CS 4644/7643: Deep Learning
Spring 2024
HW1 Solutions

Arthur Scaquetti do Nascimento

February 5, 2024

4.8)

- Key contributions: Even though this is not the first attempt to optimize NN architectures, the authors bring a neuroscientific perspective and leverage facts that strong inductive biases can lead to innate learning to develop an evolution-based search strategy for optimal NN architectures.

- Strengths: The optimization is done on a network-design level, and using genetic algorithms heuristics; therefore, there is no need to compute gradients, which is one of the bottlenecks in Deep Learning. Moreover, this is done grounded in neuroscience findings, instead of a common practice trial-and-error approach.

- Weaknesses: Even though the approach is novel, this is not the first work to tackle the need for smarter network designing, and does not outperform all previous work, such as Zhou, et al. (2019) [1]. The authors also could have incorporated pruning methods and the formulation of search for architectures in a differentiable manner to enhance their evolutionary search strategy.

4.9) I am curious to see how this method would perform in more complex RL environments (e.g., 7DoF manipulator, Deep Brain Stimulation, Minecraft, etc.) either for the direct generation of the policy as they did in the 2D environments, or as a "warm-start", namely the search for the best architecture to encapsulate the behavior of a Q-function. Especially with respect of training time and robustness to out-of distribution priors (could be treated as zero-shot). If it works well, it could mean that this should be step no.1 for RL practitioners.
Moreover, the authors criticize meta-learning, but I also wonder how applicable this is to the MAML model and other meta-learned policies.

[1] H. Zhou, J. Lan, R. Liu, and J. Yosinski. Deconstructing lottery tickets: Zeros, signs, and the supermask. arXiv preprint arXiv:1905.01067, 2019. https://arxiv.org/abs/1905.01067.