Learning Class-level Prototypes for Few-shot Learning

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Abstract

Few-shot learning aims to recognize new categories using very few labeled samples. Although few-shot learning has witnessed promising development in recent years, most existing methods adopt an average operation to calculate prototypes, thus limited by the outlier samples. In this work, we propose a simple yet effective framework for few-shot classification, which can learn to generate preferable prototypes from few support data, with the help of an episodic prototype generator module. The generated prototype is meant to be close to a certain class-level prototype and is less influenced by outlier samples. Extensive experiments demonstrate the effectiveness of this module, and our approach gets a significant raise over baseline models.

1 Introduction

Although few-shot learning has witnessed promising development in recent years, most existing methods adopt an average operation to calculate prototypes, thus limited by the outlier samples. In this work, we propose a simple yet effective framework for few-shot classification, which can learn to generate preferable prototypes from few supporting data, with the help of an episodic prototype generator module. The generated prototype is meant to be close to a certain class-level prototype and is less influenced by outlier samples. Extensive experiments demonstrate the effectiveness of this module, and our approach gets a significant raise over baseline models, and get a competitive result compared to previous methods on miniImageNet, tieredImageNet, and cross-domain (miniImageNet → CUB-200-2011) datasets.

Although few-shot classification algorithms have achieved promising performance, they rarely concentrate on designing a good strategy to generate class-level prototypes to represent each class in the support set. Some recent methods [Sung et al., 2018; Snell et al., 2017; Oreshkin et al., 2018; Lifchitz et al., 2019; Wang et al., 2018] adopt the averaging strategy (i.e., using the arithmetic mean of embeddings of support samples in each class) to approximate class-level prototypes. Although this strategy works well in ideal situations where sufficient samples are given and each of them is independently sampled from the same distribution [Khintchine, 1936]. However, in a few-shot classification, the in-
fluence of one single outlier on the averaging strategy may be significant because there are few supporting samples. This phenomenon is named as class-level prototype jitter in [Cai et al., 2020], which is shown in Figure 1.

To remedy this problem, several methods [Simon et al., 2020a; Simon et al., 2019] choose a preferable class-level prototype from the linear subspace constructed by the support set, whose main spirit is to calculate a subspace of the feature space for each category, and then project the feature vector of the query sample into the subspace, and take the distance measurement in the subspace as the criterion for predicting the category. An iterative process is proposed in IFSM [Cai et al., 2020] to optimize prototypes, which leads to high time complexity due to complex iterations. In addition, PSN [Simon et al., 2019] and IFSM [Cai et al., 2020] do not work on 1-shot tasks. And all previous methods omit the guidance of class-level prototypes, which is the average feature of a large number of samples of the same class in the training set.

To solve this problem, we propose an episodic prototype generator to extract the prototype supervised with the class-level prototype. In this way, the proposed episodic prototype generator needs to generate a prototype that can converge to a more robust prototype. This reduces the impact of outliers in the prototype calculation.

Specifically, we propose an effective framework for the few-shot classification task. The proposed method consists of three main modules: the class-level prototype generator module, the episodic prototype generator module, and the metrics module. Among them, the class-level prototype generator module aims to learn class-level prototypes (i.e., the global mean of sample features for each class in the training set) from the training data so that our algorithm can directly benefit from the class-level prototype when dealing with few-shot classification problem. The episodic prototype generator is a learnable module constructed with a Transformer [Vaswani et al., 2017]. It can help the network capture the contextual information from samples with the same category. Besides, the output of the episodic prototype generator is supervised with class-level prototypes produced by class-level prototype generator module. In this way, the proposed episodic prototype generator model can tend to get the prototype closer to the class-level prototypes and reduce the impact of outlier points. Finally, the metric module determines the category to which the query sample belongs based on the distance.

