Self-Augmentation: Generalizing Deep Networks to Unseen Classes for Few-Shot Learning

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Abstract

Few-shot learning aims to classify unseen classes with a few training examples. While recent works have shown that standard mini-batch training with a carefully designed training strategy can improve generalization ability for unseen classes, well-known problems in deep networks such as memorizing training statistics have been less explored for few-shot learning. To tackle this issue, we propose self-augmentation that consolidates regional dropout and self-distillation. Specifically, we exploit a data augmentation technique called regional dropout, in which a patch of an image is substituted into other values. Then, we employ a backbone network that has auxiliary branches with its own classifier to enforce knowledge sharing. Lastly, we present a fine-tuning method to further exploit a few training examples for unseen classes. Experimental results show that the proposed method outperforms the state-of-the-art methods for prevalent few-shot benchmarks and improves the generalization ability.

1. Introduction

Deep networks have achieved remarkable performance in classification problems [15, 29, 35, 11]. Assuming a large-scale training dataset is available, most researchers focus on training deep networks on base classes to test unseen images of trained classes. However, there is a growing interest in mimicking human abilities such as generalizing a recognition system to classify classes that have never been seen before. In particular, few-shot learning assumes only a few training examples are available for the unseen classes. This is a challenging problem since it is highly possible that a few training examples will lead to network overfitting.

One paradigm for this challenge is meta-learning [39, 30, 6], where a large-scale training set for base classes is divided into several subsets (typically called tasks) and the network learns how to adapt to those tasks. In each task, only a few training examples are given for each class to mimic the environment of a test set for unseen classes.

Meanwhile, recent works have shown that a network trained with standard supervision can produce reasonable performance on unseen classes [19, 7, 5]. In the training phase, this paradigm trains a network using a mini-batch sampled from a large-scale training dataset. In the test phase, unseen classes with a few training examples are evaluated using the same network. Thus, the goal is to develop a framework that is generalizable to unseen classes by fully utilizing the knowledge learned through base classes.

Both paradigms share commonalities in that they leverage a large annotated collection. However, the following notable difference exists: Meta-learning learns to adapt quickly to new tasks by splitting base classes into several different tasks, whereas the standard supervision constructs a parameter space in which the unseen classes can be identified using only the information for classifying the base classes at once. While the latter paradigm is closely related to classifying the unseen images belonging to the base classes, only a few studies have taken advantage of lessons learned from the classical classification problem [19, 7, 5].

To tackle this issue, we take a closer look at the generalization ability of deep networks. It is known that deep networks tend to have almost zero-entropy distributions as the softmax output produces one peaked value for a class [38]. This overconfidence can occur even with randomly labeled training data as deep networks are likely to just memorize the training statistics [36]. In our problem setting, this memorization property directly affects the performance on unseen classes as we rely heavily on the network ability trained on the dataset of base classes. The problem

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even worsens as we cannot apply a simple transfer learning strategy given that we have only a few training examples for unseen classes. Thus, to overcome the memorization issues, it is important to induce uncertainty in predictions about input images and regularize the posterior probability [23, 4, 42, 45].

With this in mind, we propose self-augmentation that incorporates regional dropout and knowledge distillation to improve the generalization ability\(^1\) for few-shot learning. Here, we use the self-augmentation term as we use input and output resources of the network itself to augment the the generalization ability. Specifically, as one of the data augmentation techniques, we employ regional dropout, which substitutes a patch of an input image into other values such as zeros [4], a patch of another image [42], and another patch of the input image. We call the last regional dropout “self-mix” as it exchanges different patches of the input image itself. With this dropout effect, the generalization ability can be improved as it prevents us from learning specific structures of a dataset. However, we found that an explicit regularization for the posterior probability is necessary to search for a proper manifold for unseen classes. To be specific, we utilize a backbone network that has auxiliary branches with its own classifier to enforce knowledge sharing. This sharing of knowledge forces each branch not to be over-confident in its predictions, thus improving the generalization ability. Cooperating with regional dropout, the experimental results show that knowledge distillation significantly boosts the performance on unseen classes. More importantly, we also show that learning base classes with the proposed framework leaves the calibration property to the classifiers of unseen classes without further training.

