Benchmarking as a Stepping Stone to Dynamic Algorithm Selection

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Background

- Phd Candidate at LIACS in the naco group
- Main interests are benchmarking and dynamic algorithm selection / configuration
- Focus on continuous, single-objective, noiseless optimization

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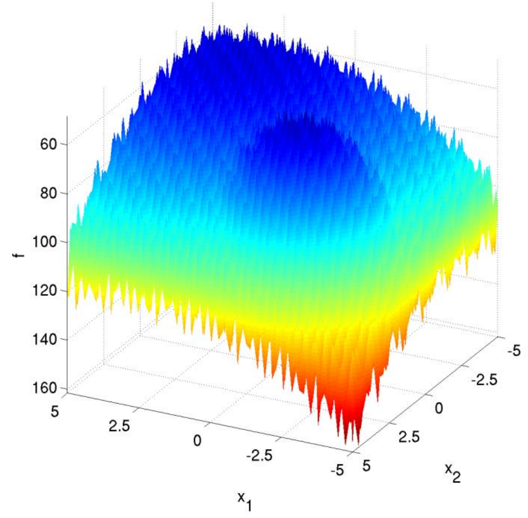
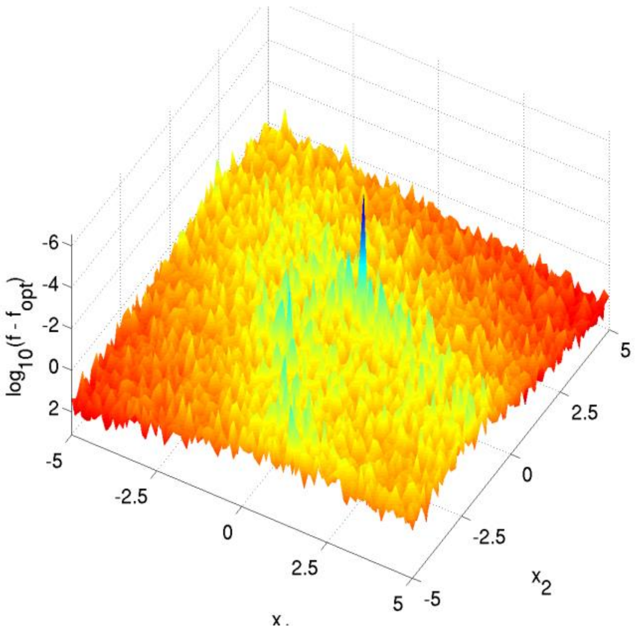
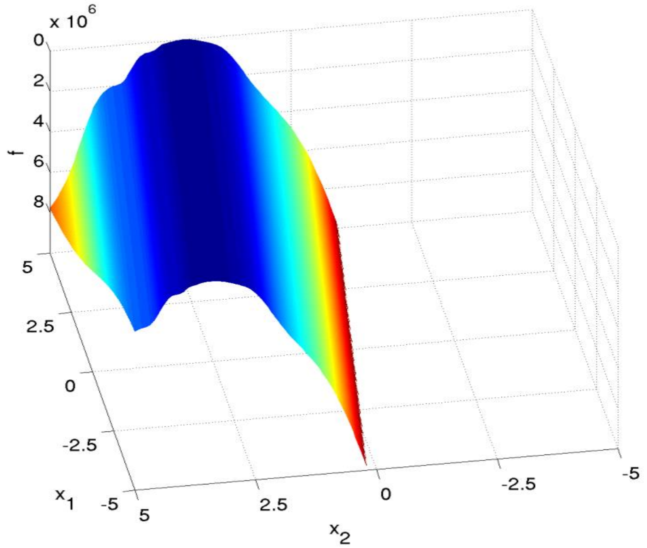
Reasons for Benchmarking

- Potential goal: 'better' algorithms
- But what does 'better' mean?
- Algorithm behaviour is more than a single number
- Goal: benchmark to gain insight into behaviour

