



Registration is open!

Date: September 2nd - 6th 2024

Place: Hannover, Germany

www.automlschool.org



**Open Calls for
Workshop Track,
Journals, Tutorials,
& nontraditional
Content!**

www.automl.cc

Towards Multi-objective Green AutoML

It's not only accuracy that matters!



The hottest temperatures



NEWS CULTURE MUSIC

CLIMATE Climate worldw...

September 13, 2023
Rebecca Hersl



CLIMATE | CANADA Canadian wildfires fueled by climate change, study shows

Stuart Braun
08/22/2023
The record extreme fires in Quebec, Canada this summer were twice as likely to happen and burned more intensely due to human-caused global heating, say researchers.



The EU Day for the Victims of the Global Climate Crisis

Executive Vice President Frans Timmermans signed a joint declaration for the Day for the Victims of the Global Climate Crisis.



healthy air



Photos

Muhammad Amdad Hossain/ZUMA Wire/IMAGO

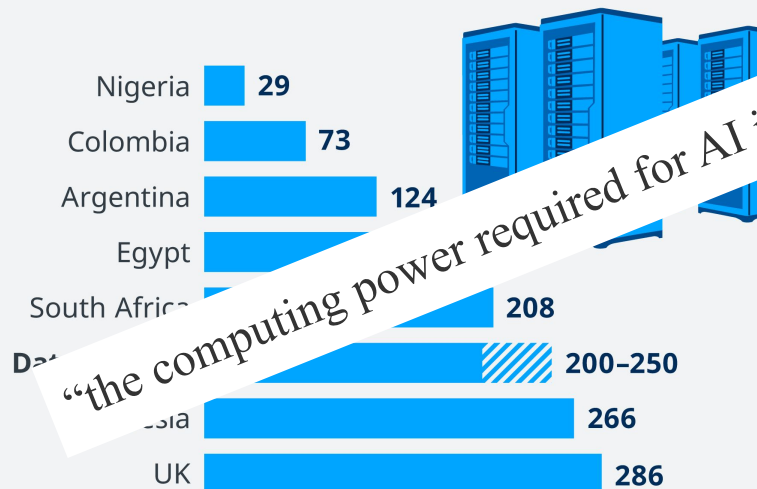
tal cities in the world. Many people moved large parts of Chittagong under water for...
Al Islam Montu reports

Sustainability is also our responsibility!

Energy Consumption of Data Centers

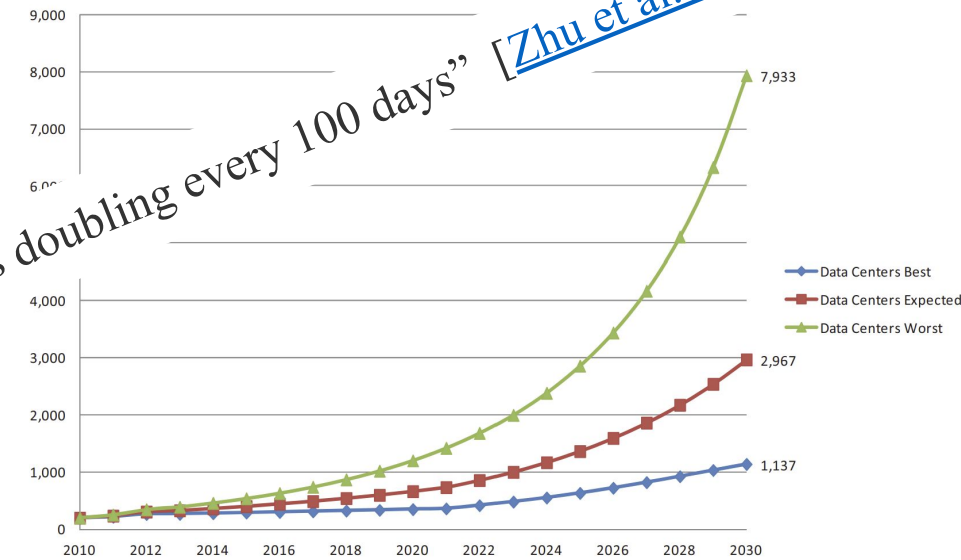
Data centers use more electricity than entire countries

Domestic electricity consumption of selected countries vs. data centers in 2020 in TWh



“the computing power required for AI is doubling every 100 days” [Zhu et al. 2023]

Electricity usage (TWh) of Data Centers



[Andrae. 2015]

Current Focus of AutoML Research

[Chevron-double-up Icons](#) by Laisa Islam Ani

[Graph Icons](#) by Secret Studio

[Chip Icons](#) by srip



Better predictive performance (e.g., accuracy)

⇒ other quality indicators (e.g., energy efficiency) are often ignored



Scaling to larger models (e.g., LLMs)

⇒ AutoML needs to be more efficient

(e.g., via multi-fidelity optimization or expert knowledge integration)

⇒ Mindset is less on energy efficiency but to apply AutoML to ever larger models (each of training of them requires more and more energy)

