









Hands-On Session: Practical Hyperparameter Optimization with SMAC3

Carolin Benjamins, Alexander Tornede










Who Are We? Alexander Tornede



-  From 10/2018 - 06/2023 PhD student with Prof. Dr. Eyke Hüllermeier at Paderborn University on the topic of Algorithm Selection
-  Since 09/2022 PostDoc in Prof. Dr. Marius Lindauer's group at Leibniz University Hannover
-  Head of SMAC's dev team
-  Member of the automl.org supergroup
-  Collaborations with other research groups
-  Focus on interactive and explainable AutoML and LLMs x AutoML
-  Background: Computer Science
-  I love playing board games with friends

Who Are We? Carolin Benjamins



-  Since 2020 PhD student with Prof. Dr. Marius Lindauer at Leibniz University Hannover
-  Member of SMAC's dev team
-  Member of the automl.org supergroup
-  Collaborations with other research groups
-  Focus on AutoML, Dynamic Algorithm Configuration, Bayesian Optimization. Interested in robotics and Contextual Reinforcement Learning.
-  Background: Mechatronics & Robotics
-  I love automation and making complex algorithms more accessible!

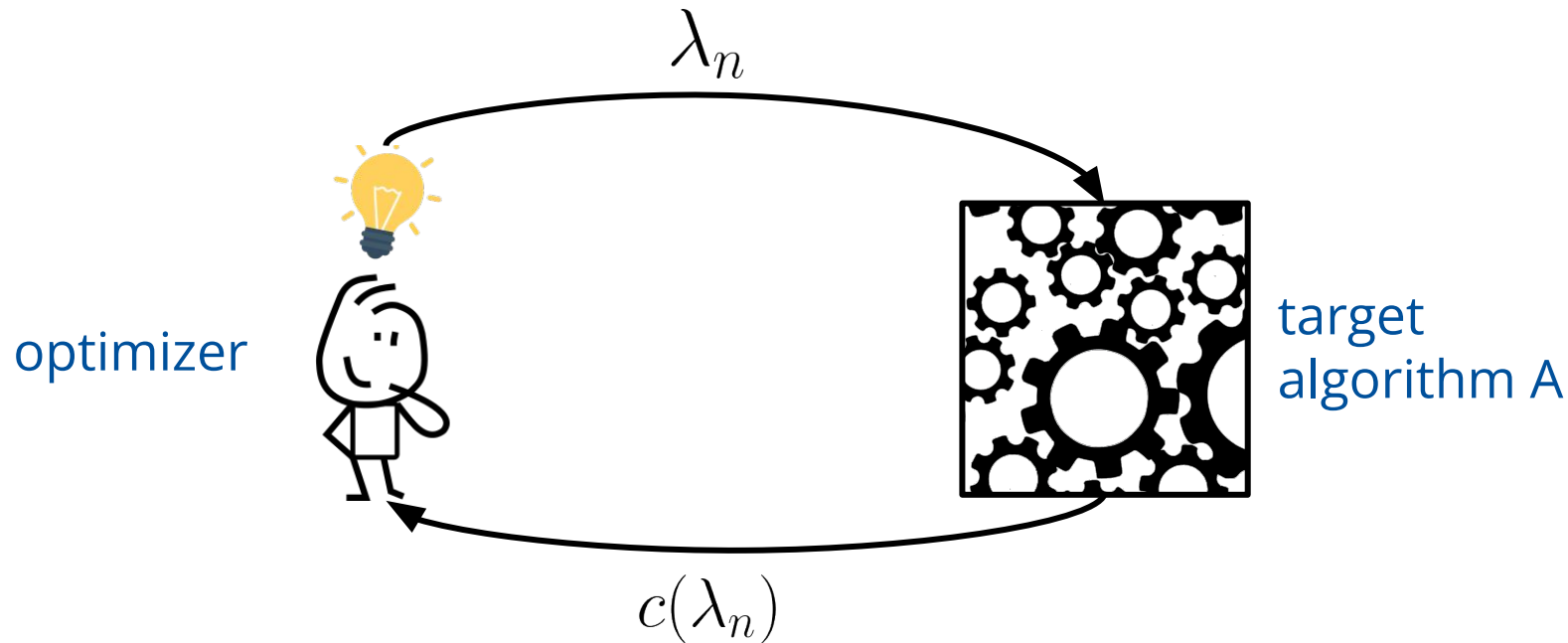


Today's Game Plan

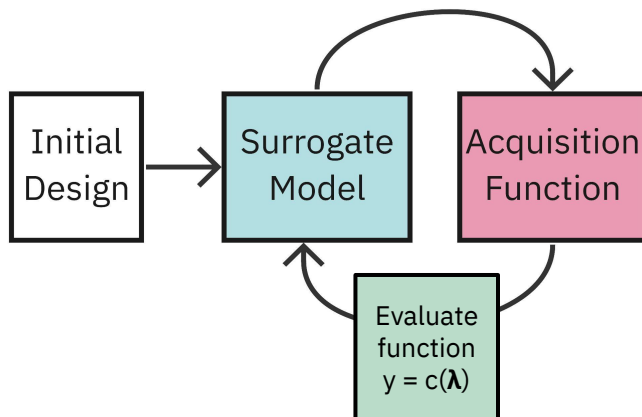
1. 14:00 - 14:25: Introduction of SMAC
2. 14:20 - 15:15: Hands-on Notebook Session
3. 15:15 - 15:30: Wrap-Up: What did we learn?

