POODLE: Improving Few-shot Learning via Penalizing Out-of-Distribution Samples

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Abstract

In this work, we propose to leverage out-of-distribution samples, i.e., unlabeled samples coming from outside target classes, for improving few-shot learning. Specifically, we exploit the easily available out-of-distribution samples (e.g., from base classes) to drive the classifier to avoid irrelevant features by maximizing the distance from prototypes to out-of-distribution samples while minimizing that to in-distribution samples (i.e., support, query data). Our approach is simple to implement, agnostic to feature extractors, lightweight without any additional cost for pre-training, and applicable to both inductive and transductive settings. Extensive experiments on various standard benchmarks demonstrate that the proposed method consistently improves the performance of pretrained networks with different architectures. Our code is available at https://github.com/lehduong/poodle.

1 Introduction

Learning with limited supervision is a key challenge to translate the research efforts of deep neural networks to real-world applications where large-scale annotated datasets are prohibitively costly to acquire. This issue has motivated the recent topic of few-shot learning (FSL), which aims to build a system that can quickly learn new tasks from a small number of labeled data.

A popular group of methods in FSL focus on strengthening the backbone network by various techniques, from increasing model capacity [6, 11], self-supervised learning (SSL) [18, 50, 64], to knowledge distillation (KD) [52]. With these techniques, few-shot methods are expected to learn better representations that are more robust and generalized. However, even if the network can discover visual features and semantic cues, few-shot learners have to deal with a key challenge - the ambiguity: as we have only a small amount of support evidence, there are multiple plausible hypotheses at the inference stage. Existing works, therefore, rely on the developed inductive bias of the network (during the pretraining stage), such as shape bias [46, 14], to reduce the hypothesis space.

In this work, we view the classification problem as conditional reasoning, i.e., “if X has P then X is Q”. Human beings are good at learning such inferences, thus quickly grasping new concepts with minimal supervision. More importantly, humans learn new concepts in context - where we have already had prior knowledge about other entities. According to mental models in cognitive science, when assessing the validity of an inference, one would retrieve counter-examples, i.e., which do not lead to the conclusion despite satisfying the premise [9, 13, 29, 54]. Thus, if there exists at least one of such counter-examples, the inference is known to be erroneous.

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Hence, we attempt to equip few-shot learning with the above ability so that it can eliminate incorrect hypotheses when learning novel tasks in a data-driven manner. Specifically, we leverage out-of-distribution data, \textit{i.e.}, samples belonging to classes separated from novel tasks\footnote{We use OOD samples and distractor samples interchangeably}, as counter-examples for preventing the learned prototypes from overfitting to their noisy features. To that end, when learning novel tasks, we adopt the \textit{large margin principle} in metric learning \cite{58} to encourage the learned prototypes to be close to support data while being distant from out-of-distribution samples.

Our approach is complementary to existing works in FSL and could be combined to advance the state of the art. Moreover, our method is agnostic to the backbone network; thus, it does not have the need of a training phase to adopt as in SSL and KD, while incurring just a little overhead at inference (for fine-tuning prototypes with approximately 200 gradient updating steps).

In summary, our contributions are as follows:

\begin{itemize}
    \item We propose a novel yet simple approach to learn the inductive bias of deep neural networks for FSL by leveraging out-of-distribution data. We empirically show that out-of-distribution data only require weak labels (\textit{i.e.}, in the form of whether a sample is in- or out-of-distribution) even in challenging problems such as cross-domain FSL.
    \item We introduce a new loss function to implement the above idea, which is applicable for both inductive and transductive inference. Our extensive experiments on different standard benchmarks show that the proposed approach consistently improves the performance of various network architectures.
    \item We validate the effectiveness of our method in various FSL settings, including cross-domain FSL.
\end{itemize}

\section{Related work}

Over the past few years, considerable amount of research efforts \cite{15, 16, 28, 33, 43, 55, 49, 63} have been invested in FSL. They can roughly be classified into two main categories: \textit{optimization-based} and \textit{metric-based} approaches. Optimization-based methods \cite{15, 16, 28, 33, 43} seek a meta-learner that can quickly adjust the parameters of another learner to a new task, given only a few support images. In particular, \cite{34, 15} propose learning to initialize a classifier whose parameters can be obtained with a small number of gradient updates on the novel classes. Metric-based approaches \cite{55, 49, 63} learn a task-agnostic embedding space for measuring the similarity between images. For example, Matching Networks \cite{55} utilizes a weighted nearest neighbor classifier, while Prototypical Networks \cite{49} uses the mean features of support images as the prototype for each class. Recently, DeepEMD \cite{63} adopts the Earth Mover’s distance to compute the distance between image patches as their distance.
We first define some notations used in the following sections. Let \( W = [w_0, \cdots, w_k] \in \mathbb{R}^{K \times D} \) be the weight matrix of the classifier, \( C_b \) and \( C_n \) are referred to as the source and target domains, respectively. More details of our baselines can be found in Section A.

**Self-supervised learning.** The goal of self-supervised learning is to learn representations from unlabeled data. For FSL, this could be achieved by combining the supervised main task with a self-supervised pretext task which includes predicting image rotations [19], predicting relative patch locations [12], or solving jigsaw puzzles [39]. A few works incorporating self-supervised learning for FSL have been developed recently, e.g., Gidaris et al. [18] suggest pre-training the embedding network by using a combination of supervised and self-supervised loss, i.e., predicting image rotations.

**Knowledge distillation.** Knowledge distillation is a machine learning technique that seeks to compress the knowledge contained in a larger model (teacher) into a smaller one (student). It was introduced by Bucilua et al. [4] and later adopted to deep learning by Hinton et al. [23]. Recently, Tian et al. [52] show that incorporating self-distillation into FSL can boost the performance by 1 – 2%.

**Transductive inference.** Transductive inference aims to leverage the query set (which can be seen as unlabeled data during inference) in addition to the labeled support set. Transductive approaches [38, 24, 42, 65, 2, 10] significantly outperform their inductive counterparts, which do not exploit the query set. For example, TPN [38] constructs a graph whose nodes are support and query images and propagates labels from the support to query images, while CAN [24] utilizes confidently classified query images as part of the support set. Recently, TIM [2] assumes a uniform distribution of novel classes, which is often the case for the current FSL benchmarks, and exploits that assumption for boosting the performance. Furthermore, [15, 51] can be considered as transductive methods since the information from query data is used for batch normalization.

In this paper, we improve the performance of the classifier on novel classes by introducing a novel loss function, which penalizes out-of-distribution samples. Our method is complementary to the above approaches and can be combined to establish a new state-of-the-art for FSL. As the time of camera-ready, we are aware of a concurrent work [8] that also leverages the distractor samples to refine the classifier in FSL. Contrast to that work, our loss function is inherently applicable to both inductive and transductive inference. Furthermore, we also discover the effectiveness of uniform random features, which obviates the need for accessible OOD samples for in-domain FSL.

### 3 Preliminary

We first define some notations used in the following sections. Let \((x, y)\) consist of a sample image \(x\) and its corresponding class label \(y\). Let \( D_b = \{(x_i, y_i)\}_{i=1}^{N_b} \) denote the labeled base samples used for feature pre-training. Next, we denote \( D_s = \{(x_i, y_i)\}_{i=1}^{N_s} \) and \( D_q = \{(x_i, y_i)\}_{i=1}^{N_q} \) as the labeled support samples and query samples respectively. Note that the labels for the query samples are only used for evaluation purposes. The support samples and query samples belong to the novel classes \( C_n \), which are separated from the base classes \( C_b \), i.e., \( C_b \cap C_n = \emptyset \). In few-shot learning, we aim to learn a classifier that exploits support data to predict labels for query samples. We use a pre-trained feature extractor, usually kept fixed, to produce input to the classifier.

In this work, we consider fine-tuning the classifier on the support set only (inductive learning) and on both the support and query set (transductive learning). We also consider both in-domain and cross-domain FSL. In the former, the novel classes \( C_n \) and the base classes \( C_b \) are from the same domain (e.g., images from Image-Net), while for the latter, \( C_n \) and \( C_b \) are from different domains and the domains of \( C_b \) and \( C_n \) are referred to as the source and target domains, respectively.