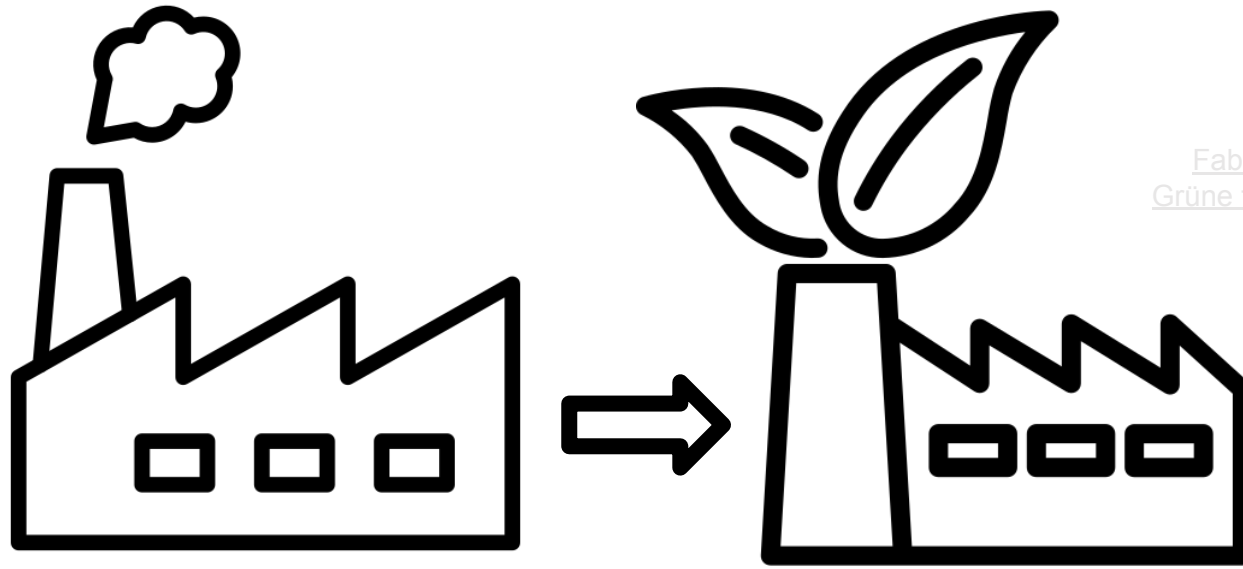


Adaptation to different hardware constraints

(e.g., embedded systems, smartphones)

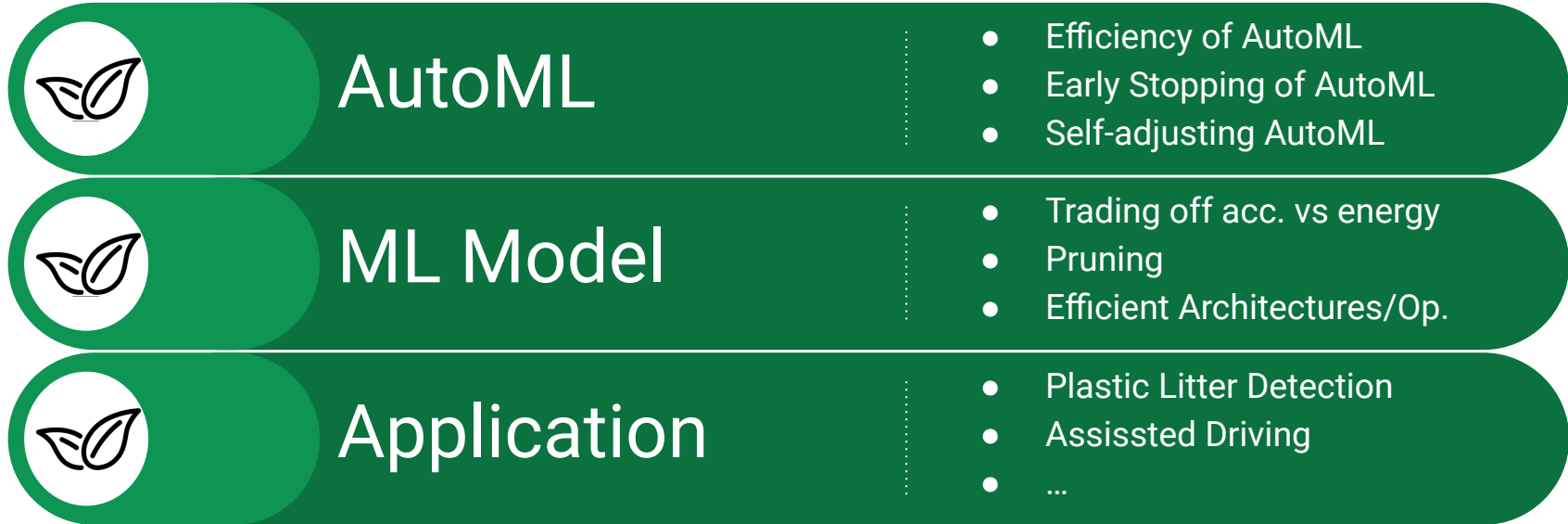
⇒ Main objective: How can I get the best out of an AI on a given hardware module?