Hyperparameter Optimization

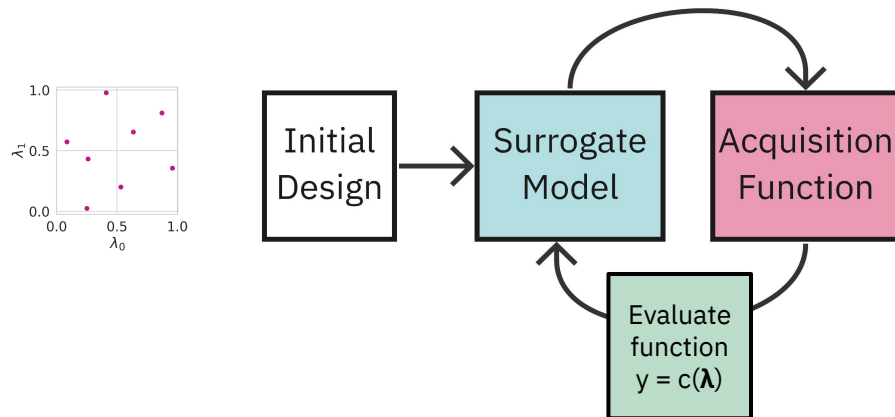
Goal: Find the best performing configuration: $\lambda^* \in \arg \min_{\lambda \in \Lambda} c(\lambda) = \arg \min_{\lambda \in \Lambda} \mathcal{L}(\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{val}}; \lambda)$



