Improving Few-Shot Learning with Auxiliary Self-Supervised Pretext Tasks

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Abstract

Recent work on few-shot learning (Tian et al., 2020a) showed that quality of learned representations plays an important role in few-shot classification performance. On the other hand, the goal of self-supervised learning is to recover useful semantic information of the data without the use of class labels. In this work, we exploit the complementarity of both paradigms via a multi-task framework where we leverage recent self-supervised methods as auxiliary tasks. We found that combining multiple tasks is often beneficial, and that solving them simultaneously can be done efficiently. Our results suggest that self-supervised auxiliary tasks are effective data-dependent regularizers for representation learning. Our code is available at: https: //github.com/nathanielsimard/improving-fs-ssl.

1. Introduction

Few-shot learning measures the ability to learn new concepts from a limited amount of examples. This is a challenging problem that usually requires different approaches from the success stories of image classification where labeled data is abundant. Recently, meta-learning (Schmidhuber, 1987; Bengio et al., 1992; Thrun & Pratt, 1998), or learning-to-learn, has emerged as a learning paradigm where a machine learning model gains experience over multiple learning episodes and uses this experience to improve its future learning performance. Significant advances in few-shot learning (Vinyals et al., 2016; Ravi & Larochelle, 2017; Snell et al., 2017; Finn et al., 2017; Oreshkin et al., 2018; Sung et al., 2018; Rusu et al., 2019; Lee et al., 2019) have been made by framing the problem within a meta-learning setting.

More precisely, few-shot learning can be seen as a sub-task of meta-learning where a learner is trained and tested on several different but still related tasks. The goal of few-shot meta-learning is to train a model that can quickly adapt to a new task using only a few datapoints and training iterations (Finn et al., 2017). During the meta-training phase, the model is trained to solve multiple tasks such that it is able to learn or adapt to new ones through the meta-testing phase. The performance of the learner is evaluated by the average test accuracy across many meta-testing tasks.

Focusing on few-shot image classification, where very few images are available for novel tasks, recent works aim to learn representations that generalize well to novel classes by training a feature representation to classify a training dataset of base classes (Finn et al., 2017; Vinyals et al., 2016; Snell et al., 2017; Gidaris & Komodakis, 2018; Qi et al., 2018). Methods to tackle this problem include optimization-based methods and metric-based methods, although recent works suggest that learning a good representation is the main factor responsible for fast adaptation in few-shot learning methods (Raghu et al., 2020; Tian et al., 2020a). Raghu et al. (2020) empirically suggested that the effectiveness of MAML (Finn et al., 2017) is due to its ability to learn a useful representation, while Tian et al. (2020a) showed that learning a good representation of the data through a proxy task is even more effective than complex meta-learning algorithms.

Self-supervised learning is another recent paradigm but for unsupervised learning where the supervisory signal for feature learning is automatically generated from the data itself. Seminal works (Doersch et al., 2015; Zhang et al., 2016; Noroozi & Favaro, 2016; Gidaris et al., 2018) have relied on heuristics to design pretext learning tasks such that high-level image understanding must be captured to solve them. Discriminative approaches based on contrastive learning in the latent space (Oord et al., 2018; Wu et al., 2018; Bachman et al., 2019; Tian et al., 2019; Henaff, 2020; Chen et al., 2020a; He et al., 2020; Chen et al., 2020c; Misra & Maaten, 2020; Chen et al., 2020b) have shown recently that self-supervised learning is especially useful with the
large availability of unlabeled data, effectively closing the gap with supervised learning when leveraging models with large capacity. These methods are trained by reducing the distance between different augmented views of the same image (positive pairs), and increasing the distance between augmented views of different images (negative pairs). More recently, BYOL (Grill et al., 2020) showed that one can also learn transferable visual representations via bootstrapping representations and without negative pairs.

In this paper, we propose to leverage self-supervised learning method(s) as auxiliary task(s) to prevent overfitting to the base classes seen during meta-training and improve transfer learning performance on novel classes. More specifically, we build upon the simple baseline proposed by Tian et al. (2020a), where the meta-training tasks are merged into a single pre-training task and a linear model is learned on top of the frozen encoder, and leverage self-supervised auxiliary task(s) as a data-dependent regularizer to learn richer and more transferable visual representations. Our multi-task framework exploits the complementarity of few-shot learning and self-supervised learning paradigms to boost performance on few-shot image classification benchmarks.

