

# HYPERPARAMETER OPTIMIZATION

- **Hyperparameters (HP)**  $\lambda$  are parameters that are *inputs* to learner  $\mathcal{I}$  which performs ERM on training data set to find optimal **model parameters**  $\theta$ . HPs can influence the generalization performance in a non-trivial and subtle way.

- **Hyperparameter optimization (HPO) / Tuning** is the process of finding a well-performing hyperparameter configuration (HPC)  $\lambda \in \tilde{\Lambda}$  for an learner  $\mathcal{I}_\lambda$ .



## OBJECTIVE AND SEARCH SPACE

Search space  $\tilde{\Lambda} \subset \Lambda$  with all optimized HPs and ranges:

$$\tilde{\Lambda} = \tilde{\Lambda}_1 \times \tilde{\Lambda}_2 \times \dots \times \tilde{\Lambda}_j$$

where  $\tilde{\Lambda}_j$  is a bounded subset of the domain of the  $i$ -th HP  $\Lambda_{j_i}$  and can be either continuous, discrete, or categorical.



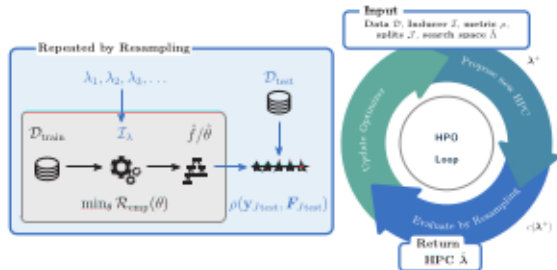
The general HPO problem is defined as:

$$\lambda^* \in \arg \min_{\lambda \in \tilde{\Lambda}} c(\lambda) = \arg \min_{\lambda \in \tilde{\Lambda}} \widehat{\text{GE}}(\mathcal{I}, \mathcal{J}, \rho, \lambda)$$

with  $\lambda^*$  as theoretical optimum, and  $c(\lambda)$  is short for estim. gen. error when  $\mathcal{I}$ , resampling splits  $\mathcal{J}$ , performance measure  $\rho$  are fixed.

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- Evals are stored in **archive**

$$\mathcal{A} = ((\lambda^{(1)}, c(\lambda^{(1)})), (\lambda^{(2)}, c(\lambda^{(2)})), \dots), \text{ with}$$
$$\mathcal{A}^{[t+1]} = \mathcal{A}^{[t]} \cup (\lambda^+, c(\lambda^+)).$$

- We can define tuner as function  $\tau : (\mathcal{D}, \mathcal{I}, \tilde{\Lambda}, \mathcal{J}, \rho) \mapsto \hat{\Lambda}$