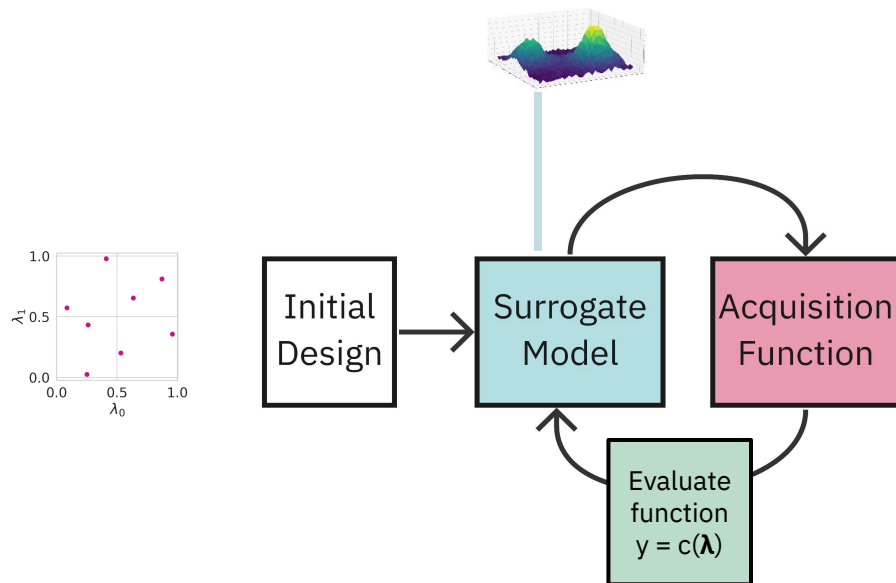
Recap: Bayesian Optimization



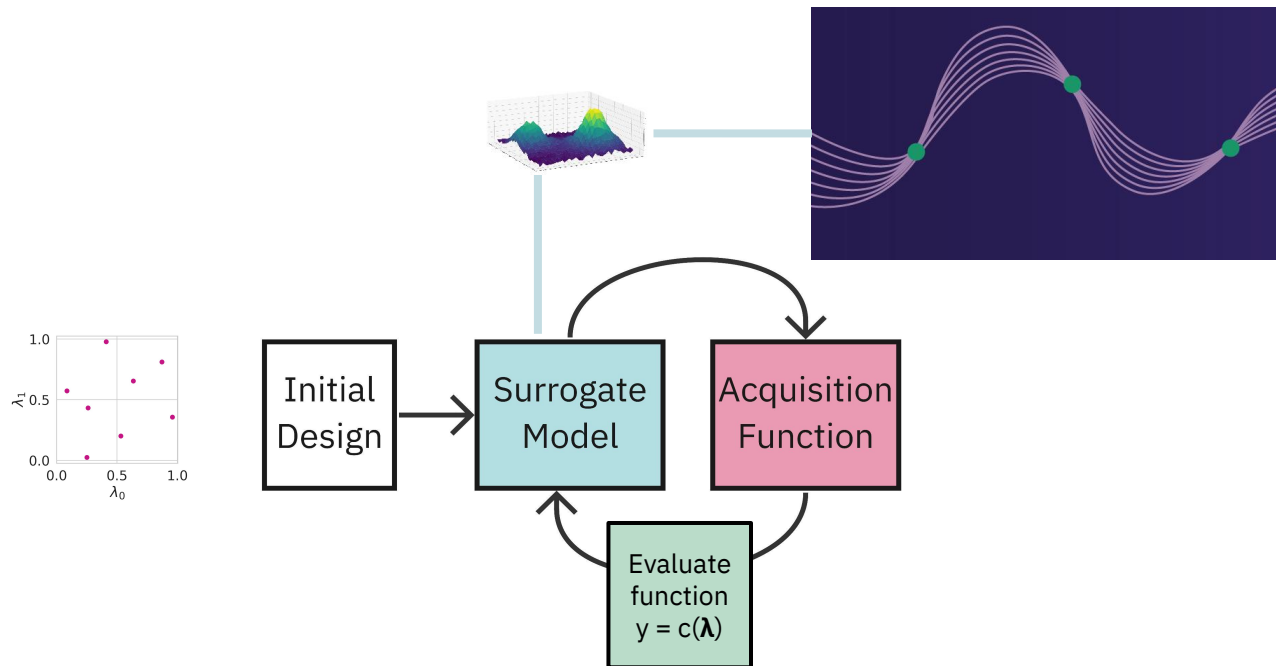
Recap: Bayesian Optimization



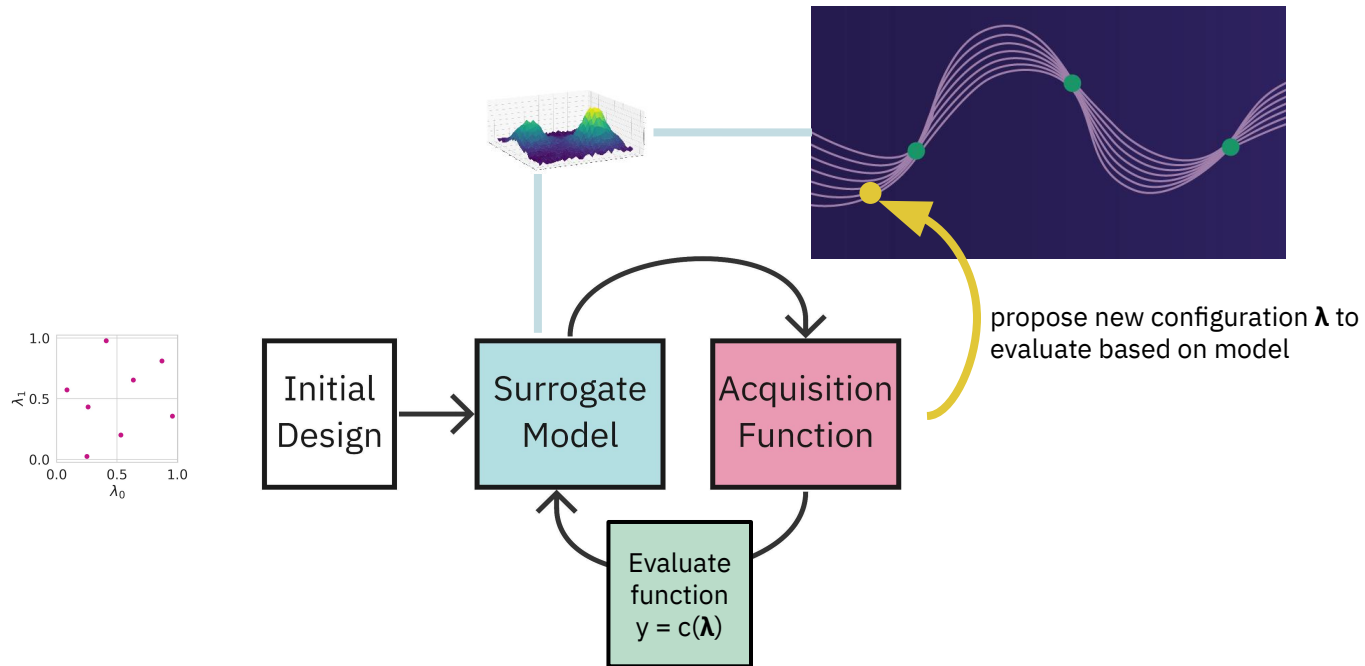
Recap: Bayesian Optimization



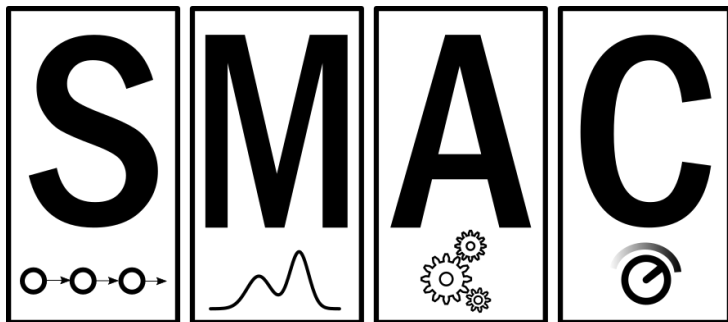
Recap: Bayesian Optimization



Recap: Bayesian Optimization



SMAC3 - A Versatile Bayesian Optimization Package for Hyperparameter Optimization



Original authors:



New team members:



Funded by:





SMAC Features (1)

