SELF-SUPERVISED CLASS-COGNIZANT FEW-SHOT CLASSIFICATION

Ojas Kishore Shirekar†  Hadi Jamali-Rad†∗
†Delft University of Technology (TU Delft), Delft, The Netherlands
∗Shell Global Solutions International B.V., Amsterdam, The Netherlands
oke.shirekar@student.tudelft.nl, hadi.jamali-rad@shell.com, h.jamalirad@tudelft.nl

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ABSTRACT

Unsupervised learning is argued to be the dark matter of human intelligence1. To build in this direction, this paper focuses on unsupervised learning from an abundance of unlabeled data followed by few-shot fine-tuning on a downstream classification task. To this aim, we extend a recent study on adopting contrastive learning for self-supervised pre-training by incorporating class-level cognizance through iterative clustering and re-ranking and by expanding the contrastive optimization loss to account for it. To our knowledge, our experimentation both in standard and cross-domain scenarios demonstrate that we set a new state-of-the-art (SoTA) in (5-way, 1 and 5-shot) settings of standard mini-ImageNet benchmark as well as the (5-way, 5 and 20-shot) settings of cross-domain CDFSL benchmark. Our code and experimentation can be found in our GitHub repository: https://github.com/ojss/c3lr2.

1 Introduction

Few-shot learning has received an upsurge of attention recently because it highlights a fundamental gap between human intelligence and data-hungry supervised deep learning methods. We humans can learn in a self-supervised fashion and/or with very little supervision. To tackle this challenge, few-shot classification is cast as the task of predicting class labels for a set of unlabeled data points (query set) given only a small set of labeled ones (support set). The query and support samples are typically drawn from the same distribution. Few-shot classification approaches are typically comprised of two sequential phases [Medina et al., 2020, Chen et al., 2020, Ji et al., 2019, Ye et al., 2020]: (i) pre-training on an abundant dataset (sometimes called “base”), followed by (ii) fine-tuning on an unseen dataset containing “novel” classes. Typically, the target classes in pre-training and fine-tuning phases are mutually exclusive. In this paper, we focus on self-supervised (also sometimes interchangeably called “unsupervised” in the literature) setting where we have no access to the class labels of the base dataset in the pre-training phase or their distribution.

The art here is to devise a synthetic class label assignment technique and corresponding loss function in the pre-training phase to efficiently transfer the learning to the fine-tuning phase. To this aim, studies have proposed two different approaches. The first approach follows a meta-learning strategy to create (synthetic) “tasks” similar to the downstream episodic training in the fine-tuning phase [Finn et al., 2017, Hsu et al., 2018, Khodadadeh et al., 2019]. The second one follows some sort of transfer learning approach, where a representation learning step in the pre-training phase is followed by episodic fine-tuning [Medina et al., 2020, Tian et al., 2020, Dhillon et al., 2019]. In the latter case, typically a feature extractor (encoder) is trained using metric learning to capture the global structure of the unlabeled data. Next, a simple predictor (typically a linear layer) is adopted in conjunction with the extractor for quick

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1Yann LeCun’s note; Meta AI blog post on self-supervised learning.
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we build upon the idea of employing contrastive learning for prototypical transfer learning following the footsteps of
An episode consists of a labeled support set,\( S \), and an unlabeled query set,\( Q \), from which the model learns and an unlabeled query set,\( Q \), on which
the model predicts. Note that both \( S \) and \( Q \) contain a set of tasks of the form \( (N,K) \).

2 Class-Cognizant Contrastive Learning (C\( ^3 \)LR)

In this section, we first describe our problem formulation. We then discuss the two phases of the proposed approach:
self-supervised pre-training and few-shot supervised fine-tuning. The mechanics of the proposed approach and a sketch of the training procedure is shown in Figure 1.

2.1 Preliminaries

Let us denote the training data of size \( M \) as \( D_\mathcal{A} = \{(x_i, y_i)\}_{i=1}^M \) with \((x_i, y_i)\) representing an image \( x_i \) and its class label \( y_i \). In the pre-training phase, we take \( L \) random samples from \( D_\mathcal{A} \) and augment each sample \( Q \) times by drawing augmentation functions \( \psi^q(.) \), \( \forall q \in [Q] \) from the set \( \mathcal{A} \). This results in a batch of size \( B = (Q + 1) L \) total samples. Note that the data labels are unknown in the pre-training phase. In the fine-tuning phase, we deal with the so-called episodic training on a set of tasks \( \mathcal{T} \) containing \( N \) classes each with \( K \) samples per task drawn from the test dataset \( D_\mathcal{H} = \{(x_j, y_j)\}_{j=1}^{M'} \) of size \( M' \). From now on, we refer to this task construct as \((N\text{-way}, K\text{-shot})\) denoted by \((N, K)\).