Extensive experiments demonstrate that the proposed method is competitive with state-of-the-art few-shot learning methods. Firstly, we directly use class-level prototype for classification and get a surprising result with an accuracy of 89.15%. The experiment proves it is wise to choose it as the classification basis. Secondly, we conduct consistent comparative experiments on two datasets to compare several representative methods of few-shot classification. We achieve the state-of-the-art performance on tieredImageNet 5-way 1-shot and 5-shot, and on miniImageNet 5-way 1-shot, with accuracy of 71.78%, 85.91% and 66.68%, respectively. Finally, we further evaluate the performance of this method on cross-domain tasks. The fact shows that our model has a strong ability to migrate and is highly competitive with other methods.

The contributions of our work are as follow:

1. We assume that the class-level prototypes can be good candidates for class-level prototypes in few-shot classification, and justify it through ablation experiments.
2. We propose a mechanism which takes support samples as input and generates class-level prototypes relatively close to corresponding class-level prototypes.
3. We show that the proposed mechanism brings a significant rise to the performance of various few-shot learning methods on miniImageNet, tieredImageNet and a cross-domain task (miniImageNet → CUB-200-2011).

2 Related Works

Few-shot learning has been of great interest for a long time, and a large quantity of few-shot learning algorithms have been proposed in the literature. These methods can be approximately divided into two categories. The first kind of approach aims at strategies of constructing a general classifier. They show feasible performance on few-shot tasks. Concretely, this can be done by inventing a certain data augmentation algorithm [Li et al., 2019] or optimization strategy based on the content of the support and query sets [Vinyals et al., 2016]. This can also be achieved by directly predicting the weights of the classifier [Rusu et al., 2019].

The other school of few-shot learning methods [Snell et al., 2017; Vinyals et al., 2016; Sung et al., 2018; Li et al., 2019; Cai et al., 2020; Simon et al., 2020a] focuses on learning a feature extractor to embed all samples in the support set and the query set, followed by a classifier making its decisions based on the embedding of query samples and embeddings of support samples. These methods are usually called metric-based few-shot learning methods. Early methods of this category directly compare the embedding of query samples to embeddings of all support samples, which are similar to weighted nearest-neighbor classifiers like Matching Network [Vinyals et al., 2016]. Prototypical Network [Snell et al., 2017] decides that it is more efficient to use prototypes, i.e., embeddings of classes to compare with embeddings of query samples.

Besides, merely using the arithmetic mean as prototypes are far from feasible. Thus, several methods have been proposed to alleviate this problem through different means. For instance, CTM [Li et al., 2019] introduces a category traversal module for generating prototypes, which can explicitly extract intra-class commonality and inter-class uniqueness. IFSM [Cai et al., 2020] assumes a relatively feasible prototype can be represented by a linear combination of embeddings of support samples from that class and adopts an iterative process to gradually optimize that linear combination. Subspace Network [Simon et al., 2020a] is based on a similar assumption. However, it generates an independent set of prototypes for each query sample and is limited to certain types of distance metrics.

Our work is somehow based on a similar idea compared to these methods, which is to generate prototypes through a learnable neural network. However, our work is different in that our model is supervised by the class-level prototype,
which is a good candidate for the prototype. This facilitates us to obtain a prototype that is closer to class-level prototype.

3 Preliminary

In this section, we introduce some notation and formalization of few-shot learning in an image classification task. Let \((x, y)\) denotes a labeled example where \(x\) is a sample and \(y\) is the corresponding ground-truth. Datasets are often divided into a base class dataset \(D_{\text{train}}\) and a novel class dataset \(D_{\text{novel}}\), and \(D_{\text{train}}\) and \(D_{\text{novel}}\) do not intersect. The purpose of few-shot learning is to build a good meta-learner \(\Phi\) for the novel classes in \(D_{\text{novel}}\) with a few labeled samples (or called support samples).

Meta-learning [Vinyals et al., 2016] is an effective way for few-shot learning, which can utilize the training set in an episodic manner by mimicking the few-shot learning setting. Meta-learning consists of two phases: meta-training and meta-test.