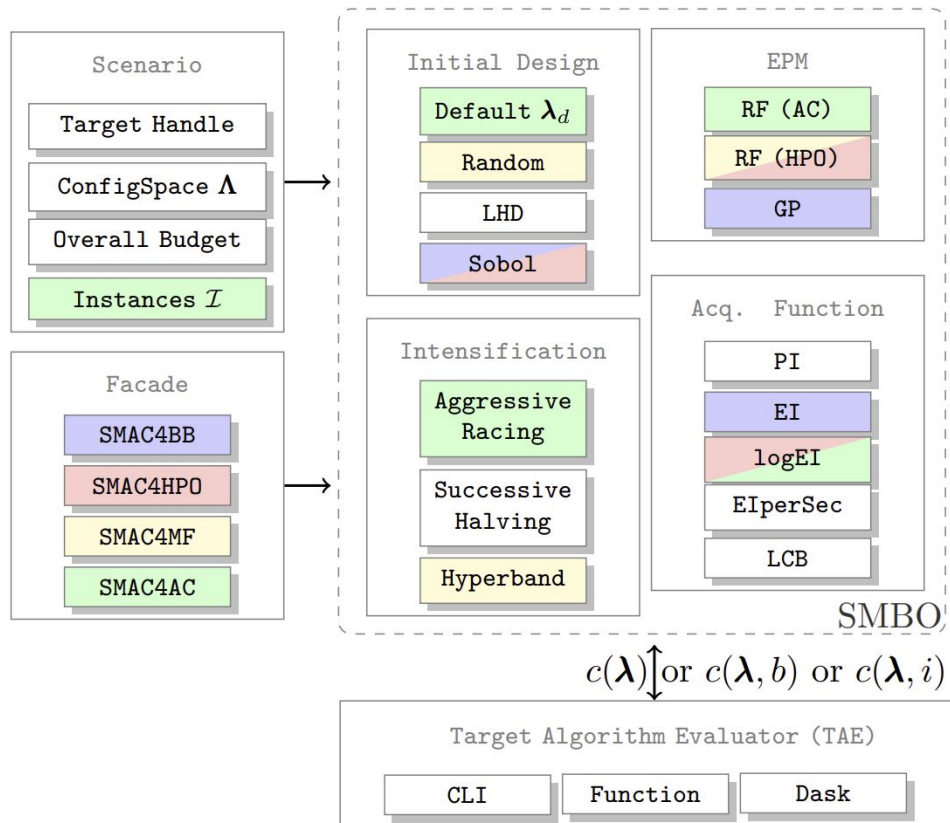
- Open source + active maintenance
- Rich search space with floats, ordinals, categoricals and conditions
- Ask-and-Tell Interface
- Continue and Warmstart Optimization
- Intensification mechanism to efficiently compare configurations
- User priors



SMAC Features (2)

- Parallelization, local and on a cluster with Dask
- Multi-fidelity optimization, e.g. when we can evaluate our function with different resolutions
- Multi-objective optimization with ParEGO
- Optimization across many tasks (aka algorithm configuration)
- Function to optimize can either be pythonic or called via a script
- Easily extensible with callbacks

Modular Design



SMAC for Black-Box Functions

$$\lambda^* \in \arg \min_{\lambda \in \Lambda} c(\lambda)$$

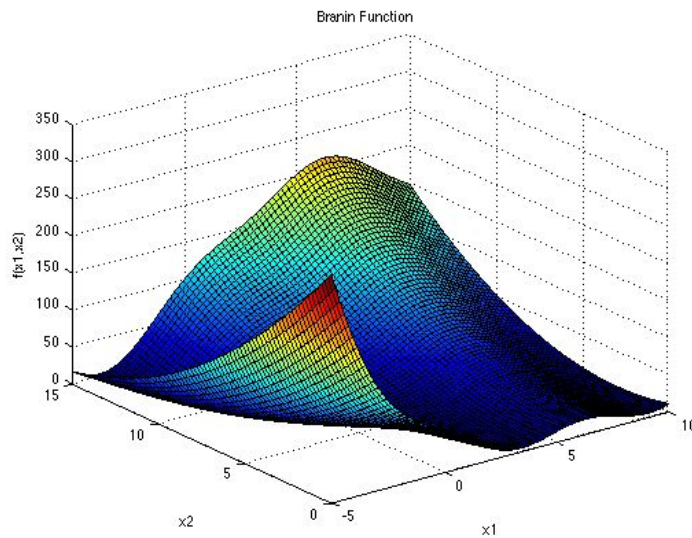
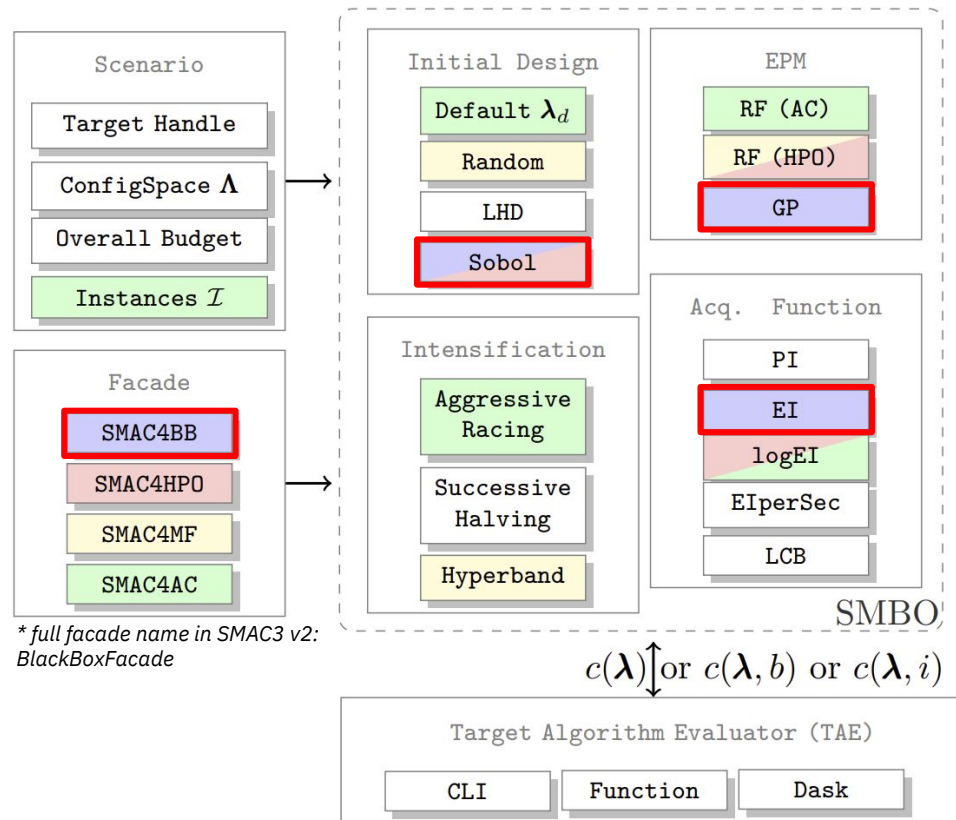