Lastly, we present a fine-tuning method to exploit a few training examples given for unseen classes. As we train a network on base classes, we have the opportunity to improve the discriminative ability of the network for unseen classes using only 1 or 5 training examples.

To sum up, our main contributions are as follows:

1) We present self-augmentation as a training framework to mitigate the memorization phenomenon of deep networks. Specifically, we design consolidating regional dropout and knowledge distillation, which are less explored in the few-shot learning area.

2) We show that the newly proposed regional dropout, called self-mix, produces state-of-the-art results when cooperating with knowledge distillation.

3) We verify that learning base classes with the proposed method leaves the calibration property to the classifiers of unseen classes without further training. To the best of our knowledge, this property transition has not been explored in the previous researches for few-shot learning.

4) Lastly, we present a novel fine-tuning method to exploit a few training examples of unseen classes, and show that the method improves the performance for all the few-shot learning benchmarks.

2. Related Work

Few-Shot Learning. The literature on few-shot learning considers training and test datasets that are disjoint in terms of classes. Depending on how the training set is handled, we can categorize it into two main branches: meta-learning and standard supervised learning.

Meta-learning approaches train a network by explicitly emulating the test environment for few-shot learning. Using a training dataset, \(n\) classes are randomly chosen with \(k\) training examples, and \(T\) queries are also randomly picked. Then, learnable parameters are obtained from the \(n \cdot k\) training examples, and a loss is generated using the \(T\) queries. A network is learned to reduce the loss by repeating this task several times. As a result, meta-learning warms a network up to classify unseen classes with a few examples. Three approaches exist for this paradigm: 1) Metric-learning to reduce the distance among features of different classes [30, 39, 34, 22, 18], 2) optimization-based approaches to initialize a parameter space so that a few training examples of unseen classes can be quickly trained with the cross-entropy loss [6, 28, 33], and 3) weight generation methods to directly generate classification weights used for unseen classes [8, 9, 24].

In contrast, the standard supervised learning trains a network as usual without splitting a training dataset into several tasks. In other words, this approach utilizes the training dataset as in the classical classification problem, but it aims to generalize unseen classes. To achieve this, dense classification applies the classification loss to all spatial information of an activation map to maximally exploit local information [19]. A previous study used self-supervision and showed that the auxiliary loss without labels can extract discriminative features for few-shot learning [7]. An ensemble method using multiple networks was also proposed to resolve the high-variance issue in few-shot learning [5].

Generalization. Many efforts have been made to understand the generalization performance of deep learning [43, 10, 23, 2, 38, 21, 36, 45]. Notably, it has been shown that deep networks easily adapt to random labels and are even well trained for images that appear as nonsense to humans [43]. Along the same lines, many works have found that deep networks produce overconfident

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\(^1\)Henceforth, we denote the term “generalization” as the ability to adapt to unseen classes, given a network trained on base classes.
classification predictions about an input, thus causing loss in the generalization performance [23, 45, 20, 36]. To resolve this issue, recently, regional dropout [4, 42] and mixing up of two images [44, 37] have been proposed as data augmentation techniques. On the other hands, other researchers showed that label smoothing [35] and knowledge distillation [12, 45, 16, 32] effectively mitigate the overfitting problem by regularizing the posterior probability. In this paper, we expand these findings and indicate that perturbing input and output information should be extensively investigated for few-shot leaning. To this end, we propose a training framework that consolidates regional dropout and knowledge distillation, and further present a novel regional dropout called self-mix. In addition, we show that a novel fine-tuning method can be used to boost the performance of few-shot learning.

3. Methodology

3.1. General Framework

In this paper, we are interested in training a network on base classes to be generalizable to unseen classes. Before elaborating on the proposed method, we introduce the general framework for training and inference.