2. Related Work

**Few-shot learning.** Recent works have mostly focused on meta-learning approaches to few-shot learning. Among these, optimization-based methods (Finn et al., 2017; Ravi & Larochelle, 2017; Lee et al., 2019; Rusu et al., 2019) aim to learn how to rapidly adapt the embedding model parameters to training examples for a given few-shot recognition task. Metric-based approaches (Vinyals et al., 2016; Snell et al., 2017; Sung et al., 2018; Gidaris & Komodakis, 2018) aim to learn a task-dependent metric over the embeddings. More concretely, such methods learn a distance metric between a query image and a set of support images given a few-shot task.

More recently, it has been shown that learning a good representation plays an important role in few-shot learning (Raghu et al., 2020; Tian et al., 2020a). Our work is directly related to that of Tian et al. (2020a). A simple image classification task is used to train on the merged meta-training data to learn an embedding model, which is re-used at meta-testing time to extract embedding for a linear classifier.

**Self-supervised learning.** Deep learning models are usually considered data hungry and require a significant amount of labeled data to achieve decent performance. This recent learning paradigm aims to mitigate the requirements for large amounts of annotated data by providing surrogate supervisory signal from the data itself. Initial works in self-supervised representation learning relied on engineered prediction tasks (Doersch et al., 2015; Zhang et al., 2016; Noroozi & Favaro, 2016; Gidaris et al., 2018), often referred to as pretext tasks. Such methods include predicting the relative position of image patches (Doersch et al., 2015; Noroozi & Favaro, 2016), the rotation degree applied to an image (Gidaris et al., 2018), the colors of a grayscale image (Zhang et al., 2016; Larsson et al., 2016), and many others.

More recently, discriminative approaches based on contrastive learning have shown great promise in self-supervised learning. Contrastive methods like MoCo (He et al., 2020; Chen et al., 2020c) and SimCLR (Chen et al., 2020a; 2020b) push representations of different views of the same image (positive pairs) closer, and spread representations of views from different images (negative pairs) apart. Beyond contrastive learning, BYOL (Grill et al., 2020) relies only on positive pairs. From a given representation, referred to as target, an online network is trained to learn an enhanced representation by predicting the target representation. Although concerns over stability and representational collapse have been raised (Fetterman & Albrecht, 2020; Tian et al., 2020b), BYOL has still proven to be an effective self-supervised representation learning technique.

**Multi-task learning.** Our work is also related to multi-task learning, a class of techniques that train on multiple task objectives together to learn a representation that works well for every task, though we are mainly interested in improving performance on the main task in this work. In this context, using multiple self-supervised pretext tasks is especially attractive as no additional labels are required. The combination of complementary tasks has been shown to be beneficial (Doersch & Zisserman, 2017; Yamaguchi et al., 2019) in self-supervised representation learning. Previous works (Gidaris et al., 2019; Su et al., 2020) explore the use of self-supervised pretext tasks as auxiliary tasks to improve metric-based few-shot learning methods. In this work, we extend these ideas to recent self-supervised techniques and focus on learning richer and more generalizable features by starting from the simpler few-shot learning baseline of Tian et al. (2020a).

3. Method

In this section, we first describe in §3.1 the few-shot learning problem addressed and introduce in §3.2 the proposed multi-task approach to improve few-shot performance with self-supervised auxiliary tasks.

3.1. Problem Formulation

Standard few-shot learning benchmarks evaluate models in episodes of $N$-way, $K$-shot classification tasks. Each task consists of a small number of $N$ classes with $K$ training examples per class. Meta-learning approaches for few-shot learning aim to minimize the generalization error across a
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Figure 1: Combining supervised and self-supervised tasks for meta-training. We train the embedding model $F_{\theta}$ with both annotated images and unlabeled images in a multi-task setting. Self-supervised tasks such as rotation prediction or representation prediction (BYOL) act as a data-dependent regularizer for the shared feature extractor $F_{\theta}$. Although additional unlabeled data can be used for the self-supervised tasks, in this work we sample images from the annotated set.

distribution of tasks sampled from a task distribution. This can be thought of as learning over a collection of tasks $\mathcal{T} = \{(D_{train}^{i}, D_{test}^{i})\}_{i=1}^{I}$, commonly referred to as the meta-training set.