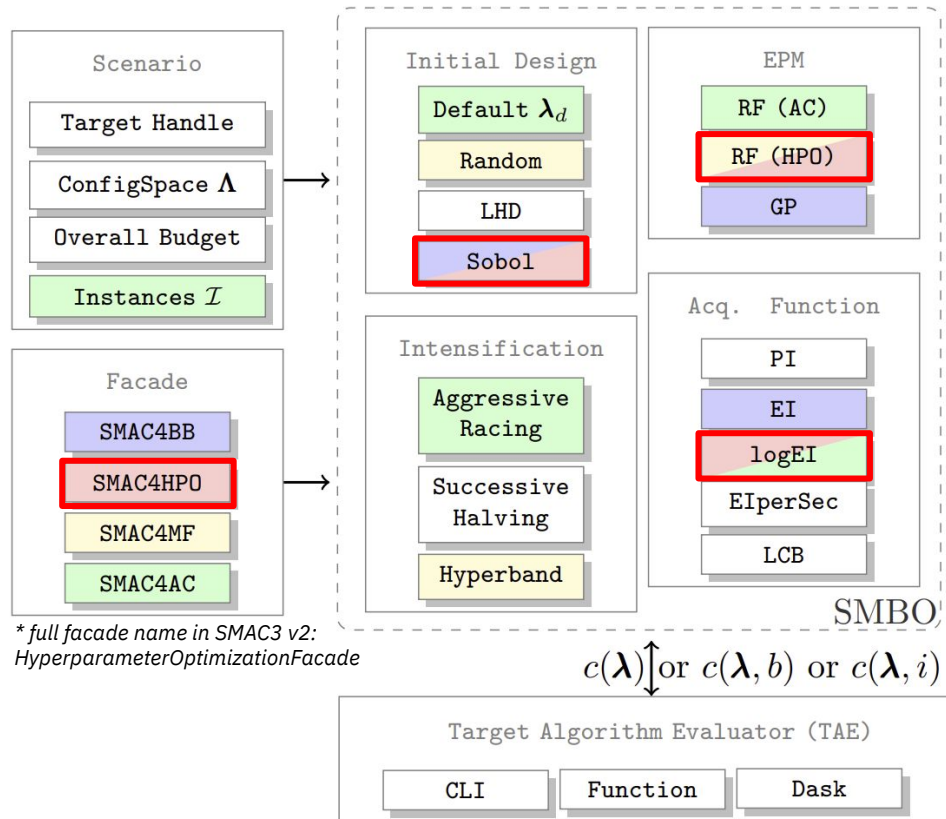
Image credit [Derek Bingham](#)



SMAC for CASH and Structured Hyperparameter Optimization

$$(A^*, \lambda^*) \in \arg \min_{A_i \in \mathbf{A}, \lambda \in \Lambda_i} c(A_i, \lambda) =$$

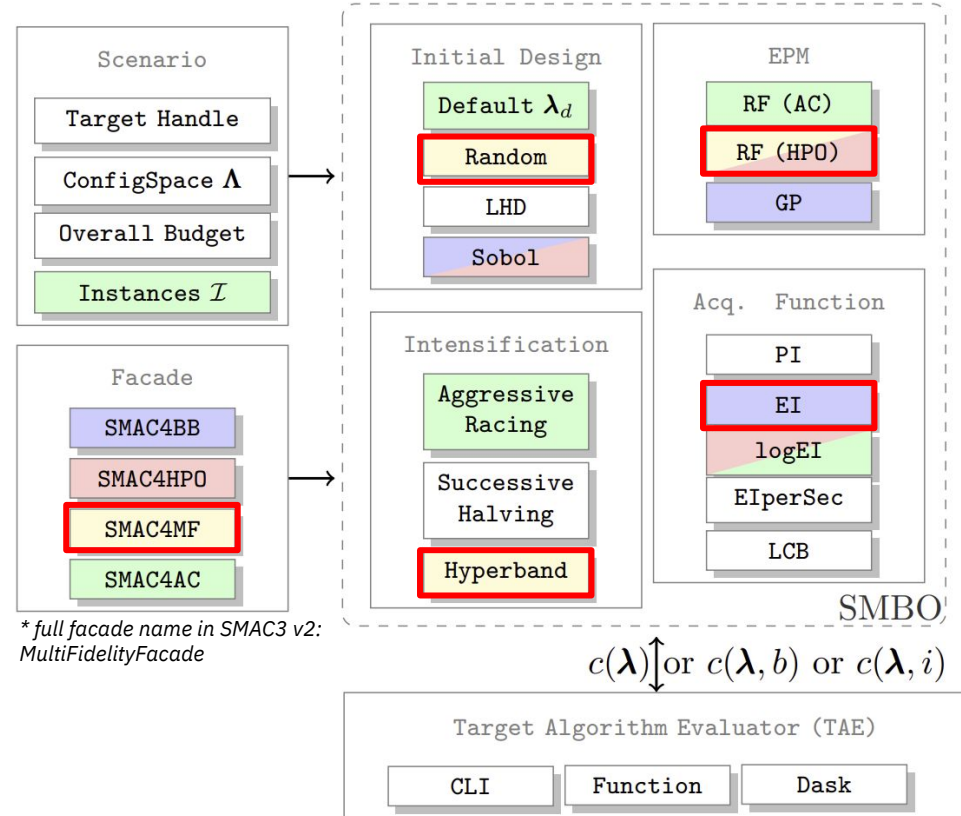
$$\arg \min_{A_i \in \mathbf{A}, \lambda \in \Lambda_i} \mathcal{L}(\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{val}}; A_i(\lambda)).$$