2.2 Self-Supervised Pre-Training

The fact that we do not have access to class labels calls for a self-supervised pre-training stage. As discussed earlier, we build upon the idea of employing contrastive learning for prototypical transfer learning following the footsteps of [Medina et al., 2020]. The **high-level idea** here is to not only enforce the latent embeddings of augmented images come

Recent studies [Medina et al., 2020, Chen et al., 2021, Dhillon et al., 2019] demonstrate that the second approach based on transfer learning outperforms meta-learning based methods in cross-domain settings, where the training and novel classes come from totally different distributions. Their results also show that a properly-devised transfer learning based unsupervised approach comes pretty close to the performance of a fully supervised counterpart [Medina et al., 2020, Ji et al., 2019], something that we will also confirm through experimentation. Most recently, a new state-of-the-art (SoTA) self-supervised pre-training and few-shot supervised fine-tuning. The mechanics of the proposed approach and a sketch SELF-SUPERVISED CLASS-COGNIZANT FEW-SHOT CLASSIFICATION A Preprint

Figure 1: C\( ^3 \)LR schematic view and training procedure. In the figure, \( x_i \) is an image sampled from the query set \( Q \).
Algorithm 1: Class-Cognizant Contrastive Learning (C^2LR)

Require: \(L, Q, f_\phi, A, \alpha, d[\cdot, \cdot]\)

while not done do
  Sample minibatch \(\{x_i\}_{i=1}^L\)
  forall \(i \in \{1, \ldots, L\}\) do
    forall \(q \in \{1, \ldots, Q\}\) do
      \(x_{i,q} = \psi^q(x_i); \psi^q \sim A.\)
  end
  \(R = \text{ReRank}\left((f_\phi(\{x_i\}_{i=1}^L), f_\phi(\{\tilde{x}_{i,q}\}_{i=1}^L))\right)\)
  \(C = \{C_1, C_2, \ldots, C_P\} \Leftarrow \text{HDBSCAN}(R)\)
  \(M = \{m_p\}_{p=1}^P; m_p = \frac{\sum_{x_i \in C_p} \phi(x_i)}{|C_p|}\)
  let \(\rho(i, q, p) = -\log \frac{\exp(-d[\phi(x_i), m_p])}{\sum_{p=1}^P \exp(-d[\phi(x_i), m_p])}\)
  let \(\ell(i, q) = -\log \frac{\exp(-d[\phi(x_i), \phi(x_j)])}{\sum_{q=1}^Q \exp(-d[\phi(x_i), \phi(x_j)])}\)
  \(L_1 = \frac{1}{QL} \sum_{q=1}^Q \sum_{i=1}^L \rho(i, q, p)\)
  \(L_2 = \frac{1}{QL} \sum_{i=1}^L \sum_{q=1}^Q \ell(i, q)\)
  \(\mathcal{L} = L_1 + L_2\)
  \(\phi \leftarrow \phi - \alpha \nabla_\phi \mathcal{L}\)
end

close to that of the source image in the embedding space (the classical contrastive setting), but also enforce embeddings of the images belonging to each cluster (and their augmentations) come closer to each other, for which a preceding unsupervised cluster formation step is required. This can help enforce similar classes into separate clusters, which will in turn be used as additional information in a modified two-term contrastive loss in Algorithm 1. Let us walk you through the process in further details.