In practice, a task is constructed on the fly during the meta-training phase and sampled as follows. For each task, $N$ classes from the set of training classes are first sampled (with replacement), from which the training (support) set $D_{train}^{i}$ of $K$ images per class is sampled, and finally the test (query) set $D_{test}^{i}$ consisting of $Q$ images per class is sampled. The support set is used to learn how to solve this specific task, and the additional examples from the query set are used to evaluate the performance for this task. Once the meta-training phase of a model is finished, its performance is evaluated on a set of held-out tasks $\mathcal{S} = \{(D_{train}^{j}, D_{test}^{j})\}_{j=1}^{J}$, called the meta-test set. During meta-training, an additional held-out meta-validation set can be used for hyperparameter selection and model selection. Training examples $D_{train} = \{(x_i, y_i)\}_{i=1}^{T}$ and testing examples $D_{test} = \{(x_q, y_q)\}_{q=1}^{Q}$ are sampled from the same distribution, and are mapped to a feature space using an embedding model $F_{\theta}$. A base learner is trained on $D_{train}$ and used as a predictor on $D_{test}$.

Merged meta-training. Following the simple baseline of Tian et al. (2020a), we merge tasks from the meta-training set into a single bigger task or dataset $D_{merge} = \{(x_i, y_i)\}_{i=1}^{K} = \cup\{D_{train}^{1}, \ldots, D_{train}^{i}, \ldots, D_{train}^{I}\}$, (1) where $D_{train}^{i}$ is a task from $\mathcal{T}$.

The objective is to learn a transferable embedding model $F_{\theta}$ which generalizes to new tasks. For a task $(D_{train}^{j}, D_{test}^{j})$ sampled from the meta-testing distribution, we freeze the embedding model $F_{\theta}$ to extract embeddings and train a base learner on $D_{train}^{j}$. The base learner is instantiated as a simple linear classifier and is re-initialized for every task.

3.2. Multi-Task Learning

Through solving non-trivial self-supervised tasks, the embedding model is encouraged to learn rich and generic image features that can be readily exploited for few-shot learning on novel classes. We propose a multi-task learning approach to extend the supervised objective with different self-supervised auxiliary tasks, where the goal is to learn a representation that works well for every task, and perhaps share knowledge between tasks, to further improve few-shot performance.

We incorporate self-supervision to our multi-task framework by adding auxiliary losses for each self-supervised task. As illustrated in Figure 1, we use the same embedding model $F_{\theta}$ to extract image features for all tasks. Based on the features extracted, a new network defined for each task is assigned
to solve its respective task, each of which contribute to the overall loss

\[ \mathcal{L}_{\text{tot}} = \sum_{t=1}^{N} \mathcal{L}_t, \quad (2) \]

where \( \mathcal{L}_t \) is the loss for the \( t \)-th task out of all \( N \) tasks.

Along with the supervised objective, we consider two additional tasks in the present work: rotation prediction (Gidaris et al., 2018) and representation prediction from different views following BYOL (Grill et al., 2020). All tasks are computed on the merged dataset \( D_{\text{merge}} \).

**Supervised.** The supervised task is the standard classification task on all categories from the merged dataset, which has been shown to be an effective baseline to generate powerful embeddings for the downstream base learner (Tian et al., 2020a). The new network \( f_o \) introduced to solve this task is instantiated as a simple linear classifier. We compute the cross-entropy loss \( \mathcal{L}_{\text{ce}} \) between predictions and ground-truth labels.

**Rotation.** In this task, the network must identify the rotation transformation applied to an image among four possible 2D rotations \( \mathcal{R} = \{0^\circ, 90^\circ, 180^\circ, 270^\circ\} \), as proposed by Gidaris et al. (2018). This auxiliary task is similar to Gidaris et al. (2019), except that we do not create four rotated copies of an input image, which effectively quadruples the batch size, but instead sample a single rotation to apply for each image in the batch. The network \( r_\phi \) specific to the rotation task is a multi-layer perceptron (MLP). The self-supervised loss \( \mathcal{L}_{\text{rel}} \) for this task is the cross-entropy loss between the rotation predictions and the generated labels.