⇒ Rarely: How can I achieve the best with the fewest possible resources?



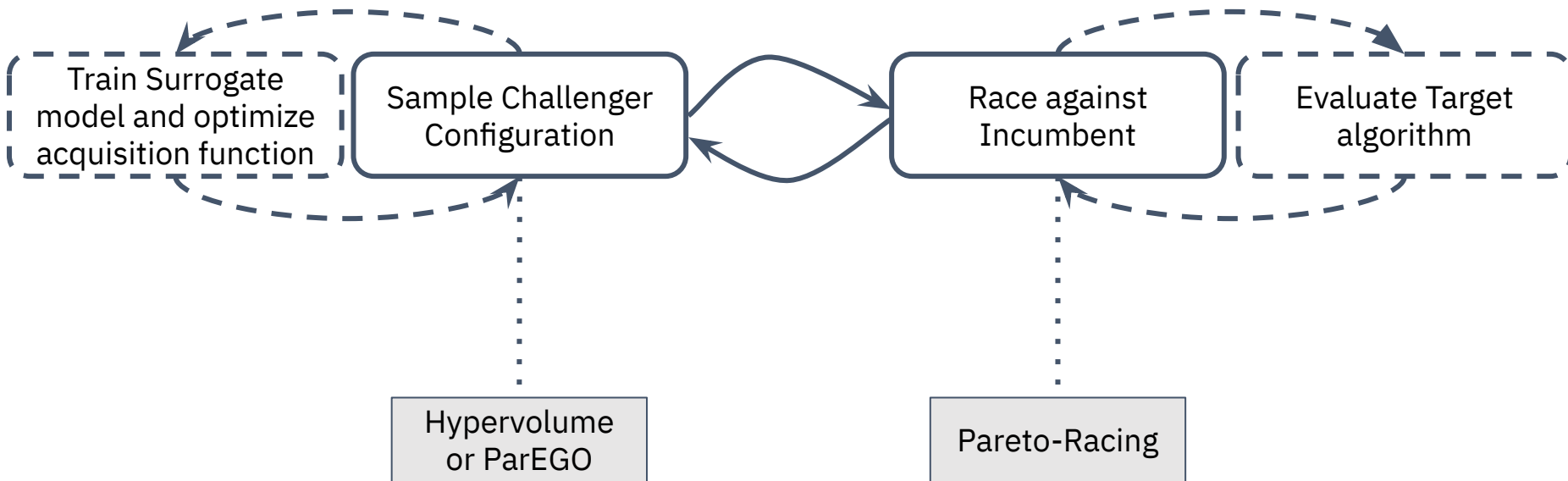
Towards Green AutoML

Hierarchy of Green AutoML



Multi-Objective SMAC for HPO & AC

Towards Multi-Objective SMAC



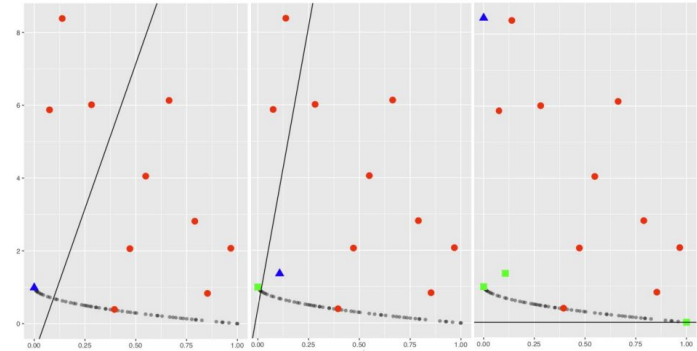
Multi-Objective Multi-Fidelity SMAC

ParEGO

- Sample a scalarization in each iteration

$$c = \max_{i=1, \dots, m} (w_i \cdot c^i(\theta)) + \rho \cdot \sum_{i=1}^m w_i \cdot c^i(\theta),$$

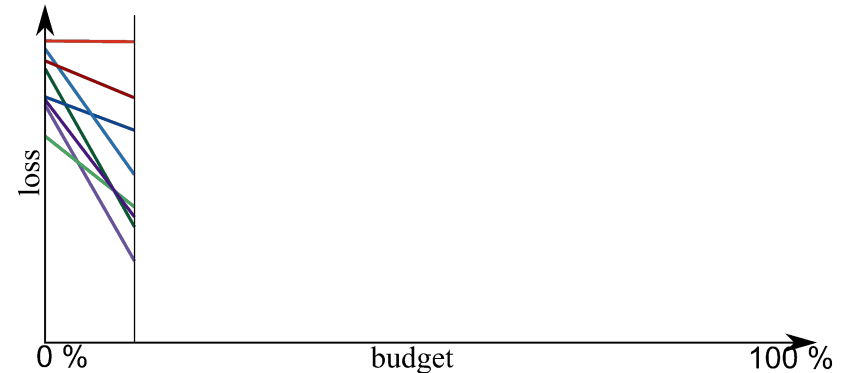
- Train a single model & proceed as always