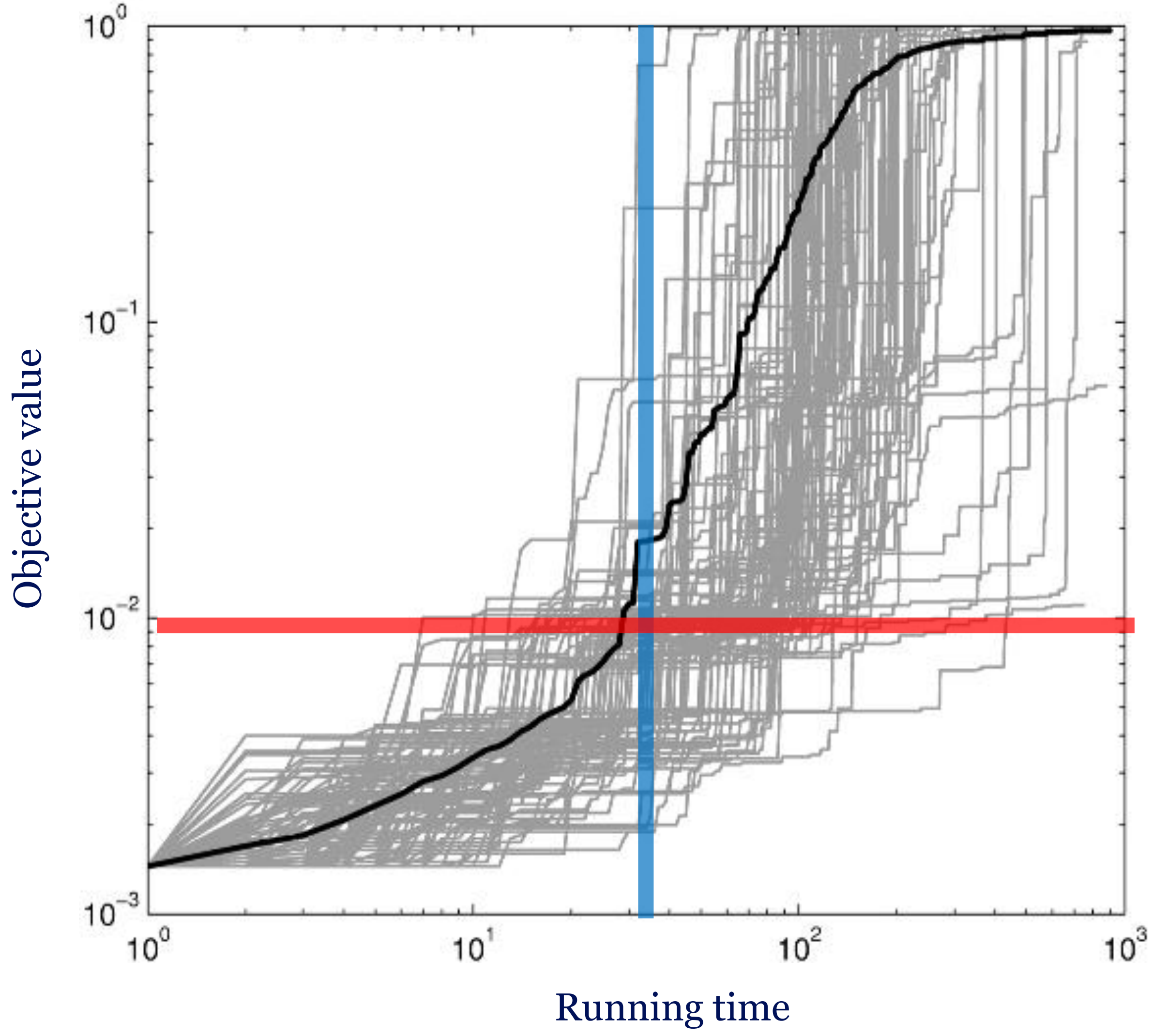






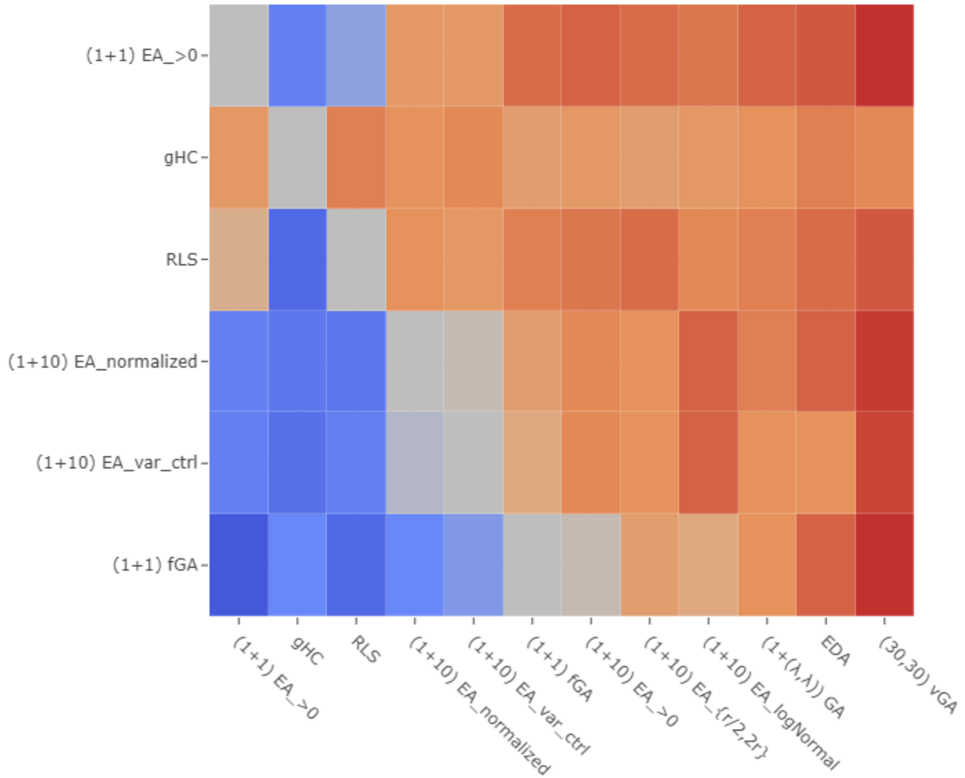
Benchmarking Perspectives

- One algorithm on one function
- Inherently stochastic
- Performance is based on perspective
- Information is lost when considering only one number / distribution

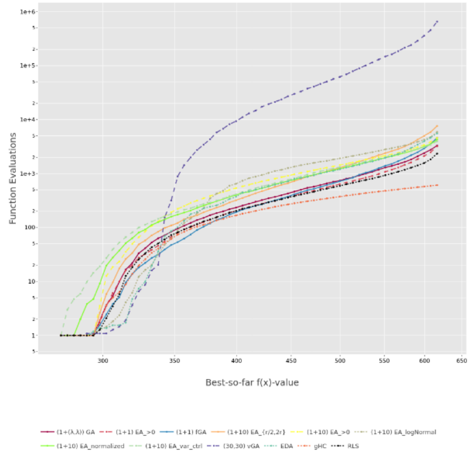


Benchmarking: IOHprofiler

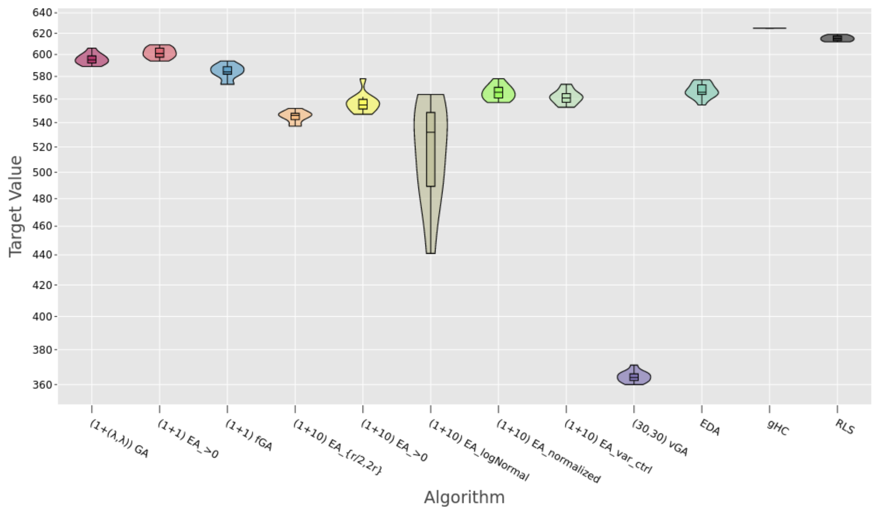
- The performance trajectory contains information on algorithm behaviour
- Tracking this allows for a wide variety of post-processing to be applied
- Can be done in an interactive manner



Expected Runtime (ERT)