**Pretrained feature extractor.** Let \( f_b \) be the feature extractor trained on the base data with the standard cross-entropy loss, which we also refer as the “simple baseline”. We also seek to strengthen the baseline with orthogonal techniques such as self-supervised learning (SSL) [18, 50] and knowledge distillation (KD) [52]. With SSL, we employ the “rot baseline”, which is trained with the standard cross-entropy loss and an auxiliary loss to predict the rotation angles of the perturbed images. We further apply the born-again strategy [17] for the rot baseline in two generations to construct the “rot + KD baseline”. More details of our baselines can be found in Section A.

**Novel tasks inference.** In the few-shot scenario, we freeze the feature extractor \( f_b \) and train a classifier for each task. Let \( W = [w_0, \cdots, w_k] \in \mathbb{R}^{K \times D} \) be the weight matrix of the classifier,
We formulate the regularization as a new objective function for training. To capitalize on negative samples, we introduce our novel technique for few-shot learning namely Margin Nearest Neighbors (LMNN) [58, 58]. In these works, Weinberger et al. [58] propose a loss function with two competing terms to learn a distance metric for nearest neighbor classification: a “pull” term to penalize the large distance between the embeddings of two nearby neighbors, which likely belong to the same class, and a “push” term to penalize the small distance between the embeddings of samples of difference classes.

4 Proposed approach

We introduce our novel technique for few-shot learning namely Penalizing Out-Of-Distribution sampleLEs (POODLE). Specifically, we attempt to regularize few-shot learning and improve the generalization of the learned prototypes by leveraging prior knowledge of in- and out-of-distribution samples. Our definition is as follows. Positive samples are in-distribution samples provided in the context of the current task that includes both support and query samples. Negative samples, in contrast, do not belong to the context of the current task, and hence are out-of-distribution. Negative samples can either provide additional cues that reduce ambiguity, or act as distractors to prevent the learner from overfitting. Note that negative samples should have the same domain as positive samples so that their cues are insightful to the learner, but positive and negative samples are not required to have the same domain as the base data.

To effectively use positive and negative samples in few-shot learning, the following conditions must be met: 1) The regularization guided by out-of-distribution samples can be combined with traditional loss functions for classification; 2) The regularization should be applicable for both inductive and transductive inference; and 3) The requirement on negative data should be minimal i.e., does not need any sort of labels except for aforementioned conditions.

4.1 Refining prototype with distractor samples

We formulate the regularization as a new objective function for training. To capitalize on negative samples to reduce the ambiguity, we propose leveraging the large-margin principle as in Large Margin Nearest Neighbors (LMNN) [58, 58]. In these works, Weinberger et al. propose a loss function with two competing terms to learn a distance metric for nearest neighbor classification: a “pull” term to penalize the large distance between the embeddings of two nearby neighbors, which likely belong to the same class, and a “push” term to penalize the small distance between the embeddings of samples of difference classes.

In this work, we seek to learn prototypes for all categories instead of a distance metric. We do not have labels (i.e., categories) of all samples (e.g., transductive inference) but only the prior knowledge about whether a sample is in- or out-of-distribution. Thus, we adapt the above objective of margin maximization for these two groups, namely in- and out-of-distribution, with the distance function being the sum of distances from a sample to all prototypes. The goal is minimizing distances from positive samples to prototypes, while maximizing distances from negative samples to prototypes.
In our objective function, we keep the original “pull” term while introducing our new “push” term: we do not explicitly enforce large distances between positive samples and negative samples, but only attempt to maximize distances between prototypes and negative samples:

$$\mathcal{L}_{\text{naive}} = \sum_{i=1}^{N_{\text{pos}}} \sum_{k=1}^{K} \gamma \cdot d(w_k, x_i) - \sum_{j=1}^{N_{\text{neg}}} \sum_{k=1}^{K} \gamma \cdot d(w_k, x_j)$$  \hspace{1cm} (2)$$

Note that $\gamma$ is scaling factor of distance-based classifier as in Equation 1. However, this objective does not take into account class assignments for positive samples. To tackle this problem, we use weighted distances between prototypes and samples to simultaneously optimize both objectives:

$$\mathcal{L}_{\text{margin}} = \sum_{i=1}^{N_{\text{pos}}} \sum_{k=1}^{K} \gamma \cdot d(w_k, x_i) \mathcal{S}_G[p(k|x_i, W)] - \sum_{j=1}^{N_{\text{neg}}} \sum_{k=1}^{K} \gamma \cdot d(w_k, x_j) \mathcal{S}_G[p(k|x_j, W)]$$  \hspace{1cm} (3)$$

where $\mathcal{S}_G[\cdot]$ is the stop-gradient operator. Intuitively, the positive sample will “pull” the prototypes to its location proportional to its distance to the prototypes. Subsequently, the prototype of each class will move closer to the positive samples of that class. At the same time, the prototype is enforced to move away from the negative samples, thus discarding features that might lead to high similarity to out-of-distribution data.

We note that removing $\mathcal{S}_G[\cdot]$ in Equation 3 would result in a different underlying objective, which empirically leads to a decrease in performance. Particularly, the objective without stop-gradient will also be compounded of an auxiliary term for entropy maximization (see Section B). Thus, devoid of meticulous regularization would deteriorate the performance. The above observation is in line with Boudiaf et al. [2]. In summary, POODLE optimizes the classifier on novel tasks with the following objectives:

$$\mathcal{L}_{\text{POODLE}} = \mathcal{L}_{\text{ce}} + \alpha \cdot \mathcal{L}_{\text{pull}} - \beta \cdot \mathcal{L}_{\text{push}}$$  \hspace{1cm} (4)$$

where $\alpha$ and $\beta$ control the “push” and “pull” coefficients respectively and $\mathcal{L}_{\text{ce}}$ denotes the standard cross-entropy loss. To the best of our knowledge, the proposed objective is the first loss function (in test phase) that can be effective for both inductive and transductive inference. Please see the supplemental document for the pseudo-code (Section C).

4.2 On negative samples

Choice of negative samples. For in-domain FSL, we simply leverage the base data as negative samples. For cross-domain FSL, one approach would be using a set of samples drawn from classes that are disjoint to novel classes $C_u$ as negative examples. However, in some cases such negative examples might not be available. Thus, we consider another approach where we have a set of unlabeled data of a set of classes $C_u$ from the target domain ($C_u$ might overlap with $C_n$) as negative examples, similar to [40]. We name the above two approaches as disjoint and noisy negative sampling, respectively in the context of cross-domain FSL. Intuitively, when the number of categories of unlabeled data (i.e., $|C_u|$) grow larger, the noise of mixing positive and negative samples in noisy negative samples pool will be reduced.

The burden of additional data. It is worth pointing out that POODLE does not break the setup of FSL as it does not require any additional data of novel classes, thus, still has a few samples from novel tasks. As POOODLE obligates additional data in the form of OOD samples, one might ask how practical the algorithm is. For in-domain FSL, the negative samples can be easily obtained by adopting the training data as we already know $C_n \cap C_k = \emptyset$. Even in extreme case where we only have access to the pretrained models, we empirically find that ($\ell_2$-normalized) uniformly random noise can work surprisingly well (Section 4.3). For cross-domain FSL, even though POOODLE requires additional OOD data, we find that these samples can be: 1) noisy with both positive and negative samples; and 2) fairly efficient - in our experiments, we can “reuse” 400 OOD samples for all tasks, which is very efficient compared to other methods that might use up to 20% unlabeled data of training set [40].

4.3 Intriguing effectiveness of uniform random features

One caveat of POOODLE is the obligation of accessing to OOD samples. Fortunately, we find that POOODLE can use the uniform random features on the hypersphere as negative samples for in-domain
FSL. Particularly, we can uniformly sample latent vectors from $S^{D-1}$ as an alternative to the distractor samples from base training data, thus, eliminating the need for accessing to training data.

Our use of uniform distribution as negative examples is inspired by that feature uniformity is a desirable property for contrastive loss [56, 5], and so a good representation prefers such uniformity. The problem of uniformly distributing points on the unit hypersphere is related to minimizing pairwise loss [30, 1], which links well to the theory of supervised classification with softmax and cross-entropy (equivalent to minimizing pairwise loss or maximizing mutual information) [3, 44].