Img Source: Bischl@AutoML MOOC

Successive Halving / Hyperband

- Run successive halving as always by using the scalarized metric above
- Check whether the configurations evaluated on the highest budget should be part of the Pareto Front



Img Source: AutoML.org

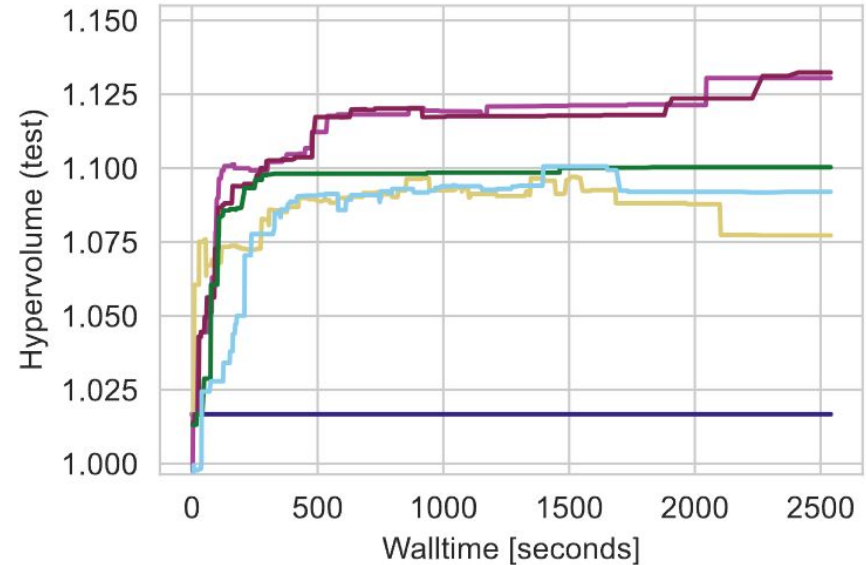
Multi-Objective Algorithm Configuration

It can be done better:

- MO-SMAC has the potential to outperform MO-ParamILS (Bayesian-Optimization based AC vs. Local-Search based AC)
- On average, ParEGO-variant is not the best MOO approach

→ **More details in Jeroen's talk in a few minutes**

- ★ MO-SMAC-PHVI
- ▲ SMAC
- ✕ Random Search
- Default
- ◀ MO-SMAC-PE
- ▼ MO-ParamILS



Leveraging AutoML for Sustainable Deep Learning: A Multi-Objective HPO Approach on Deep Shift Neural Networks

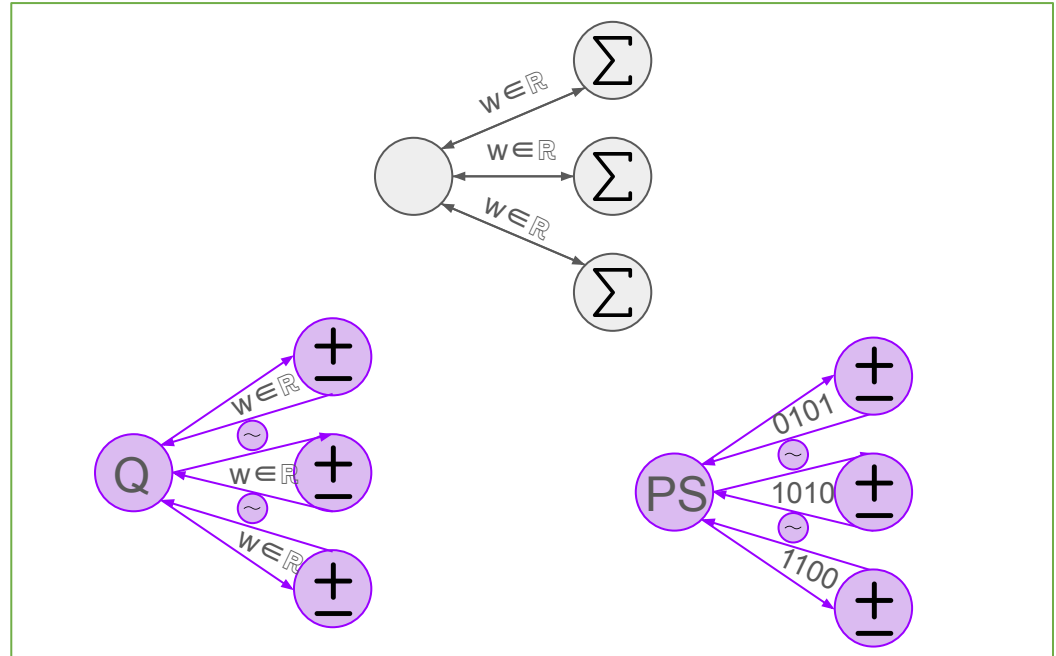
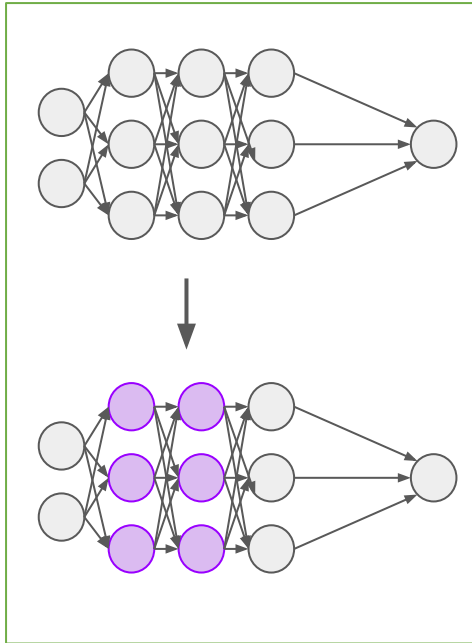
[Hennig et al. 2024]



