstream datasets. As our results show, these performance gains are not uniform across MD-v2 test sources. This raises the following questions: To what extents do specific findings in transfer learning carry over to MD-v2?

Implementation details matter We scale down BiT-L to the typical few-shot classification regime (ResNet-18, 126 × 126 inputs) in order to control for network architecture and input resolution. Figure 1 shows that while transfer learning remains competitive with meta-learning approaches, SOTA approaches on Meta-Dataset (SUR, CTX) still achieve the best MD-v2 performance in that regime (although as noted above, their performance degrades severely on VTAB-v2 tasks). This observation is consistent with recent work which shows that such transfer learning baselines are competitive, but not optimal, on few-shot classification tasks, both on Meta-Dataset (Chen et al., 2020b) and on smaller benchmarks (Chen et al., 2019; Dhillon et al., 2020).

Interestingly, the scaled-down BiT model’s performance profile differs from that of MD-Transfer, despite sharing the same network capacity and input resolution: it underperforms on MD-v2’s Omniglot, Aircraft, and Traffic Sign (Figure 2) but outperforms MD-Transfer on VTAB-v2.

This highlights the fact that several design decisions influ-
ence performance, some of which are seldom discussed in the literature. For instance, Saikia et al. (2020) reports that using cross-domain and cross-task data for hyperparameter tuning yields few-shot classification improvements in a cross-domain setting, and Gulrajani & Lopez-Paz (2020) advocates that the model selection strategy should be considered as part of the model specification when evaluating domain adaptation approaches. MD-Transfer benefits from training on multiple MD-v2 sources, however this difference pales in comparison to the differences introduced by different hyperparameters in the baselines.

**Scale helps, but less so on OOD MD tasks**  
Figure 3 shows a global trend where increasing the input resolution and network performance helps with performance on MD-v2, but with a few exceptions. Omniglot and QuickDraw are non-natural, highly out-of-distribution with respect to ImageNet, and contain fairly low resolution images. On these tasks, increasing capacity and resolution does not have a clear positive effect; in fact, on Omniglot larger models perform worse. Traffic Sign also contains low resolution images; it benefits from an increase in resolution, but there is not a clear trend with respect to network size. Overall, while the 224 × 224 ResNet-50 variant of BiT trained on ImageNet is able to surpass CTX’s average performance on MD-v2 by 1.69%, it mainly does so by increasing the performance gap on data sources for which it already outperforms CTX.

**BiT-L’s normalization strategy matters**  
Figure 6 shows that replacing BiT-L’s group normalization and weight standardization (GNWS) with batch normalization (BN) degrades its performance on MD-v2. This result is remarkably consistent, and appears on all tasks. Since BN is problematic for few-shot classification (Bronskill et al., 2020), GNWS shows promise alongside alternatives such as Bronskill et al. (2020)’s TaskNorm layer.

**Sometimes more data is a good solution**  
BiT-L trained on JFT is obviously at an advantage in terms of data, but interestingly Figure 4 shows that the trend is very much test source-dependent on MD-v2. For Traffic Sign the trend reverses: BiT-L is better off training on ImageNet than on ImageNet-21k or JFT.

Overall ImageNet-21k and JFT exhibit similar performance profiles, with two notable exceptions: training on JFT increases performance on Aircraft, and a similar effect is observed with ImageNet-21k on Fungi. Furthermore, for some MD-v2 test sources such as Omniglot, QuickDraw and Traffic Sign BiT-L underperforms CTX even when trained on a much larger upstream task. This suggests that the extent to which data scaling helps with performance is highly dependent on the contents of the dataset itself.

We run two ablations to verify this hypothesis (Figure 5). We train ResNet-50 BiT models on three variants of JFT: (green) JFT itself, (orange) JFT deduplicated based on all MD-v2 test sources (≈ 0.002% of JFT’s training data), and (purple) JFT where all aircraft-, bird-, and fungi-related classes were removed (≈ 3% of JFT’s training data). While the effect of deduplication is negligible, the removal of classes related to some of MD-v2’s test sources has a drastic impact on Aircraft and Birds performance, even if the corresponding reduction in training data is relatively small. This result is consistent with our findings that SUR performs best on tasks which match its pre-training sources: while individual image duplicates appear unimportant, domain coverage is, and large-scale datasets are more likely to cover more domains.

5. Conclusion

We introduce a few-shot classification evaluation protocol called VTAB+MD which aims to facilitate exchanging and comparing ideas between the transfer learning and few-shot classification communities. Our extensive evaluation of recent competitive approaches show that a carefully engineered training and fine-tuning of large scale networks (as exemplified by BiT) is a remarkably competitive and robust baseline for few-shot classification, and that this approach generalizes across large-scale, multi-dataset benchmarks.