Therefore, using uniform distribution as negative samples works for in-domain FSL because they will approximate the features of samples from base training data. For cross-domain FSL, this approach will fail because random features (which are similar to samples from the training domain) have a large discrepancy with the target domain, thus, not inducing meaningful cues. Intuitively, the more similar between domains of OOD and test samples, the higher performance gain POODLE can achieve. Our experiments in Section 5.4 empirically prove aforementioned postulation.

5 Experiments

In this section, we conduct extensive experiments to demonstrate the performance gain of our method on standard inductive, transductive, cross-domain FSL. To demonstrate the robustness of our method across datasets/network architectures, we keep the hyperparameters fixed for all experiments.

5.1 Experimental setup

Datasets. We evaluate our approach on three common FSL datasets. The mini-Imagenet dataset [55] consists of 100 classes chosen from the ImageNet dataset [47] including 64 training, 16 validation, and 20 test classes with 60,000 images of size $84 \times 84$. The tiered-Imagenet [45] is another FSL dataset which is also derived from the ImageNet dataset with 351 base, 97 validation, and 160 test classes with 779,165 images of size $84 \times 84$. Caltech-UCSD Birds (CUB) has 200 classes split into 100, 50, 50 classes for train, validation and test following [6]. Furthermore, we also carry out experiments on iNaturalist 2017 (iNat) [53], EuroSAT [22], and ISIC-2018 (ISIC) [7] for the (extreme) cross-domain FSL. The description for these datasets can be found in the supplemental document (Section D.1).

Implementation details. We use ResNet12 as our feature extractor. It is a residual network [60] with 12 layers split into 4 residual blocks. For pre-training on the base classes, we train our backbones with the standard cross-entropy loss for 100 epochs. The optimizer has a weight decay of $5e^{-4}$, and the initial learning rate of 0.05 is decreased by a factor of 10 after 60, 80 epochs in mini-ImageNet and 60, 80, 90 epochs in tiered-ImageNet. We use the batch size of 64 for all the networks. For fine-tuning on the novel classes, we utilize Adam optimizer [31] with fixed learning rate of 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and do not use weight decay. The classifier is trained with 250 iterations. The coefficients of ‘push/pull’ loss are $\alpha = 1$ and $\beta = 0.5$ respectively. For negative samples, we randomly select $K = 400$ samples from the out-of-distribution samples pool for each novel task. We evaluate the performance of POODLE in 5-way-1-shot and 5-way-5-shot settings on 2000 random tasks with 15 queries each.

5.2 Standard FSL

We first experiment with the standard FSL setup (also known as in-domain FSL) in which the number of query samples is uniformly distributed among classes.

Evaluation with various baselines. Table 1 shows the results of our approach with various baselines, which described in Section 3, with the inductive inference (positive samples are support images). As can be seen, our approach consistently boosts the performance of all baselines by a large margin (1-3%). Interestingly, the POODLE-R variant outperforms the CE loss variant significantly and performs comparatively with the POODLE-B variant. We hypothesize that the normalized representations of the samples extracted from the base classes are uniformly distributed.

Table 2 demonstrates the efficacy of each loss term of POODLE in transductive inference (positive samples are support and query images). We can see that using the ‘pull’ loss with query samples
Table 1: Comparison to different baselines for the standard FSL (a.k.a in-domain FSL) on mini-ImageNet, tiered-ImageNet and CUB in the inductive setting with Resnet-12 as backbone. Here, POODLE-B and POODLE-R indicate that the negative samples are sampled from the base classes and the random uniform distribution respectively.

| Baseline | Variant | mini-ImageNet | tiered-ImageNet | CUB |
|----------|---------|---------------|----------------|-----|
|          |         | 1-shot | 5-shot | 1-shot | 5-shot | 1-shot | 5-shot | 1-shot | 5-shot |
| Simple   | CE Loss | 61.33  | 80.76  | 67.42  | 84.44  | 75.60  | 89.88  |
|          | POODLE-B | 63.79  | **81.41**  | 69.26  | 84.97  | 75.96  | **90.06**  |
|          | POODLE-R | **64.38**  | 81.35  | **69.34**  | **85.03**  | **76.22**  | 89.99  |
| Rot      | CE Loss | 64.57  | 82.89  | 68.26  | 85.09  | 76.39  | 91.10  |
|          | POODLE-B | 66.78  | **83.65**  | 69.74  | 85.45  | 77.26  | 91.30  |
|          | POODLE-R | **67.20**  | 83.54  | **69.86**  | **85.56**  | **77.35**  | **91.43**  |
| Rot + KD | CE Loss | 65.91  | 82.95  | 69.43  | 84.93  | 79.70  | 92.28  |
|          | POODLE-B | 67.50  | **83.71**  | 70.42  | **85.26**  | **80.23**  | **92.36**  |
|          | POODLE-R | **67.80**  | 83.50  | **70.47**  | **85.24**  | **80.05**  | **92.37**  |

improve the inductive baseline significantly, being as effective as other transductive algorithms. Combining with “push” term, the classifier is further enhanced.

We also conduct experiments with additional loss functions including self-supervised loss (SSL) and knowledge distillation (KD) in Figure 2a. Our approach consistently improves the generalization of all baselines without additional computation cost (in the training phase) as justified in Figure 2b. The improvement of POODLE on other backbones and datasets is reported in the supplemental document (Section D.2).

Comparison to the state-of-the-art approaches. We report the performance of our network in comparison with state-of-the-art methods in both transductive and inductive settings (with and without information from the query images) in Table 3. We can see that our approach remarkably improves the performance of the baseline and achieves a comparable performance with the state-of-the-art approaches in the tiered-ImageNet. In mini-ImageNet and CUB we significantly outperform the prior work in both inductive and transductive settings. Experimental results on other backbones are reported in the supplementary document (Section D.2).
Figure 2: (a) Effectiveness of our approach applied to standard FSL. (a) Our approach consistently yields accuracy gains on different backbones, in comparison with those obtained by self-supervised loss (SSL) and knowledge distillation (KD) in 5-way-1-shot protocol on mini-Imagenet with inductive setting. (b) Total time and memory cost (in training stage) when adopting SSL, KD, and our method. Note that we apply KD for $T = 2$ generation as in [52]. No large overhead is incurred in our method.

Table 3: Comparison to the state-of-the-art methods on mini-ImageNet, tiered-Imagenet and CUB using inductive and transductive settings. The results obtained by our models (blue pearl-shaded) are averaged over 2,000 episodes.

| Method                  | Transd. | Backbone | 1-shot | 5-shot | 1-shot | 5-shot | 1-shot | 5-shot |
|-------------------------|---------|----------|--------|--------|--------|--------|--------|--------|
| MAML [15]               | ResNet-18 | 49.6    | 65.7   | -      | -      | 68.4   | 83.5   |
| RelatNet [24]           | ResNet-18 | 52.5    | 69.8   | -      | -      | 68.6   | 84.0   |
| MatchNet [55]           | ResNet-18 | 52.9    | 68.9   | -      | -      | 73.5   | 84.5   |
| ProtoNet [49]           | ResNet-18 | 54.2    | 73.4   | -      | -      | 73.0   | 86.6   |
| Neg-cosine [36]         | ResNet-18 | 62.3    | 80.9   | -      | -      | 72.7   | 89.4   |
| MetaOpt [32]            | ResNet-12 | 62.6    | 78.6   | 66.0   | 81.6   | -      | -      |
| SimpleShot [57]         | ResNet-18 | 62.9    | 80.0   | 68.9   | 84.6   | 68.9   | 84.0   |
| Distill [52]            | ResNet-12 | 64.8    | 82.1   | 71.5   | 86.0   | -      | -      |
| Rot + KD + POODLE       | ResNet-12 | 67.80   | 83.72  | 70.42  | 85.26  | 80.23  | 92.36  |
| RelatNet + T [24]       | ResNet-12 | 52.4    | 65.4   | -      | -      | -      | -      |
| TPN [38]                | ResNet-12 | 59.5    | 75.7   | -      | -      | -      | -      |
| TEAM [42]               | ResNet-12 | 60.1    | 75.9   | -      | -      | -      | -      |
| Ent-min [10]            | ResNet-12 | 62.4    | 74.5   | 68.4   | 83.4   | -      | -      |
| CAN+T [24]              | ResNet-12 | 67.2    | 80.6   | 73.2   | 84.9   | -      | -      |
| LaplacianShot [65]      | ResNet-18 | 72.1    | 82.3   | 79.0   | 86.4   | 81.0   | 88.7   |
| TIM-GD [2]              | ResNet-18 | 73.9    | 85.0   | 79.9   | 88.5   | 82.2   | 90.8   |
| Simple + POODLE         | ResNet-12 | 74.21   | 83.71  | 78.72  | 86.57  | 87.04  | 91.84  |
| Rot + KD + POODLE       | ResNet-12 | 77.56   | 85.81  | 79.67  | 86.96  | 89.93  | 93.78  |

5.3 Cross-domain FSL

In this section, we conduct experiments to demonstrate the efficacy of our approach even with a challenging task: extreme cross-domain FSL as first introduced in [21, 40]. Many FSL algorithms are known to fail in such a challenging scenario [6].

