AutoML: Dynamic Configuration & Learning

Learning to Adjust Learning Rates

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Learning Problem [Daniel et al. 2016]

- Optimization of a function:

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$$F(\mathbf{X}; \theta) = \frac{1}{N} \sum_{i=1}^{N} f(\mathbf{x}^{(i)}; \theta)$$

Learning Step Size Policies [Daniel et al. 2016]

- Idea: Learn the hyperparameters of the weight update (short notation)

$$\theta^{(t+1)} = \theta^{(t)} - \alpha^{(t)} \nabla F(\theta^{(t)})$$

$$\nabla F(\theta^{(t)}) = \frac{1}{N} \sum_{i=1}^{N} \nabla f_i(\theta^{(t)})$$

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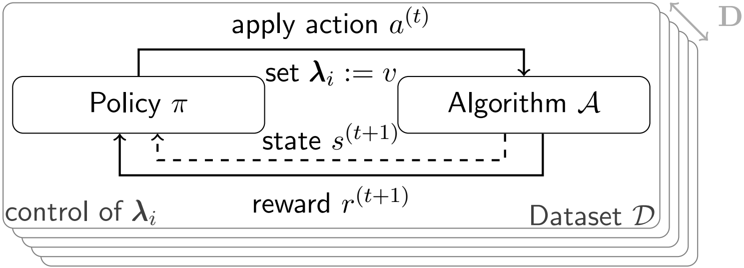
- Idea: Use reinforcement learning to learn a policy $\pi : s \mapsto a$ to control the learning rate (or other adaptive hyperparameters)

Recap: Reinforcement Learning for Dynamic Algorithm Configuration



To apply that, we need to define:

1. State description
2. Action space
3. Reward function

RL for Step Size Policies: State [Daniel et al. 2016]

Predictive change in function value:

$$s_1 = \log\left(\mathsf{Var}(\Delta \tilde{f}_i)\right)$$

$$\Delta \tilde{f}_i = \tilde{f}(\mathbf{x}^{(i)}; \theta + \delta\theta) - f(\mathbf{x}^{(i)}; \theta)$$

where $\tilde{f}(\mathbf{x}^{(i)}; \theta + \delta\theta)$ is done by a first order Taylor expansion

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Disagreement of function values:

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Uncertainty Estimate (noise level):

$$s_{K+i} \leftarrow \gamma s_{K+i} + (1-\gamma)(s_i - \hat{s}_i)^2$$

RL for Step Size Policies: Learning [Daniel et al. 2016]

Reward (average loss improvement over time):

$$r = \frac{1}{T-1} \sum_{t=2}^{T} \left(\log(L^{(t-1)}) - \log(L^{(t)}) \right)$$

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- can be learnt for example via Relative Entropy Policy Search (REPS) [Peter et al. 2010]

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  i.e., good performance for many different DNN architectures
  - $\rightsquigarrow$ Sample architectures e.g., with different numbers of filters and layers
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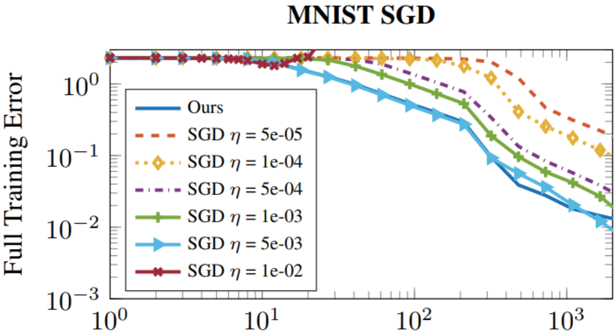

"Ours" refers to the approach by [Daniel et al. 2016] and η is the learning rate