Deep Shift Neural Networks

[Elhoushi et al. 2019]

By converting parameters and operations into their bit representations, precision is reduced and the computing effort is minimized.



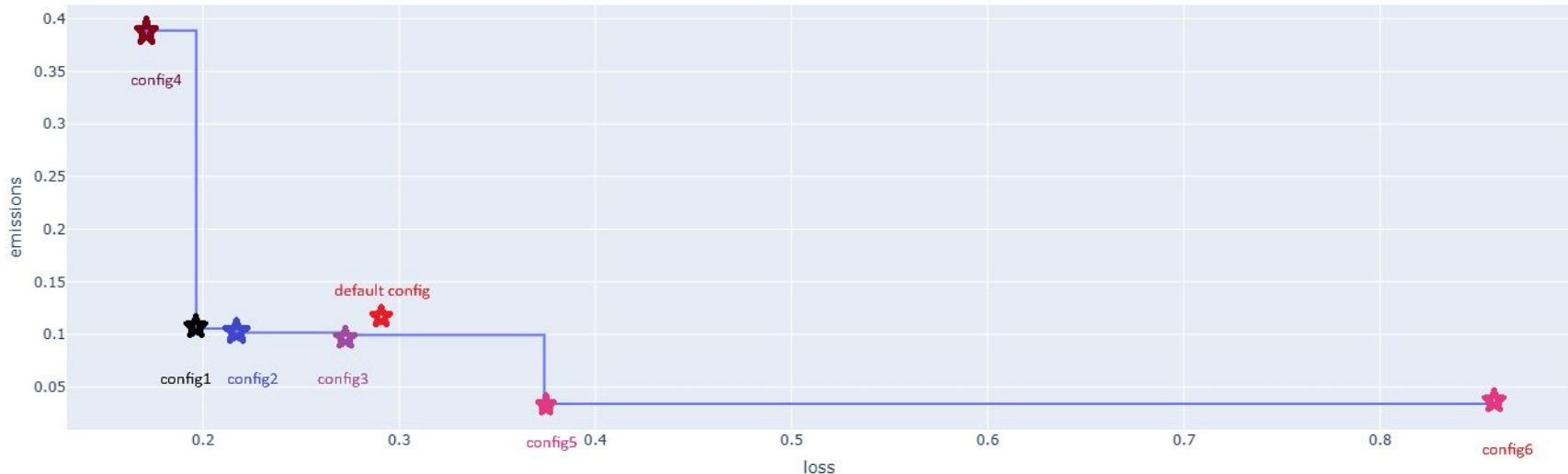
Approach

- Combination of multi-fidelity optimization and multi-objective optimization (using ParEGO) using SMAC3
 - a. Scalarize
 - b. Sample configurations based on surrogate model
 - c. Run Hyperband
- Optimizing for accuracy vs. emissions (CO₂eq)
- Evaluation on CIFAR10 with a base architecture of ResNet20

Hyperparameter	Search Space	Default
Batch Size	[32, 128]	128
Optimizer	{SGD, Adam, Adagrad, Adadelta, RMSProp, RAdam, Ranger}	SGD
Learning Rate	[0.001, 0.1]	0.1
Momentum	[0.0, 0.9]	0.9
Weight Decay	[1e-6, 1e-2]	0.0001
Weight Bits	[2, 8]	5
Activation Integer Bits	[2, 32]	16
Activation Fraction Bits	[2, 32]	16
Shift Depth	[0, 20]	20
Shift Type	{Q, PS}	PS
Rounding	{deterministic, stochastic}	deterministic

Results & Insights

- Tradeoff is fragile in both objectives
- Config2 improves accuracy by 2.63% absolutely and emissions by 32% in terms of relative improvement
- A bunch of insights into how to design DSNNs effectively, see [[Hennig et al. 2024](#); extended version submitted to ECAI]



