IFSM: A Iterative Feature Selection Mechanism for Few-Shot Image Classification

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Abstract

Nowadays many deep learning algorithms have been employed to solve different types of problems in the area of computer vision; however, most of them require a great amount of training data and tend to struggle in few-shot learning tasks. On the other hand, those methods designed for few-shot learning usually face the difficulty that once one or more samples show a relatively large bias, the predicted result may be much less reliable due to the fact that the sample will cause a large shift of class-level features during few-shot learning. To solve this problem, this paper presents a novel and Iterative Feature Selection Mechanism (IFSM) for few-shot image classification, which can be applied to lots of metric-based few-shot learners.

IFSM learns to construct a more feasible class-level feature which is less affected by samples with relatively large biases, using an iterative approach. The proposed mechanism is tested on three previous state-of-the-art few-shot learning methods, and the experimental results show that the proposed mechanism considerably improves (by 1% to 2%) the image classification accuracies of both methods on the miniImagenet, tieredImagenet or CUB benchmarks in 5-way 5-shot tasks. This approves the effectiveness and generality of the proposed mechanism.

Background

A simple but effective solution to the few-shot classification problem is to train a neural network to produce embeddings of both support samples and query samples, followed by comparing the embeddings of query samples to those of support samples. The classifier then utilizes the result of this comparison to predict the category of each query sample. When dealing with image classification tasks where the support set contains more than one image per class, it's a widely used approach to embed each class into one embedding vector, which represents the commonality in the corresponding class (named a *class-level feature* here).

Many few-shot methods perform an average operation with in each class on the embeddings of support samples, to get the class-level features of the classes (This kind of class-level features will be referred to as *class-level averages* hereinafter). Such an average operation is simple and effective, and introduces the least error when the number of samples is large and all training images are independently sampled from the same distribution. However, when faced with the few-shot learning problem, the influence of any outlier cast on the average can be significant, which makes it difficult for the average to represent the class well, as is shown in Fig. 1 (which is quite probable).

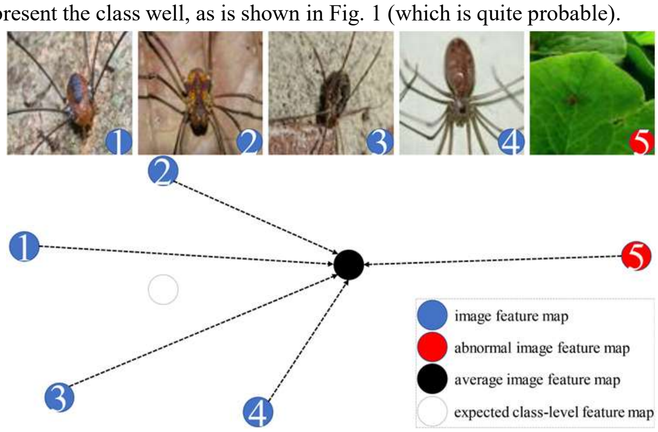

Fig. 1. Class-level averages when outlier exists. Five images from class 'insect'. Feature maps of image 1 to 4 have reasonable distribution, but the insect in image 5 is relatively small and the feature map of image 5 significantly causes the average class-level feature jitter from the white dot to black.

Proposed Mechanism

To alleviate the problem caused by direct class-level averages, we instead propose this Iterative Feature Selection Mechanism to filter out the outliers when calculating class-level features. The overall framework is illustrated in Fig. 2.

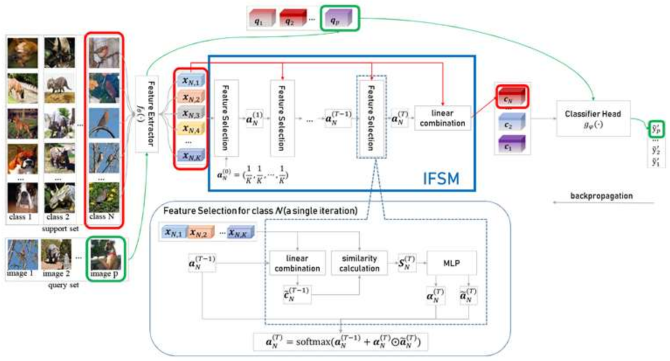

Fig. 2. Iterative Feature Selection Mechanism. An example for IFSM applied to a few-shot classifier, on an N-way K-shot few-shot classification task. Only the process of generating the class-level feature of class N is shown in the figure, for simplicity. Each block called **Feature Selection** indicates an iteration in IFSM.

In our mechanism, we use an iterative process consisting of T consecutive iterations to generate better class-level features. In each iteration t, for each class i it will generate a new class-level feature $\boldsymbol{c}_i^{(t)}$ and the weights of the linear representation of $\boldsymbol{c}_i^{(t)}$ on $x_{N,1}, x_{N,2}, \dots, x_{N,K}$. The output of the T-th iteration will be the output of the module.

Experiments

In Table 1 we apply our IFSM on two previous state-of-the-art methods (Prototypical Network and Dense Classification) and find out that it boosts their performance to state-of-the-art. Experiments are performed on 5-way 5-shot few-shot classification tasks, with miniImagenet and tieredImagenet being the datasets.

Method	Backbone	*mini*ImageNet	*tiered*ImageNet
Matching Network [2]	Conv4	55.31±0.73	-
Prototypical Network [1][a]	Conv4	68.20±0.66	-
Prototypical Network[b]	Conv4	65.86±0.68	-
Relation Network [3]	Conv4	65.32±0.70	-
PSN [11]	Conv4	66.62±0.69	-
Subspace Network [9]	Conv4	66.41±0.66	-
MAML [21]	Conv4	63.11±0.92	-
MetaSGD [5]	Conv4	64.03±0.94	-
TAML [23]	Conv4	66.05±0.85	-
IFSM(ours)+PN	Conv4	**66.98±0.68**	-
TADAM [10]	ResNet-12	76.70±0.30	-
CAML [22]	ResNet-12	72.35±0.71	-
Predict Parameters [25]	WRN	73.74±0.19	-
DC [12]	ResNet-12	79.77±0.19	-
DC[c]	ResNet-12	81.26±0.61	83.82±0.59
FEAT [17]	ResNet-12[d]	82.05 —	84.79±0.16
DFMN [18][e]	ResNet-12	82.15±0.45	85.29±0.49
IFSM(ours)+DC	ResNet-12	**82.29±0.56**	**85.50±0.63**

Table 1. Benchmark results. 5-way 5-shot test results on *mini*Imagenet and *tiered*Imagenet, Various backbones are used.