Our investigation highlights interesting avenues for future research. BiT’s scaling advantage diminishes when moving to tasks that are extremely out-of-distribution, and leveraging information from multiple upstream training tasks (as exemplified by SUR) may prove beneficial in that respect. Meta-learning approaches are hindered from making use of large backbones and input resolutions due to engineering/implementation difficulties, but we may yet see the true benefits of meta-learning when these issues have been overcome.
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A. Additional experiment details

Experiments presented in this work are run in two main computing infrastructure: TPU-v3 (all BIT experiments) and Nvidia V100 (rest).

For Prototypical networks, ProtoMAML and MD-Transfer, model and hyperparameter selection is based on the average query accuracy over episodes sampled from all of MD-v2’s validation classes. For each approach we perform a hyperparameter search using Triantafillou et al. (2020)’s search space (Tables 1, 2, and 3, presented alongside the best values found), for a total of 99 runs for each approach.

We re-train CrossTransformers on episodes sampled from all ImageNet classes, with 50% of the episodes converted to SimCLR episodes — this corresponds to the CTX+SimCLR Eps setting in Doersch et al. (2020). We use the recommended hyperparameters and perform a light sweep over learning rates in {0.01, 0.001, 0.0006, 0.0001} and found Doersch et al. (2020)’s recommended 0.0006 learning rate to be optimal in our case as well. Model selection is performed using MD-v2 validation episodes — this is a slight departure from CrossTransformers’ ImageNet-only protocol that is made necessary by the fact that all ImageNet classes participate in training episodes in MD-v2.

Since pre-trained SUR backbones were already made available by the authors,7 we re-used all of them with two exceptions: (1) we re-trained the ImageNet backbone on all ImageNet classes using the provided training script (because the original backbone was trained on Meta-Dataset’s ImageNet training classes), and (2) we ignored the VGG Flowers backbone (because the dataset is included as one of VTAB-v2’s downstream tasks). We ran Dvornik et al. (2020)’s inference code as-is for evaluation.

All Big Transfer models are pre-trained as described in (Kolesnikov et al., 2020). The pre-processing at training time is at 224 resolution, using random horizontal flipping and inception crop (Szegedy et al., 2015). In all of our experiments, during transfer we only resize images to the desired resolution (126 or 224) at both fine-tuning and evaluation time. While higher resolution and further data augmentation further improves performance, we remove this additional confounding factor.

B. Detailed figures and accuracy tables

We show a detailed breakdown of VTAB-V2 accuracies (Figure 7) for investigated approaches. We also provide detailed accuracy tables (Tables 4 through 9) for all plots displayed in the main text. For MD-v2 we show 95% confidence intervals computed over 60 episodes for BiT learners and 600 episodes for all other approaches.

C. Bridging the Performance Gap Between MD-Transfer Baseline and ProtoMAML

Given the stark differences between ProtoMAML and MD-Transfer on VTAB-v2, we ran a few additional experiments in order to better explain these discrepancies. We swapped their evaluation hyperparameters, meaning that we fine-tuned MD-Transfer for 10 steps using a learning rate of 0.0054 without using a cosine classifier (MD-Transfer (ProtoMAML hypers)) and that we ran ProtoMAML’s inner-loop for 100 steps using a learning rate of $1 \times 10^{-2}$ with a linear classification head (ProtoMAML (MD-Transfer hypers)). Note that this does not completely bridge the hyperparameter gap between the two approaches, but it does bring them closer to each other. The remaining differences are that (1) the validation procedure used for early stopping is different, and (2) ProtoMAML initializes the output layer with class prototypes, whereas the output layer weights in MD-Transfer are sampled from a normal distribution. Additionally, to isolate the effect of cosine-classification, we run MD-Transfer with a linear classification head while keeping the learning rate and number of training steps the same (MD-Transfer (linear head)).

Figure 8 shows that ProtoMAML gets better results on MD-v2 with MD-Transfer hyperparameters (more fine-tuning steps with a smaller learning rate), with apparent gains on Quickdraw and Traffic Signs. ProtoMAML’s prototypical initialization seems to yield better performance for “in-domain” datasets (i.e. datasets participating to the training split of classes), however we observe diminishing returns for test-only datasets like Traffic Sign.

Disabling cosine classification (MD-Transfer (linear head)) seems to harm fine-tuning performance greatly on all datasets except QuickDraw. Traffic Signs in particular benefits greatly from a cosine classification head, as evidenced by the 10% drop in performance observed when switching to a linear classification head. On VTAB, again, MD-Transfer hyperparameters help improve ProtoMAML performance, hinting at the fact that the hyperparameter selection procedure used for ProtoMAML is sub-optimal.