Recall that we have two setups for cross-domain FSL (Section 4.2), in which cases, the negative samples are drawn from disjoint and noisy negative samples pool. Here, we provide the detailed setting of each scheme when transferring a network trained on mini-Imagenet to target domains. It is worth mentioning that we only consider inductive inference for comparison with prior work.

Disjoint negative samples. As mentioned before, we evaluate the results of cross-domain FSL on test split of these datasets while employing the train split to draw negative samples. Since the number of categories in EuroSAT and ISIC is relatively small (10 and 7 respectively) compare to the number...
Table 4: The results of the domain-shift setting from mini-Imagenet to CUB, iNat, ISIC, and EuroSAT with Rot + KD baseline. The results obtained by our models (blue pearl-shaded) are averaged over 2,000 episodes. The baselines with * notation show the results using the setup of disjoint negative samples, and the baselines without the * show the results using the setup of noisy negative samples.

| Baseline       | CUB 1-shot | CUB 5-shot | iNat 1-shot | iNat 5-shot | ISIC 1-shot | ISIC 5-shot | EuroSAT 1-shot | EuroSAT 5-shot |
|---------------|-----------|-----------|-----------|-----------|-----------|-----------|----------------|----------------|
| Transfer [40] | -         | -         | -         | -         | 30.71     | 43.08     | 60.73          | 80.30          |
| SimCLR [40]   | -         | -         | -         | -         | 26.25     | 36.09     | 43.52          | 59.05          |
| Transfer + SimCLR [40] | - | - | - | - | 32.63 | 45.96 | 57.18 | 77.61 |
| STARTUP (no SS) [40] | - | - | - | - | 32.24 | 46.48 | 62.90 | 81.81 |
| STARTUP [40] | -         | -         | -         | -         | 32.66     | 47.22     | 63.88          | 82.29          |
| Rot + KD + CE | 49.98     | 69.44     | 48.90     | 66.58     | 32.35     | 43.81     | 65.00          | 80.01          |
| Rot + KD + POODLE-R * | 50.04     | 69.78     | 48.94     | 66.87     | 32.21     | 43.87     | 63.97          | 79.85          |
| Rot + KD + POODLE-B * | 52.61     | 70.78     | 50.62     | 67.31     | 33.56     | 44.17     | 66.21          | 80.51          |

of “way” in novel task (5), we only concern with iNat and CUB. Precisely, we follow [6] and [57] to split CUB and iNat respectively.

**Noisy negative samples.** We assume that we have 20% unlabeled data from the target domain and the rest 80% of data is used for testing. Although a large number of classes are beneficial to POODLE as discussed above, we also carry out experiments with ISIC and EuroSAT to evaluate the performance of extreme cross-domain FSL with our approach.

From the Table 4 we can see that the improvement of POODLE with the disjoint negative samples (the bottom rows) and the noisy negative samples (the middle rows) when transferring knowledge from mini-ImageNet to iNat, CUB, ISIC, and EuroSAT. We can observe that despite the extreme gap between target/source domains and a very noisy mix of in- and out-of-distribution samples in negative samples pool (in case of EuroSAT and ISIC), POODLE can successfully boost the performance of baselines in all experiments. We also report the performance of other approaches, which have same setup as noisy negative samples, in Table 4.

5.4 Ablation study

In this section, we present results of some presentative ablation study to get more insight of POODLE behaviors. For more in-depth experiments, we refer reader to supplementary document.

5.4.1 The effect of domain discrepancy between positive-negative samples

Intuitively, the more similar between domains of OOD and test samples, the higher performance gain POODLE can achieve. To understand how our method works when OOD data is from various domains, we train our classifier and compare the performance when using random uniform distribution and other datasets as negative examples. The result of this experiment is reported in Table 5. We can observer that the more similar of OOD domain to test domain, the higher the performance gain we can achieve. Thus, we should always aim to leverage the OOD samples of test domain.

**On the performance of random features:** For in-domain FSL i.e., test domains are mini-Imagenet and tiered-Imagenet, using uniform examples has the best and second-best accuracy when tested on mini-ImageNet and tiered-ImageNet, respectively. As aforesaid, the uniform random features will reflect the distribution of mini-Imagenet samples (which the network is pre-trained on). Thus, random features are effective for in-domain FSL.

For cross-domain FSL, (i.e., test domains are CUB and EuroSAT), using random uniform features - which is approximately equal to using samples from mini-Imagenet - does not work because the discrepancy between the source and target domain is extremely large, e.g., animal (mini-Imagenet) vs satellite images (EuroSAT).
Table 5: Evaluating (simple) Resnet-12 trained on mini-Imagenet on different test/OOD domains in the 1-shot inductive protocol (10,000 episodes). random, mini, tiered, CUB, EuroSAT denote mini-Imagenet, tiered-Imagenet, CUB, EuroSAT dataset respectively. The OOD/test samples are drawn from the standard train/test split of each dataset, respectively. The 95% confidence interval is roughly 0.20 for all results.

| OOD domain | w/o OOD | random | mini | tiered | CUB | EuroSAT |
|------------|---------|--------|------|--------|-----|---------|
| **Test domain** | | | | | | |
| mini       | 61.63   | 64.30  | 64.08 | 63.72  | 62.71 | 61.76   |
| tiered     | 63.04   | 64.28  | 64.01 | 64.50  | 63.85 | 62.78   |
| CUB        | 48.55   | 48.88  | 49.01 | 49.10  | 51.40 | 49.18   |
| EuroSAT    | 65.18   | 63.85  | 64.58 | 64.25  | 64.70 | **66.04** |

Table 6: The results of the various approaches to learn a better classifier with pretrained Rot + KD baseline on mini-Imagenet. The results are obtained by averaging over 10,000 episodes.

| Method | 1-shot | 5-shot |
|--------|--------|--------|
| baseline | 66.32 ± 0.20 | 82.99 ± 0.13 |
| 1) w/ learning cosine classifier | 66.66 ± 0.20 | 82.84 ± 0.13 |
| 2) w/ naive OOD | 66.36 ± 0.20 | 83.08 ± 0.13 |
| 3) w/ large-margin w/o negative samples | 66.32 ± 0.20 | 83.01 ± 0.13 |
| 4) w/ label smoothing | 66.13 ± 0.20 | 80.81 ± 0.13 |
| POODLE-B | **67.84 ± 0.20** | **83.72 ± 0.13** |
| POODLE-R | **68.20 ± 0.20** | **83.60 ± 0.13** |

5.4.2 Comparison against simple approaches for enhance pretrained models

To better understand the effectiveness of our method, we also compare to four methods that learn better classifiers on novel classes with pre-trained features. The results are reported in Table 6.

1. Learning cosine classifier: The classifier in inference phase is fine-tuned using CE loss with the support samples of each task. In our experiments, this approach does not bring any meaningful improvement similar to [57].