Training. We define a classifier as $C\left( f \left( \cdot, \Theta^{1:B} \right) \right)$, where $f\left( \cdot, \Theta^{1:B} \right)$ is a feature extractor. Here, we denote the parameters from Block 1 to $B$ as $\Theta^{1:B}$, assuming that we use a block-wise network such as ResNet [11]. For the classifier, we use the cosine similarity that has been exploited for few-shot learning [8, 24]. Thus, the $k$-th output of the classifier for a training example $x_i$ can be defined as

$$C_k \left( f \left( x_i; \Theta^{1:B} \right) \right) = \text{softmax} \left( \tau f_i^T \overline{w}_k \right),$$

where $\overline{f}_i$ is the L2 normalized feature for $x_i$ and $\overline{w}_k$ is the L2 normalized weight for the $k$-th class. $\tau$ is used as a scale parameter for stabilized training [8, 3]. Based on the definition, $C^{\text{Base}}$ is denoted as the classifier using base weights, and similarly $C^{\text{Novel}}$ is denoted using novel weights.

Then, we consider the mini-batch training with $N_{bs}$ examples and the cost function for our training method is expressed as

$$J(\Theta) = \frac{1}{N_{bs}} \sum_{i=1}^{N_{bs}} \ell \left( C \left( f \left( \bar{x}_i; \Theta^{1:B} \right) \right); \bar{y}_i \right) + R,$$

where there exist three components: (a) the virtual training example $\bar{x}_i$ and label $\bar{y}_i$, (b) a loss function $\ell$ and (c) a regularizer $R$. We sequentially elaborate on the components in the following subsections.

Inference. After training base classes, we report the classification performance on unseen classes that have only a few training examples. We consider that a test dataset has $C^N$ classes, which are disjoint to $C^B$ classes for a training dataset. Thus, this inference process measures how well the network trained on base classes is generalized to unseen classes. For this measurement, we randomly sample $n$ classes from $C^N$ classes, and pick $k$ examples from each class. The typical numbers for few-shot learning are $n = 5$ and $k = 1$ or 5. This setting is called $n$-way $k$-shot classification.

After the sampling process, we generate the weight of the $j$-th unseen class as follows:

$$w_j^N = \frac{1}{k} \sum_{i=1}^{k} f_{i,j},$$

Figure 1. Overview of the proposed self-augmentation framework. The main network consists of three classifiers, two of which are derived from intermediate layers of the main branch. In the training phase, we first apply regional dropout to input images, which removes a part of the image by replacing it with other values. All the classifiers try to learn a more generalizable parameter space by minimizing the cross entropy loss and regularizing their prediction scores to have a similar distribution via the KL divergence. For inference, we simply use the main classifier to evaluate images from unseen classes. The right figure shows the case of 3-way 1-shot learning as an example.
where \( f_{i,j} \) is the feature of the \( i \)-th example given for the \( j \)-th unseen class. Then, a query \( x_q \) is classified as
\[
\arg\max_k C_{k}^{Novel} (f (x_q; \Theta_{1:B})),
\]
where \( C_{k}^{Novel} \) is defined in Eq. (1) with the above novel weights. We iterate these sampling and inference processes several times to obtain the 95% confidence interval.

### 3.2. Self-Augmentation

To improve the generalization performance, we propose a training framework called self-augmentation, which consolidates regional dropout and knowledge distillation. Unlike Dropout [31], regional dropout randomly picks a region of an input image and substitutes the pixels of the region into other values. We incorporate the regional dropout in the few-shot learning problem and show that the generalization performance can be significantly boosted when collaborating with knowledge distillation. The overall architecture of the proposed method is shown in Fig. 1.

#### 3.2.1 Regional Dropout

Regional dropout is applied to raw input images to produce a transformed virtual example. We first introduce a general form of regional dropout as follows:
\[
\tilde{x} = T \left( \{x_i\}_{i=1}^2 \right)
\]
\[
\tilde{y} = \lambda y_1 + (1 - \lambda) y_2,
\]
where \( T : x_1[P_1] \rightarrow x_2[P_2] \) denotes by the abuse of notation, the patch \( P_1 \) of \( x_1 \) is replaced by the patch \( P_2 \) of \( x_2 \). \( \lambda \in [0, 1] \) is a mixture coefficient to determine the influence of each raw image and \( y_i \) is a one-hot vector. The type of regional dropout is mainly determined by how we choose \( \{x_i\}_{i=1}^2 \) and \( \{P_i\}_{i=1}^2 \) as shown in Fig. 1.

