Week 6 Paper Review

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Abstract

This is a brief review of [1], [2].

1 Meta-Learning with Implicit Gradients

The paper presents an innovative approach to meta-learning that uses implicit gradients to enable efficient and effective learning of meta-parameters. The authors present iMAML, a method for optimization-based meta-learning that removes the need for differentiating through the inner optimization path, allowing the decoupling of the outer meta-gradient computation from the choice of the inner optimization algorithm.

This allows using a variety of inner optimization methods. Moreover, the inner optimization path need not be stored nor differentiated through, thereby making iMAML memory efficient and scalable to a large number of inner optimization steps. A theoretical analysis is also provided to show that an ϵ–approximate meta-gradient can be computed via iMAML using $O(log(1/\epsilon))$ gradient evaluations and O(1) memory, meaning the memory required does not grow with the number of gradient steps.

To have sufficient learning in the inner level while also avoiding over-fitting, L2 regularization is explored which proves to be easier to implement than the original truncated gradient descent. The meta-gradient computation step to calculate the inverse of the 2nd order derivative is difficult and hence some approximations are discussed to iteratively get the value.

The authors demonstrate the effectiveness of their approach on several benchmark tasks, including image classification and reinforcement learning. They compare iMAML to several state-of-the-art algorithms and show that their method achieves superior performance in terms of computation time, memory, and accuracy.

2 Learning to Adapt in Dynamic, Real-World Environments Through Meta-Reinforcement Learning

The paper presents an innovative approach to the problem of adapting to new environments in reinforcement learning using a meta-learning framework. The authors propose a model-based meta-RL that enables fast, online adaptation of large and expressive models in dynamic environments, i.e., that is able to adapt to unseen situations or sudden and drastic changes in the environment, and is also sample efficient to train.

Each timestep is considered to be a new “task" where any detail or setting could have changed at any timestep. This view induces a more general meta-RL problem setting by allowing the notion of a task to represent anything from existing in a different part of the state space, to experiencing disturbances, or attempting to achieve a new goal. 2 separate instatiations are provided, ReBAL and GrBAL, which utilizes a recurrent model to learns its own update rule, and gradient-based meta-learning to perform online adaptation respectively.

Preprint. Under review.

Experiments show this approach to be more sample-efficient than classic Model-based and MAML-RL. It shows fast adaptation due to online-learning and generalization over terrains and tasks. Overall, the experiments were extremely thorough.

References

[1] Rajeswaran, A., Finn, C., Kakade, S., & Levine, S. (2019). Meta-Learning with Implicit Gradients. ArXiv. https://doi.org/10.48550/arXiv.1909.04630

[2] Nagabandi, A., Clavera, I., Liu, S., Fearing, R. S., Abbeel, P., Levine, S., & Finn, C. (2018). Learning to Adapt in Dynamic, Real-World Environments Through Meta-Reinforcement Learning. ArXiv. https://doi.org/10.48550/arXiv.1803.11347