AutoML: Dynamic Configuration & Learning

Dynamic Configuration

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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 $\pi^* : s_t \times \mathcal{D} \mapsto \boldsymbol{\lambda}$ by optimizing its cost across a distribution of datasets:

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

Dynamic Algorithm Configuration as Contextual MDP [Biedenkapp et al. 2020]

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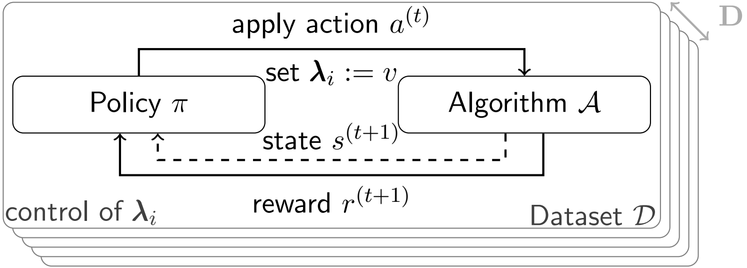
Context $\mathcal{D}$	A given dataset (or task)



Solving Dynamic Algorithm Configuration

Solve unknown MDP by using reinforcement learning (RL):

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

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$\rightsquigarrow$ equivalent to Dynamic Algorithm Configuration definition

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

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