

AutoML: Dynamic Configuration & Learning

Dynamic Configuration

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Iterative Optimization Heuristics

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- other examples: restart probability of search, mutation rate of evolutionary algorithms, ...

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- Still not guaranteed that optimal setting of e.g. learning rate schedules will lead to optimal learning behavior
 - ▶ Learning rate schedules are only heuristics

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the *dynamic algorithm configuration problem* is to obtain a policy $\pi^* : s_t \times \mathcal{D} \mapsto \lambda$ by optimizing its cost across a distribution of datasets:

$$\pi^* \in \arg \min_{\pi \in \Pi} \int_{\mathbf{D}} p(\mathcal{D}) c(\pi, \mathcal{D}) \, d\mathcal{D}$$

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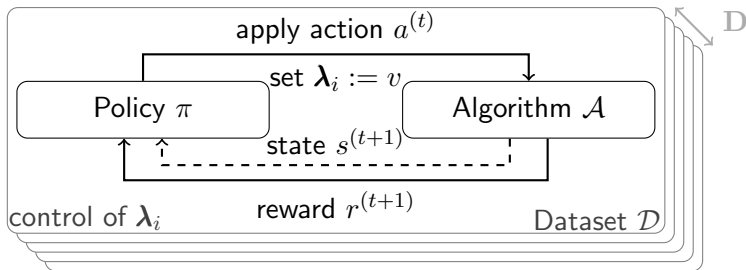
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Context \mathcal{D} A given dataset (or task)



Solving Dynamic Algorithm Configuration

Solve unknown MDP by using reinforcement learning (RL):

$$\mathcal{V}_{\mathcal{D}}^{\pi}(s^{(t)}) = \mathbb{E} \left[\sum_{k=0}^{\infty} \gamma^k r_{\mathcal{D}}^{(t+k+1)} \mid s^{(t)} = s \right]$$

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\rightsquigarrow equivalent to Dynamic Algorithm Configuration definition

- Challenge: Evaluating a policies on all datasets is often not feasible

Dynamic Algorithm Configuration across Datasets [Biedenkapp et al. 2020]

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 - ▶ Focus on "easy" tasks where the agent can improve most:

$$\max_{\pi, \mathbf{v}} \mathcal{C}(\pi, \mathbf{v}, K) = \sum_{i=1}^{|\mathbf{D}|} \mathbf{v}_i \mathcal{R}_i(\pi) - \frac{1}{K} \sum_{i=1}^{|\mathbf{D}|} \mathbf{v}_i$$

with θ being the agent's policy parameters and \mathbf{v} being a masking vector for choosing the tasks at hand.