2. Naive OOD: we fine-tune a \((k + 1)\)-way classifier with 1 additional class for OOD samples using CE loss. Naive OOD performs worse because the OOD samples are drawn from several classes of the training set, which are well-clustered and separated, we cannot find a "prototype" with a linear classifier to match all of them.

3. Large-margin w/o negative samples: only use push term in POODLE. This approach is not better than cosine-distance because the initialized prototype (mean of all samples from specific class) is already well-clustered and optimal *i.e.*, close to the ground-truth class prototype and far away from others for the observed samples.

4. Label smoothing: we use label smoothing for CE loss (ground-truth class has the probability of 0.9 and uniformly distribute 0.1 to the rest. This method does not work well because it only makes learned prototypes not be far away from samples from other classes.

6 Conclusions and future work

In this work, we have proposed the concept of leveraging out-of-distribution samples set to improve the generalization of few-shot learners and realize it by a simple yet effective objective function. Our approach consistently boosts the performance of FSL across different backbone networks, inference types (inductive/transductive), and the challenging cross-domain FSL.

Future work might seek to exploit different sampling strategies (*i.e.*, how to select negative samples) to further boost the performance and reduce time/memory complexity; another interesting direction is enhancing the robustness of the classifier when we have both positive and negative samples in the same sampling pool; leveraging domain adaptation to reduce the need of in-domain negative samples is also a promising research direction.
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A Baseline Implementation

Simple Baseline. As stated above, the simple baseline is constructed by training the feature extractor on base class with standard cross-entropy loss, which yields the objective function:

$$L^{\text{simple}} = L_{\text{class}}(\theta, \psi; D_b) = \frac{1}{N_b} \sum_{i=0}^{N_b} \sum_{j=0}^{|C_i|} y_{ij} \log p_{\psi}(j|f_\theta(x_i))$$

(5)

where $\theta$ and $\psi$ represent parameters of feature extractor and the linear classification, respectively.

Rotation Baseline. For SSL, we implement the "rotation baseline" (Rot baseline). In detail, during global classification training, we rotate each image with all predefined angles: $x'_i = T(x_i, r) \forall r \in R$ with $R = \{0^\circ, 90^\circ, 180^\circ, 270^\circ\}$ and enforce the encoder to recognize the correct translation. Thus, the combined objective function of this baseline can be defined as:

$$L^{\text{rot}} = L^{\text{simple}} + \lambda_{\text{ssl}} L_{\text{ssl}}(\theta, \phi; D_b, R)$$

(6)

Precisely, we utilize a separate classifier $g_b$ on top of feature extractor $f_\theta$ to predict the perturbation of images via cross-entropy loss with four classes corresponding to four possible translations similar to Gidaris et al. [18]. Accordingly, the SSL loss function $L_{\text{ssl}}$ is given by:

$$L_{\text{ssl}}(\theta, \phi; D_b, R) = \frac{1}{N_b|R|} \sum_{i=0}^{N_b} \sum_{j=0}^{|R|} \sum_{k=0}^{|R|} \mathbb{I}(k = j) \log p_{\phi}(k|f_\theta(x'_i))$$

(7)

Here, $\mathbb{I}(\cdot)$ is the indicator function and $p_{\phi}(\cdot|f_\theta)$ denotes the (predicted) probability of rotation angle.

Rotation + KD Baseline. The "rotation + kd baseline" (Rot + KD baseline) is constructed by combining knowledge distillation [23] with rotation classification. Explicitly, we first train the feature extractor following the configuration of rotation baseline, and then exert the born-again strategy [17] to perform knowledge distillation for $T$ generations. The loss function of this baseline is given by:

$$L^{\text{rot+kd}} = L^{\text{rot}} + \lambda_{\text{kd, class}} L_{\text{kd, class}}(\theta_t, \psi_t; D_b, \theta_{t-1}, \psi_{t-1}, \tau) + \lambda_{\text{kd, ssl}} L_{\text{kd, ssl}}(\theta_t, \phi_t; D_b, R, \theta_{t-1}, \phi_{t-1}, \tau)$$

(8)

The above objectives optimize $L_{\text{class}}$ and $L_{\text{ssl}}$ with both groundtruth labels along with the prediction from teacher models i.e., the model (of the same architecture) trained from the previous generation:

$$L_{\text{kd, class}}(\theta_t, \psi_t; D_b, \theta_{t-1}, \psi_{t-1}, \tau) = \frac{1}{N_b} \sum_{i=0}^{N_b} \sum_{j=0}^{|C_i|} p_{\psi_{t-1}}(j|f_{\theta_{t-1}}(x_i), \tau) \log p_{\psi_t}(j|f_{\theta_t}(x_i), \tau)$$

(9)

$$L_{\text{kd, ssl}}(\theta_t, \phi_t; D_b, R, \theta_{t-1}, \phi_{t-1}, \tau) = \frac{1}{N_b|R|} \sum_{i=0}^{N_b} \sum_{j=0}^{|R|} \sum_{k=0}^{|R|} p_{\phi_{t-1}}(k|f_{\theta_{t-1}}(x'_i), \tau) \log p_{\phi_t}(k|f_{\theta_t}(x'_i), \tau)$$

(10)

Following Tian et al. [52], we distill the network for $T = 2$ generations and use the last checkpoint of previous generation as the teacher for next generation. For simplicity, we set the hyperparameters $\lambda_{\text{ssl}} = \lambda_{\text{kd, ssl}} = \lambda_{\text{kd, class}} = 1$ and $\tau = 4$ for all experiments.

B On the importance of stop-gradient operator

In this section, we elaborate the bleak outcome when removing the stop-gradient operator of loss function in Equation 3. As discussed before, the soft-weight in "pull/push" loss terms should be used to guide the degree of force. Directly optimize these soft weights would lead to different underlying objective that jointly maximizing conditional entropy as we show below.

First, we define the objective function (for each positive/negative term) in Equation 3 as weighted distance loss:

$$L_{wd} = \sum_{k=1}^{K} \gamma \cdot d(w_k, x_i) S_G[p(k|x_i, W)]$$

(11)
Furthermore we define the log-sum-exp loss function as:

\[ \mathcal{L}_{lse} = - \log \sum_{k=1}^{K} \exp(-\gamma \cdot d(w_k, x_i)) \]  

(12)

**Lemma B.1.** The two loss function \( \mathcal{L}_{wd} \) and \( \mathcal{L}_{lse} \) have same set of solutions.

**Proof.** This can be proved by taking the gradient of two terms w.r.t. \( j \)th prototype. Particularly, the gradient of \( \mathcal{L}_{lse} \) w.r.t. \( w_j \) is given by:

\[
\frac{\partial \mathcal{L}_{lse}}{\partial w_j} = - \frac{1}{\sum_{k=1}^{K} \exp(-\gamma \cdot d(w_k, x_i))} \times \frac{\partial \sum_{k=1}^{K} \exp(-\gamma \cdot d(w_k, x_i))}{\partial w_j} 
\]

(13)

On the other hand, the gradient of \( \mathcal{L}_{wd} \) term w.r.t. to \( w_j \) is given by:

\[
\frac{\partial \mathcal{L}_{wd}}{\partial w_j} = p(j|x_i, W) \cdot \frac{\partial (\gamma \cdot d(w_j, x_i))}{\partial w_j} 
\]

(16)

Thus, both loss function should optimize the same underlying objective.

**Corollary B.1.1.** Taking out the stop-gradient operator in “weighted distance” loss results in a objective that jointly minimizing conditional entropy of label given raw features and weighted distance (i.e., the old loss function).

**Proof: We refer to this objective function as “Expected Distance” loss. We can prove above corollary by rewriting the objective function as below:

\[
\mathcal{L}_{wd} = \sum_{k=1}^{K} \gamma \cdot d(w_k, x_i) \cdot p(k|x_i, W) = - \sum_{k=1}^{K} p(k|x_i, W) \log \left[ \exp \left( -\gamma \cdot d(w_k, x_i) \right) \right] 
\]

(19)

\[
\mathcal{L}_{wd} = - \sum_{k=1}^{K} \left[ p(k|x_i, W) \log \frac{\exp(-\gamma \cdot d(w_k, x_i))}{\sum_{k'} \exp(-\gamma \cdot d(w_{k'}, x_i))} + p(k|x_i, W) \log \sum_{k'} \exp(-\gamma \cdot d(w_{k'}, x_i)) \right] 
\]

(20)

\[
\mathcal{L}_{wd} = \left( - \sum_{k=1}^{K} p(k|x_i, W) \log p(k|x_i, W) \right) - \log \sum_{k'} \exp \left( -\gamma \cdot d(w_{k'}, x_i) \right) 
\]

(21)

Using the Lemma B.1 and Equation 19, we can observe that without the stop-gradient operator, underlying objective combining empirical (Monte-Carlo) estimate of conditional entropy of label given extracted features and “weighted” distance (i.e., “old” loss).