D. Larger-scale SUR experiments

In this section we investigate increasing the capacity (ResNet-50) and input resolution (224 × 224) of SUR backbones. We re-train backbones for all seven of MD-v2’s training sources of data using BiT’s upstream training hyperparameters and adjusting the number of training steps as needed to ensure convergence. We trained two backbone variants: one with a regular linear classification head, and one with a temperature-adjusted cosine classifier head. Backbones were trained for:

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7https://github.com/dvornikita/SUR
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| Hyperparameter       | Search space               | Best     |
|----------------------|----------------------------|----------|
| Backbone             | \{ResNet-18, 4-layer convnet\} | ResNet-18|
| Resolution           | \{84, 126\}                | 126      |
| Outer-loop LR        | log-uniform(1e-6, 1e-2)     | 0.0004   |
| Outer-loop LR decay freq. | \{100, 500, 1k, 2.5k, 5k, 10k\} | 1k       |
| Outer-loop LR decay rate | uniform(0.5, 1.0)            | 0.6478   |
| Inner-loop LR        | log-uniform(5e-3, 5e-1)     | 0.0054   |
| Inner-loop steps     | \{1, 6, 10\}               | 10       |
| Additional inner-loop steps (evaluation) | \{0, 5\} | 0        |

Table 1. ProtoMAML hyperparameter search space.

| Hyperparameter       | Search space               | Best     |
|----------------------|----------------------------|----------|
| Backbone             | \{ResNet-18, 4-layer convnet\} | ResNet-18|
| Resolution           | \{84, 126\}                | 126      |
| Training LR          | log-uniform(1e-6, 1e-2)     | 3.429372573483445e-06 |
| Fine-tuning LR       | \{1e-5, 1e-4, 1e-3, 1e-2, 1e-1, 2e-1\} | 1e-2    |
| Fine-tuning steps    | \{50, 75, 100, 125, 150, 175, 200\} | 100     |
| Fine-tune with Adam? | \{True, False\}            | True     |
| Cosine classifier head? | \{True, False\}          | True     |
| Cosine logits multiplier | \{1, 2, 10, 100\}       | 10       |
| Weight-normalize the classifier head? | \{True, False\}         | True     |
| Fine-tune all layers? | \{True, False\}          | True     |

Table 2. MD-Transfer hyperparameter search space.

| Hyperparameter       | Search space               | Best     |
|----------------------|----------------------------|----------|
| Backbone             | \{ResNet-18, 4-layer convnet\} | ResNet-18|
| Resolution           | \{84, 126\}                | 126      |
| LR                   | log-uniform(1e-6, 1e-2)     | 0.0003   |
| LR decay freq.       | \{100, 500, 1k, 2.5k, 5k, 10k\} | 500      |
| LR decay rate        | uniform(0.5, 1.0)           | 0.8857   |

Table 3. Prototypical Networks hyperparameter search space.

- **ImageNet**: 90 epochs
- **Quickdraw**: 4 epochs
- **Birds, Omniglot, Fungi**: 900 epochs
- **Textures**: 1350 epochs
- **Aircraft**: 4500 epochs

The LR schedule is adjusted proportionally to the number of epochs. For simplicity we select the final backbone checkpoints rather than selecting based on an episodic loss.

Figure 9 shows an appreciable 5% improvement on VTAB-v2, most of which is driven by an improvement on specialized tasks. On the other hand, the aggregate performance gain on MD-v2 is negligible. While performance on MSCOCO, Fungi, Birds, and Textures is increased significantly, the larger input resolution and backbone capacity has a negligible or detrimental effect on QuickDraw, Omniglot, and Aircraft. We hypothesize that the drop in Aircraft performance is due to the large batch size used by BiT and a suboptimal model selection strategy.