We now consider two ways to perform the regional dropout in the present work: CutMix [42] and CutOut [4].

**CutMix.** Given a mini-batch, \( x_2 \) is sampled as \( x_2 \neq x_1 \) and \( P_2 \) is randomly chosen according to \( \lambda \sim U (0, 1) \). The location of \( P_1 \) is set to that of \( P_2 \) and the pixels are replaced by \( P_2 \).

**CutOut.** We set \( x_2 = [0] \) and \( \lambda = 1 \). Thus, only \( x_1 \) is used and a randomly chosen \( P_1 \) is zeroed out.

Given that there is room for a different configuration not overlapping with CutMix and CutOut, we further introduce a novel concept of regional dropout.

**Self-mix.** For this, \( x_2 = x_1 \) and \( \lambda = 1 \). Then, the patches \( P_1 \) and \( P_2 \) are randomly chosen. In other words, given a raw image, the locations of random patches are exchanged.

### Discussion

As regional dropout chooses a random region of an input image and replaces the pixels for other values, it perturbs the data statistics. This prevents the network from memorizing the data statistics of base classes and improves the generalization performance for unseen classes. However, CutMix [42] and CutOut [4] have a disadvantage. As shown in Fig. 1, CutMix encourages the network to learn two labels simultaneously. However, it has been reported that such label smoothing impairs the ability of knowledge distillation [20]. Considering that our proposed framework employs knowledge distillation, it is less effective for CutMix to exploit the full capacity of our framework. On the other hands, CutOut converts the pixels of the region into zeros, which leads to information loss. To solve these problems, we propose self-mix, which exchanges the locations of the patches of an input image itself. Given that self-mix does not have any information loss and label smoothing issues, we find that it generates a synergy effect with knowledge distillation.

#### 3.2.2 Knowledge Distillation

Knowledge distillation has been studied to mitigate the overfitting problem by regularizing the posterior probability [12, 45, 16, 32]. Although a recent work showed that knowledge distillation among multiple networks can ease off the high-variance characteristic in few-shot learning [5], this method requires 20 networks for the best performance. Thus, we incorporate self-distillation into our training framework, which employs auxiliary classifiers [16, 32] as shown in Fig. 1. The concept is to create independent predictions for an input image and share the information that has been learned by each classifier. To ensure that the auxiliary classifiers share their own information, we apply the Kullback–Leibler (KL) divergence as a regularizer \( R \) [32]. In summary, the general form in Eq. (2) can be modified for our training framework as follows:
\[
J(\Theta) =
\frac{1}{N_{bs}} \sum_{i=1}^{N_{bs}} \sum_{j=1}^{N_{aux}} \ell \left( C_{j}^{Base} (f (\tilde{x}_i; \Theta_{1:l-1} \cup \Theta_{l:B}^{l:B})) ; \tilde{y}_i \right) + \frac{1}{2N_{aux}} \sum_{i=1}^{N_{aux}} \sum_{j=1, j \neq i}^{N_{aux}} D_{KL} \left( C_{i}^{Base} || C_{j}^{Base} \right).
\]

