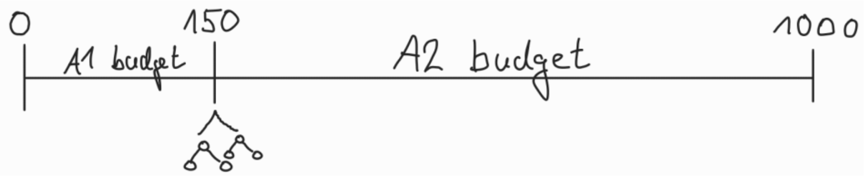
# Towards Dynamic Switching in Per-Run Algorithm Selection

July 10, 2025

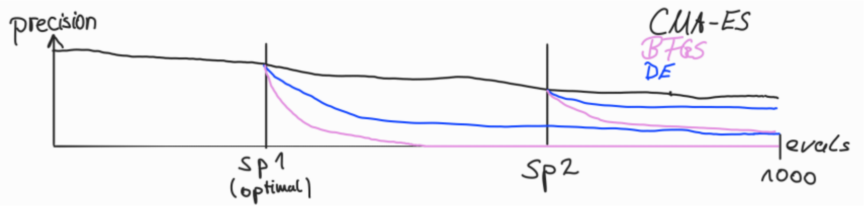
RWTH AACHEN UNIVERSITY

## Why is Dynamic Switching Necessary?




- Approach from Kostovska et al. 2022:
  1. After 150 evaluations, calculate ELA features from CMA-ES samples
  2. Random Forest regression models predict target precisions of the six $\mathcal{A}2$ algorithms
  3. Choose $\mathcal{A}2$ algorithm with lowest predicted precision
  4. Warm-start second algorithm
- $\mathcal{A}1$ budget is static!

## Why is Dynamic Switching Necessary?

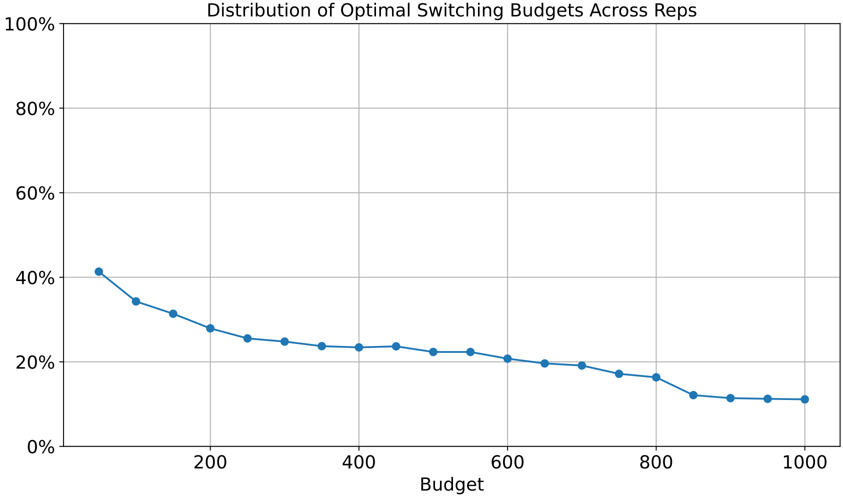



- Recording of 2400 runs conducted on BBOB functions

## BBOB Test Suite (Hansen et al. 2016)

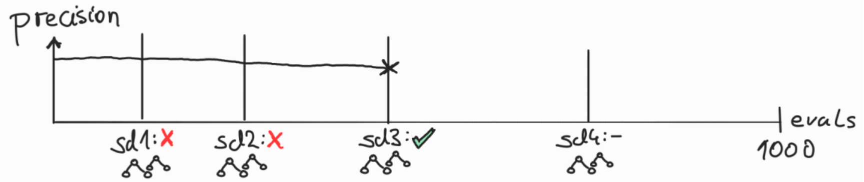
- Set of 24 synthetic noiseless black-box functions
- Each function has several instances
- Standard benchmarking set

# Why is Dynamic Switching Necessary?

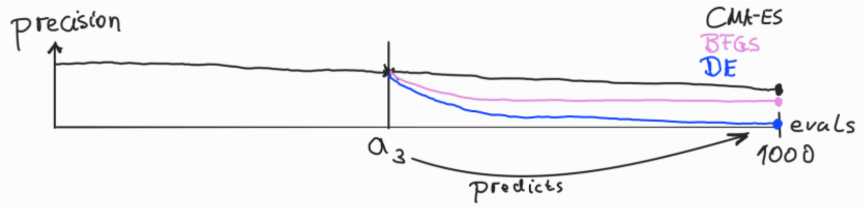


# General Setup

## 1. Switching Decision




## 2. Algorithm Selection



## First Approach

- For each run, we try to find the switching points defined as above
- Selection process consists of two parts:

### Switching Decision

- Let $s_1, \ldots, s_n$ be the considered switching points
- At switching point $s_i$, we predict the precision of the best algorithm at $s_i, s_{i+1}, \ldots, s_n$
- We switch if the predicted precision of the current switching point is the lowest

### Algorithm Selection

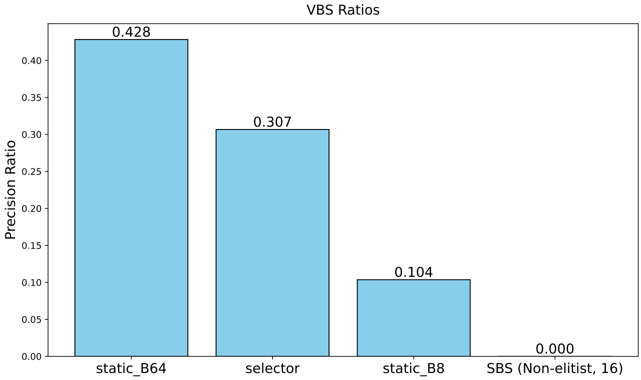
- Predict the precisions of all six algorithms, switch to the algorithm with the lowest precision

## First Approach: Our setup

- Switching points: $8, 16, \ldots, 96, 100, 150, 200, \ldots, 1000$
- Machine learning input:
  - ELA features from CMA-ES samples
  - CMA-ES internal state during the last iteration
- Model training on first 5 instances of all BBOB functions, 20 runs each
- Evaluation on instances 6 and 7, 20 runs each
- Metric:

$$\frac{m_{SBS} - m_{selector}}{m_{SBS} - m_{VBS}}$$

# First Approach: Results




Poor Performance

- Switching decision based on performance of best algorithm
  $\Rightarrow$ Switch too early
- ELA features do not capture enough run-specific information

## Second Approach

Let $s_1, \ldots, s_n$ be the switching points, $a_1, \ldots, a_n$ be the algorithm selectors and $sd_1, \ldots, sd_n$ be the switching decision models

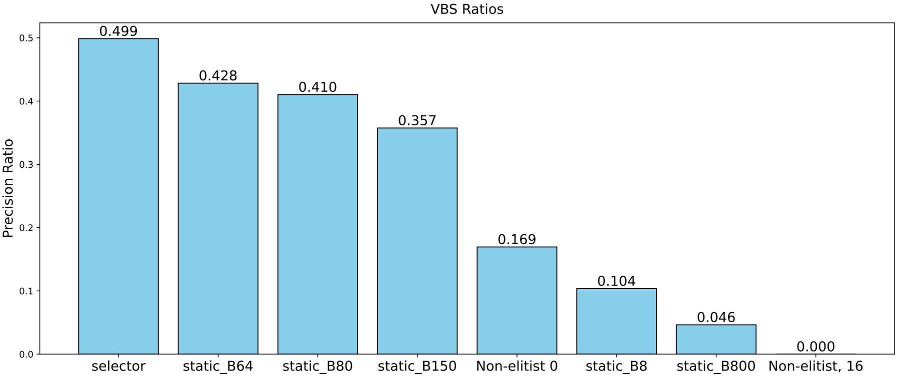
### 1. Evaluate Performances of $a_1, \ldots, a_n$

1. Record the performances of $a_1, \ldots, a_n$ on first five instances
2. For each function, determine which $a_i$ performed best
   $\Rightarrow s_i$ is optimal for that function

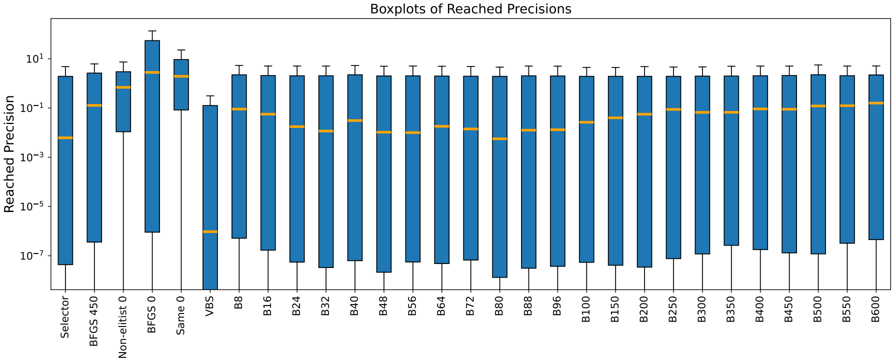
### 2. Training data for $sd_1, \ldots, sd_n$