SMAC for Expensive Tasks and Automated Deep Learning

$$\lambda^* \in \arg \min_{\lambda \in \Lambda} c(\lambda, b_{max}) =$$

$$\arg \min_{\lambda \in \Lambda} \mathcal{L}(\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{val}}; \lambda, b_{max}).$$

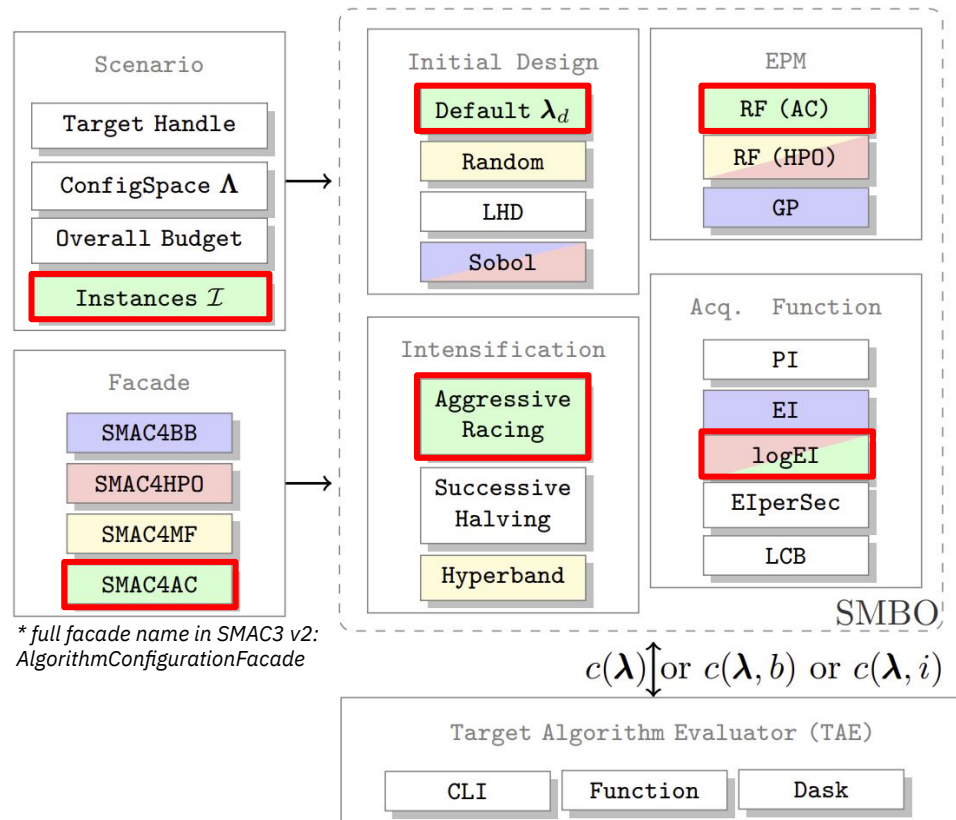


* full facade name in SMAC3 v2:
MultiFidelityFacade

SMAC for Algorithm Configuration

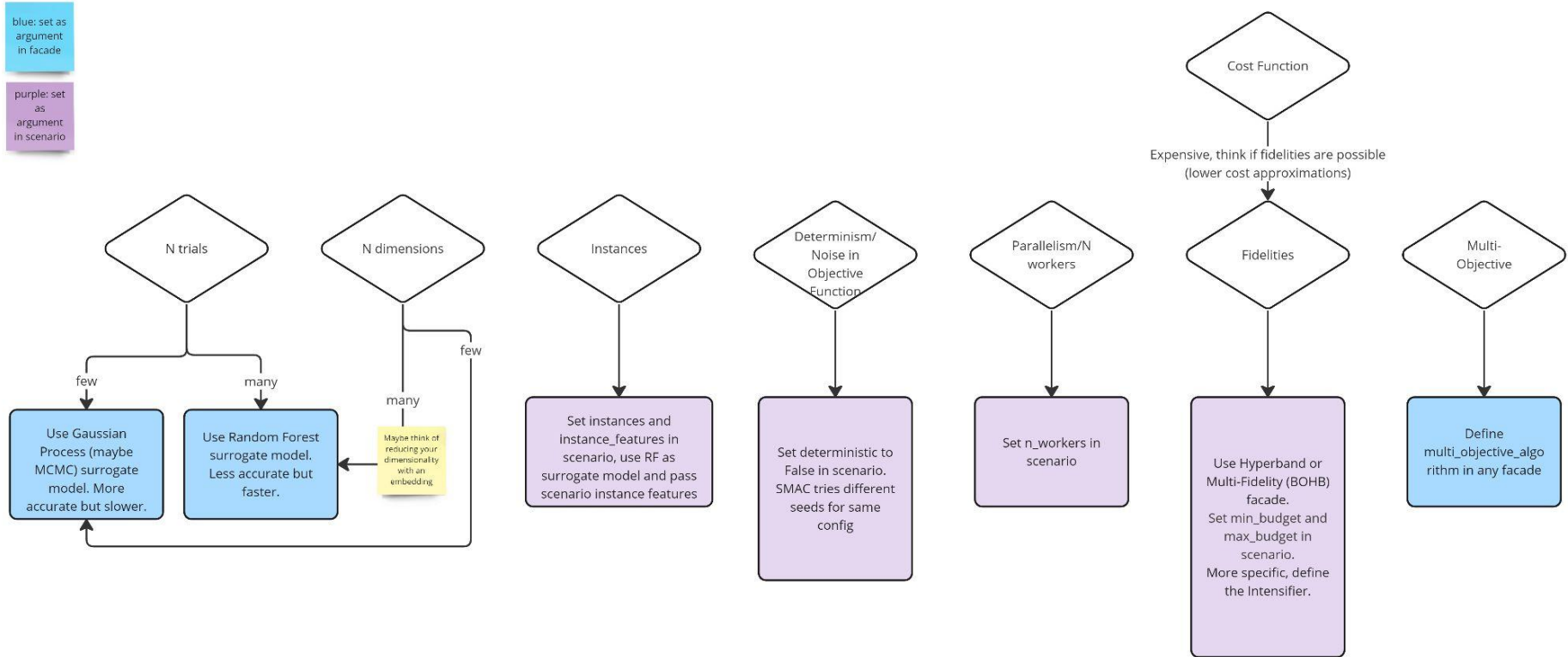
$$\lambda^* \in \arg \min_{\lambda \in \Lambda} c(\lambda) =$$