Here, \( N_{aux} \) is the number of auxiliary classifiers, and for mathematical simplicity we regard the main classifier as one of the auxiliary classifiers. We use the cross-entropy loss for \( \ell \). \( \Theta_{1:l-1} \cup \Theta_{l:B}^{l:B} \) means that the parameters before the \( l \)-th block are shared among the auxiliary classifiers and the \( l : B \) blocks are learned independently for the \( j \)-th classifier. The classifiers also can share some parts of parameters as \( \Theta_i \cap \Theta_{j : B}^{j : B} \neq \emptyset \).
Why Auxiliary Classifiers? Several works have found that deep networks are prone to over-confident predictions, and this hinders a network from learning generalization[23, 45, 36]. In other words, it is possible that an over-confident network results in a decision boundary that is sharp[38] as highly optimized for the statistics of a training dataset. However, unseen classes does not follow the seen classes distribution and a sharp boundary is likely to produce unstable predictions for two slightly different examples of an unseen class. Thus, to alleviate the possible sudden jumps, we employ auxiliary classifiers that share their own information. This helps an explicit regularization about the softmax output produces better generalization ability than regional dropout as an input perturbation.

3.3. Learning Local Representations
We have proposed how to train a network on base classes to produce global representations, which can be generalizable to unseen classes. In the test stage, we have $n$-way $k$-shot training examples and $T$ queries for unseen classes. Thus, we now present how to fine-tune the global representations to yield local representations adjusted for the $n \cdot k$ examples.

Preliminary. For fine-tuning, random transformations are applied on training examples to produce novel weights and fake queries as follows:

- For training:
  \[ x_1, x_2, \ldots, x_{n \cdot k} \xrightarrow{\text{Random Transf.}} \tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_{n \cdot k} \]

- For fake queries:
  \[ x_1, x_2, \ldots, x_{n \cdot k} \xrightarrow{\text{Random Transf.}} \tilde{x}_1^q, \tilde{x}_2^q, \ldots, \tilde{x}_{n \cdot k}^q \]

where $\tilde{x}_i$ is used to create a novel weight and $\tilde{x}_i^q$ is used to induce a loss. It is worth noting that we only have access to the $n \cdot k$ examples, and we are never informed about the real queries.

Training. Our objective is not to destroy the well-learned global representations and we promise to be more discriminative after fine-tuning. Thus, we clone the last block of the pre-trained network and only fine-tune the block. The features extracted from the separate networks are denoted as

\[ f^\text{Global}_i := f (\tilde{x}_i; \Theta_{\text{pre}}) \]
\[ f^\text{Bias}_i := f (\tilde{x}_i; \Theta_{\text{pre}}^{-1} \cup \Theta^B), \]

where $\Theta_{\text{pre}}$ denotes the pre-trained parameters for the base classes. Local representation is defined as the sum of the two features. Similarly, the features for queries can be defined as $f^\text{Global}_{i,q}$ and $f^\text{Bias}_{i,q}$. Then, according to Eq. (3), the weight for the $j$-th unseen class is produced by

\[ w^N_j = \frac{1}{k} \sum_{i=1}^{k} (f^\text{Global}_{i,q} + f^\text{Bias}_{i,q}). \]  

As we have formed novel weights and features for fake queries, a cost function can be defined as

\[ J(\Theta) = \frac{1}{n \cdot k} \sum_{i=1}^{n \cdot k} f (C^\text{Novel}_{i,q} (f^\text{Global}_{i,q} + f^\text{Bias}_{i,q}); \tilde{y}_i) \]
\[ + \gamma \sum_{j=1}^{n} \sum_{i=1}^{k} \| f^\text{Global}_{i,j} - f^\text{Bias}_{i,j} \|_2, \]  

where the regularizer $\gamma$ prevents the fine-tuned block $\Theta^B_T$ from destroying the well-learned feature space given that only a few training examples are available. Overall, we try to learn the bias term to increase the distance between classes that are close to each other so that they are more distinguishable. The overall concept is illustrated in Fig. 2.

**Inference.** A query is classified by the trivial softmax output, but this time we use $T$ real queries. Our proposed fine-tuning method can be applied to any global representations trained on base classes.

### 4. Experiments

We evaluate the proposed method on the widely used datasets for few-shot learning. We also perform ablation studies to validate the generalization effects of our methods.