**BYOL.** In BYOL (Grill et al., 2020), the online network directly predicts the output of one view from another view given by the target network. Essentially, this is a representation prediction task in the latent space, similar to contrastive learning except that it only relies on the positive pairs. In this task, the online network is composed of the shared encoder \( F_o \), the MLP projection head \( q_\phi \) and the predictor \( g_\phi \) (also an MLP). The target network has the same architecture as the online network (minus the predictor), but its parameters are an exponential moving average (EMA) of the online network parameters as illustrated in Figure 1. Denoting the parameters of the online network as \( \theta_o = \{\theta, \phi\} \), those of the target network as \( \xi \) and the target decay rate \( \tau \in [0, 1) \), the update rule for \( \xi \) is:

\[ \xi \leftarrow \tau \xi + (1 - \tau) \theta_o \quad (3) \]

The self-supervised loss \( \mathcal{L}_{\text{BYOL}} \) is the mean squared error between the normalized predictions and target projections as defined in Grill et al. (2020). Effectively, this task enforces the representations for different views of positive pairs to be closer together in latent space, which provides transformation invariance to the pre-defined set of data augmentations used for BYOL.

Although the multi-task framework proposed is very flexible and could easily be extended to additional tasks, the naïve implementation which does not share the transformed inputs for each task still has some overhead with each task added. Effectively, for each set of transformations associated to the different tasks, different views of the same input image are generated, which is essentially a new input in the batch. For example, given an input image from the merged dataset, the default data augmentations from the supervised task would create an augmented view of the input used to compute the supervised loss, and applying a rotation to the input image would generate a different view of the input. Not only does this double the batch size, but the inputs are not actually shared across tasks to compute the different losses. If instead the set of transformations are shared across tasks, the different tasks would be solved for the same inputs. In this scenario, the different losses are computed and backpropagated on the same inputs, which is much more efficient. In §4.4, we explore this more efficient setting by combining the supervised and BYOL tasks using the stronger data augmentation strategy from BYOL in both. More concretely, we generate an augmented view of an input image and compute the supervised loss on the first augmented view, while another augmented view of the same input is generated to solve the representation prediction task in BYOL.

### 4. Experimental Results

In this section, we evaluate our proposed multi-task framework on two widely used few-shot image recognition benchmarks: miniImageNet (Vinyals et al., 2016) and CIFAR-FS (Bertinetto et al., 2018).

**Datasets.** The miniImageNet dataset (Vinyals et al., 2016) has recently become a standard benchmark for few-shot learning algorithms. It consists of 100 classes randomly sampled from ImageNet, with each class containing 600 down-sampled images of size 84 × 84. The CIFAR-FS dataset (Bertinetto et al., 2018) is derived from the original CIFAR-100 dataset by randomly splitting 100 classes into 64 classes for training, 16 for validation and 20 for testing. Each image is 32 × 32 pixels. In our experiments, we upsampled the images to 96 × 96 pixels\(^1\).

\(^1\)This is due to the limitations of using smaller scale images with BYOL, which strongly relies on random crops as image augmentation. Initial experimental results showed that BYOL on its own could only achieve 47.09 ± 0.96% accuracy on CIFAR-FS, which is significantly lower than the results reported in Table 1.
Evaluation metrics. As mentioned in §3.1, few-shot algorithms are evaluated on a large number of $N$-way $K$-shot classification tasks. Each task is created by randomly sampling $N$ novel classes from the meta-test set, and then within the selected images randomly selecting $K$ training (support) images and $Q$ test (query) images (without overlap). In this work, we focus on $N = 5, K = 5$ (5-way 5-shot) classification, using the remainder of the $Q$ test samples to evaluate performance on the sampled task.

4.1. Implementation Details

Network architectures. We mainly conduct our experiments using a ResNet-18 (He et al., 2016) as our embedding model $F_\theta$ due to resource limitations, with an output feature vector of size 512. Following previous works (Tian et al., 2020a; Snell et al., 2017; Lee et al., 2019; Oreshkin et al., 2018; Dhillon et al., 2020), we also report some results using ResNet-12 as our backbone for comparison. Our ResNet-12 is identical to that used in Tian et al. (2020a). Note that this modified ResNet-12 is wider than the original ResNet-18 and makes use of DropBlock (Ghiasi et al., 2018) as a regularizer, which results in a substantial gain in performance over ResNet-18 but at the cost of longer training time. Additionally, the resulting embedding size is 640.