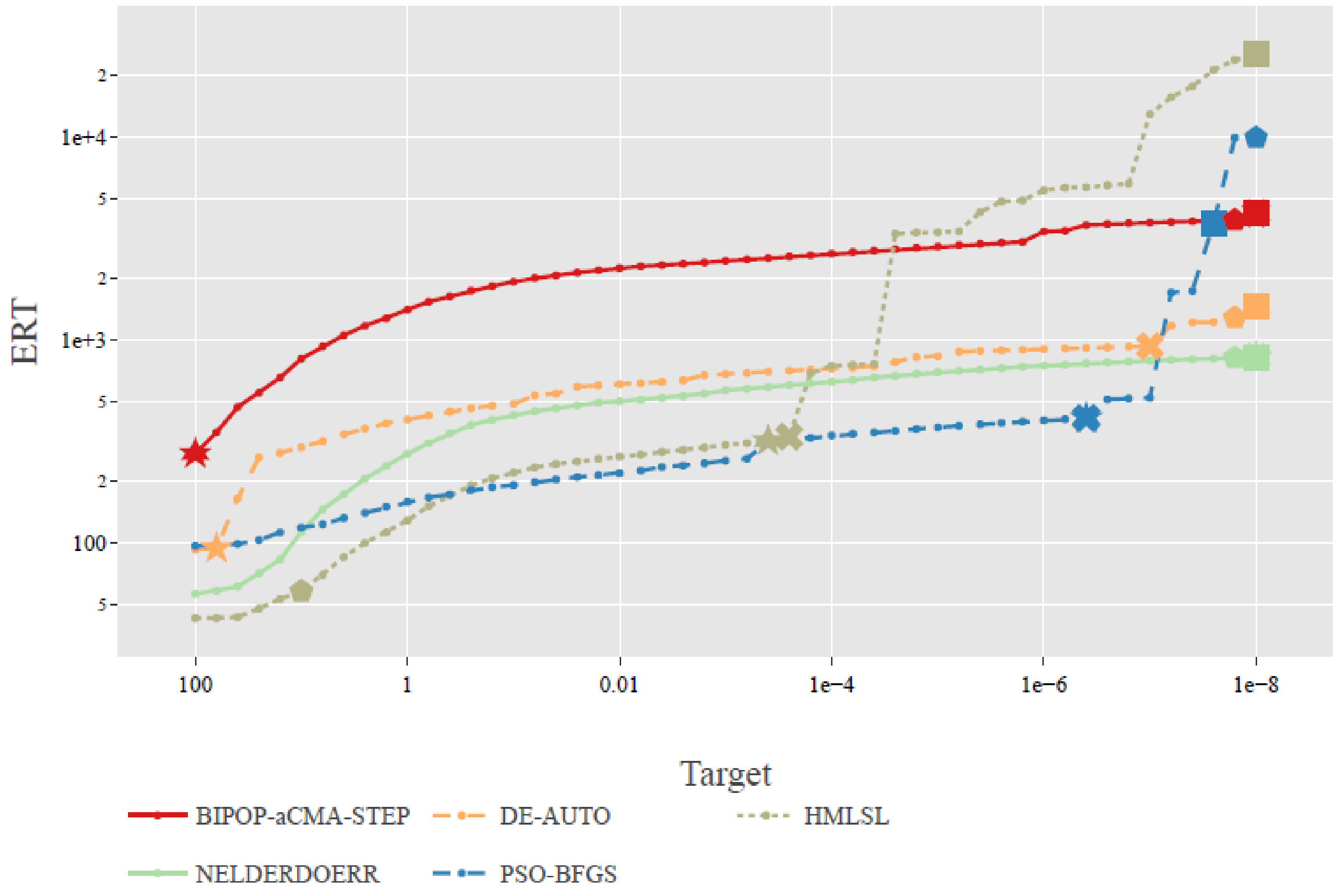
Fixed-Budget Probability Density



[1]

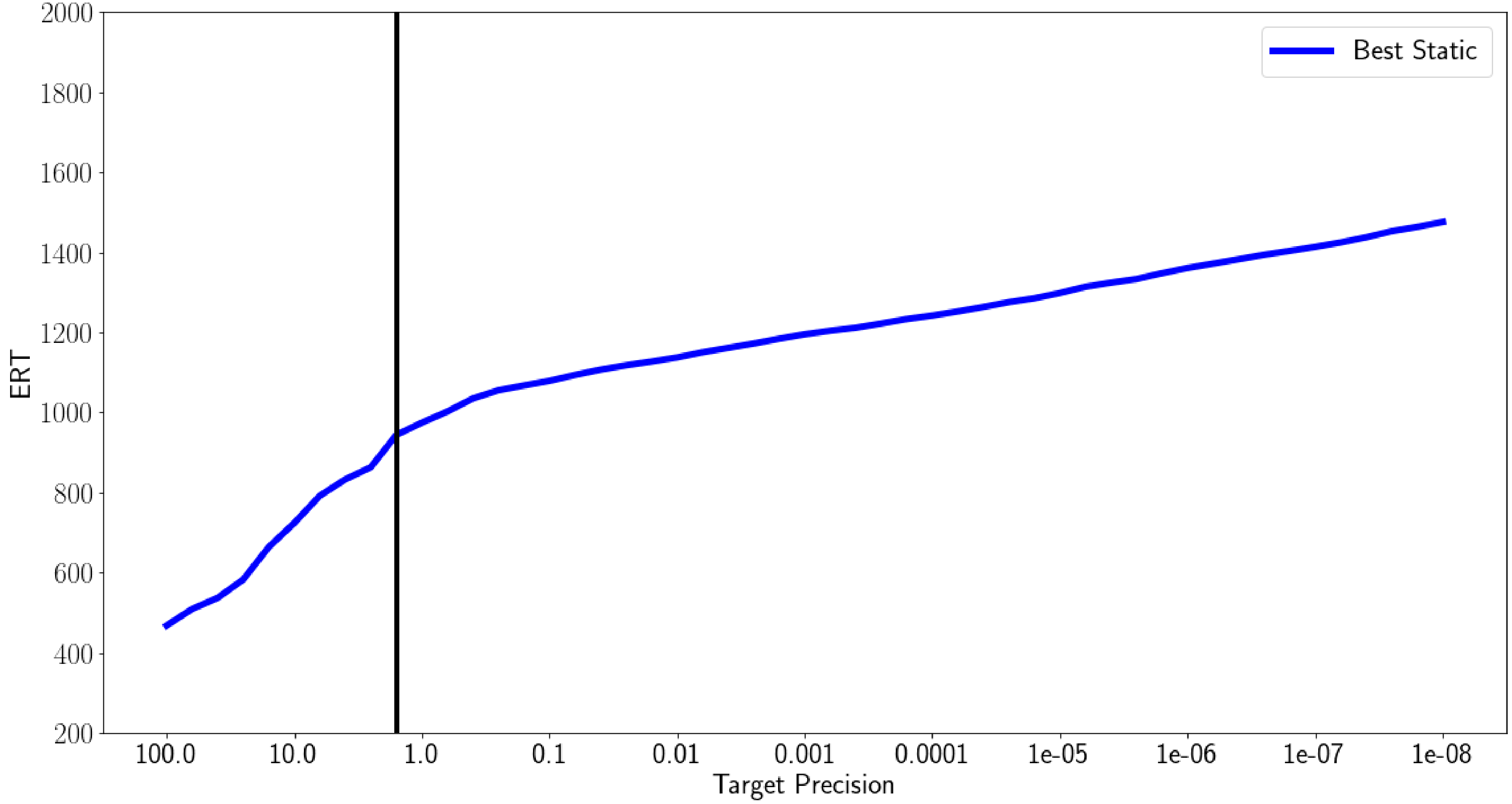
Benchmarking to Dynamic Algorithm Selection

- Looking at performance trajectories gives insight to when an algorithm performs well
- We even see large differences within functions
- We might be able to exploit this by switching between them



[2]