Algorithm 1 starts with batch generation (lines 2 to 7): each mini-batch consists of \(L\) random samples \(\{x_i\}_{i=1}^L\) from \(D_n\), where \(x_i\) is treated as a 1-shot support sample for which we create \(Q\) randomly augmented versions \(\tilde{x}_{i,q}\) as query samples (line 5). This leads to a batch size of \(B = (Q + 1)L\). Then embeddings are generated by passing the samples through an encoder \(f_\phi\) network. This is where the first major modification to ProtoTransfer [Medina et al., 2020] comes into play. Before the contrastive loss comes into action, we apply re-ranking and clustering (lines 8 to 10) to discover class-level global structure of data and enforce similar classes into separate clusters in the embedding space. Note that this step remains to be unsupervised in that the class labels are not required. The re-ranking step (line 8) makes use of the \(k\)-reciprocal nearest neighbors as the distance metric between latent embeddings [Zhong et al., 2017], which has been shown to outperform the Euclidean distance [Ji et al., 2019] when used for subsequent clustering. HDBSCAN clustering [McInnes et al., 2017] is then applied on the re-ranked embeddings \(R\) and returns a set of clusters populated in \(C\). HDBSCAN is versatile enough to discover and create required number of clusters \(P\). With clusters at hand, we are now in a position to extend the standard loss proposed in [Medina et al., 2020] to contain a class-cognizant term (in lines 11 and 13), with lines 12 and 14 reflecting on the classical contrastive loss of ProtoTransfer [Medina et al., 2020]. This new loss term \(L_1\) enables a progressive improvement in class-level cluster formation and in turn learning similar representations for cluster members, while \(L_2\) encourages clustering of the embeddings of the augmented query samples \(\{f_\phi(\tilde{x}_{i,q})\}\) around their prototypes \(\{f_\phi(x_i)\}\). Here, both terms use an Euclidean distance metric in the embedding space denoted by \(d[\cdot, \cdot]\). Finally, the new loss \(\mathcal{L} = L_1 + L_2\) is optimized with mini-batch stochastic gradient decent with respect to the parameters \(\phi\) of the encoder networks \(f_\phi\).

2.3 Supervised Fine-Tuning

The pre-trained encoder \(f_\phi\) will be used for the downstream few-shot classification task. To this aim, following [Medina et al., 2020, Snell et al., 2017], we concatenate \(f_\phi\) with a single-layer nearest-neighbor classifier \(f_\theta\) (resulting in a similar architecture as in ProtoNet [Snell et al., 2017]) and fine-tune this last layer. In this phase, we first calculate the
class prototypes \( c_n \) (embeddings) for class \( n \) using the encoder \( f_\theta \) on the support set \( S_n \):

\[
c_n = \frac{1}{|S_n|} \sum_{(x_i, y_i) \in S_n} f_\theta(x_i).
\]

These prototypes are then used to initialize the classifier \( f_\theta \) following [Medina et al., 2020].

### 3 Experimentation

In this section, we first discuss our experimental setup; we then present our numerical results.

#### 3.1 Experimental Setup

**Datasets.** We conduct several in-domain experiments to benchmark \( C^3 \)LR. For this purpose, we make use of commonly adopted datasets Omniglot [Lake et al., 2015] and mini-Imagenet [Vinyals et al., 2016] to compare against unsupervised few-shot learning approaches. Omniglot contains 1623 different handwritten characters borrowed from 50 unique alphabets out of which we use 1028 characters for training, 172 for validation and 423 for testing. We resize the grayscale images to \( 28 \times 28 \) pixels. Mini-ImageNet contains 100 classes with 600 samples in each class amounting to a total of 60,000 images that we resize to \( 84 \times 84 \) pixels. Out of the 100 classes, we use 64 classes for training, 16 for validation and 20 for testing. For both datasets, the settings are the most commonly adopted ones in literature [Vinyals et al., 2016, Medina et al., 2020, Ji et al., 2019, Khodadadeh et al., 2019]. The augmentations (in \( \mathcal{A} \)) used for the experiments follow [Medina et al., 2020]. We also compare our method on a more challenging cross-domain few-shot learning (CDFSL) benchmark [Guo et al., 2019]. This benchmark consists of four datasets with increasing similarities to mini-ImageNet. In that order, we have grayscale chest X-ray images from ChestX [Wang et al., 2017], dermatological skin lesion images from ISIC2018 [Codella et al., 2019], satellite aerial images from EuroSAT [Helber et al., 2017], and crop disease images from CropDiseases [Mohanty et al., 2016]. We also use Caltech-UCSD Birds (CUB) dataset [Wah et al., 2011] for further analysis of cross-domain performance. CUB is composed of 11,788 images from 200 unique bird species. We use 100 images for training, 50 for validation and 50 for test.

