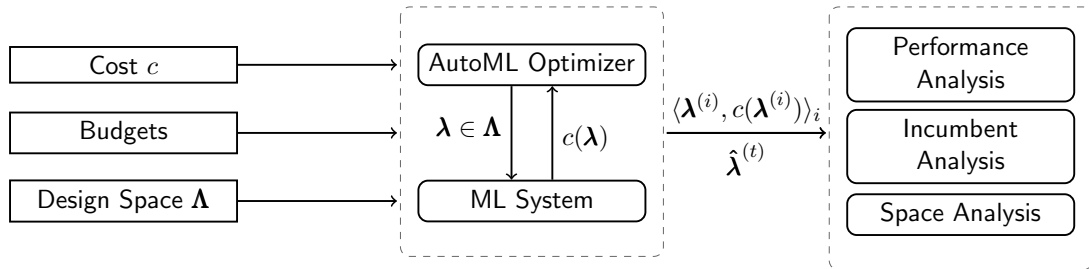


AutoML: Interpretability

Global Hyperparameter Importance

Bernd Bischl Frank Hutter Lars Kotthoff
Marius Lindauer Joaquin Vanschoren

Idea



~> focus on which hyperparameters are important across the entire search space

Importance Analysis of Surrogate Model

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- Potential drawback:
 - ▶ The surrogate model might overfit to different subsets of the hyperparameters (if we don't provide sufficient data)

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fANOVA [Sobobl. 1993]

Write performance predictions as a sum of components:

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Variance Decomposition

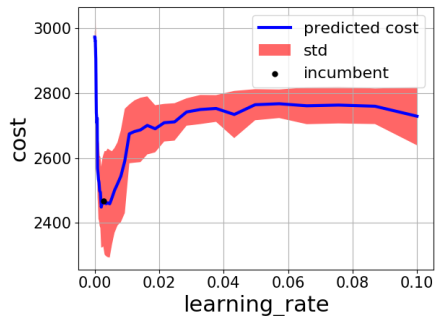
$$V = \frac{1}{||\boldsymbol{\Lambda}||} \int_{\boldsymbol{\lambda}_1} \dots \int_{\boldsymbol{\lambda}_n} [(\hat{y}(\boldsymbol{\lambda}) - \hat{f}_0)^2] d\boldsymbol{\lambda}_1 \dots d\boldsymbol{\lambda}_n$$

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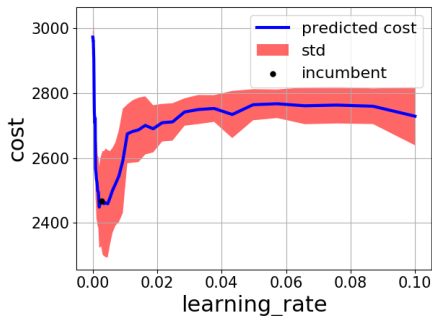


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Source: [Lindauer et al. 2019]

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- **Warning:** The optimum on these curves does not have to be the global optimum across all hyperparameters

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- How much of the variance can be explained by a hyperparameter (or combinations of hyperparameters) marginalized over all other parameters?

Table: Exemplary analysis of PPO on cartpole

Hyperparameter	Explained Variance
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[Biedenkapp et al. 2018]
- ~> You should run both to get a good understanding of why an AutoML tool chose a configuration