Task-specific networks. From these embeddings, the image classifier $f_\theta$ is instantiated as a simple linear layer for classification. The rotation network $r_\phi$ is an MLP which consists in a linear layer with output size the same as the embedding size, followed by batch normalization, rectified linear units (ReLU), a linear layer with output size the same as the embedding size, and a final linear layer with output dimension equal to the number of rotation degrees to classify (here, 4). For BYOL, we use the following configurations. The projection MLP $g_\varphi$ consists in a linear layer with output size 2048 followed by batch normalization (Ioffe & Szegedy, 2015), rectified linear units (ReLU) (Nair & Hinton, 2010), and a final linear layer with output dimension 128. The predictor $\hat{g}_\varphi$ uses the same architecture as $g_\varphi$. The target encoder $F_\theta$ uses the same architecture as the embedding model $F_\theta$, and the target projection head $g_\xi$ uses the same architecture as $g_\varphi$.

Optimization setup. As an optimizer, we adopt SGD with a momentum of 0.9 and a weight decay of $5e^{-4}$. The initial learning rate is 0.05 and decayed by a factor of 0.1 according to a multi-step learning schedule. All models are trained for 90 epochs on CIFAR-FS with a decay step at epochs 45, 60 and 75, except when BYOL is used (alone or in combination with other tasks). In this setting, we only decay the learning rate at epochs 60 and 80 since BYOL usually converges more slowly. On miniImageNet, all models are trained for 100 epochs with a decay step at epochs 60 and 80, regardless of task combinations. For BYOL, the exponential moving average parameter $\tau$ is set to 0.99. We use a batch size of 128 for all experiments.

Data augmentation. During pre-training on the merged meta-training dataset, we adopt random crop, color jittering and random horizontal flip as in Tian et al. (Tian et al.). For stronger data augmentation in BYOL, we adopt random crop, random color jittering, random grayscale, random horizontal flip and random gaussian blur similar to Fetterman & Albrecht (2020). Given that each task may require its own set of transformations, we use Kornia (Riba et al., 2020) for efficient GPU-based data augmentation in PyTorch (Paszke et al., 2019). Additional details can be found in Appendix D.

Early stopping. For training the base learner, we use the same optimizer setup with SGD, and train for a maximum of 300 steps, stopping early if the loss reaches a small threshold on the support set. Model selection is done on the held-out meta-validation set.

4.2. Self-Supervision Alone is not Enough

We first evaluate self-supervised representation learning with the two tasks explored in this work, rotation prediction and representation prediction (BYOL). Our results on CIFAR-FS (Table 1) and miniImageNet (Table 2) show that, on its own, the rotation prediction pretext task limits the generality of the learned representations, significantly lagging behind in few-shot accuracy. On the other hand, the representation prediction task from different views (BYOL) shows great promise in representation learning, achieving results that are not that far from the supervised baseline3.

Note that the performance gap between BYOL and the supervised baseline on miniImageNet is bigger than the one observed on CIFAR-FS. We attribute this to the slow convergence of BYOL. As noted in §4.1, we changed the learning schedule for CIFAR-FS but did not do so for miniImageNet. Thus, we expect the gap to be smaller on miniImageNet with slightly longer training.

4.3. Combining Supervised and Self-Supervised Tasks

On CIFAR-FS, we explore different combinations of tasks for our multi-task framework of Figure 1. In Table 1, our results show that both the rotation prediction task and BYOL improve the supervised baseline, though the biggest boost

3Note that we did not perform any extensive experiments to search for the optimal hyperparameter and learning schedule configurations for BYOL. Thus, the gap between BYOL and the supervised baseline could most likely be closed even further, perhaps just by adopting a longer training schedule.
Additional experiments where we leverage both augmented work in strong data augmentation techniques (DeVries & Taylor, 2017; Zhang et al., 2018; Yun et al., 2019; Cubuk et al., 2019; 2020). Effectively, data augmentation is an important regularization technique that has been shown to improve generalization. Furthermore, we show that in this setting the addition of BYOL as a self-supervised auxiliary task still boosts the performance. As mentioned in §3.2, when used in combination with BYOL, both tasks share the same transformed inputs as part of our multi-task framework. Additional experiments where we leverage both augmented views generated to compute both the supervised and BYOL losses can be found in Table 4 (Appendix C).

Table 1: Evaluating representation learning methods for few-shot recognition on CIFAR-FS. Average 5-way 5-shot classification accuracies on the test set with 95% confidence intervals. We evaluate our method with 2 runs, where in each run the accuracy is the mean accuracy of 250 randomly sampled tasks. Models with † use stronger data augmentation for the supervised objective. Sup. refers to the supervised task, Rot. to the rotation prediction task and BYOL to the representation prediction task in Grill et al. (2020).

| Method      | Backbone | Accuracy (%) |
|-------------|----------|--------------|
| Sup.        | ResNet-18| 79.54 ± 0.92 |
| Rot.        | ResNet-18| 49.26 ± 1.01 |
| BYOL        | ResNet-18| 70.50 ± 0.99 |
| Sup. + Rot. | ResNet-18| 79.96 ± 0.93 |
| Sup. + BYOL | ResNet-18| 81.41 ± 0.89 |
| Sup. + BYOL + Rot. | ResNet-18 | 81.68 ± 0.98 |
| Sup.†       | ResNet-18| 81.87 ± 0.92 |
| Sup.† + BYOL | ResNet-18 | 82.44 ± 0.91 |

4.4. Data Augmentation: Stronger is Better

In order to ensure that the performance improvement from BYOL is not strictly due to the stronger data augmentation strategy used by the task, we conduct experiments using the same data augmentations for the supervised baseline. An additional experiment without data augmentation for the supervised task is presented in Appendix A.

On both CIFAR-FS (Table 1) and miniImageNet (Table 2), we find that stronger data augmentation improves the supervised baseline. This is in line with a lot of the recent work in strong data augmentation techniques (DeVries & Taylor, 2017; Zhang et al., 2018; Yun et al., 2019; Cubuk et al., 2019; 2020). Effectively, data augmentation is an important regularization technique that has been shown to improve generalization. Furthermore, we show that in this setting the addition of BYOL as a self-supervised auxiliary task still boosts the performance. As mentioned in §3.2, when used in combination with BYOL, both tasks share the same transformed inputs as part of our multi-task framework. Additional experiments where we leverage both augmented views generated to compute both the supervised and BYOL losses can be found in Table 4 (Appendix C).

Table 2: Evaluating representation learning methods for few-shot recognition on miniImageNet. Average 5-way 5-shot classification accuracies on the test set with 95% confidence intervals. We evaluate our method with a single run, where the accuracy is the mean accuracy of 250 randomly sampled tasks. Models with † use stronger data augmentation for the supervised objective. Sup. refers to the supervised task, Rot. to the rotation prediction task and BYOL to the representation prediction task in Grill et al. (2020).

| Method      | Backbone | Accuracy (%) |
|-------------|----------|--------------|
| Sup.        | ResNet-18| 67.26 ± 0.89 |
| Rot.        | ResNet-18| 39.39 ± 0.83 |
| BYOL        | ResNet-18| 51.20 ± 0.97 |
| Sup. + BYOL + Rot. | ResNet-18 | 68.59 ± 0.92 |
| Sup.†       | ResNet-18| 69.42 ± 0.94 |
| Sup.† + BYOL | ResNet-18 | 71.47 ± 0.90 |

4.5. Comparison with Prior Work

For comparison with prior work, we also report some results in Table 3 using ResNet-12 as our backbone. Our supervised baseline is similar to the simple baseline of Tian et al. (2020a), except that we do not use any additional tricks like feature normalization, augmenting the number of support images, and our base learner is not a logistic regression classifier with L-BFGS optimizer from scikit-learn (Buitinck et al., 2013). Due to resource limitations, we do not employ the additional rotation prediction task in our multi-task framework, though we expect it would slightly improve the reported performance based on our experiments in §4.3.