Overall these results are encouraging, but a more thorough investigation is needed before we can draw definitive conclusions.
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| Data source       | MD-Transfer | ProtoMAML | ProtoNets | CTX         | BiT-ResNet-101x3 | BiT-ResNet-18 |
|-------------------|-------------|-----------|-----------|-------------|------------------|---------------|
| Omniglot          | 80.92 ± 1.20% | 68.35 ± 1.28% | 65.47 ± 1.35% | 84.55 ± 0.94% | 72.35 ± 4.70% | 71.87 ± 4.38% |
| Aircraft          | 75.45 ± 1.20% | 58.18 ± 0.96% | 54.25 ± 1.03% | 85.31 ± 0.83% | 78.34 ± 3.57% | 70.23 ± 3.78% |
| Birds             | 61.23 ± 1.30% | 69.69 ± 0.98% | 64.78 ± 0.98% | 72.92 ± 1.07% | 91.02 ± 1.49% | 81.65 ± 2.26% |
| DTD               | 66.66 ± 1.01% | 68.71 ± 0.83% | 64.91 ± 0.76% | 77.29 ± 0.71% | 87.06 ± 2.61% | 78.62 ± 2.86% |
| QuickDraw         | 61.12 ± 1.06% | 55.52 ± 1.02% | 53.26 ± 1.02% | 73.29 ± 0.78% | 65.08 ± 4.13% | 64.81 ± 3.71% |
| Fungi             | 35.39 ± 1.08% | 38.88 ± 1.05% | 36.37 ± 1.08% | 47.95 ± 1.19% | 60.68 ± 4.43% | 49.81 ± 4.28% |
| Traffic Sign      | 85.31 ± 0.95% | 53.83 ± 1.05% | 50.27 ± 1.05% | 80.12 ± 0.97% | 76.23 ± 4.68% | 69.53 ± 4.55% |
| MSCOCO            | 39.66 ± 1.05% | 43.32 ± 1.12% | 41.08 ± 0.99% | 51.39 ± 1.06% | 69.74 ± 2.69% | 57.84 ± 3.03% |
| Caltech101        | 70.00 %     | 78.81 %     | 74.18 %     | 84.24 %     | 88.59 %     | 83.32 %     |
| CIFAR100          | 32.57 %     | 36.22 %     | 31.13 %     | 37.51 %     | 58.35 %     | 49.37 %     |
| Flowers102        | 66.69 %     | 65.39 %     | 61.99 %     | 81.75 %     | 81.88 %     | 76.38 %     |
| Pets              | 49.06 %     | 68.33 %     | 58.33 %     | 70.88 %     | 89.97 %     | 78.95 %     |
| Sun397            | 15.05 %     | 8.05 %      | 17.73 %     | 24.79 %     | 35.47 %     | 27.00 %     |
| SVHN              | 83.54 %     | 45.31 %     | 38.06 %     | 67.22 %     | 79.23 %     | 80.71 %     |
| EuroSAT           | 89.41 %     | 83.02 %     | 80.63 %     | 86.43 %     | 94.64 %     | 93.53 %     |
| Resiscs45         | 65.46 %     | 57.79 %     | 54.11 %     | 67.65 %     | 76.71 %     | 71.03 %     |
| Patch Camelyon    | 81.11 %     | 76.75 %     | 74.26 %     | 79.77 %     | 82.97 %     | 79.73 %     |
| Retinopathy       | 58.07 %     | 73.51 %     | 28.82 %     | 35.48 %     | 73.85 %     | 67.06 %     |
| CLEVR-count       | 40.09 %     | 30.32 %     | 30.33 %     | 27.89 %     | 70.73 %     | 50.59 %     |
| CLEVR-dist        | 52.97 %     | 34.29 %     | 39.99 %     | 29.61 %     | 54.19 %     | 58.79 %     |
| dSprites-loc      | 83.81 %     | 36.68 %     | 32.95 %     | 23.19 %     | 95.38 %     | 93.39 %     |
| dSprites-ori      | 46.70 %     | 18.69 %     | 15.60 %     | 46.92 %     | 61.13 %     | 52.15 %     |
| SmallNORB-azi     | 36.40 %     | 12.20 %     | 12.21 %     | 37.02 %     | 17.50 %     | 23.17 %     |
| SmallNORB-elev    | 31.29 %     | 18.26 %     | 18.02 %     | 21.62 %     | 36.40 %     | 28.92 %     |
| DMLab             | 43.14 %     | 33.28 %     | 32.12 %     | 31.92 %     | 45.58 %     | 41.86 %     |
| KITTI-dist        | 64.70 %     | 56.96 %     | 55.70 %     | 54.34 %     | 82.24 %     | 76.15 %     |
| MD-v2             | 63.22 %     | 57.06 %     | 53.80 %     | 71.60 %     | 75.06 %     | 68.04 %     |
| VTAB (all)        | 56.11 %     | 46.33 %     | 42.01 %     | 50.46 %     | 68.04 %     | 62.90 %     |
| VTAB (natural)    | 52.82 %     | 50.35 %     | 46.90 %     | 61.07 %     | 72.25 %     | 65.97 %     |
| VTAB (specialized)| 73.51 %     | 72.77 %     | 59.45 %     | 67.33 %     | 82.04 %     | 77.84 %     |
| VTAB (structured) | 49.89 %     | 30.08 %     | 29.62 %     | 34.06 %     | 57.89 %     | 53.13 %     |

Table 4. V TAB+MD accuracies for approaches trained only on ImageNet.
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| Data source       | MD-Transfer   | ProtoMAML     | ProtoNets     | SUR            | BiT-ResNet-101x3 (JFT) |
|-------------------|---------------|---------------|---------------|----------------|------------------------|
| Omniglot          | 82.04 ± 1.27% | 90.15 ± 0.65%| 85.29 ± 0.89%| 92.84 ± 0.52% | 76.45 ± 4.04%         |
| Aircraft          | 76.77 ± 1.16% | 82.10 ± 0.60%| 74.34 ± 0.81%| 84.44 ± 0.58% | 93.30 ± 1.44%         |
| Birds             | 61.23 ± 1.29% | 73.36 ± 0.92%| 68.00 ± 1.01%| 75.80 ± 0.96% | 97.06 ± 0.53%         |
| DTD               | 65.98 ± 1.07% | 66.32 ± 0.76%| 65.26 ± 0.69%| 70.35 ± 0.72% | 88.96 ± 2.14%         |
| QuickDraw         | 61.29 ± 1.06% | 66.37 ± 0.95%| 60.57 ± 1.00%| 81.71 ± 0.57% | 71.27 ± 3.77%         |
| Fungi             | 35.47 ± 1.05% | 46.32 ± 1.11%| 39.84 ± 1.10%| 63.72 ± 1.08% | 62.59 ± 4.29%         |
| Traffic Sign      | 84.71 ± 0.94% | 50.28 ± 1.05%| 49.79 ± 1.07%| 49.99 ± 1.08% | 69.13 ± 5.34%         |
| MSCOCO            | 39.56 ± 1.00% | 39.00 ± 1.04%| 39.65 ± 1.03%| 49.41 ± 1.08% | 76.36 ± 2.23%         |
| Caltech101        | 70.58 %       | 73.06 %       | 71.98 %       | 82.33 %        | 91.78 %                |
| CIFAR100          | 31.33 %       | 29.72 %       | 27.70 %       | 33.69 %        | 76.32 %                |
| Flowers102        | 66.08 %       | 60.22 %       | 57.11 %       | 55.72 %        | 99.33 %                |
| Pets              | 49.09 %       | 56.61 %       | 50.99 %       | 76.34 %        | 95.45 %                |
| Sun397            | 13.94 %       | 8.05 %        | 14.19 %       | 27.49 %        | 57.24 %                |
| SVHN              | 83.20 %       | 46.78 %       | 41.93 %       | 18.66 %        | 66.47 %                |
| EuroSAT           | 88.74 %       | 80.07 %       | 77.74 %       | 78.91 %        | 95.33 %                |
| Resiscs45         | 63.67 %       | 53.48 %       | 50.79 %       | 62.40 %        | 85.76 %                |
| Patch Camelyon    | 81.53 %       | 75.85 %       | 73.75 %       | 75.60 %        | 81.81 %                |
| Retinopathy       | 57.61 %       | 75.83 %       | 28.04 %       | 27.91 %        | 72.02 %                |
| CLEVR-count       | 40.30 %       | 32.72 %       | 31.96 %       | 29.99 %        | 61.54 %                |
| CLEVR-dist        | 52.86 %       | 35.43 %       | 39.35 %       | 37.06 %        | 55.96 %                |
| dSprites-loc      | 85.87 %       | 41.96 %       | 38.07 %       | 29.96 %        | 96.80 %                |
| dSprites-ori      | 46.41 %       | 23.00 %       | 16.25 %       | 19.84 %        | 63.84 %                |
| SmallNORB-azi     | 36.49 %       | 13.42 %       | 12.27 %       | 12.86 %        | 13.78 %                |
| SmallNORB-elev    | 31.16 %       | 18.76 %       | 17.38 %       | 18.15 %        | 29.68 %                |
| DMLab             | 43.03 %       | 32.49 %       | 31.83 %       | 33.31 %        | 48.22 %                |
| KITTI-dist        | 58.65 %       | 54.43 %       | 42.05 %       | 52.32 %        | 78.62 %                |
| MD-v2             | 63.38 %       | 64.24 %       | 60.34 %       | 71.03 %        | 79.39 %                |
| VTAB (all)        | 55.59 %       | 44.96 %       | 40.19 %       | 42.92 %        | 70.55 %                |
| VTAB (natural)    | 52.37 %       | 45.74 %       | 43.98 %       | 49.04 %        | 81.10 %                |
| VTAB (specialized)| 72.89 %       | 70.65 %       | 57.58 %       | 61.20 %        | 83.73 %                |
| VTAB (structured) | 49.35 %       | 31.52 %       | 28.65 %       | 29.19 %        | 56.05 %                |

Table 5. VTAB+MD accuracies for approaches trained on more data (all of MD-v2’s training sources, unless noted otherwise).
Comparing Transfer and Meta Learning Approaches on a Unified Few-Shot Classification Benchmark

| Data source       | BiT-ResNet-18 (126 × 126) | BiT-ResNet-18 (224 × 224) | BiT-ResNet-50 (126 × 126) | BiT-ResNet-50 (224 × 224) | CTX     |
|-------------------|---------------------------|---------------------------|---------------------------|---------------------------|---------|
| Omniglot          | 71.87 ± 4.38%            | 72.73 ± 4.64%            | 68.56 ± 4.68%            | 68.03 ± 4.86%            | 84.55 ± 0.94% |
| Aircraft          | 70.23 ± 3.78%            | 73.61 ± 3.80%            | 74.09 ± 3.64%            | 77.42 ± 3.55%            | 85.31 ± 0.83% |
| Birds             | 81.65 ± 2.26%            | 87.22 ± 1.88%            | 86.82 ± 1.57%            | 90.82 ± 1.46%            | 72.92 ± 1.07% |
| DTD               | 78.62 ± 2.86%            | 82.62 ± 2.70%            | 82.35 ± 2.56%            | 84.97 ± 2.53%            | 77.29 ± 0.71% |
| QuickDraw         | 64.81 ± 3.71%            | 66.34 ± 3.60%            | 66.98 ± 3.62%            | 66.56 ± 3.60%            | 73.29 ± 0.78% |
| Fungi             | 49.81 ± 4.28%            | 53.93 ± 4.44%            | 54.63 ± 4.20%            | 59.37 ± 4.25%            | 47.95 ± 1.19% |
| Traffic Sign      | 69.53 ± 4.55%            | 73.39 ± 4.34%            | 71.09 ± 4.66%            | 73.52 ± 4.69%            | 80.12 ± 0.97% |
| MSCOCO            | 57.84 ± 3.03%            | 59.97 ± 2.89%            | 64.55 ± 2.93%            | 65.69 ± 2.71%            | 51.39 ± 1.06% |

| Data source       | BiT-ResNet-18 (224 × 224) | BiT-ResNet-50 (224 × 224) | CTX     |
|-------------------|---------------------------|---------------------------|---------|
| Caltech101        | 83.32 %                   | 84.59 %                   | 85.69 % | 87.22 % | 84.24 %     |
| CIFAR100          | 49.37 %                   | 47.10 %                   | 55.85 % | 54.42 % | 37.51 %     |
| Flowers102        | 76.38 %                   | 82.65 %                   | 81.87 % | 83.33 % | 81.75 %     |
| Pets              | 78.95 %                   | 83.91 %                   | 86.07 % | 87.91 % | 70.88 %     |
| Sun397            | 27.09 %                   | 29.11 %                   | 31.62 % | 33.29 % | 24.79 %     |
| SVHN              | 80.71 %                   | 83.40 %                   | 78.47 % | 70.40 % | 67.22 %     |
| EuroSAT           | 93.53 %                   | 93.82 %                   | 94.14 % | 94.44 % | 86.43 %     |
| Resisc45          | 71.03 %                   | 74.12 %                   | 74.92 % | 76.13 % | 67.65 %     |
| Patch Camelyon    | 79.73 %                   | 80.67 %                   | 81.55 % | 83.06 % | 79.77 %     |
| Retinopathy       | 67.06 %                   | 74.47 %                   | 71.15 % | 70.24 % | 35.48 %     |
| CLEVR-count       | 50.59 %                   | 55.25 %                   | 53.69 % | 74.03 % | 27.89 %     |
| CLEVR-dist        | 58.79 %                   | 58.69 %                   | 54.59 % | 51.55 % | 29.61 %     |
| dSprites-loc      | 93.39 %                   | 98.59 %                   | 92.53 % | 82.72 % | 23.19 %     |
| dSprites-ori      | 52.15 %                   | 46.46 %                   | 51.40 % | 55.11 % | 46.92 %     |
| SmallNORB-azi     | 23.17 %                   | 20.71 %                   | 20.10 % | 17.79 % | 37.02 %     |
| SmallNORB-elev    | 28.92 %                   | 21.75 %                   | 26.95 % | 32.07 % | 21.62 %     |
| DMLab             | 41.86 %                   | 43.74 %                   | 42.54 % | 43.18 % | 31.92 %     |
| KITTI-dist        | 76.15 %                   | 78.78 %                   | 77.80 % | 79.93 % | 54.34 %     |
| MD-v2             | 68.04 %                   | 71.48 %                   | 71.14 % | 73.30 % | 71.60 %     |
| VTAB (all)        | 62.90 %                   | 64.32 %                   | 64.50 % | 65.38 % | 50.46 %     |
| VTAB (natural)    | 65.97 %                   | 68.46 %                   | 69.93 % | 69.43 % | 61.07 %     |
| VTAB (specialized)| 77.84 %                   | 80.77 %                   | 80.44 % | 80.97 % | 67.33 %     |
| VTAB (structured) | 53.13 %                   | 53.00 %                   | 52.45 % | 54.55 % | 34.06 %     |

Table 6. VTAB+MD accuracies for BiT learners trained on various input resolutions and network capacities. CrossTransformers (CTX) accuracies are provided for context. All approaches are trained only on ImageNet.
Comparing Transfer and Meta Learning Approaches on a Unified Few-Shot Classification Benchmark

| Data source    | BiT-ResNet-50 (GNWS) | BiT-ResNet-50 (BN) |
|----------------|----------------------|--------------------|
| Omniglot       | 68.03 ± 4.86%        | 61.66 ± 5.13%      |
| Aircraft       | 77.42 ± 3.55%        | 76.82 ± 3.71%      |
| Birds          | 90.82 ± 1.46%        | 87.59 ± 1.84%      |
| DTD            | 84.97 ± 2.53%        | 83.72 ± 3.39%      |
| QuickDraw       | 66.56 ± 3.69%        | 63.83 ± 4.03%      |
| Fungi          | 59.37 ± 4.25%        | 53.77 ± 4.43%      |
| Traffic Sign   | 73.52 ± 4.69%        | 70.46 ± 4.70%      |
| MSCOCO         | 65.69 ± 2.71%        | 61.50 ± 2.73%      |
| Caltech101     | 87.22 %              | 88.72 %            |
| CIFAR100       | 54.42 %              | 53.78 %            |
| Flowers102     | 83.33 %              | 85.45 %            |
| Pets           | 87.91 %              | 88.24 %            |
| Sun397         | 33.29 %              | 31.60 %            |
| SVHN           | 70.40 %              | 85.57 %            |
| EuroSAT        | 94.44 %              | 95.35 %            |
| Resisc45       | 76.13 %              | 79.02 %            |
| Patch Camelyon | 83.06 %              | 80.13 %            |
| Retinopathy    | 70.24 %              | 73.13 %            |
| CLEVR-count    | 74.03 %              | 43.10 %            |
| CLEVR-dist     | 51.55 %              | 49.65 %            |
| dSprites-loc   | 82.72 %              | 83.19 %            |
| dSprites-ori   | 55.11 %              | 46.49 %            |
| SmallNORB-azi  | 17.79 %              | 18.93 %            |
| SmallNORB-elev | 32.07 %              | 34.32 %            |
| DMLab          | 43.18 %              | 44.67 %            |
| KITTI-dist     | 79.93 %              | 76.97 %            |
| MD-v2          | 73.30 %              | 69.92 %            |
| VTAB (all)     | 65.38 %              | 64.35 %            |
| VTAB (natural) | 69.43 %              | 72.22 %            |
| VTAB (specialized) | 80.97 %           | 81.91 %            |
| VTAB (structured) | 54.55 %             | 49.67 %            |

Table 7. VTAB+MD accuracies for BiT learners trained with either group normalization + weight standardization (GNWS) or batch normalization (BN). All approaches are trained only on 224 × 224 ImageNet examples.
| Data source         | BiT-ResNet-101x3 (ImageNet) | BiT-ResNet-101x3 (ImageNet-21k) | BiT-ResNet-101x3 (JFT) | CTX       |
|--------------------|-----------------------------|---------------------------------|------------------------|-----------|
| Omniglot           | 72.35 ± 4.70%               | 78.49 ± 4.00%                  | 76.45 ± 4.04%          | 84.55 ± 0.94% |
| Aircraft           | 78.34 ± 3.57%               | 75.49 ± 4.32%                  | 93.30 ± 1.44%          | 85.31 ± 0.83% |
| Birds              | 91.02 ± 1.49%               | 98.10 ± 0.45%                  | 97.06 ± 0.53%          | 72.92 ± 1.07% |
| DTD                | 87.06 ± 2.61%               | 89.79 ± 2.40%                  | 88.96 ± 2.14%          | 77.29 ± 0.71% |
| QuickDraw          | 65.08 ± 4.13%               | 69.16 ± 3.79%                  | 71.27 ± 3.77%          | 73.29 ± 0.78% |
| Fungi              | 60.68 ± 4.43%               | 70.70 ± 3.91%                  | 62.59 ± 4.29%          | 47.95 ± 1.19% |
| Traffic Sign       | 76.23 ± 4.68%               | 72.51 ± 4.73%                  | 69.13 ± 5.34%          | 80.12 ± 0.97% |
| MSCOCO             | 69.74 ± 2.69%               | 76.07 ± 2.26%                  | 76.36 ± 2.23%          | 51.39 ± 1.06% |
| Caltech101         | 88.59 %                     | 89.54 %                        | 91.78 %                | 84.24 %    |
| CIFAR100           | 58.35 %                     | 78.08 %                        | 76.32 %                | 37.51 %    |
| Flowers102         | 81.88 %                     | 99.09 %                        | 99.33 %                | 81.75 %    |
| Pets               | 89.97 %                     | 92.00 %                        | 95.45 %                | 70.88 %    |
| Sun397             | 35.47 %                     | 50.35 %                        | 57.24 %                | 24.79 %    |
| SVHN               | 79.23 %                     | 69.08 %                        | 66.47 %                | 67.22 %    |
| EuroSAT            | 94.64 %                     | 95.63 %                        | 95.33 %                | 86.43 %    |
| Resiscs45          | 76.71 %                     | 80.77 %                        | 85.76 %                | 67.65 %    |
| Patch Camelyon     | 82.97 %                     | 81.26 %                        | 81.81 %                | 79.77 %    |
| Retinopathy        | 73.85 %                     | 75.27 %                        | 72.02 %                | 35.48 %    |
| CLEVR-count        | 70.73 %                     | 66.75 %                        | 61.54 %                | 27.89 %    |
| CLEVR-dist         | 54.19 %                     | 53.85 %                        | 55.96 %                | 29.61 %    |
| dSprites-loc       | 95.38 %                     | 90.00 %                        | 96.80 %                | 23.19 %    |
| dSprites-ori       | 61.13 %                     | 62.47 %                        | 63.84 %                | 46.92 %    |
| SmallNORB-azi      | 17.50 %                     | 15.40 %                        | 13.78 %                | 37.02 %    |
| SmallNORB-elev     | 36.40 %                     | 37.05 %                        | 29.68 %                | 21.62 %    |
| DMLab              | 45.58 %                     | 45.37 %                        | 48.22 %                | 31.92 %    |
| KITTI-dist         | 82.24 %                     | 78.45 %                        | 78.62 %                | 54.34 %    |
| **MD-v2**          | 75.06 %                     | 78.79 %                        | 79.39 %                | 71.60 %    |
| **VTAB (all)**     | 68.04 %                     | 70.02 %                        | 70.55 %                | 50.46 %    |
| **VTAB (natural)** | 72.25 %                     | 79.69 %                        | 81.10 %                | 61.07 %    |
| **VTAB (specialized)** | 82.04 %                   | 83.23 %                        | 83.73 %                | 67.33 %    |
| **VTAB (structured)** | 57.89 %                    | 56.17 %                        | 56.05 %                | 34.06 %    |

Table 8. VTAB+MD accuracies for BiT-L learners trained on varying amounts of upstream data. CrossTransformers (CTX) accuracies are provided for context. All approaches are trained on 224 × 224 inputs.
Comparing Transfer and Meta Learning Approaches on a Unified Few-Shot Classification Benchmark

![Graph](image)

**Figure 7.** VTAB-v2 accuracies, broken down by downstream task, for approaches trained only on ImageNet (top) or larger-scale datasets (bottom).

| Data source | BiT-ResNet-50 (JFT) | BiT-ResNet-50 (JFT, deduplicated) | BiT-ResNet-50 (JFT, class-ablated) |
|-------------|----------------------|-----------------------------------|-----------------------------------|
| Omniglot    | 69.37 ± 4.42%        | 69.89 ± 4.71%                    | 69.10 ± 4.42%                    |
| Aircraft    | 87.13 ± 2.28%        | 86.27 ± 2.25%                    | 73.09 ± 3.76%                    |
| Birds       | 92.50 ± 1.24%        | 92.59 ± 1.16%                    | 79.22 ± 2.92%                    |
| DTD         | 87.43 ± 2.05%        | 87.48 ± 2.21%                    | 87.72 ± 2.14%                    |
| QuickDraw   | 63.99 ± 4.23%        | 63.65 ± 4.23%                    | 64.45 ± 4.05%                    |
| Fungi       | 56.03 ± 4.22%        | 56.48 ± 4.47%                    | 54.94 ± 4.53%                    |
| Traffic Sign| 66.21 ± 4.94%        | 66.13 ± 5.03%                    | 63.79 ± 4.98%                    |
| MSCOCO      | 70.39 ± 2.44%        | 71.06 ± 2.40%                    | 70.15 ± 2.55%                    |
| **MD-v2**   | **74.13 %**          | **74.19 %**                       | **70.31 %**                       |

Table 9. VTAB-MD accuracies for BiT-L learners trained on ablated JFT variants. The deduplicated variant of JFT removes all images that are found in MD-v2 test sources, and the class-ablated variant removes all images belonging to airplane-, birds-, and fungi-related classes. All approaches are trained on $224 \times 224$ inputs.
Figure 8. Ablation study for different hyperparameters found by ProtoMAML and MD-Transfer, broken down by downstream task. All backbones are trained the all MD-V2 training data.

Figure 9. Ablation study for different hyperparameters found by ProtoMAML and MD-Transfer, broken down by downstream task, for Meta Dataset-v2 (top) and VTAB (bottom). All backbones are trained the all MD-V2 training data.