**Discussion.** As noted by Bouffia et al. [2], optimizing the conditional entropy loss requires special scrutiny, since the optima could result in trivial solutions on the simplex vertices i.e., assigning all samples to a single class. Particularly, a small value of learning rate and fine-tuning the whole network (similar to [10]) are crucial to prevent dramatic deterioration in performance. In their experiments [2], they found that training the classifier with conditional entropy and cross-entropy loss significant decrease the performance of few-shot learner. Beside, utilizing the conditional entropy for “push” loss does not affect the performance of classifier since it does not lead to collapsed solutions.
C Pseudo Code

We provide the pseudo-code of POODLE in a coding style similar to Pytorch as in Algorithm 1.

Algorithm 1: PyTorch-style pseudocode for POODLE.

```python
# f: classifier
# support: support images
# support_labels: labels of support images
# query: query images
# alpha: weight of positive term
# beta: weight of negative term

# sample negative data
neg_data = sample_from_train_set()

# construct positive data
if transductive:
    n_support = support.size(0)
p_pos_data = concatenate([support, query])
else:
    pos_data = support

for i in range(n_steps):
    # compute logits
    pos_out = f(pos_data)
    neg_out = f(neg_data)

    # compute POODLE loss
    pull_loss = sum(pos_out * softmax(pos_out).detach())
    push_loss = sum(neg_out * softmax(neg_out).detach())
poodle_loss = alpha * pull_loss - beta * push_loss

    # compute CE loss
    ce_loss = sum(support_label * log_softmax(pos_out[:n_support]))
    loss = ce_loss + poodle_loss

    # optimization step
    loss.backward()
optimizer.step()
```

D Additional results

In this section, we provide more experimental results when applying POODLE for various network architectures and conducting ablation study to verify its effectiveness under numerous configurations. Note that by POODLE, we refer to POODLE-B i.e., negative samples are drawn from base classes, unless otherwise state.

D.1 Dataset

In this section, we briefly describe the datasets used for evaluating performance of cross-domain FSL below.

- iNatural-2017 [59]: This heavy-tailed dataset consists of 859,000 images from over 5,000 species of plants and animals. For disjoint negative sampling, we follow the meta-iNat benchmark [59, 57] i.e., splitting the dataset to 908 classes for sampling negative samples and 227 classes for evaluation.
- EuroSAT [22]: This dataset covers total 27,000 labeled images of Sentinel-2 satellite images, which consist of 10 classes and the patches measure 64 × 64 pixels.
- ISIC-2018 (ISIC) [7]: This dataset covers dermoscopic images of skin lesions. Precisely, we use the training set for task 3 (i.e., lesion disease classification), which contains 10,015 images with 7 ground truth classification labels.
It is worth mentioning that, for the sake of simplicity, we apply the same image transformation as in mini-Imagenet to these cross-domain datasets. Thus, the resolution of processed images of cross-domain datasets are $84 \times 84$ in our implementation. In contrast, the benchmark protocol using the image resolution of $224 \times 224$ [21]. A higher image resolution helps improve the performance of classifier significantly as we demonstrate in Section D.5.4. Nevertheless, POODLE successfully boosts the performance of all baselines in cross-domain FSL by a large margin.

D.2 Standard FSL

In this section, we provide the experimental results of backbones other than Resnet-12. Specifically, we consider widely adopted architectures, namely Conv-4-512 [55], WideResnet [62], Mobilenet [25], and Densenet [27]. Particularly:

- **Conv-4-512**: We follow [55] to implement this architecture. More concretely, it is consisted of 4 convolutional layers with hidden channels of 64 and the output dimension is 512.

- **WRN-28-10** [62]: We follow [48, 57] and use the wide residual network with 28 convolutional layers and widening factor of 10.

- **DenseNet-121** [27]: Similar to [57], we adopt the 121-layers architecture while removing the first two-down sampling layers and using the kernel size of $3 \times 3$ for the first convolutional layer.

- **MobileNet** [25]: We follow [57] and use the standard MobileNet for ImageNet [25] but remove the first two-down-sampling layers of the network.

For all aforementioned architectures, we adopt the same training configuration of Resnet-12 as described in Section 5, excepts for WRN-28-10 we use the batch size of 32 for all datasets. Beside that, we use the negative samples from base classes i.e., POODLE-B in all experiments unless otherwise stated.

Table 7 shows the improvement of POODLE with various backbones of different network architectures on mini-Imagenet. We can see that our approach consistently enhance the accuracy of all baselines by a large margin i.e., $2 - 4\%$ in 1-shot protocol and $0.5 - 1\%$ in 5-shot protocol.

In Table 8, we present the comparison between performance achieved by WRN-28-10 with our approach and other algorithms on mini- and tiered-Imagenet. It can be observed that combining POODLE with other techniques such as SSL and KD achieves comparable or outperform state-of-the-art techniques for both inductive/transductive inference on two datasets.

D.3 Results of reimplemented transductive algorithms

In this section, we report the accuracy of our reimplemented of transductive algorithms and their originally reported performance (balanced query set). In Table 9, we present the performance of our reproduced transductive algorithms (on Resnet-12). We can see that our implementation achieve comparable or higher accuracy than the original work even though we adopt the more efficient architecture (i.e., Resnet-12 compared to Densenet).

D.4 Imbalanced query set

So far, prior works in (transductive) FSL mainly concern with balanced query samples i.e., numbers of query images for each class are equal. However, in practice, there is no guarantee that this setting is hold. In this section, we conduct experiments to benchmark the performance of different transductive algorithms under class-skew i.e., imbalanced query data. We simulate the long-tail distribution of the query samples through the Dirichlet distribution. Precisely, for each novel task, we sample the number of queries for every category from a Dirichlet distribution with concentration $\kappa$ for all classes so that the total number of query images is always 75 (similar to the experiments in the previous section).

In the “pull” loss term, we employ a “soft” weights for minimizing distance between prototypes and samples without any explicit regularization for distance between prototypes. In conventional setup for transductive learning, the number of query samples of each category are uniformly distributed, hence, the positive samples of each category implicitly constrains the prototype by “pulling” corresponding prototype. Under an extremely imbalanced query set, the positive samples from the dominated class
Table 7: Comparison to different baselines for the standard FSL (a.k.a in-domain FSL) on mini-ImageNet with various network architectures. The results are evaluated with 10,000 random sampled tasks. The 95% confidence interval of 1-shot and 5-shot classification are roughly 0.2 and 0.1, respectively.