On CIFAR-FS, our multi-task framework outperforms previous works by at least 1.5%. Note that our simple supervised baseline, even without the tricks used in Tian et al. (2020a), still performs better than their best distilled model. We attribute this to the higher resolution input images, which we upsampled to 96 × 96. On miniImageNet however, our simple baseline without their tricks is comparable to the results reported in their ablation study. We show that our framework improves this slightly weaker baseline, and anticipate that additional tricks such as feature normalization would complement our work to further improve the results.

Although Gidaris et al. (2019) use a much larger network (WRN-28-10), we still include their results in Table 3 for comparison as their work uses self-supervised rotation prediction as an auxiliary loss, which is very much related to our work. We expect a larger network to be more effective in learning richer features, and the results to improve with a larger architecture.
We hypothesize that solving an additional task in parallel with the supervised objective, improves few-shot performance. Although the related method BYOL reports poor performance, we found that an additional task to solve, the exponential moving average constant is not required to avoid representational collapse. On CIFAR-FS, we report an accuracy of 82.19$\pm$0.83% for this run, compared to 82.51$\pm$0.82% when using $\tau = 0.99$ on the same seed.

We hypothesize that solving an additional task in parallel with the BYOL loss (e.g. supervised objective) provides additional gradient that prevents collapse. Similar behaviour has been observed by Schwarzer et al. (2020) when using a reinforcement learning objective in parallel.

## 4.6. Avoiding Collapse with BYOL

Although the related method BYOL reports poor performance when instantaneously updating the target network ($\tau = 0$) as it destabilizes training, we found that with an additional task to solve, the exponential moving average constant is not required to avoid representational collapse. On CIFAR-FS, we report an accuracy of 82.19$\pm$0.83% for this run, compared to 82.51$\pm$0.82% when using $\tau = 0.99$ on the same seed.

We hypothesize that solving an additional task in parallel with the BYOL loss (e.g. supervised objective) provides additional gradient that prevents collapse. Similar behaviour has been observed by Schwarzer et al. (2020) when using a reinforcement learning objective in parallel.

## 5. Conclusion

Based on the simple baseline of Tian et al. (2020a), we have proposed a multi-task framework with self-supervised auxiliary tasks to improve few-shot image classification. Based on our detailed experiments on CIFAR-FS and miniImageNet, we show that leveraging self-supervision improves transfer learning performance on novel classes. Our experiments show that the rotation prediction task, when paired with the supervised objective, improves few-shot performance, but that the representation prediction task (BYOL) is most beneficial. This result suggests that BYOL is a strong data-dependent regularizer by enforcing the representations for different views of the same image to be closer together in latent space. Furthermore, we show that these two tasks are mutually beneficial, and can be used in combination to improve few-shot classification performance under our multi-task framework. Finally, the proposed framework can be used efficiently when the transformations of the different tasks are shared to solve each task simultaneously.

### Future work

In this work, we sample images from the annotated set for the self-supervised tasks. On the other hand, these auxiliary tasks do not depend on class labels. Thus, one could easily extend to learn from additional unlabeled data and further improve few-shot performance. This makes our multi-task framework especially appealing in scenarios where labeled data is scarce. Future works could extend the use of our framework to the semi-supervised few-shot learning setting and leverage additional unlabeled data.

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### Table 3: Comparison to prior work on CIFAR-FS and miniImageNet

Average 5-way 5-shot classification accuracies on the test set with 95% confidence intervals. We evaluate our method on a single run, where the accuracy is the mean accuracy of 250 randomly sampled tasks. Models with * use stronger data augmentation for the supervised objective. *Sup.* refers to the supervised task and BYOL to the representation prediction task in Grill et al. (2020).

| Method                          | Backbone       | CIFAR-FS       | miniImageNet   |
|--------------------------------|----------------|----------------|----------------|
| Prototypical Networks (Snell et al., 2017) | ResNet-12      | 83.5$\pm$0.5   | 78.63$\pm$0.48 |
| TADAM (Oreshkin et al., 2018)     | ResNet-12      | –              | 76.70$\pm$0.30 |
| MetaOptNet (Lee et al., 2019)     | ResNet-12      | 84.3$\pm$0.5   | 78.63$\pm$0.48 |
| RFS-simple (Tian et al., 2020a)   | ResNet-12      | 86.0$\pm$0.5   | 79.64$\pm$0.44 |
| RFS-distill (Tian et al., 2020a)  | ResNet-12      | 86.9$\pm$0.5   | **82.14$\pm$0.43** |
| CC + rot (Gidaris et al., 2019)   | WRN-28-10      | 86.1$\pm$0.2   | 79.87$\pm$0.33 |
| Sup.                            | ResNet-12      | 87.65$\pm$0.75 | 77.62$\pm$0.70 |
| Sup.* + BYOL                    | ResNet-12      | **88.46$\pm$0.68** | **78.30$\pm$0.69** |
Improving Few-Shot Learning with Auxiliary Self-Supervised Pretext Tasks