#### 4.1. Experimental Setup

**Datasets.** *mini*ImageNet [39] consists of 100 classes randomly selected from ILSVRC-2012 [27] and each class has 600 images, each sized $84 \times 84$. We follow the split proposed in [25], namely 64, 16 and 20 classes for training, validation and testing, respectively. *Tiered*ImageNet [26] has 608 classes randomly selected from ILSVRC-2012 [27] and these classes are grouped into 34 higher level categories. They are then split into 20, 6 and 8 categories to further build 341, 91 and 100 classes for training, validation and testing, respectively. A much larger number of images (totally 779,165 images) are sized $84 \times 84$. CIFAR-FS [1] consists of 100 classes randomly selected from CIFAR-100 [14] and each class has 600 images, each of size $32 \times 32$. The classes are split into 64, 16 and 20 classes for training, validation and testing, respectively.

**Evaluation.** We report the performance averaged over 2,000 randomly sampled tasks from the test set to obtain the 95% confidence interval. We use $T = 15$ test queries for the 5-way 5-shot and the 5-way 1-shot, as in [39, 30, 25].

**Implementation Details.** For all the datasets, we report the results using ResNet-12 [17], which has four blocks. Each block consists of three $3 \times 3$ Convolution-BatchNorm-LeakyReLU (0.1) and one $2 \times 2$ max pooling. The depths of the four blocks are $64 \rightarrow 160 \rightarrow 320 \rightarrow 640$. Auxiliary classifiers are branched from the 2nd and 3rd blocks of ResNet-12. The two auxiliary classifiers have two and one new ResNet blocks, respectively. We use stochastic gradient descent (SGD) with a Nesterov momentum of 0.9 and a weight decay of 0.0005. We fix the scale parameter for the classifier to $\tau = 20$.

For fine-tuning, we also use the SGD and $\gamma$ is set to 0.1 for 1-shot learning and 0.01 for 5-shot learning. The random transformations for the training and fake queries are composed of the regional dropout and light data augmentation such as cropping and flipping, which are same as those for training the base classes.

#### 4.2. Performance of Self-Augmentation

We show how the performance improves by adopting various regional dropout methods and self-distillation. For comparison, we report the performance of a baseline using light augmentation such as random cropping and horizontal flipping. In addition, we also compare a well-known calibration training technique called MixUp [44], which mixes two images and the labels. Table 1 indicates five notable aspects: (1) Self-augmentation significantly outperforms the baseline using light augmentation only. (2) Although either regional dropout or self-distillation can improve the generalization capability, exploiting both methods leads to higher performance gains. (3) As discussed in Sect. 3.2.2, the proposed self-mix has a synergistic effect with self-distillation as it does not require pixel removal [4] or mixed labels [44, 42]. (4) When using CutMix [42] for fine-tuning, the performance remains almost the same. As only a few training examples exist, we conjecture that the mixed labels produced by CutMix increase the complexity of fine-tuning. The same argument can be applied to MixUp. (5) Fig. 3 shows that there exist cases where the fine-tuning method fixes the deep network to focus on more discriminative parts. For the following experiments, we report the results with self-mix exclusively as our default regional dropout method.

| Method          | miniImageNet |
|-----------------|--------------|
|                 | 1-shot       | 5-shot       |
| Baseline        | 61.42±0.45%  | 78.32±0.33%  |
| MixUp           | 61.26±0.45%  | 78.89±0.32%  |

**Regional Dropout**

| Method  | miniImageNet |
|---------|--------------|
|         | 1-shot       | 5-shot       |
| CutOut  | 62.38±0.44%  | 79.18±0.33%  |
| CutMix  | 62.81±0.45%  | 79.82±0.33%  |
| Self-Mix| 62.85±0.45%  | 79.83±0.32%  |

**Self-Distillation**

| Method  | miniImageNet |
|---------|--------------|
|         | 1-shot       | 5-shot       |
| MixUp   | 62.52±0.45%  | 80.22±0.33%  |
| CutOut  | 64.61±0.44%  | 81.57±0.31%  |
| CutMix  | 64.44±0.45%  | 81.58±0.32%  |
| Self-Mix| 65.27±0.45%  | 81.84±0.32%  |

| Method  | miniImageNet |
|---------|--------------|
|         | 1-shot       | 5-shot       |
| MixUp   | 62.52±0.44%  | 80.05±0.32%  |
| CutOut  | 64.93±0.45%  | 82.34±0.30%  |
| CutMix  | 64.67±0.45%  | 81.52±0.31%  |
| Self-Mix| 65.37±0.45%  | 82.68±0.30%  |

Table 1. 5-way few-shot classification accuracies on miniImageNet with 95% confidence intervals. Baseline refers to a vanilla network without any additional tricks. See Sect. 4.2 for details.
Figure 3. Visualization of the fine-tuning effect. Using class activation map [46], we find that in some cases, fine-tuning focuses on more discriminative parts within an image. As a result, only self-augmentation with fine-tuning correctly classifies the above images. This suggests that a network can be further enhanced even with a few training examples using a carefully designed strategy.

4.3. Comparison with the State-of-the-Art Methods

We compare the proposed method with the state-of-the-art algorithms. As shown in Table 2, self-augmentation with fine-tuning clearly outperforms the others by a large margin. It is worth noting that recent techniques [41, 18] perform well in certain environments such as 1-shot or 5-shot, or on a certain dataset, while the proposed method works decently in all settings. This indicates that it is worthwhile investigating the generalization ability of the standard supervision in relation to few-shot learning.

5. Additional Analysis

We further analyse the generalization ability and the network calibration of the proposed framework. First, we show that self-augmentation is tolerant of a challenging domain shift problem. Second, we validate that learning base classes with the proposed framework leaves the calibration effect to the classifiers of unseen classes.

5.1. Domain Shift: minImageNet to CUB

After training a network on minImageNet, we perform 5-way classification on CUB [40]. This is a challenging problem as (1) CUB is designed for fine-grained image classification with 200 bird species, (2) the distributions of the two datasets are largely different and (3) we only have 1 or 5 training examples for few-shot learning. With these difficulties, Table 3 shows that self-augmentation significantly surpasses the previous works [34, 30, 3, 5].
Figure 4. Calibration results for various methods on miniImageNet. We measure (a) expected calibrated error and plot (b) reliability diagram to evaluate how well our method is effective to mitigate overconfidence. Both results show that self-augmentation can be well-calibrated for both base and unseen classes.

5.2. Network Calibration

Confidence calibration is the task of making the prediction score that a network produces to match the true correctness likelihood. A recent work showed that deep networks tend to be poorly calibrated and this leads to the loss of the reliability of the prediction result [10]. However, a recognition system should be accurate and also need to be informed if the prediction is likely to be incorrect. Especially, in terms of the system reliability, it is more important for a network to be well-calibrated for few-shot learning due to the small number of training examples. Thus, we show that how well our method calibrates the network compared to others. Specifically, we obtained the reliability diagram by collecting the average accuracies fallen within a range of the winning softmax output (confidence) and we calculated the calibration error by the difference between the accuracy and confidence scores [10]. If a network classifies an image with a certain confidence score, this score should be close to the true accuracy. As shown in Fig. 4, we observe that self-augmentation is well-calibrated compared to others even on unseen classes. From a different perspective, the discrepancy in the calibration performance can be regarded as an outcome of the accuracy improvement. While Table 1 supports this perspective, we further show that a better calibrated network can produce a discriminative feature space for unseen classes as shown in Fig. 5.

6. Conclusion

In this paper, we show that unseen classes with a few training examples can be classified with a standard supervised training. Especially, we aim at generalizing a deep network to unseen classes by alleviating the memorization phenomenon, which are less studied for few-shot learning. To achieve this, we design consolidating regional dropout and knowledge distillation to perturb the input and output information. Then, we show that the newly proposed regional dropout, called self-mix, produces state-of-the-art results when cooperating with self-distillation. We also present a novel fine-tuning method to exploit a few training examples of unseen classes, which improves the performance for all the few-shot learning benchmarks. Lastly, we show that the proposed method produces a well-calibrated network, which can be used as an indicator for prediction reliability.
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