In the meta-training phase, data is randomly sampled from \(D_{\text{train}}\) to simulate a scenario \(T\), and the few-shot learning meta-learner \(\Phi_{\theta}\) is trained with thousands of randomly sampled scenarios. In each scenario, the sampled data are divided into a support set \(S\) and a query set \(Q\), which satisfies that the elements of \(S\) and \(Q\) do not intersect, but are drawn from the same class. The support set \(S\) and the query set \(Q\) are formalized as follow:

\[
S = \{x_i | y_i = k, (x_i, y_i) \in D_{\text{s}}\},
\]
\[
Q = \{x_i | y_i = k, (x_i, y_i) \in D_{\text{q}}\}.
\]

In the meta-test phase, the learned few-shot learning meta-learner \(\Phi_{\theta}\) is tested with a large number of episodes drawn from \(D_{\text{novel}}\), and the average prediction accuracy is used to measure the learning ability of \(\Phi_{\theta}\).

In this paper, we consider only the \(N\)-way \(K\)-shot few-shot learning paradigm, where each support set \(S\) contains \(N\) classes, each class includes \(K\) samples, and the query set \(Q\) consists of unlabeled samples belonging to the classes of support set \(S\).

Meta-learner \(\Phi_{\theta}\) is trained to fit few-shot classification tasks by minimizing the prediction loss on the query set \(Q\) as in Eq. (2).

\[
\arg \min_{\theta} \frac{1}{N_{q}} \sum_{(x_i, y_i) \in Q} \mathcal{L}(y_i, \Phi_{\theta}(x_i, S)),
\]

where \(N_{q}\) is the number of samples in \(Q\), and \(\mathcal{L}\) is the loss function. The meta-learner \(\Phi_{\theta}\) is required to train with thousands of randomly sampled tasks under the constraint of the loss function \(\mathcal{L}\).

However, the proposed framework is trained using distance loss. The details are given in Section 4.

4 Method

4.1 Framework

The key idea of our model is to elaborate how to get a better prototype supervised with a class-level prototype in case of insufficient support samples. To overcome the class-level prototype jitter problem, we propose a pipeline to fit class-level prototype using few support samples. Figure 2 shows the overall architecture of our proposed model. The proposed algorithm consists of three main components: a class-level prototype generator module, an episodic prototype generator module and a metric module.

As illustrated in Figure 2, class-level prototype works in three steps. The training data are first fed into the class-level prototype generator module. A generic classifier is first trained with the training set and the parameters of the classifier are frozen. Then, the features of all samples in each category are obtained using the trained classifier. Finally, the arithmetic means of all sample features in each category are used as class-level prototype. Class-level prototype generator module provides a backbone with fixed parameters for the following episodic prototype generator module. The episodic prototype generator is designed to produce prototype that is closer to class-level prototype, which is detailed in Section 4.3. The metric module accomplishes the recognition of images by measuring the distance between the episodic prototype features and the feature vectors of images in query set. We will introduce the details of these modules in the following.

4.2 Class-level Prototype Generator Module

The class-level prototype generator module aims at generating the average of the features of all samples in the same class. Existing few-shot learning methods are usually trained and tested on \(\text{mini} \text{ImageNet}\) [Vinyals et al., 2016] and \(\text{tiered} \\text{ImageNet}\) [Ren et al., 2018]. Each class of the training set \(D_{\text{train}}\) consists of a considerable number of samples. In this paper, we consider the global class prototype as the best candidate for the class-level prototype. And then propose the class-level prototype to optimize the episodic prototype. Specific optimization method will be described in detail in Section 4.3. We focus on how to calculate class-level prototype in this part.

