Paper review for "Finn et al.: Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks"

EECS 598 Paper Review – Week 10 - Changyuan Qiu

Human could learn new skills quickly with just minutes of experience, and meta learning (or learning to learn) aims at creating artificial agents that could learn new tasks fast and flexibly just like human.

Here the authors propose Model-Agnostic Meta-Learning (MAML), a meta-learning method based on learning easily adaptable model parameters through gradient descent. The key idea underlying MAML is to train the model's initial parameters such that the model has maximal performance on a new task **after the parameters have been updated** through one or more gradient steps computed with a small amount of data from that new task.

Compared with prior meta-learning methods which mainly focus on learning and update function or learning rule, this paper does not introduce additional parameters to learn nor require a particular learner architecture. This enables MAML to be combined with any model representation any and any differentiable object that supports gradient-based training. Regarding experiments, they first evaluate MAML model's performance on regression problem by training and fine-tuning a MAML model for simple regression of sine wave and comparing it with a fully pretrained model. The MAML models significantly outperforms the pre-trained one, can estimate the sine wave approximately with no data points, demonstrates the capacity to quickly adapt to the sine wave with only 5 datapoints (even when they are all in one half of the input range), and continues to improve with additional gradient steps. Secondly, they evaluate MAML's performance on classification problems by applying it to few-show image recognition on the Omniglot and MiniImagenet dataset, where MAML achieves SOTA on all the benchmarks, getting amazing results like $99.9 \pm 0.01\%$ 5-shot 5-way

accuracy on Omniglot and 63.15 $\pm$ 0.91% 5-shot 5-way accuracy on MiniImagenet. Finally they evaluate MAML on reinforcement learning tasks like 2D Navigation and Locomotion, and the results demonstrate that MAML is able to learn quickly-adaptable model with 1 step of gradient update and is able to get consistent improvement with more updates.

Regarding limitations of this paper, for the image classification experiment on Omniglot where tasks are classifying handwritten characters, it is not clear whether the improvement in performance is due to the ability to better handle higher number of tasks (5-way accuracy and 20-way accuracy) or it is because the additional tasks are simple tasks and don't have much different distributions. Also, it is possible that one gradient update step (smallest update unit) could change the parameters significantly so that to harm the performance of the model across other tasks.