| Network  | Baseline | Variant   | Inductive 1-shot | Inductive 5-shot | Transductive 1-shot | Transductive 5-shot |
|----------|----------|-----------|------------------|------------------|---------------------|---------------------|
| WRN-28-10 | Simple   | CE Loss   | 61.23            | 81.08            | 61.23               | 81.08               |
|          |          | POODLE    | **64.94**        | **81.88**        | **71.49**           | **83.48**           |
|          |          | Rot       | 64.77            | 83.66            | 64.77               | 83.66               |
|          |          | POODLE    | **68.27**        | **84.45**        | **75.24**           | **85.95**           |
|          |          | Rot + KD  | 67.12            | 84.15            | 67.12               | 84.15               |
|          |          | POODLE    | **69.67**        | **84.84**        | **77.30**           | **86.34**           |
| DenseNet-121 | Simple   | CE Loss   | 64.88            | 81.99            | 64.88               | 81.99               |
|          |          | POODLE    | **66.53**        | **82.55**        | **75.55**           | **84.62**           |
|          |          | Rot       | 66.51            | 83.92            | 66.51               | 83.92               |
|          |          | POODLE    | **68.68**        | **84.52**        | **77.85**           | **86.49**           |
|          |          | Rot + KD  | 68.66            | 84.17            | 68.66               | 84.17               |
|          |          | POODLE    | **70.29**        | **84.80**        | **78.57**           | **84.49**           |
| Conv-4-512 | Simple   | CE Loss   | 50.90            | 70.44            | 50.90               | 70.44               |
|          |          | POODLE    | **53.60**        | **71.08**        | **58.61**           | **72.78**           |
|          |          | Rot       | 51.36            | 70.81            | 51.36               | 70.81               |
|          |          | POODLE    | **54.04**        | **71.69**        | **58.84**           | **73.24**           |
|          |          | Rot + KD  | 51.46            | 70.42            | 51.46               | 70.42               |
|          |          | POODLE    | **53.87**        | **71.36**        | **58.50**           | **72.87**           |
| MobileNet | Simple   | CE Loss   | 60.99            | 77.45            | 60.99               | 77.45               |
|          |          | POODLE    | **61.75**        | **77.87**        | **70.63**           | **80.04**           |
|          |          | Rot       | 64.57            | 80.86            | 64.57               | 80.86               |
|          |          | POODLE    | **65.45**        | **81.37**        | **74.81**           | **83.50**           |
|          |          | Rot + KD  | 65.41            | 80.60            | 65.41               | 80.60               |
|          |          | POODLE-I  | **66.02**        | **81.18**        | **74.55**           | **83.09**           |

might pull all the prototypes to their region by learning similar features of samples from different classes. In that case, increasing the value of $\beta$ to prevent the collapsed solution is necessary.

Table 10 presents the results of different transductive learning algorithms under the imbalanced query set. The detailed performance of the reproduced algorithms compared to the original papers are reported in Section D.3. The coefficient of “push” term is set to $\alpha = 1$. Since TIM [2] explicitly use the uniform distribution information of samples in the query set, its performance drastically drops in the imbalanced FSL. Other variants of K-means are more robust to the long-tail distribution, but they are far inferior to POODLE with $\beta = 0.75$.

D.5 Ablation study

D.5.1 Removing stop-gradient operator

As discussed before in Section B, the stop-gradient operator is of paramount important to avoid trivial solutions. In this section, we consider different choice of usage of the stop-gradient operator namely not using it in both “push/pull” terms, use only with one of two term, and use it for both terms in Table 11.

From the table, we can see that the stop-gradient operator does not affect the performance much in inductive inference. It can be explained as the posterior distribution of support data already has a high probability for “correct” classes and the conditional entropy term does not affect much. In
Table 8: Comparison to the state-of-the-art methods on mini-ImageNet, and tiered-Imagenet using inductive and transductive settings on WRN-28-10. The results obtained by our models (pear-shaded) are averaged over 10,000 episodes.

| Method                  | Transd. | mini-ImageNet 1-shot | mini-ImageNet 5-shot | tiered-ImageNet 1-shot | tiered-ImageNet 5-shot |
|-------------------------|---------|----------------------|----------------------|------------------------|------------------------|
| LEO [48]                |         | 61.8                 | 77.6                 | 66.3                   | 81.4                   |
| SimpleShot [57]         |         | 63.5                 | 80.3                 | 69.8                   | 85.3                   |
| MatchNet [55]           | x       | 64.0                 | 76.3                 | -                      | -                      |
| CC+rot+unlabeled [18]  |         | 64.0                 | 80.7                 | 70.5                   | 85.0                   |
| FEAT [61]               |         | 65.1                 | 81.1                 | 70.4                   | 84.4                   |
| Simple                  |         | 61.23                | 81.08                | 67.63                  | 83.93                  |
| Simple + POODLE         |         | 64.94                | 81.88                | 70.25                  | 84.64                  |
| Rot + KD                |         | 67.12                | 84.15                | -                      | -                      |
| Rot + KD + POODLE       |         | **69.67**            | **84.84**            | -                      | -                      |
| AWGIM [20]              |         | 63.1                 | 78.4                 | 67.7                   | 82.8                   |
| Ent-min [10]            |         | 65.7                 | 78.4                 | 73.3                   | 85.5                   |
| SIB [26]                |         | 70.0                 | 79.2                 | -                      | -                      |
| BD-CSPN [37]            |         | 70.3                 | 81.9                 | 78.7                   | 86.92                  |
| LaplacianShot [65]      | ✓       | 74.9                 | 84.1                 | 80.2                   | 87.6                   |
| TIM-ADM [2]             |         | 77.5                 | 87.2                 | 82.0                   | 89.7                   |
| TIM-GD [2]              |         | **77.8**             | **87.4**             | **82.1**               | **89.8**               |
| Simple + POODLE         |         | 71.49                | 83.48                | 76.27                  | 85.83                  |
| Rot + KD + POODLE       |         | 77.30                | 86.34                | -                      | -                      |

Table 9: Results of our implementations of various transductive methods compared to original works on mini-ImageNet. The results of our implementations (pear-shaded) are evaluated on Resnet-12 + Rot + KD baseline with 2,000 random sampled tasks.

| Methods             | Network    | 1-shot        | 5-shot        |
|---------------------|------------|---------------|---------------|
| Mean-shift          | Resnet-12  | 73.49 ± 0.55  | 84.24 ± 0.32  |
| Mean-shift [35]     | DenseNet-121 | 71.39 ± 0.27  | 82.67 ± 0.15  |
| Bayes k-means       | Resnet-12  | 71.40 ± 0.50  | 83.79 ± 0.31  |
| Bayes k-means [35]  | DenseNet-121 | 72.05 ± 0.24  | 80.34 ± 0.17  |
| Soft k-means        | Resnet-12  | 74.55 ± 0.49  | 84.53 ± 0.30  |
| Soft k-means [45]   | Conv-4-64  | 50.09 ± 0.45  | 64.59 ± 0.28  |
| CAN_T               | Resnet-12  | 71.04 ± 0.53  | 84.21 ± 0.30  |
| CAN_T [24]          | Resnet-12  | 67.19 ± 0.55  | 80.64 ± 0.35  |
| TIM                 | Resnet-12  | 77.69 ± 0.55  | 87.40 ± 0.29  |
| TIM [2]             | Resnet-18  | 73.90 ± n/a   | 85.00 ± n/a   |

transductive inference, removing the stop-gradient operator on “pull” term results in noticeable decrease in accuracy as we articulate in Section B. On the other hand, taking out stop-gradient operator on “push” term does not worsen the performance since it does not lead to trivial solutions.

D.5.2 Sensitive to $\alpha$ and $\beta$

So far, we only fixed the coefficient of “push/pull” loss with $\alpha = 1$ and $\beta = 0.5$, we now consider different configurations of these parameters to understand the sensitive of POODLE to these hyperparameters. Precisely, we report the accuracy gain of POODLE with different combination of $\alpha$ and $\beta$ taken from the list $[0.0, 0.25, 0.5, 0.75, 1.0, 2.0, 5.0]$ as in Figure 3.