To obtain the class-level prototype, a classifier is first trained using \(D_{\text{train}}\). The classifier consists of a backbone network \(\mathcal{F}_{\theta}\) and a fully connected network with a softmax layer and is optimized using cross-entropy loss. Specifically, the backbone network \(\mathcal{F}_{\theta}\) is used to extract the features of images with a type of residual network [He et al., 2016]. The detailed structure of the backbone network \(\mathcal{F}_{\theta}\) is presented in Section 5.2.

Then, the trained backbone network \(\mathcal{F}_{\theta}\) is used to extract the features of samples in each class in the training set, and the arithmetic mean of all features in the same class is adopted as class-level prototype.

\[
g_i = \frac{1}{M} \sum_{j=1}^{M} \mathcal{F}_{\theta}(x_{ij}),
\]

where \(M\) is the total number of samples in the \(i\)-th class, \(x_{ij}\) indicates the input sample.

4.3 Episodic Prototype Generator Module

When calculating the prototype of an episode using the arithmetic mean in a few-shot learning scenario, the prototypes are
often affected by outlier points. In this section, we propose an episodic prototype generator module, which is designed to narrow the difference between the prototype and the class-level prototype. The proposed episodic prototype generator generates a prototype under the supervision of a class-level prototype, and the final optimization goal is to obtain a prototype that is closer to the class-level prototype.

To achieve this, in each episode, the samples \(\{x_1, \ldots, x_K\}\) in the same class are first fed into the pre-trained feature extractor \(F_\theta\), which can obtain their feature vectors, denoted as \(f_{ij} = F_\theta(x_{ij})\). Then, the extracted feature vectors \(\{f_{i1}, \ldots, f_{iK}\}\) are fed into the episodic prototype generator \(G_\gamma\) and produce episodic prototype \(f'_i\), denoted as Eq. 4.

\[
f'_i = G_\gamma(f_{i1}, \ldots, f_{iK}),
\]

where \(\gamma\) is the parameters of the episodic prototype generator \(G\), \(i\) indicates the \(i\)-th category.

Finally, we compute the distance between the episodic prototype \(f'_i\) and class-level prototype \(\hat{f}_i\) and use the distance loss to optimize the parameters \(\gamma\) of the episodic prototype generator \(G_\gamma\). Euclidean distance is adopted to measure the distance loss in this paper.

\[
\mathcal{L}_{distance} = \frac{1}{N} \sum_{i=1}^{N} \mathcal{M}(f'_i, \hat{f}_i),
\]

where \(\mathcal{M}\) is a distance metric module, \(N\) indicates the number of categories in an episode, \(\hat{f}_i\) is the class-level prototype of the \(i\)-th category in an episode.

In this paper, we employ a multi-head self-attention mechanism [Vaswani et al., 2017] as the feature generator \(G\), which considers the contextual information of samples in the same episode. The multi-head self-attention mechanism outputs the refined feature vectors of the input samples. We use the mean of updated feature vectors as prototypes. These prototypes can converge to the class-level prototype with the help of the loss function \(\mathcal{L}_{distance}\), thus eliminating the effect caused by outliers in input samples.

### 4.4 Metric Module

The metric module \(\mathcal{M}\) classifies the images in the query set. First, the trained backbone network \(F_\theta\) is used to extract the features of samples in the query set. Then, the metric module \(\mathcal{M}\) classifies the query samples according to the distance between the features of images in the query set and the episodic prototype features \(\{f'_1, \ldots, f'_N\}\). In this paper, Euclidean distance is chosen as the metric to obtain the classification accuracy.

## 5 Experiments

### 5.1 Datasets

**miniImageNet.** It contains 100 classes with 600 images in each class. Following the previous work [Sung et al., 2018; Snell et al., 2017], we divide this dataset into training, validation, and testing sets, with 64, 16, and 20 classes, respectively.

