# The Application of Gradient-based Meta-learning Scheme on Few-shot Learning

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## 1 Motivation

Deep neural networks have made great success in a mount of tasks especially on supervised learning tasks, e.g. image classification, face recognition, object detection, etc. However, most of such tasks require many labeled samples for traning, i.e., hundreds or thousands of samples for each category, which is hard and expensive to label manually. While human-beings are capable of recognizing a category of objects with just several obervations. Inspired by this, researchers raise a problem named Few-shot Learning, which aims to train a model from few labeled data much less than previous large-scale datasets. Usually, few-shot datasets only contain 1 (or 5, 10, etc.) samples for each category. If trainable models can also achieve high performance on few-shot data, it will greatly promote the development of machine learning and artificial intelligence. However, it is not easy to achieve high-performance few-shot learning by just applying existing algorithms since few-shot samples can not describe sufficient variations of data. Apparently, models just trained on few-shot data will suffer significant deteriorations when transfer to more general scenarios. But why we human-beings are capable of learning from few samples and still maintain high accuracy? One important explaination is that we possess the ability of "how to learn" and we have built many prior knowledge in our early age. Inspired by this phenomenon, researchers raise Meta-learning, i.e. learning to learn, to imitate the cognitive process of human-beings. Meta-learning is a strategy that can teach machine learning models how to distill general knowledge from many different tasks and do fast adaption to a new task. Recently, Finn *et al.* propose a model-agnostic meta-learning scheme MAML [1], which is a gradient-based method and can be easily applied into any advanced deep models. Naturally, it can also be transferred to few-shot learning problem. Previous works [2, 3] have made some attempts to further improve the few-shot learning performance based on gradient-based meta-learning scheme. In this project, we are planning to deeply study current few-shot learning methods experimentally and do some comparisons and discussions.

## 2 Method

Firstly, we are planning to survey a batch of papers related to few-shot learning and gradient-based meta-learning. Then we will select several representative works, e.g. [2, 3] to do further study and implementations. During the process of implementations, we will analyze the shortcomings of these methods and try to come up with some new ideas to address one or several problems.

## 3 Data

The representative datasets of few-shot learning are miniImageNet [4] and Fewshot-CIFAR100 (FC100) [5, 6]. Details are decribed as follows:

- *miniImageNet* [4] is proposed by Vinyals [4] for few-shot learning evaluation. Its complexity is high due to the use of ImageNet images, but requires less resource and infrastructure than running on the full ImageNet dataset [7]. In total, there are 100 classes with 600 samples of 84×84 color images per class. These 100 classes are divided into 64, 16, and 20 classes respectively for sampling tasks for meta-training, meta-validation and meta-test.

- *Fewshot-CIFAR100* [5, 6] is based on the popular object classification dataset CIFAR100 [5]. The splits were proposed by [6]. It offers a more challenging scenario with lower image resolution and more challenging meta-training/test splits that are separated according to object super-classes. It contains 100 object classes and each class has 600 samples of $32 \times 32$ color images. The 100 classes belong to 20 super-classes. Meta-training data are from 60 classes belonging to 12 super-classes. Meta-validation and meta-test sets contain 20 classes belonging to 4 super-classes, respectively. These splits accord to super-classes, thus minimize the information overlap between training and val/test tasks.

# References


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