$$\arg \min_{\lambda \in \Lambda} \sum_{i \in \mathcal{I}} c'(\lambda, i)$$





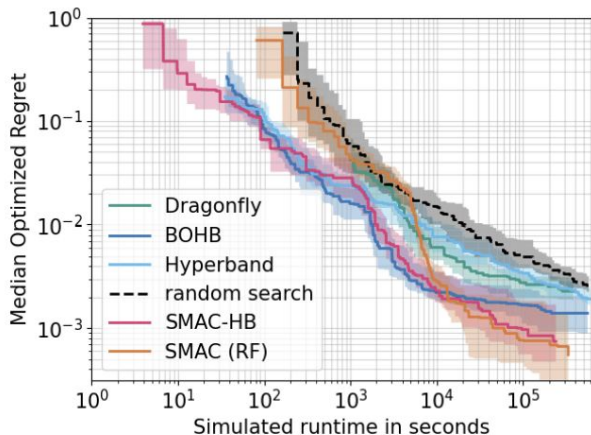
Facades Are Only Shortcuts!



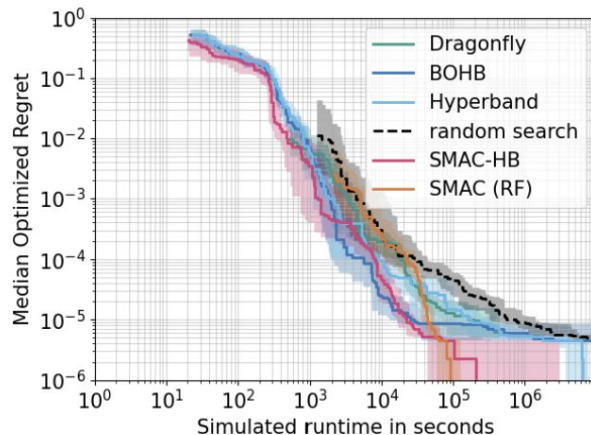
Comparison to Other Packages

Package	Complex Hyperparameter Space	Multi-Objective	Multi-Fidelity	Instances	Command-Line Interface	Parallelism
HyperMapper	✓	✓	✗	✗	✗	✗
Optuna	✓	✓	✓	✗	✓	✓
Hyperopt	✓	✗	✗	✗	✓	✓
BoTorch	✗	✓	✓	✗	✗	✓
OpenBox	✓	✓	✗	✗	✗	✓
HpBandSter	✓	✗	✓	✗	✗	✓
SMAC	✓	✓	✓	✓	✓	✓

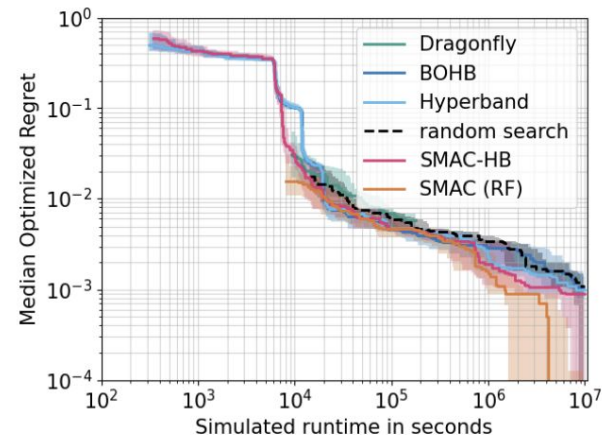
NetLetter (6D)