We can observe from Figure 3 that POODLE is robust to the change of $\alpha$ and $\beta$: the accuracy of network is improved as long as the value of $\alpha$ is larger than $\beta$. Furthermore, the improvement in accuracy usually does not change much when varying $\alpha$ and $\beta$.
Table 10: Results of transductive learning on imbalance query data of mini-ImageNet. The results obtained by our models (blue pearl-shaded) are averaged over 2,000 episodes. $\kappa$ denotes the concentration parameter of the Dirichlet distribution.

| Methods      | $\kappa = 0.5$ | $\kappa = 1$ | $\kappa = 2$ | $\kappa = 5$ |
|--------------|----------------|--------------|--------------|--------------|
|              | 1-shot | 5-shot | 1-shot | 5-shot | 1-shot | 5-shot | 1-shot | 5-shot |
| Inductive    | 66.91  | 82.75  | 66.16  | 82.62  | 66.10  | 83.01  | 66.23  | 83.16  |
| Mean-shift [35] | 68.88  | 80.54  | 70.31  | 81.82  | 71.78  | 83.16  | 72.92  | 83.98  |
| Bayes k-means [35] | 69.69  | 82.86  | 69.91  | 82.95  | 70.64  | 83.54  | 71.39  | 83.83  |
| Soft k-means [45] | 65.31  | 75.65  | 68.61  | 78.90  | 71.56  | 84.06  | 71.18  | 84.25  |
| CAN_T [24]  | 72.30  | 83.53  | 71.28  | 83.62  | 71.09  | 84.06  | 71.18  | 84.25  |
| TIM [2]     | 47.65  | 52.79  | 54.86  | 61.32  | 61.84  | 68.73  | 68.74  | 76.39  |

$\kappa = 0.5$

POODLE-B $\beta = 0.00$ | 61.16  | 76.40  | 66.02  | 79.88  | 70.03  | 82.43  | 73.03  | 84.23  |
POODLE-B $\beta = 0.50$ | 64.56  | 81.01  | 69.14  | 83.63  | 72.91  | 85.14  | 75.79  | 85.78  |
POODLE-B $\beta = 0.75$ | 75.20  | 86.51  | 74.06  | 86.17  | 74.77  | 86.48  | 74.74  | 86.34  |
POODLE-B $\beta = 1.00$ | 75.48  | 88.36  | 71.14  | 86.31  | 70.20  | 85.53  | 68.94  | 84.31  |

Table 11: Results of different settings of stop-gradient in push and pull terms. The results are evaluated with 2,000 random sampled tasks on Resnet-12 with Rot + KD baseline. The 95% confidence interval of 1-shot and 5-shot classification are roughly 0.45 and 0.3 for inductive setting and 0.6 and 0.4 for transductive, respectively. Results of inductive baseline for 1-shot and 5-shot are 66.32 ± 0.20 and 82.99 ± 0.13, respectively.

| Method   | Stop-grad | Inductive | Transductive |
|----------|-----------|-----------|--------------|
|          | Push | Pull | 1-shot | 5-shot | 1-shot | 5-shot | 1-shot | 5-shot |
| POODLE-B | ✓    | ✓    | 67.52  | 83.71  | 77.58  | 85.87  |
|          | ✓    | ✓    | 67.50  | 83.56  | 62.04  | 82.87  |
|          | ✓    | ✓    | 67.37  | 83.73  | 78.51  | 86.28  |
|          | ✓    | ✓    | 67.37  | 83.64  | 72.04  | 85.08  |
| POODLE-R | ✓    | ✓    | 67.80  | 83.50  | 77.25  | 85.52  |
|          | ✓    | ✓    | 67.80  | 83.39  | 66.55  | 83.65  |
|          | ✓    | ✓    | 67.77  | 83.43  | 78.11  | 85.83  |
|          | ✓    | ✓    | 67.77  | 83.36  | 73.29  | 84.77  |

D.5.3 Number of sampled negative data

Intuitively, a larger number of negative samples will provide more informative cues to the classifier, however, they might require a notable memory footprint and have significant latency. We conduct experiment to quantify the impact of number of negative samples to the accuracy of POODLE in Table 12. These results indicate that higher number of negative samples consistently leads to better performance, however, the gain in accuracy is relatively small.

Table 12: Results of our methods with different number of out-of-distribution samples per task. The results are evaluated with 10,000 random sampled tasks on Resnet-12 with Rot + KD baseline. The 95% confidence interval of 1-shot and 5-shot classification are roughly 0.20 and 0.10 for both inductive and transductive inference. Results of inductive baseline for 1-shot and 5-shot are 66.32 ± 0.20 and 82.99 ± 0.13, respectively.

| Number of negative samples | 1-shot | 5-shot | 1-shot | 5-shot |
|----------------------------|--------|--------|--------|--------|
| 50                         | 67.61  | 77.38  | 83.54  | 85.56  |
| 100                        | 67.71  | 77.61  | 83.62  | 85.64  |
| 200                        | 67.77  | 77.69  | 83.69  | 85.70  |
| 500                        | 67.84  | 77.73  | 83.71  | 85.73  |
Figure 3: Ablation study on the affect of positive and negative coefficient of POODLE (i.e., $\alpha$ and $\beta$) to accuracy gain of (simple baseline) ResNet-12 on mini-Imagenet compared to no fine-tuning at all with 10,000 random tasks. The baseline where we directly assign the prototype of each class to the mean of its support images obtains accuracy of 61.63 ± 0.20 and 80.78 ± 0.11 for 1-shot and 5-shot classification, respectively.

### D.5.4 Higher image resolution

Existed works in FSL usually employ the standard image pre-processing schemes such as resizing to $84 \times 84$ pixels. We consider using a slightly different setup where we resize the image to a higher resolution than 84 during training and testing. We keep all other hyper-parameters and configurations as in simple baseline. We report the accuracy of these models with POODLE in both inductive and transductive inference in Table 13. It can be observed that the higher resolution usually leads to better performance. Nevertheless, POODLE successfully raises the accuracy in all cases up to 5% in inductive 1-shot classification.

### D.5.5 Different number of finetuning steps

In previous experiments, we fixed the number of fine-tuning steps when employing POODLE with $T = 250$ steps. We now consider different numbers of fine-tuning steps and evaluate its impact on the final performance of the classifier. Particularly, we report the accuracy of the classifier fine-tuned with POODLE and standard cross-entropy loss with various number of steps in Table 14. In our experiments, we find that POODLE is not sensitive to number of gradient updates and do not requires a high number of steps to achieve good performance. This finding allows us to accelerate the fine-tuning steps and reduce the computational cost for inference phase.
Table 13: Comparing the performance of simple baseline on mini-Imagenet with different image resolutions. POODLE-I and POODLE-T indicate the result of our algorithm in inductive and transductive inference. The results are evaluated with 10,000 random sampled tasks. The 95% confidence interval of 1-shot and 5-shot classification are roughly 0.2 and 0.1, respectively. **Bold** numbers indicate significant improvement (i.e., p-value ≤ 0.05) compared to weakest corresponding entries.

| Network  | Resolution | CE Loss | 1-shot | 5-shot |
|----------|------------|---------|--------|--------|
|          |            | POODLE-I | POODLE-T | POODLE-I | POODLE-T |
| Resnet-12 | 84 × 84 | 61.63 | 64.08 | 74.46 | 80.78 | 81.41 | 83.70 |
|          | 140 × 140 | 62.66 | 65.90 | 75.08 | 82.06 | 82.89 | 84.88 |
|          | 180 × 180 | **64.85** | 67.05 | **76.17** | 82.52 | 83.19 | **85.31** |
|          | 224 × 224 | 62.90 | **67.22** | 74.46 | **82.59** | **83.61** | 85.23 |
| WRN-28-10 | 84 × 84 | 61.23 | 64.94 | **71.49** | 81.08 | 81.88 | 83.48 |
|          | 140 × 140 | **61.76** | 66.27 | 71.23 | **81.73** | **82.70** | **84.05** |
|          | 180 × 180 | 61.72 | **66.34** | 70.61 | 81.67 | 82.65 | 83.90 |

Table 14: Results of our methods with different number of update iterations. The results are evaluated with 2,000 random sampled tasks on Resnet-12 with Rot + KD baseline. The 95% confidence interval of 1-shot and 5-shot classification are roughly 0.45 and 0.3 for inductive setting and 0.5 and 0.3 for transductive, respectively. Results of inductive baseline for 1-shot and 5-shot are 65.91 ± 0.44 and 82.95 ± 0.30, respectively. **Bold** numbers indicate significant improvement (i.e., p-value ≤ 0.05) compared to weakest corresponding entries.

| Finetuning steps | CE Loss | 1-shot | 5-shot |
|------------------|---------|--------|--------|
|                  | POODLE-I | POODLE-T | POODLE-I | POODLE-T |
| 50               | 66.18 | 67.61 | 74.75 | **83.05** | 83.72 | 85.57 |
| 100              | 66.17 | 67.54 | 77.03 | 82.94 | 83.71 | 85.78 |
| 250              | 66.17 | 67.52 | 77.58 | 82.76 | 83.69 | 85.87 |
| 400              | 66.17 | 67.49 | **77.63** | 82.68 | 83.70 | 85.87 |