1. For ELA-features and CMA-ES data belonging to a run at $s_i$, we label them as true iff $s_i$ is greater or equal than the optimal switching point of the run's function
2. For each $s_i$, train a binary classifier, predicting whether or not to switch

# Second Approach: Results



# Second Approach: Results



# Permutation Test: Selector vs Static Baseline

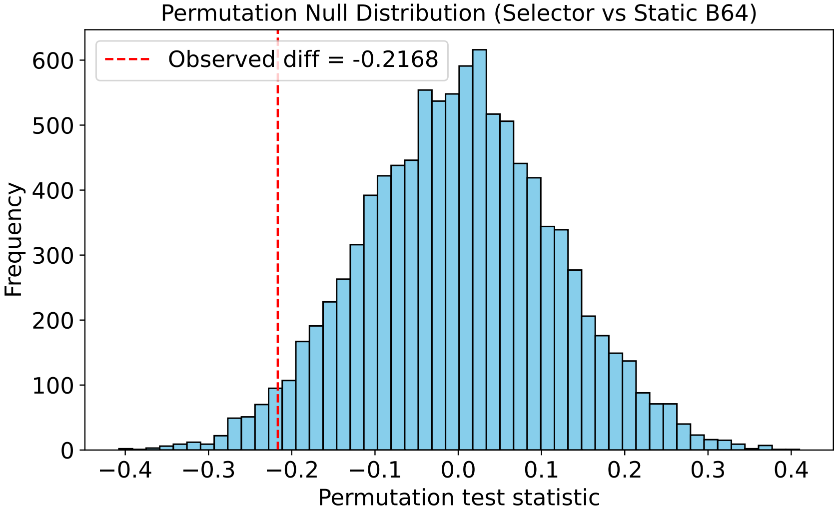
## Setup

- Data: Precision values per run for selector and static baseline selectors
- Test: Permutation test using SciPy with 10,000 resamples
- Statistic: Mean difference in reached precision

## Null Hypothesis

- Null Hypothesis ($H_0$):
  The selector and static baseline have the same distribution of precision values. Any observed difference is due to random chance.

# Permutation Test Results



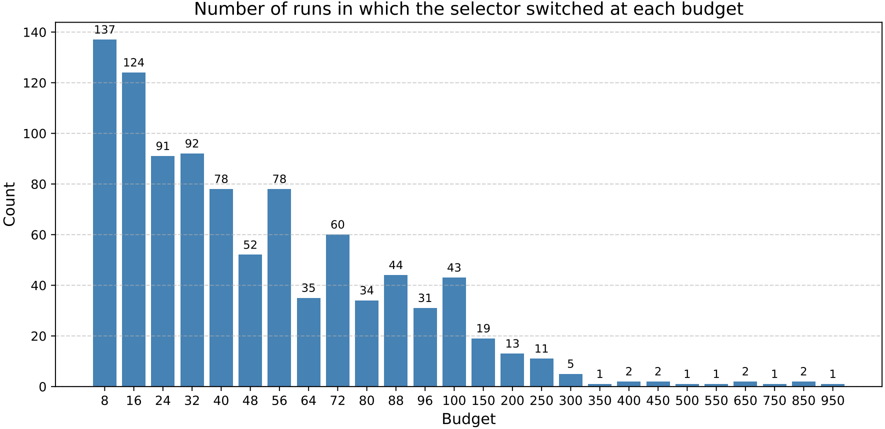
## Next Step: Evaluate Robustness

- Repeat experiments for dimension 10
- BBOB functions are purely synthetic
- Evaluation of the selector on LassoBench (Šehić et al. 2022)
  - Real-world HPO functions for weighted lasso regression
- Function from LassoBench do not have instances
  $\Rightarrow$ Train-test splits using different runs on each function

# Conclusion

- Dynamic Switching leads to improvements over static switching
- First approach did not work
  - ELA features do not seem to capture run-specific information
  - Suboptimal performance of algorithm selectors across budgets
- Second approach leads to significant improvements over static switching
- Next step: Evaluate robustness of the selector

# Switching Budgets: First Approach



# Switching Budgets: Second Approach