**tieredImageNet.** It consists of a total of 779,165 images with 608 classes. Each image in tieredImageNet has a size of \(84 \times 84\). It is a much more challenging dataset because of the realistic regime of test classes that are less similar to training ones. In our experiments, we follow the setting of [Li et al., 2019] where 351 classes are used to make up the training set, 97 for validation and 160 for testing.
miniImageNet → CUB-200-2011. To evaluate the effects of the proposed algorithm in a cross-domain scenario, we use the miniImageNet as our training set and the validation set and testing set are from CUB-200-2011 [Wah et al., 2011]. The miniImageNet involves generic objects, while CUB-200-2011 contains 200 classes and 11,788 fine-grained bird images. This dataset mainly validates the cross-domain learning capability of the model.

5.2 Implementation Details

Backbone. We adopt a 12-layer residual network (ResNet-12) [He et al., 2016] as the backbone network of our algorithm [Lifchitz et al., 2019; Lee et al., 2019; Simon et al., 2020b]. ResNet-12 is composed of four residual blocks [He et al., 2016]. Each residual block contains three $3 \times 3$ convolutional layers and a shortcut connection. At the same time, every convolutional layer is followed by a BatchNorm layer and a LeakyReLU activation function (negative slope 0.1). In our experiments, the backbone network is pre-trained on the training set $D_{base}$ like [Rusu et al., 2019].

Training Schema. As many few-shot learning methods [Snell et al., 2017; Sung et al., 2018], we utilize a meta-training strategy to train our model. Specifically, in each N-way K-shot episode, we randomly sample K images per class to make up a support set, and 15 images per class for the query set. The total training process lasts 200 epochs, and each epoch contains 200 episodes. We adopt stochastic gradient descent (SGD) as the optimizer. The learning rate is initially set to 0.01 and is multiplied by 0.618 whenever the validation score does not improve in 7 consecutive epochs.

Evaluation protocols. We evaluate our model on the validation at the end of each epoch and verify the performance of our model in the testing set. Specifically, we test the models with 600 randomly sampled tasks and calculate the mean and 95\% confidence interval of the prediction accuracy. In each sampling task, we randomly sampled 15 images for each category.

5.3 Comparison with State-of-the-arts

In Table 1, we compare the performance of our algorithm with several state-of-the-art few-shot learning methods on miniImageNet and the tieredImageNet. On the tieredImageNet and the miniImageNet, our algorithm achieves a more favorable score than other methods on 1-shot classification. On the tieredImageNet, our solution outperforms other methods on 1-shot and 5-shot classification by a larger margin. Centroid alignment [Afrasiyabi et al., 2020] is slightly better than ours when dealing with 5-way 5-shot tasks on miniImageNet. However, Centroid alignment [Afrasiyabi et al., 2020] adopts WRN-28-10 as the backbone, which introduces a lot more parameters than ResNet-12. As is pointed out in [Chen et al., 2019a], the parameter size of the backbone has a great impact on the performance of a few-shot learning method. Note that PSN [Simon et al., 2019], DSNet-MR [Simon et al., 2020a] and PN+IFSM [Cai et al., 2020] are all proposed to optimize the class-level prototypes by learning to form an affine subspace or by an iterative optimization mechanism, respectively. But PSN [Simon et al., 2019] and
The proposed module has a larger improvement compared with ProtoNet+Lock. Besides, the larger improvement of 7.55% in 1-shot setting and 1.34% in 5-shot settings compared with ProtoNet+Lock. This shows the effectiveness of our episodic prototype generator module. All the experiments are performed on 5-way 1-shot and 5-way 5-shot tasks, with miniImageNet being the dataset.