NBHPONaval (9D)



Nas1Shot1_2



Take-Aways:

1. SMAC with a RF as black-box HPO approach “SMAC (RF)” outperforms other approaches with TPE and GP models
2. SMAC’s implementation of BOHB [Falkner et al. 2018] “SMAC-HB” (also using a RF as surrogate) has a very strong any-time performance

Hands-On Notebook Session



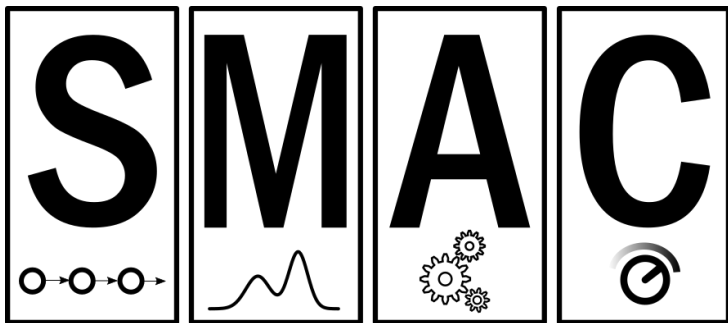
Leibniz
Universität
Hannover

<https://tinyurl.com/fallschoolsmac>

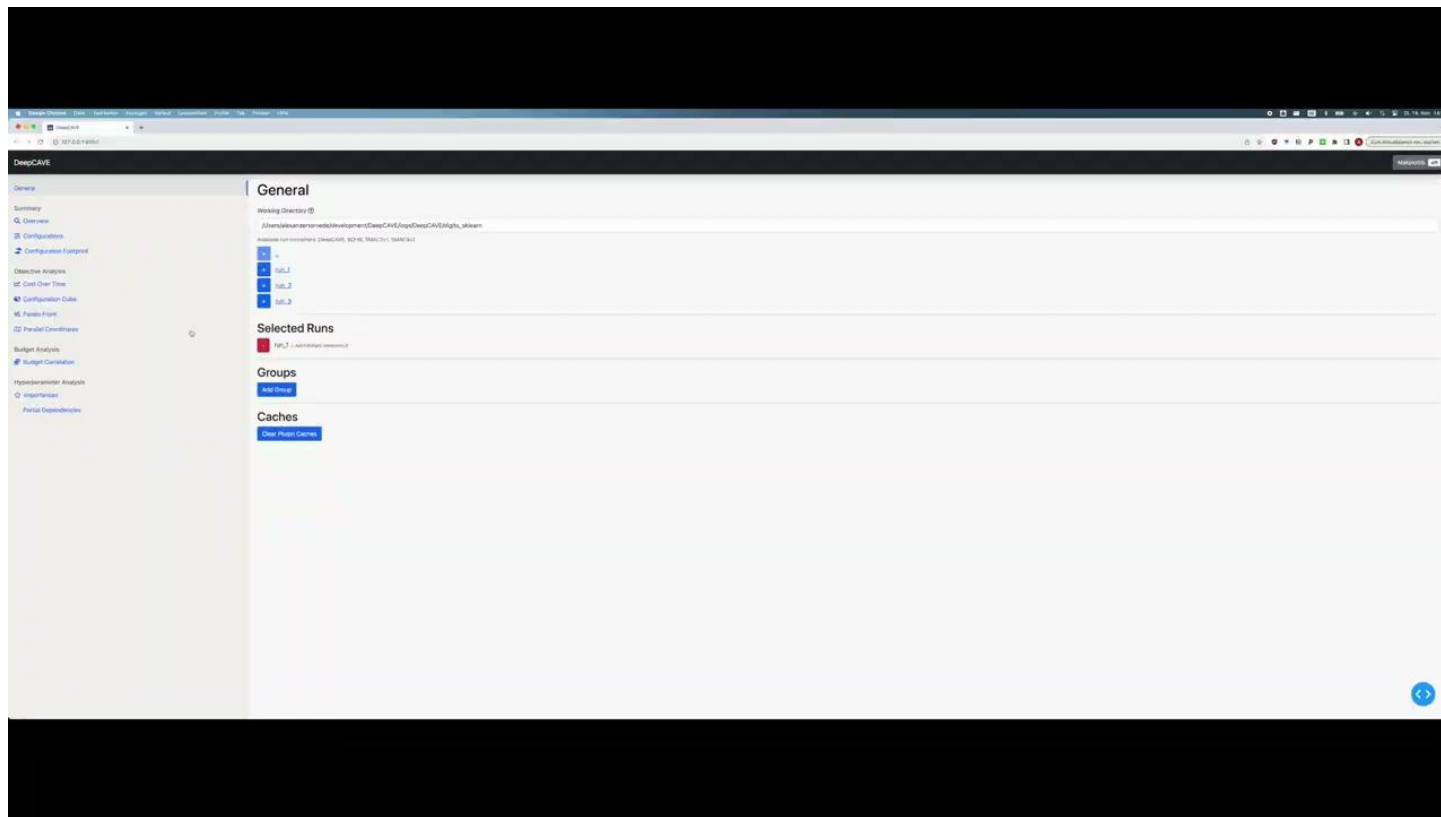


Wrap-Up: What Did We Learn?

- How to perform HPO with SMAC
- SMAC is highly modularized offering many customization options
- SMAC offers different facades for easy usages in many use cases
- We welcome collaborations and contributions 😊



DeepCave Sneak Peek



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