Check out our poster in the
2nd poster session today



1 1
1 0 2
1 0 0 4
Leibniz
Universität
Hannover

Hyperparameter Importance Analysis for Multi-Objective AutoML

[\[Theodorakopoulos et al. 2024\]](#)



dfki
ai

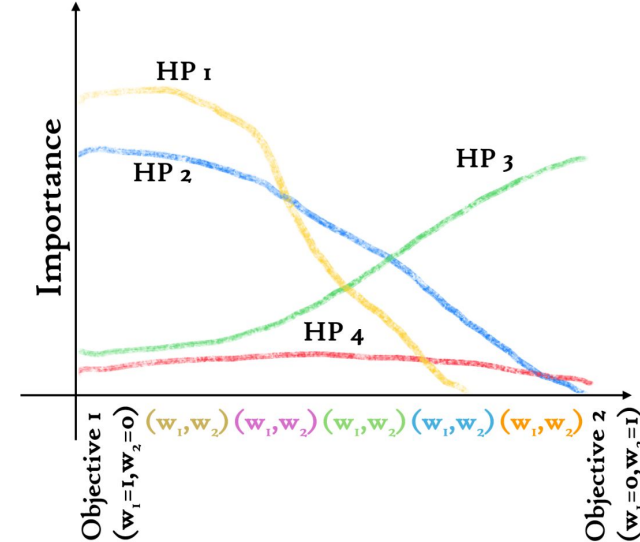
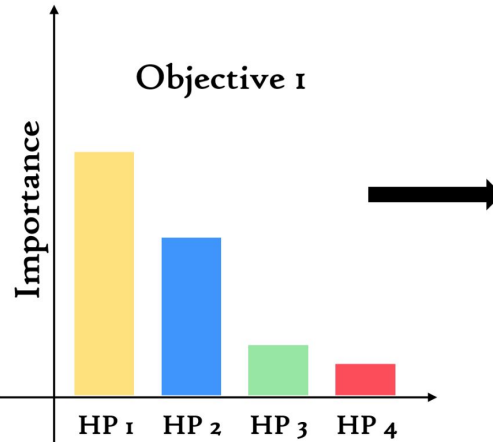
1 1
1 0 2
1 0 0 4
Leibniz
Universität
Hannover

Multi-Objective fANOVA

- fANOVA for HPI

[[Hutter et al. 2014](#)]:

How much of the performance variance in the entire configuration space can be explained by varying one (or several) hyperparameter?



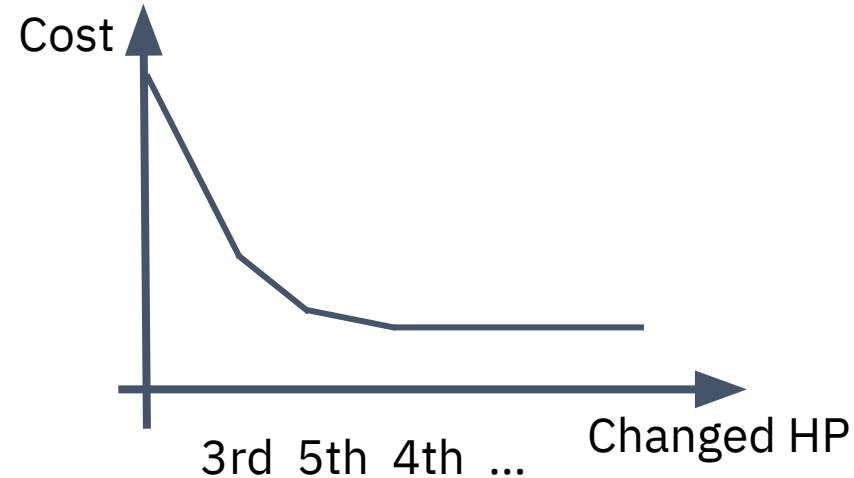
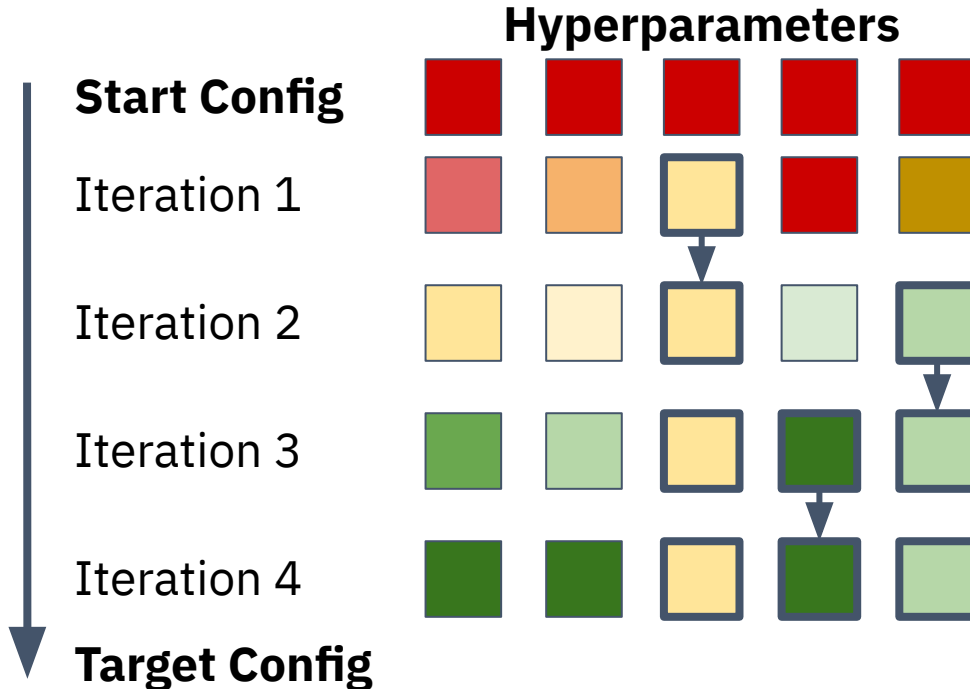
- Main idea:

Iterate over all possible scalarizations

- Train a surrogate model on scalarized performance
 - evaluate fANOVA

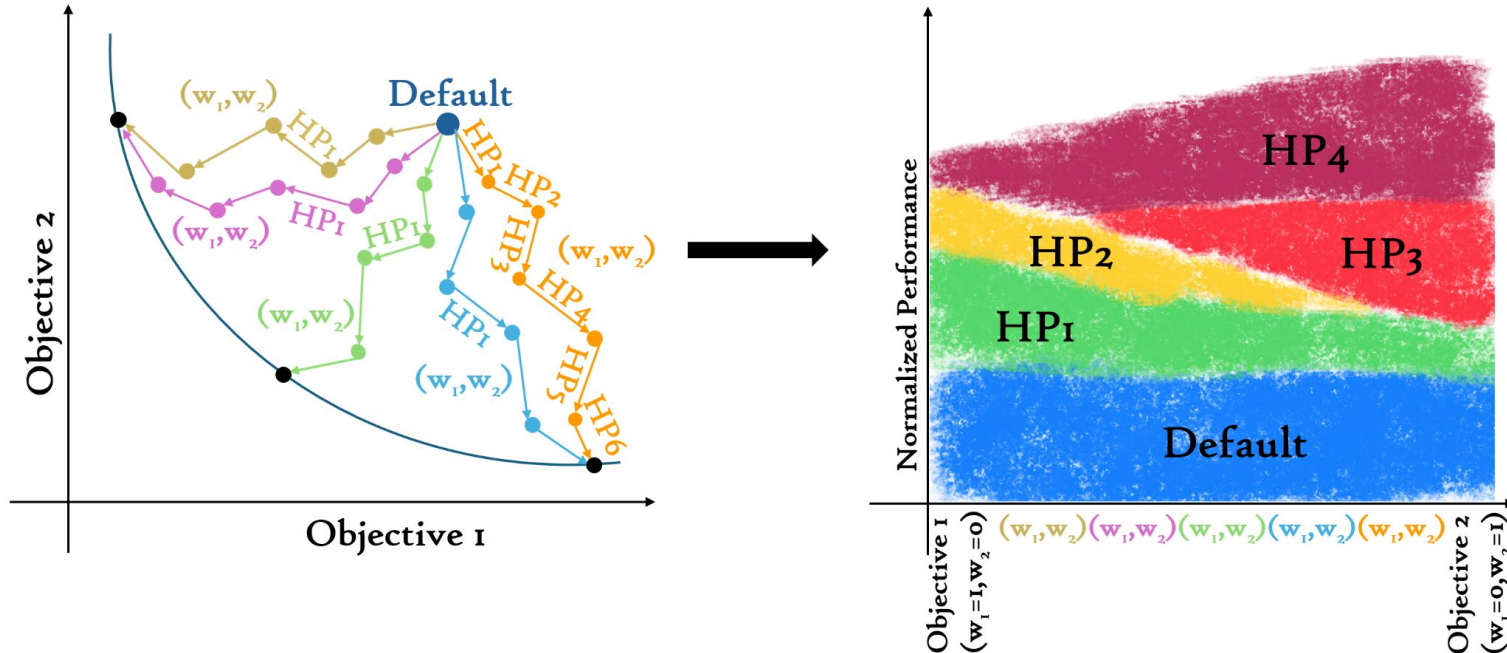
Ablation Paths

- Traditional ablation study:
 - Change only a single design decision and evaluate it
- Greed Ablation Paths [[Fawcett and Hoos. 2016](#)]