Idea Behind Dynamic Algorithm Selection



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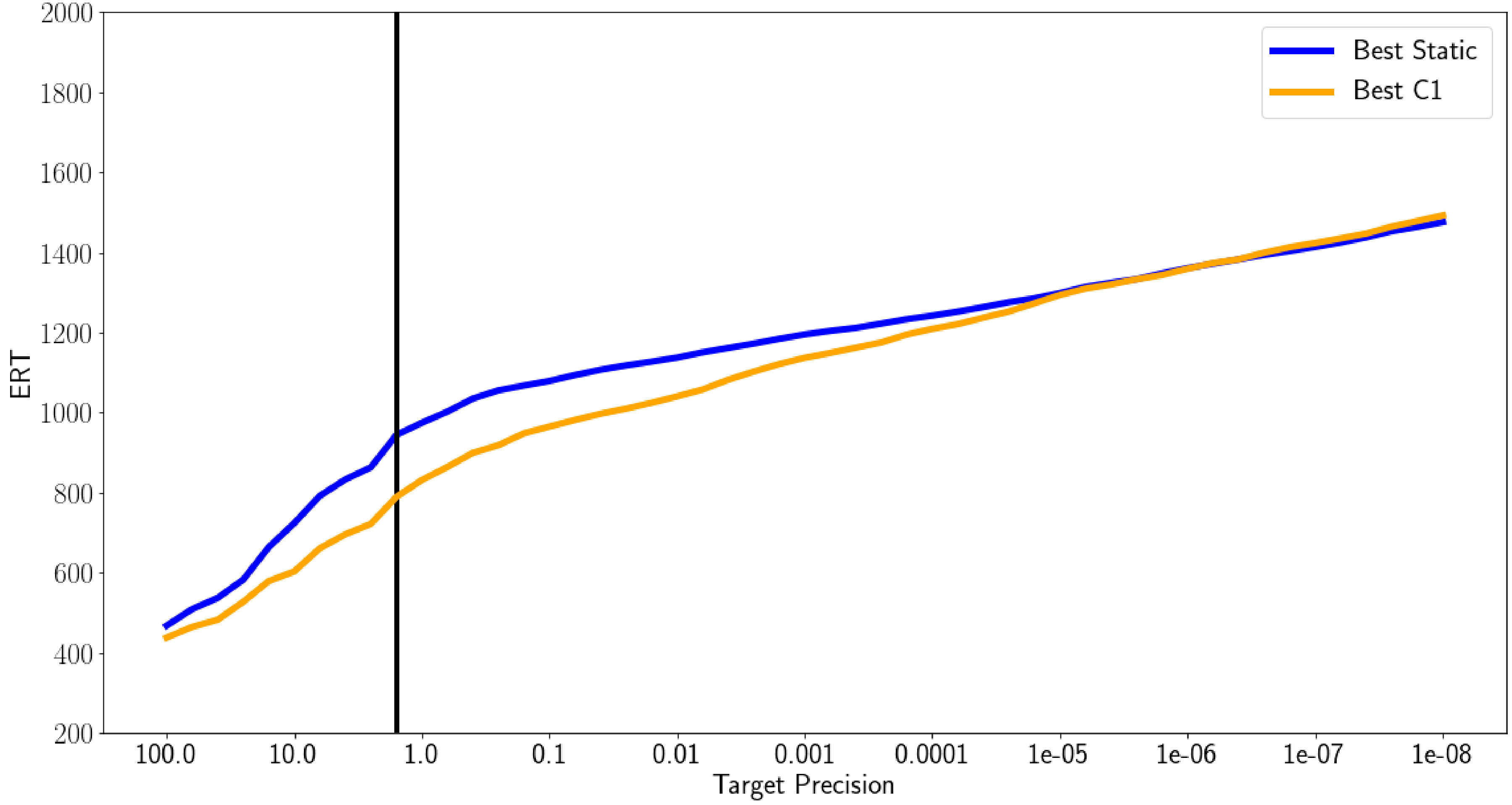
Idea Behind Dynamic Algorithm Selection



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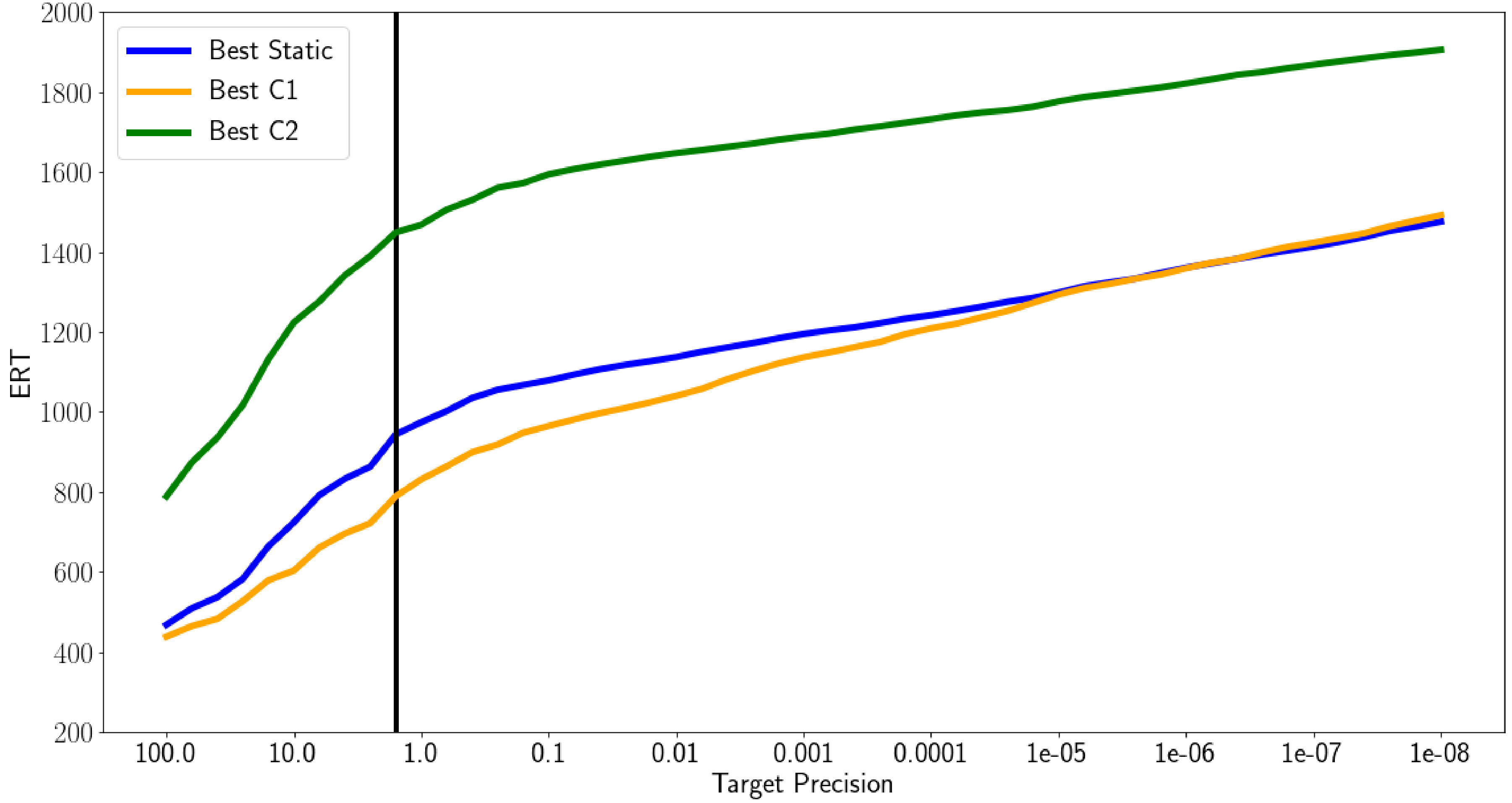
Idea Behind Dynamic Algorithm Selection