### Table 2: Few-shot classification accuracy (%) on a cross-domain task (miniImageNet → CUB-200-2011). † indicates that the experimental results are from [Chen et al., 2019a]. Bold: the best.

| Methods               | 5-way 5-shot |
|-----------------------|--------------|
| Baseline++† [Chen et al., 2019a] | 62.04 ± 0.76 |
| MatchingNet† [Vinyals et al., 2016] | 53.07 ± 0.74 |
| MAML† [Finn et al., 2017] | 51.34 ± 0.72 |
| ProtoNet† [Snell et al., 2017] | 62.02 ± 0.70 |
| RelationNet† [Sung et al., 2018] | 57.71 ± 0.73 |
| Ours                  | **62.60 ± 0.75** |

PN+IFSM [Cai et al., 2020] cannot be applied to the 1-shot classification task. DSN-MR [Simon et al., 2020a] has more flexibility than PSN [Simon et al., 2019] and PN+IFSM [Cai et al., 2020]. DSN-MR [Simon et al., 2020a] uses the same backbone as we do, but our method has higher accuracy.

### 5.4 Performance in Cross-domain Scenario

In Table 2, we experiment our method on cross-domain tasks, which is trained on miniImageNet and tested on CUB-200-2011. In our experiment, ResNet-12 is used as the backbone, which is the same as the comparable method. Table 2 shows that our method is the best performer on cross-domain tasks, which means that the episodic prototype generator can benefit in the cross-domain scenario.

### 5.5 The Effect of Episodic Prototype Generator

We conduct ablation experiments to verify the effectiveness of our mechanism. All the experiments are performed on 5-way 1-shot and 5-way 5-shot tasks, with miniImageNet being the dataset.

### Table 3: Ablation studies on effect of prediction accuracy (%).

| Methods               | 1-shot     | 5-shot     |
|-----------------------|------------|------------|
| ProtoNet+Lock         | 59.13 ± 0.86 | 80.88 ± 0.58 |
| ProtoNet              | 61.17 ± 0.82 | 79.86 ± 0.55 |
| Ours                  | **66.68 ± 0.81** | **82.22 ± 0.56** |
| Class-level prototype | 89.15 ± 0.37 | 89.15 ± 0.37 |

In Table 3, we first test ProtoNet+Lock and ProtoNet. The former has frozen backbone parameters, while the latter is learnable during the training phase. They both use the arithmetic mean as the episodic prototype. Our method is based on ProtoNet+Lock with the feature generator module applied. As can be seen from Table 3, the proposed module has a larger improvement of 7.55% in 1-shot setting and 1.34% in 5-shot settings compared with ProtoNet+Lock. Besides, the proposed module also shows a larger improvement compared to ProtoNet, which has learnable parameters. This shows the effectiveness of our episodic prototype generator module.

We also report the prediction results using class-level prototype, which are the ideal results. This experiment uses the class-level prototypes of each support sample to classify the query samples, and the purpose of reporting this result is to explore the upper bound of the capability of our proposed method. At the same time, we can see that the prediction accuracy can reach 89.15% when using the class-level prototype as the episodic prototype. There leaves a big gap for improvement, and we believe that the gap can be further reduced by improving the ability of the episodic prototype generator module.

To verify the validity of the proposed method, we visualize the features of the support samples, class-level prototypes, and mean prototype features using t-SNE [Maaten and Hinton, 2008] in Figure 3. The mean prototype feature is generated by ProtoNet [Snell et al., 2017], which uses the same backbone as our model, and the episodic prototypes are generated by our model. It shows that there are outliers in the purple and blue classes, resulting in a large gap between the mean prototype of these two classes and their class-level prototypes, while the episodic prototype can be closer to class-level prototype. It shows that our method can obtain a more robust prototype in the presence of outliers.

The above experiments show that in the presence of outliers, the proposed episodic prototype generator can obtain more robust prototypes and improve the prediction accuracy in the presence of few-shot learning.

### 6 Discussion

In a few-shot learning scenario, the arithmetic mean prototype tends to be influenced by outlier points. Through experimental observations, we find class-level prototype can greatly improve few-shot learning model. In this paper, we propose a simple method to learn class-level prototypes from few support samples. This method is based on the idea that we can generate more reliable prototypes supervised with class-level prototypes. The proposed method can produce competitive
results than most metric-based few-shot learning methods, only by improving the prototype.

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