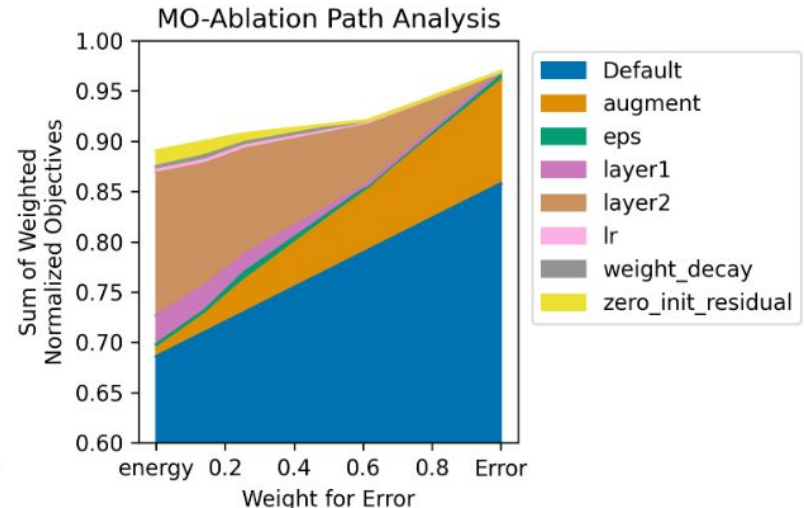
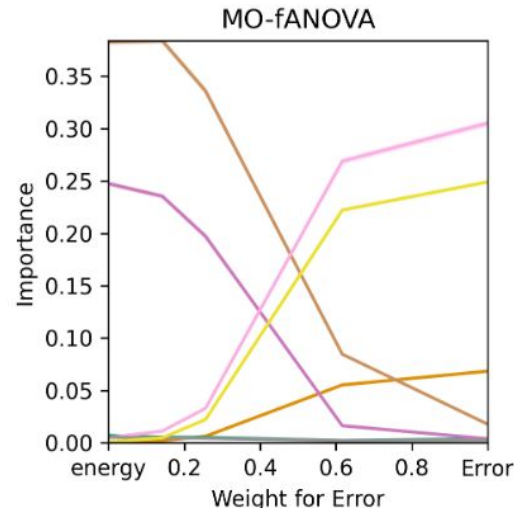
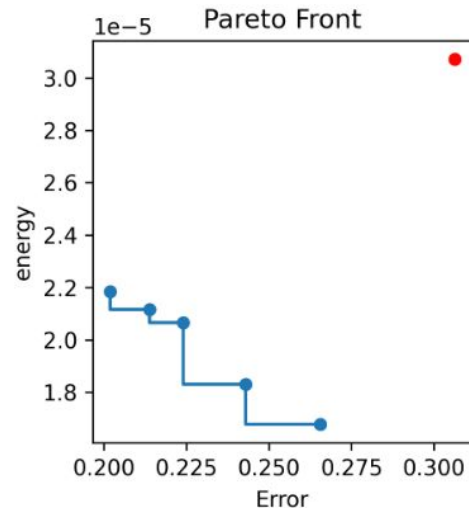
Multi-Objective Ablation Paths

- Same idea as before: (i) Scalarization + (ii) Running Ablation Path
- Reference point: Default configuration




Exemplary Results & Important Insights

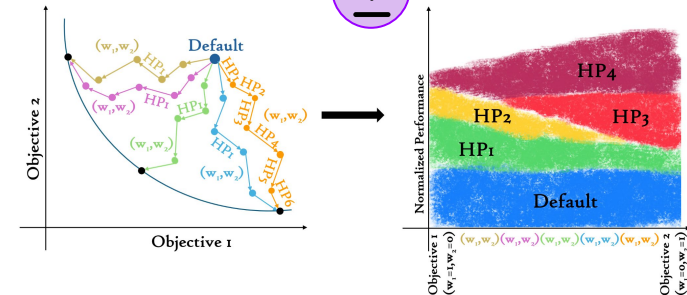
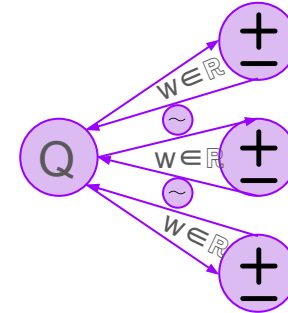
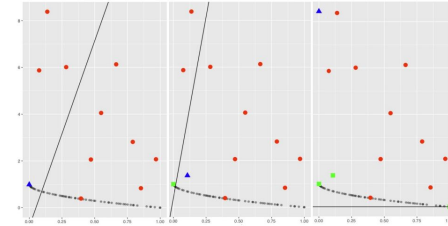
- For different objectives, different hyperparameters are (potentially) important
 - Some hyperparameters might be important for all tradeoffs
 - How can we exploit this insight in building better MOO-HPO algorithms?
- For a tradeoff of objectives, more hyperparameters are important
→ harder optimization problem!



Conclusions

Take Home Messages

- MOO is a key towards better designed models and algorithms
- There is a lot to learn from applying multi-objective optimization to different AutoML problems
 - both in terms of the underlying target, as well as the AutoML problem
- Future work:
 - Integration into 
 - Studying the landscape of MOO-AutoML problems?
 - Taking into account changing hyperparameter importance
- **We can be part of the solution!**





Institute of Artificial Intelligence



Institute

Studies

Research



Institute

Open Positions

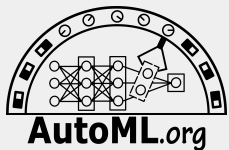


OPEN POSITIONS

(Post)Doctoral Researcher (m/f/d) within the field of Automated Machine Learning



Find Us



 [automl-org](https://www.linkedin.com/company/automl-org)

 [automl](https://github.com/automl)

 [@AutoML_org](https://www.youtube.com/@AutoML_org)



 [luh-ai](https://www.linkedin.com/company/luh-ai)

 [LUH-AI](https://github.com/luh-ai)

 [@luh-ai](https://www.youtube.com/@luh-ai)



Funded by:

