Proceedings of Machine Learning Research 176:1–8, 2022 NeurIPS 2021 Competition and Demonstration Track

Supplementary Material for Lessons learned from the NeurIPS 2021 MetaDL challenge: Backbone fine-tuning without episodic meta-learning dominates for few-shot learning image classification

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Editors: Douwe Kiela, Marco Ciccone, Barbara Caputo

Appendix A. Datasets

Table 1 summarizes the datasets. Figure 1 shows sample images per dataset.

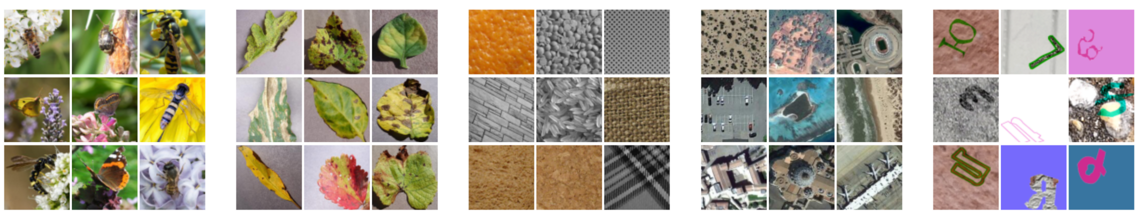
Appendix B. Related Work

While deep neural networks are capable of achieving performance superior to humans on various tasks (Krizhevsky et al., 2012; Mnih et al., 2015; He et al., 2015), they are notorious for requiring large amounts of data and processing power, restricting their success to domains where such resources are available. Humans, on the other hand, are more efficient learners as they can effectively draw on their prior knowledge and learning experience

* The two first authors are principal challenge organizer and dataset preparer; the other authors are in alphabetical order.

Table 1: MetaDL 2021 datasets summary

Domain	Dataset	Competition Phase	Categories	Images	Source
Ecology	Plankton	Feedback	91	3,640	Heidi M. Sosik (2015)
	Insects	Final	114	4,560	Serret et al. (2019)
Bio-medicine	Multiderma	Feedback	51	2,040	Sun et al. (2016)
	Plant Village	Final	37	1,480	Hughes and Salathé (2015) Geetharamani and Arun Pandian (2019)
Manufacturing	Texture DTD	Feedback	47	1,880	Cimpoi et al. (2014)
	Textures	Final	64	2,560	Fritz et al. (2004) Mallikarjuna et al. (2006) Kylberg (2011) Lazebnik et al. (2005)
Remote sensing	Mini RSICB	Feedback	45	1,800	Li et al. (2020)
	Mini RESISC	Final	45	1,800	Cheng et al. (2017)
OCR	OmniPrint-MD-mix	Feedback	706	28,240	Sun et al. (2021)
	OmniPrint-MD-5-bis	Final	706	28,240	Sun et al. (2021)



(a) Insects (b) Plant Village (c) Textures (d) Mini RESISC (e) OmniPrint-MD-mix

(f) Plankton (g) Multiderma (h) Texture DTD (i) Mini RSICB (j) OmniPrint-MD-5-bis

Figure 1: NeurIPS 2021 meta-learning challenge datasets sample images

(Jankowski et al., 2011). Improving the learning efficiency of deep neural networks is being extensively studied within the area of few-shot learning (Wang et al., 2020; Bendre et al., 2020; Lu et al., 2020). We discuss the two main paradigms that are used to address this.

Meta-learning Meta-learning (Naik and Mammone, 1992; Thrun, 1998; Schmidhuber, 1987; Brazdil et al., 2022) aims to learn, from previous learning experiences, how to learn (Vanschoren, 2018; Hospedales et al., 2021; Huisman et al., 2021b). Matching networks aim to learn a good embedding such that a nearest-neighbour classifier can be effective

(Vinyals et al., 2016). Prototypical networks build on this technique by comparing inputs to class prototypes instead of instances (Snell et al., 2017). Relation networks replace the distance metric with a neural network (Sung et al., 2018). Model-based approaches, such as MANNs (Santoro et al., 2016), Meta-Nets (Munkhdalai and Yu, 2017), TURTLE (Huisman et al., 2021a) and SNAIL (Mishra et al., 2018), embed a given dataset into an activation state and use this state to make predictions for new data points. Optimization-based approaches use optimization, such as gradient descent, to learn new tasks. One of the most popular techniques from this approach is MAML (Finn et al., 2017), which aims to learn good initialization hyperparameters from which new tasks can be learned in a few gradient update steps. This work has been the inspiration for many follow-up works, such as Meta-SGD (Li et al., 2017), which also learns suitable learning rates, Reptile (Nichol et al., 2018), which is a first-order variant on MAML, and LEO (Rusu et al., 2019), whose goal is to learn the initialization hyperparameters in a low-dimensional latent space.

Transfer learning Transfer learning (Weiss et al., 2016; Tan et al., 2018; Pan and Yang, 2009) aims to transfer knowledge from a source task or domain (or set thereof), where a large amount of data may be present, to a target domain, where data may be sparse. One popular transfer learning approach in deep learning is to pre-train a network on a given source domain (e.g., ImageNet (Krizhevsky et al., 2012)), followed by fine-tuning parts (such as only the output layer) of the network on the target domain (Huang et al., 2013; Oquab et al., 2014). In this case, the knowledge transfer is parameter-based. Many other forms of transfer also exist, such as mapping-based, instance-based, and adversarial-based transfer (Tan et al., 2018).

Recent works illustrate that simple pre-training and fine-tuning can outperform more complicated meta-learning techniques (Chen et al., 2019; Tian et al., 2020) which raises the question of whether a good embedding is enough for achieving good few-shot learning performance. However, this could also indicate that the few-shot benchmarks such as Mini-ImageNet (Vinyals et al., 2016; Ravi and Larochelle, 2017), TieredImageNet (Ren et al., 2018), and CUB (Wah et al., 2011) are not challenging enough because test examples come from the same dataset as the one used for training.

Related competitions and benchmarks This competition is part of an established series of competitions such as the AutoML competition series (Guyon et al., 2019), the AutoDL competition series (Liu et al., 2021), the AutoCV competition series and the MetaDL competition series (El Baz et al., 2021). This competition is an extension to our previous hosted competition in the MetaDL series (El Baz et al., 2021). It challenges participants with a more challenging set of datasets, that were specifically designed for this challenge.

The Open Algorithm Selection Competition (OASC) is a competition that is closely related to meta-learning (Lindauer et al., 2017, 2019). In that competition, for a given dataset, an appropriate algorithm needs to be selected. While several machine learning datasets are present in the competition, it focuses also on algorithm selection beyond machine learning (e.g., MIP and SAT).

Meta-dataset is another notable benchmark used for few-shot learning. It is a collection of 10 datasets that are commonly used in few-shot learning (Triantafillou et al., 2020). Our competition setup with various datasets is partly inspired by this initiative.

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