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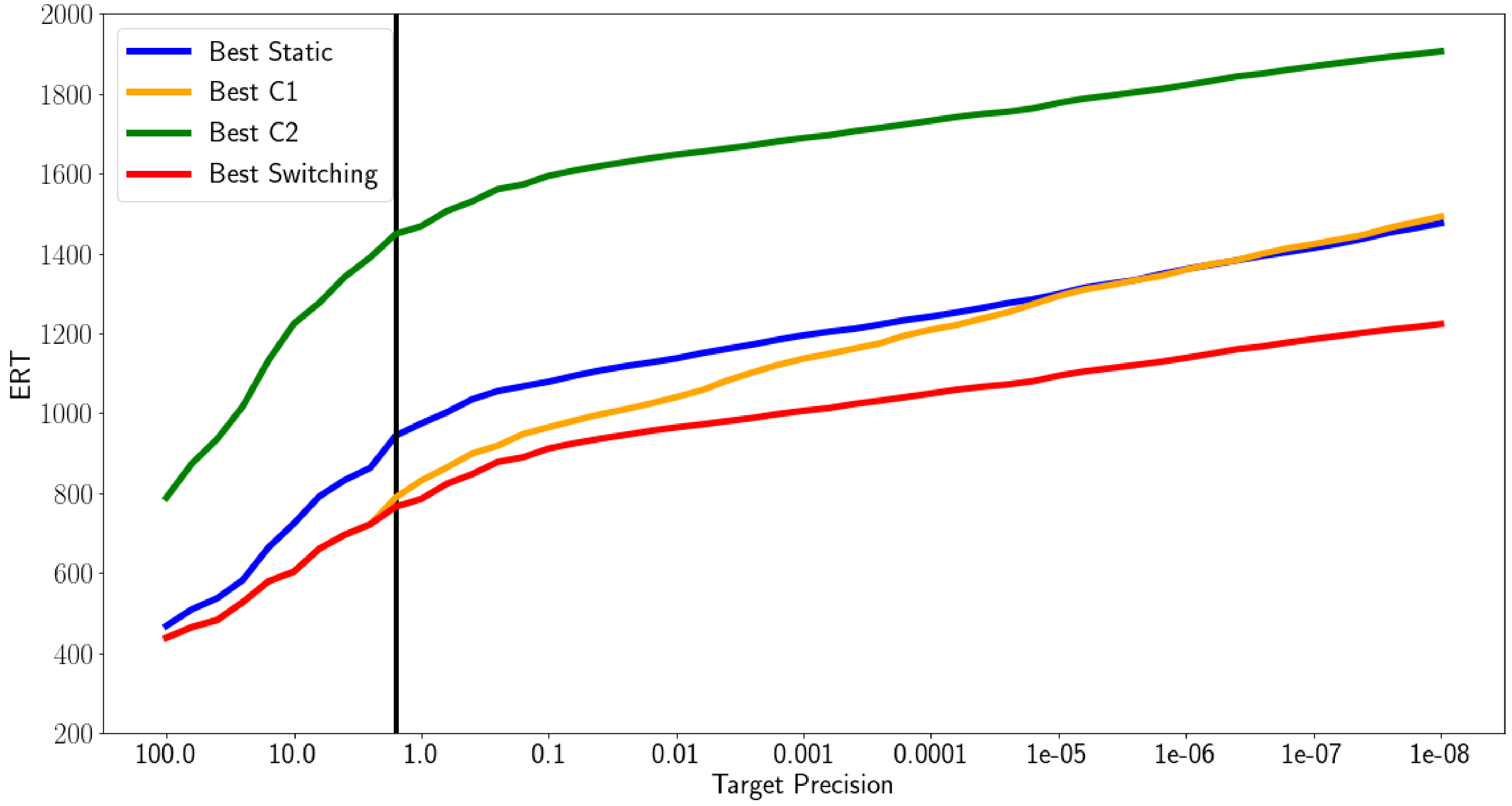
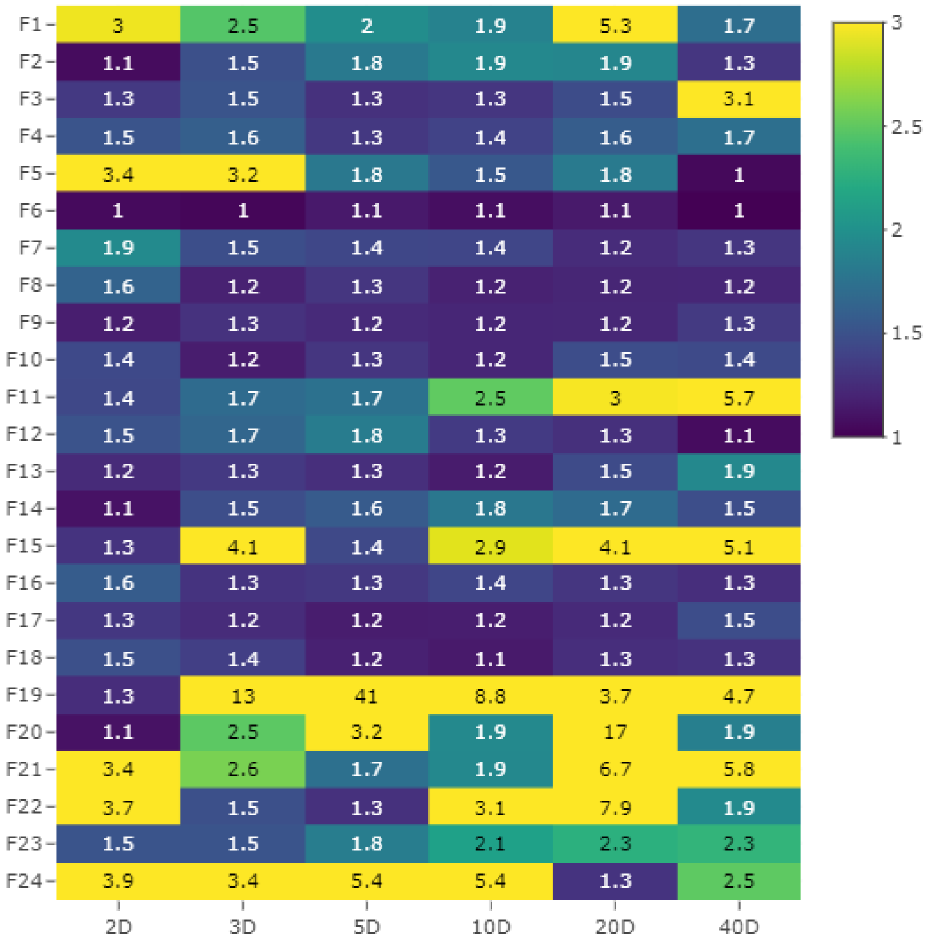


[3]

Potential of Dynamic Algorithm Selection

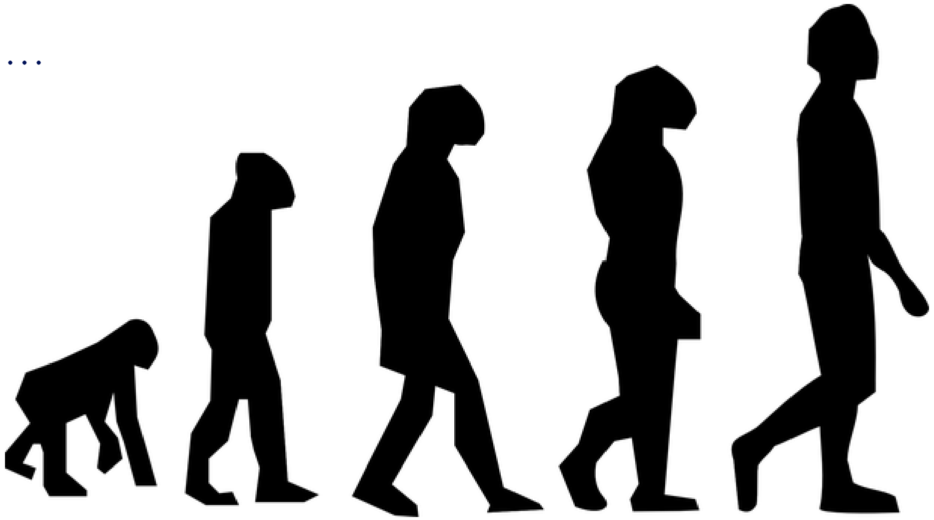
- Use available benchmark data from COCO, containing more than 100 algorithms
- Identify the potential of switching between any of them
- By ‘glueing’ together performance after reaching each target
- Can be used to identify smaller algorithm portfolios with the largest potential

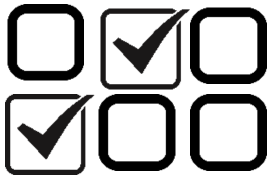


[2]

Usecase: CMA-ES

- Alternative: restrict to one algorithm family
- Allows for easier switching
- Modular CMA-ES framework:
    - Elitism
    - Active update
    - (B)IPOP
    - …

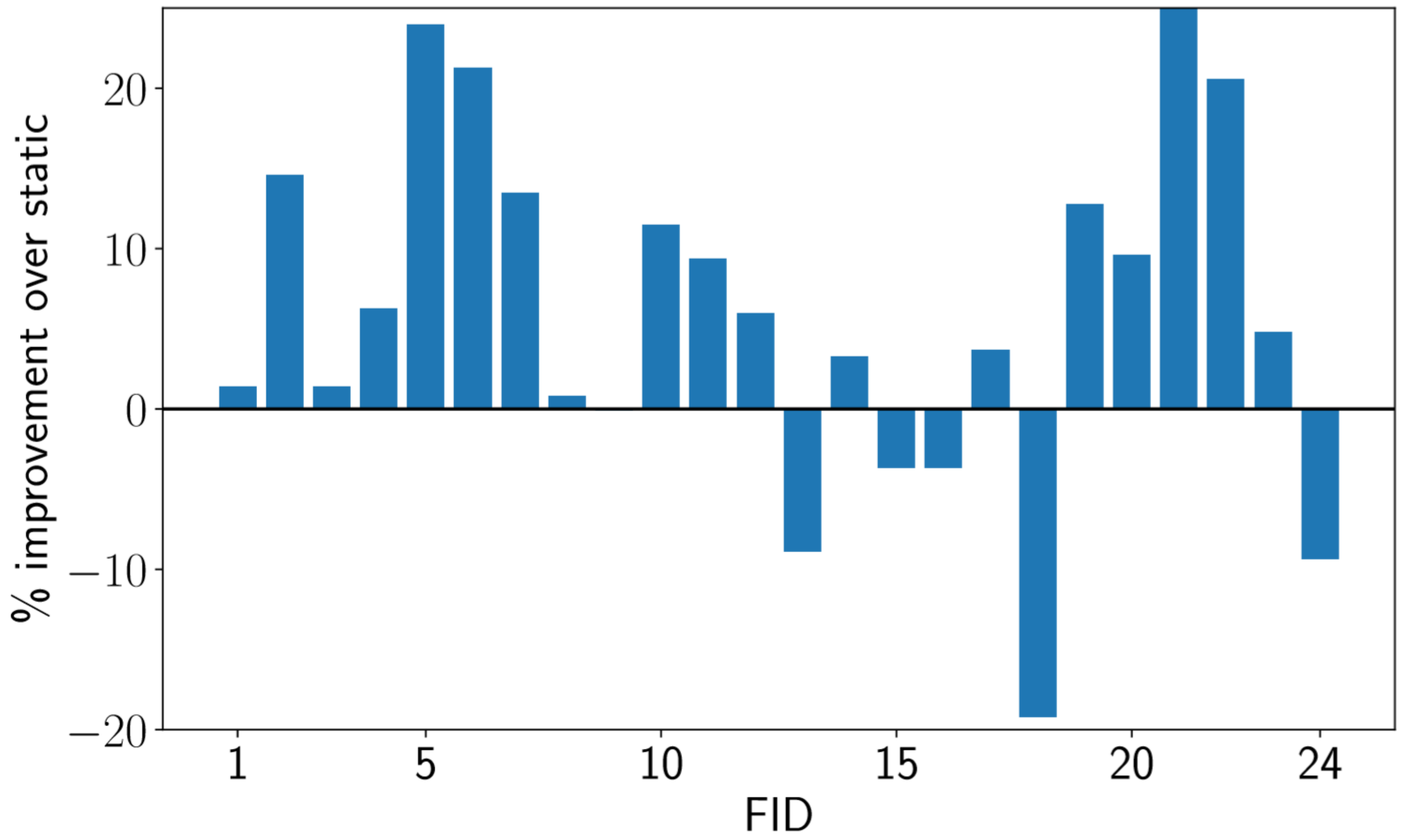




[4,5]

Switching between CMA-ES Variants

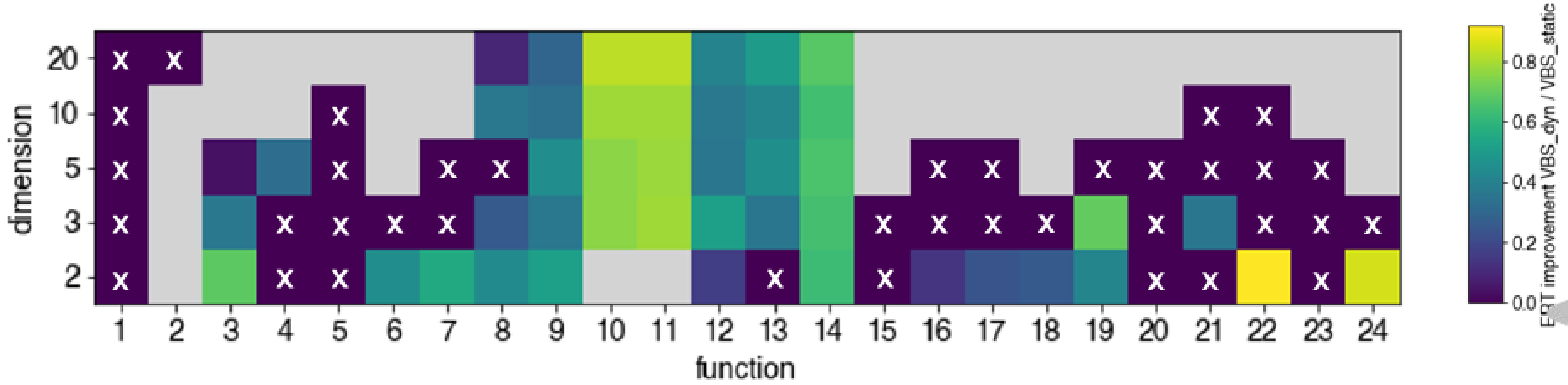
- Perform the switch identified by performance data
- Take top 50 combinations, rerun 250 times to reduce noise
- Compare to best static variant
- Only modify parameters, preserve internal state



[6]

Realizing Dynamic Algorithm Selection

- Switching from one CMA-ES to another is ‘doable’
- But, the principle can be used between any algorithms
- Requires some warm-starting procedure
- But, data shows that there is a lot of potential in this approach!
- Create small portfolio of algorithms to test



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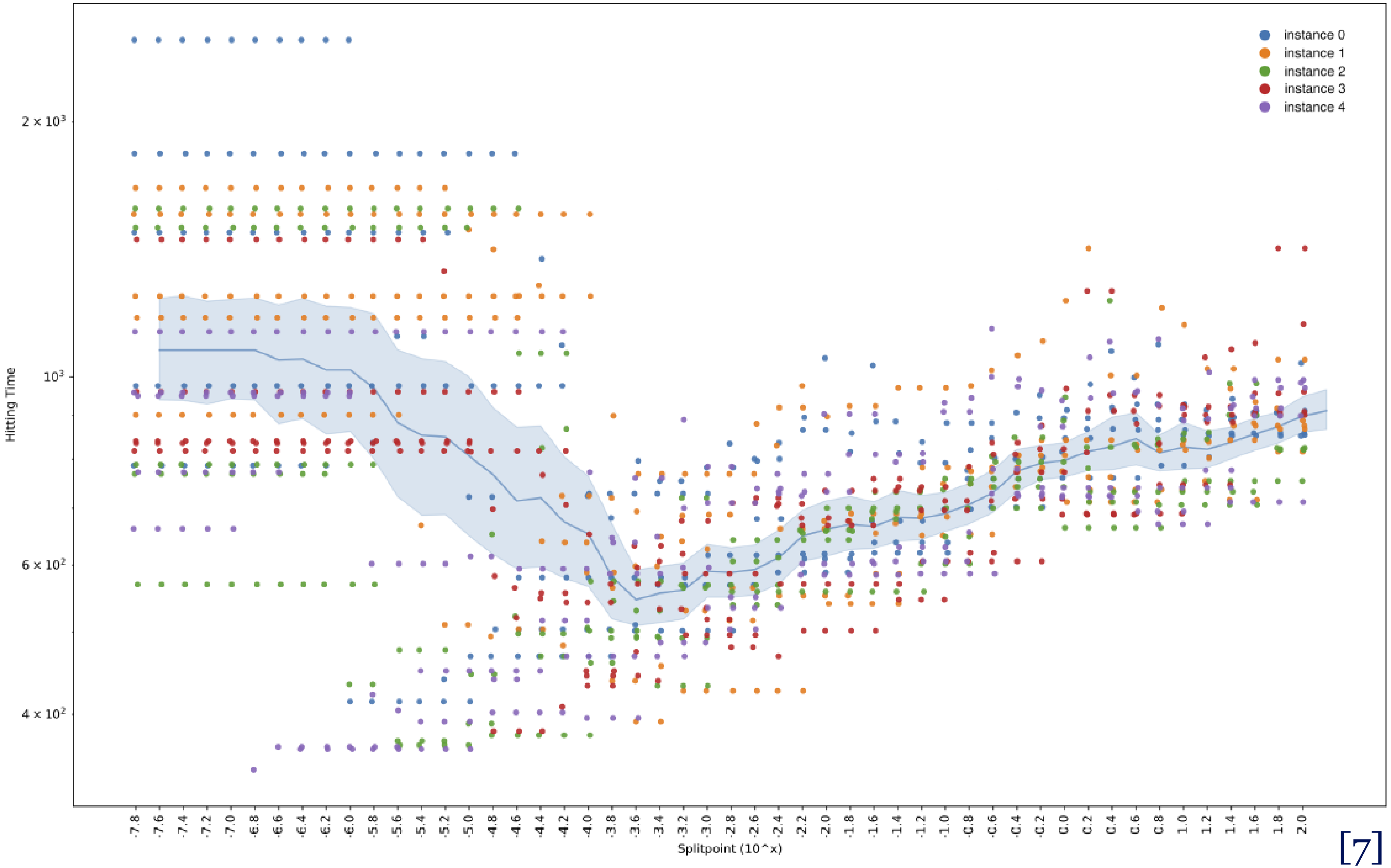
Towards Landscape-Aware Switching

- Benefit from switching seems to change per run
- If detected, can see more benefits
- ELA features could be beneficial



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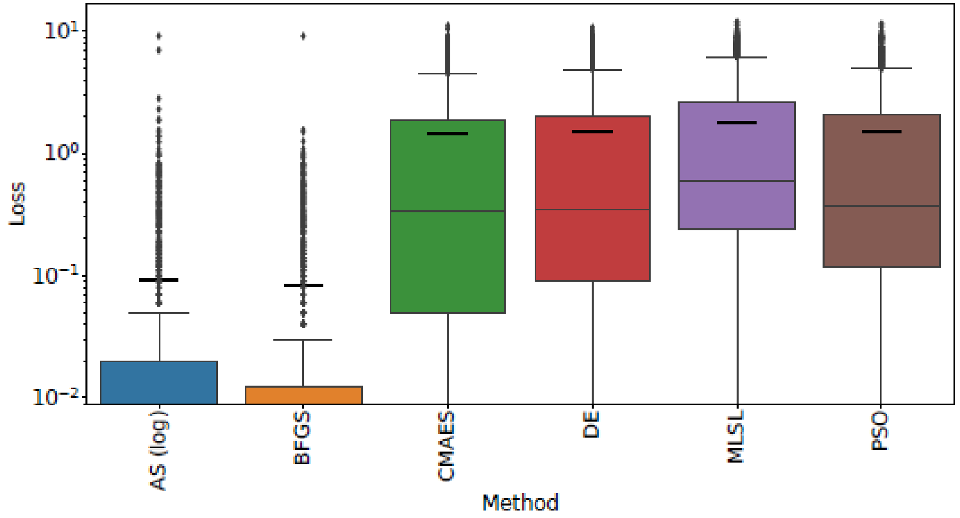
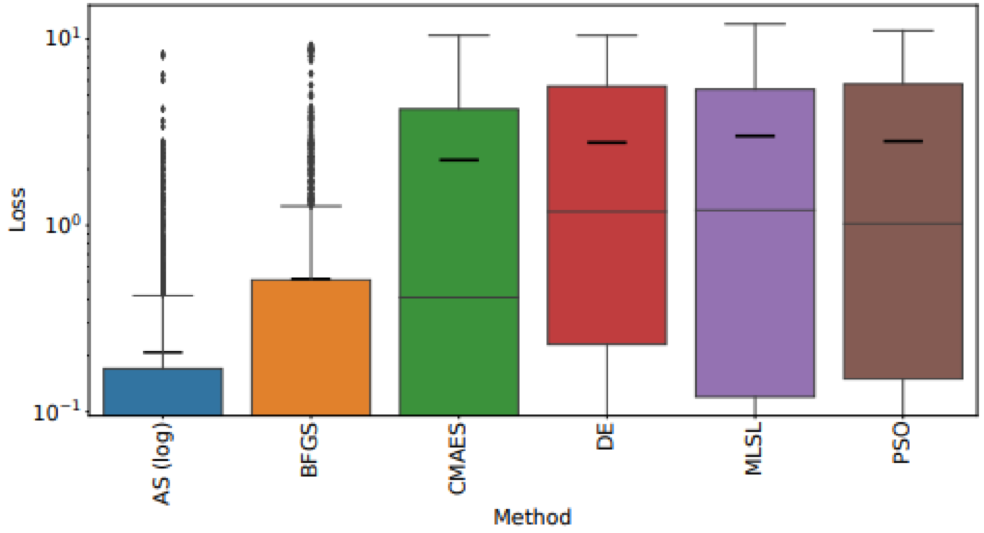
Per-run Dynamic Algorithm Selection

- Start with CMA-ES, switch to another algorithm in portfolio
- Based on ELA features collected in 150 evaluations
- Basic warm-starting mechanisms



(a) Budget 100

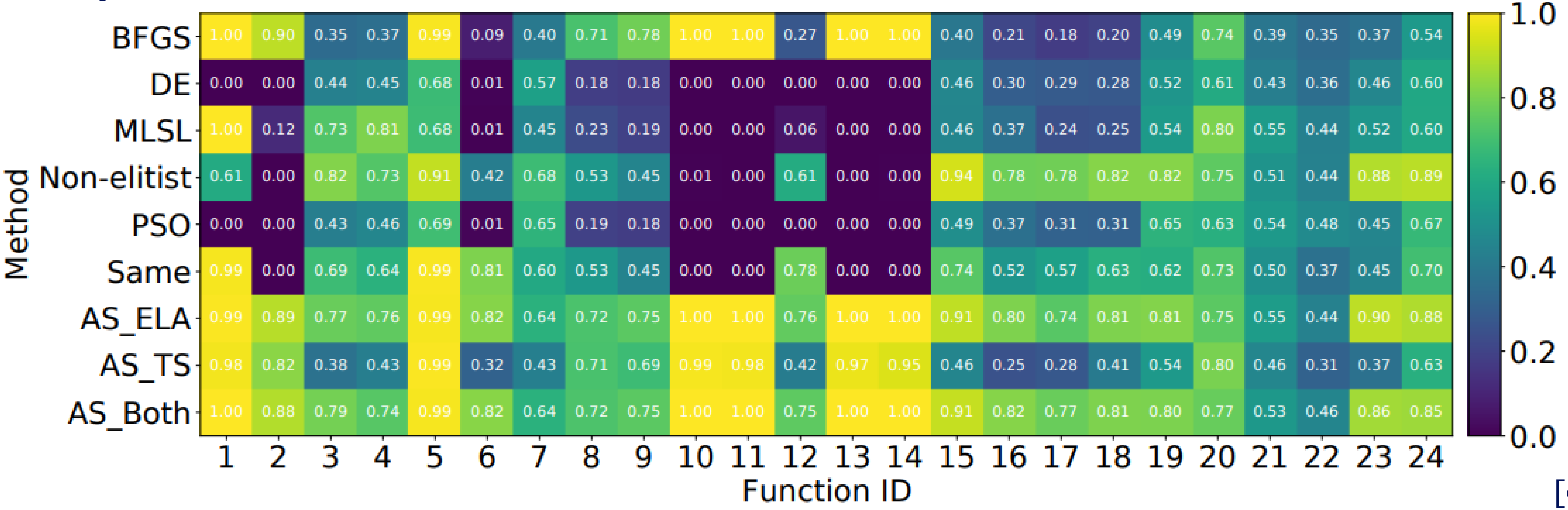


(b) Budget 900

[8]

Per-run Dynamic Algorithm Selection

- Extended portfolio to 6 algorithms, slightly improved warm-starting
- Consider performance ratios (relative difference in fixed-budget performance between method and the best choice per run)
- 3 Algorithm Selectors: ELA-based, TS-based (internal CMA-ES state features) and combined



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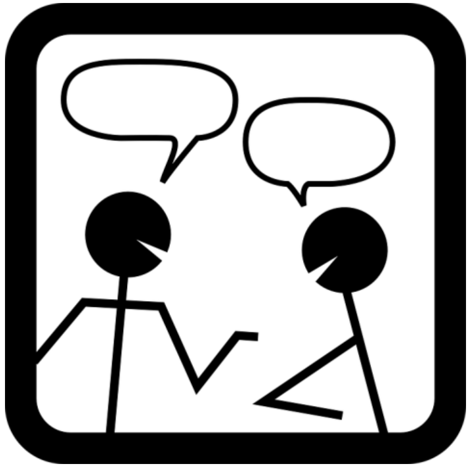
Challenges

- Need to investigate better warm-starting mechanisms
- Find a good way to identify promising dynamic algorithms
- Deal with the inherent stochasticity of algorithms
- Choose the point at which to perform the switch dynamically

Summary

- Benchmarking is more than just a number
- Data collected gives insights to build new ideas
- Dynamic algorithm selection has potential
- But, many open challenges



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