**Training.** The Conv4 model [Vinyals et al., 2016] is pre-trained on the respective training splits of the datasets, with an initial learning rate of 0.001, multiplied by 0.5 every 25,000 steps via the Adam optimizer [Kingma and Ba, 2014]. Based on the derivations in [Snell et al., 2017] and similar usage in [Medina et al., 2020], we initialize the classification layer \( f_\theta \) with weights set to \( W_n = 2c_n \) and biases set to \( b_n = -\|c_n\|^2 \). For validation, we create 15 (\( N \)-way, \( K \)-shot) tasks using the validation split from which the corresponding validation accuracy and loss are calculated. Experiments involving CDFSL benchmark follow [Guo et al., 2019, Medina et al., 2020], where we pre-train a ResNet10 encoder using \( C^3 \)LR on mini-ImageNet images of size \( 224 \times 224 \) for 400 epochs with the Adam optimizer and a constant learning rate of 0.001.

**Evaluation scenarios and baseline.** Our testing scheme uses 600 test episodes on which the pre-trained encoder (using \( C^3 \)LR) is fine-tuned and tested. All our results indicate 95% confidence intervals over 3 runs with 600 test episodes. The standard deviation values are thus calculated according to the 3 runs to provide more solid measures for comparison. For our in-domain benchmarks, we test on (5-way, 1-shot) and (5-way, 5-shot) classification tasks. While our cross-domain testing is done using (5-way, 5-shot) and (5-way, 20-shot) classification tasks. We compare our performance with a suit of recent self-supervised few-shot baselines such as ProtoTransfer [Medina et al., 2020], UFLST [Ji et al., 2019], LASIUM [Khodadadeh et al., 2020] and CACTUS [Hsu et al., 2018], to name a few. Furthermore, we also compare with a set of supervised approaches (such as MAML [Finn et al., 2017], ProtoNet [Snell et al., 2017], etc.) the best performing of which are obviously expected to outperform ours as well as other self-supervised methodologies.

#### 3.2 Performance Evaluation

**In-domain evaluation.** Table 1 summarizes our performance evaluation results on Omniglot and mini-Imagenet datasets for (\( N \)-way, \( K \)-shot) scenarios with \( N = 5 \) and \( K = 1, 5 \). The top section compares the performance of the proposed approach (\( C^3 \)LR) with the most recent relevant self-supervised competitors. As can be seen, for Omniglot, we outperform ProtoTransfer [Medina et al., 2020] (which we build on) by about 1% in both \( K = 1, 5 \) shot scenarios. We score the second overall best in (5-way, 1-shot) falling behind UFLST [Ji et al., 2019]. For the mini-Imagenet benchmark, to our knowledge, we set a new SoTA outperforming ProtoTransfer by 2%+. Interestingly, our performance beats some of the supervised baselines (bottom section of the table) adopting similar encoder architecture Conv4 for mini-ImageNet and comes close to \( K = 5 \)-shot performances on Omniglot. Obviously, the SoTA supervised few-shot
We compare the performance against ProtoTransfer and two of its variants with UMTRA \cite{Khodadadeh et al., 2019} and find that we marginally come short of ProtoTransfer, for the other three datasets we outperform the second best competitor. The important message here is that the proposed approach enhances ProtoTransfer in generalizing to truly unseen domains.

| Method | (N, K) | Omniglot | mini-ImageNet |
|--------|--------|----------|---------------|
| CACTUs-MAML \cite{Hsu et al., 2018} | (5,5) | 68.84 ± 0.80 | 87.78 ± 0.50 |
| CACTUs-ProtoNet \cite{Hsu et al., 2018} | (5,5) | 68.12 ± 0.84 | 83.58 ± 0.61 |
| UMTRA \cite{Khodadadeh et al., 2019} | - | 83.80 | 95.43 |
| AAL-ProtoNet \cite{Antoniou and Storkey, 2019} | (5,5) | 84.66 ± 0.70 | 89.14 ± 0.27 |
| AAL-MAML++ \cite{Antoniou and Storkey, 2019} | (5,20) | 88.40 ± 0.75 | 97.96 ± 0.32 |
| UFLST \cite{Ji et al., 2019} | - | 97.03 | **99.19** |
| UDLA-ProtoNet \cite{Qin et al., 2020} | (5,5) | 83.26 ± 0.55 | 95.29 ± 0.22 |
| UDLA-MetaOptNet \cite{Hsu et al., 2018} | - | 94.46 ± 0.35 | 98.83 ± 0.12 |
| U-SoSN+ ArL \cite{Zhang et al., 2021} | (5,5) | 97.70 ± 0.29 | 99.28 ± 0.10 |
| LASIUM \cite{Khodadadeh et al., 2020} | - | 97.68 ± 0.07 | - |
| ProtoTransfer (L = 50) \cite{Medina et al., 2020} | (5,5) | 88.00 ± 0.64 | 96.48 ± 0.26 |
| ProtoTransfer (L = 200) | (5,5) | 88.37 ± 0.74 | 96.54 ± 0.41 |
| C\textsuperscript{3}LR (ours) | (5,1) | 89.30 ± 0.64 | 97.38 ± 0.23 |