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Appendix

A. Regularizing for Stability

During our initial experiments, we tried combining the supervised task without any data augmentation with the BYOL auxiliary task. The goal of this experiment was to find out if BYOL was sufficient to enforce invariance to the transformations used as part of its data augmentation strategy, without directly applying any transformations to the inputs of the supervised task. As shown in Figure 2 the training was highly unstable, with the two tasks competing against each other. This resulted in a performance worse than the supervised baseline, achieving a few-shot accuracy of $78.98 \pm 0.92\%$ with a ResNet-18 backbone. We believe additional regularization (e.g. Dropout (Srivastava et al., 2014)) to the backbone could have mitigated this effect, but this is still an interesting finding.

![Figure 2: Learning curves of our multi-task framework, using a supervised objective (no data augmentation) and BYOL auxiliary task. Losses of each task during the training of the BYOL task and supervised task without any data augmentation over 90 epochs. Training seems to stabilize after epoch 60, where the learning rate was decayed.](image)

B. Qualitative Analysis

We are interested in learning a linearly separable representation of the input so that a simple linear classifier can be trained on unseen classes and discriminate between them. Hence, it is possible to proceed to a qualitative evaluation of the learned representations by visualizing the embedding space. As illustrated by the t-SNE (van der Maaten & Hinton, 2008) visualization in Figure 3, multiple different clusters are easily identifiable even though there are some points that are still intertwined with points that belong to other classes. The fact that such clusters exist on unseen classes is quite interesting, and reinforces the statement that a good representation of the data is extremely important in few-shot learning (Raghu et al., 2020; Tian et al., 2020a).

![Figure 3: t-SNE visualization of the embedding space for a sampled 5-way task (unseen) on CIFAR-FS. The embeddings result from a model trained with the supervised and BYOL tasks.](image)

C. Additional Supervised + BYOL Experiment

In Table 4, we show the difference in performance when leveraging all (2) augmented views generated for the BYOL task with the supervised objective as well. Effectively, the supervised loss is computed on 2 augmented views for each image in the batch instead of only the first augmented view. Results were inconclusive.

| Dataset      | Sup. per image | Accuracy (%) |
|--------------|----------------|--------------|
| CIFAR-FS     | 1              | 82.43 ± 0.92 |
| CIFAR-FS     | 2              | 82.33 ± 0.89 |
| miniImageNet | 1              | 71.47 ± 0.90 |
| miniImageNet | 2              | 71.95 ± 0.78 |

D. Image Augmentations

The image augmentations parameters for the different settings are listed in Listing 1. Default augmentations are the same as (Tian et al., 2020a), and hard augmentations are for the BYOL task (and supervised task in some experiments).
import random
import kornia.augmentation as K
import kornia.filters as F

class RandomApply(object):
    def __init__(self, fn, p):
        self.fn = fn
        self.p = p

    def __call__(self, x):
        if random.random() > self.p:
            return x
        return self.fn(x)

size = (96, 96) if CIFAR_FS else (84, 84)
pad = 4 if CIFAR_FS else 8

default_tfm = [
    K.RandomCrop(size, padding=pad),
    K.ColorJitter(brightness=0.4, contrast=0.4, saturation=0.4, p=1.0),
    K.RandomHorizontalFlip(p=0.5)
]

hard_tfm = [
    K.ColorJitter(brightness=0.4, contrast=0.4, saturation=0.4, hue=0.1, p=0.8),
    K.RandomGrayscale(p=0.2),
    K.RandomHorizontalFlip(p=0.5),
    RandomApply(F.GaussianBlur2d(kernel_size=(3, 3), sigma=(1.5, 1.5)), p=0.1),
    K.RandomResizedCrop(size, scale=(0.35, 1.0), p=1.0)
]