Table 2: Accuracy (%± std.) for (N-way, K-shot) classification on mini-ImageNet with pre-training on CUB.

| Training | Testing |
|----------|---------|
| ProtoTransfer (L = 50) \cite{Medina et al., 2020} | ProtoTune \cite{Medina et al., 2020} |
| ProtoTransfer (L = 200) | ProtoTune |
| C\textsuperscript{3}LR (ours) | ProtoTune |

Table 3: Accuracy (%± std.) of (N-way, K-shot) classification on the CDFSL benchmark. Style: best and second best.

| Method (N, K) | ChestX | ISIC | EuroSAT | CropDiseases |
|--------------|--------|------|---------|--------------|
| UMTRA-ProtoNet \cite{Medina et al., 2020} | 24.94 ± 0.43 | 28.04 ± 0.44 | 39.21 ± 0.53 | 44.62 ± 0.49 |
| UMTRA-ProtoTune \cite{Medina et al., 2020} | 25.00 ± 0.43 | 30.41 ± 0.44 | 38.47 ± 0.55 | 51.60 ± 0.54 |
| ProtoTransfer \cite{Medina et al., 2020} | 26.71 ± 0.46 | 33.82 ± 0.48 | 45.19 ± 0.56 | 59.07 ± 0.55 |
| C\textsuperscript{3}LR (ours) | 26.00 ± 0.41 | 33.39 ± 0.47 | 45.93 ± 0.54 | 59.95 ± 0.53 |

Learning approaches have the advantage of having access to all the labels, as such due to the supervision signal, are expected to outperform the unsupervised approaches like ours.

**Cross-domain evaluation.** So far we have demonstrated that the proposed approach excels in in-domain scenarios. The next step is to assess the performance under more challenging cross-domain scenarios (Table 2 and Table 3) where we pre-train on a certain dataset in an unsupervised fashion, then fine-tune and test on a different dataset. Table 2 illustrates the results of a Conv4 encoder trained on CUB and tested on tasks derived from mini-ImageNet. Here again C\textsuperscript{3}LR shows a clear improvement of 3%+ compared to ProtoTransfer (with pre-training sample sizes L = 50, 200). The important message here is that the proposed approach enhances ProtoTransfer in generalizing to truly unseen data. To further investigate the performance on cross-domain scenarios, we next focus on CDFSL benchmark \cite{Guo et al., 2019} containing several datasets. Here, we pre-train on mini-ImageNet and fine-tune and test on ChestX \cite{Wang et al., 2017}, ISIC2018 \cite{Codella et al., 2019}, EuroSAT \cite{Helber et al., 2017}, and CropDiseases \cite{Mohanty et al., 2016}. We compare the performance against ProtoTransfer and two of its variants with UMTRA \cite{Khodadadeh et al., 2019} as pre-training strategy (all proposed in \cite{Medina et al., 2020}). We also compare with a couple of closely related supervised approaches from \cite{Guo et al., 2019}, for the sake of reference. As can be seen, except for ChestX where we marginally come short of ProtoTransfer, for the other three datasets we outperform the second best competitor.
(ProtoTransfer) by about 0.5%+ to 4.5%+ with the most significant improvement in the case of EuroSAT. Interestingly, once again the performance of C3LR is not far off that of the related supervised approaches (bottom of the table) even sometimes outperforming the supervised approaches especially in (5-way, 20-shot) scenarios.

4 Concluding Remarks

Inspired by the idea of using contrastive learning for unsupervised few-shot classification, we build upon the recently proposed idea of ProtoTransfer [Medina et al., 2020] by incorporating class cognizance through: (i) an unsupervised iterative re-ranking and clustering step, followed by (ii) an adjusted optimization loss formulation. We demonstrate that our proposed approach (C3LR) offers considerable performance improvement above its predecessor ProtoTransfer in both in/cross-domain few-shot classification scenarios setting a new SoTA in mini-ImageNet and CDFSL benchmarks.

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