Benchmarking and analyzing iterative optimization heuristics with IOHprofiler

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The most up-to-date version of these slides can be found at: https://github.com/IOHprofiler/GECCO-Tutorial

Introduction

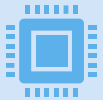
- Benchmarking is a key component in the field of optimization algorithms
- Need data to judge effectiveness of a new algorithm relative to state-of-the-art
- But benchmarking is not just a number showing algorithm A is better than algorithm B!

Benchmarking

Benchmarking can be used to gain important insights about algorithms and problems

Highlights interplay between problem and algorithm

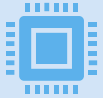
Differences in performance show potential for new developments



Data-driven studies of algorithm selection, configuration, dynamic switching...

Requirements for benchmarking

Ease of access

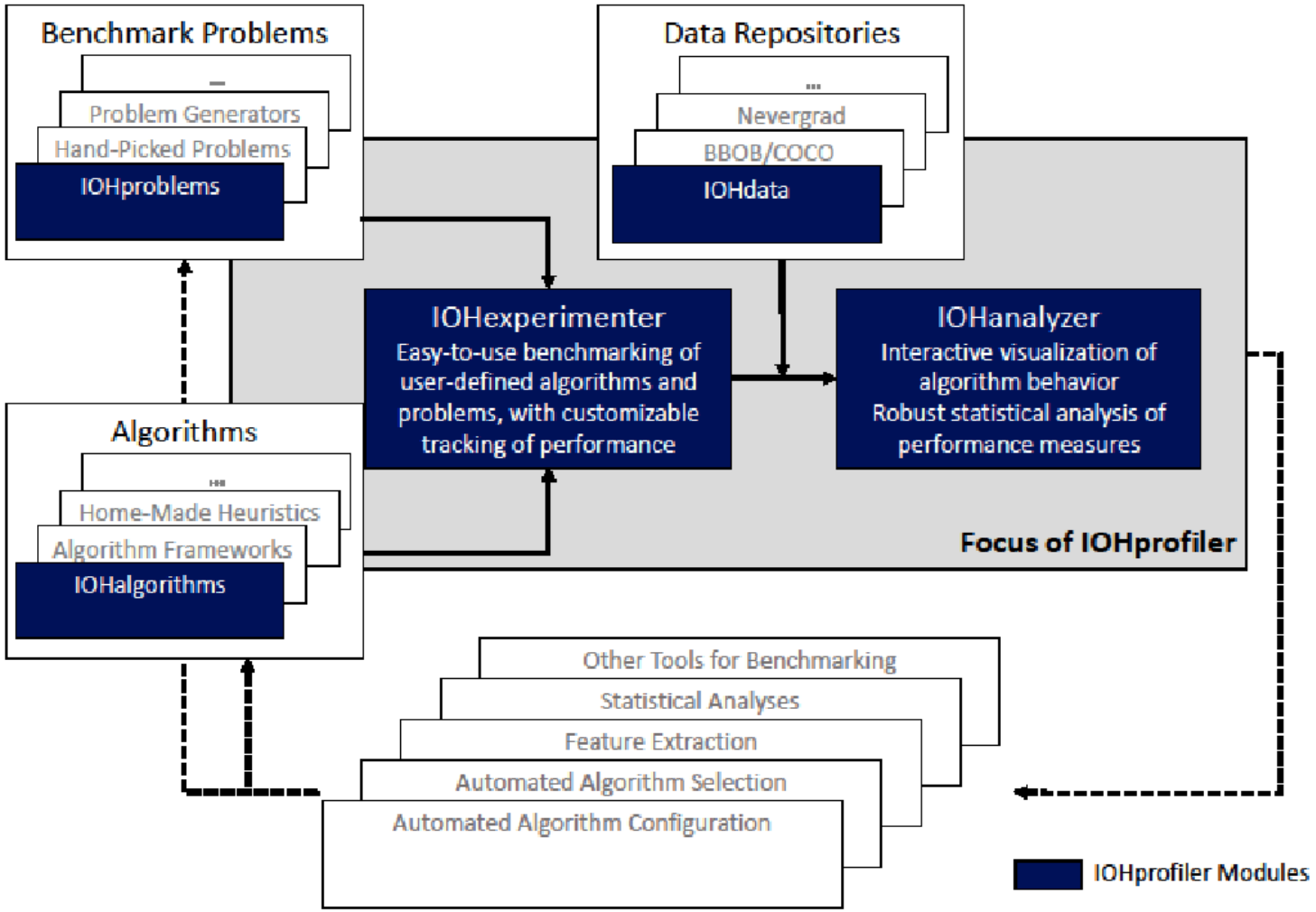


Flexible to the specific requirements of the user

Interoperability with other common tools

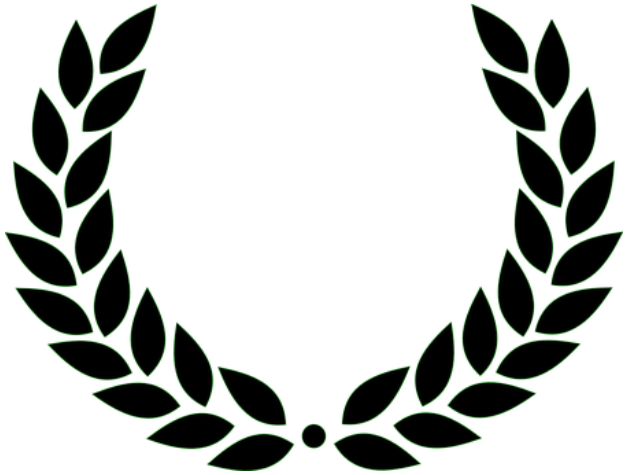
Standardized to ensure reproducibility

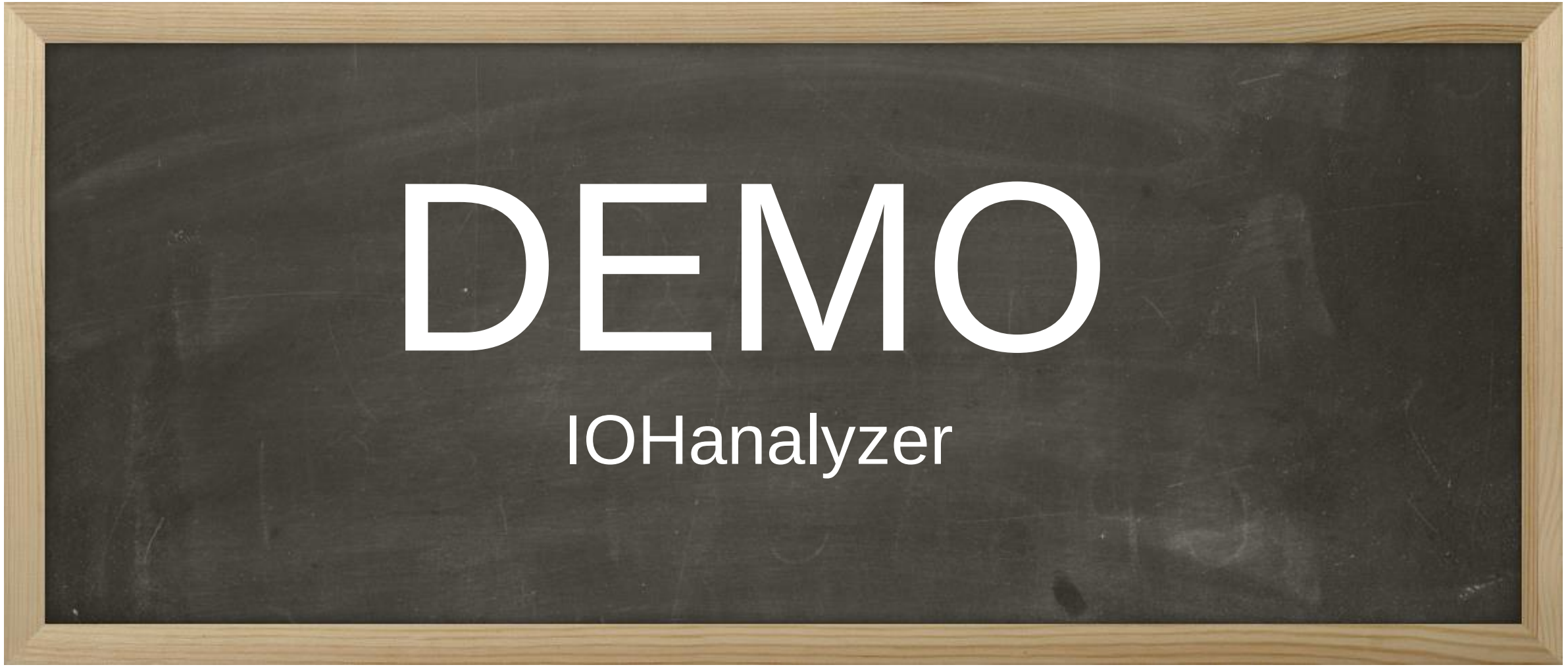
IOHprofiler Architecture Overview



IOHanalyzer overview

- Performance can not be captured in a single number
- Analysis of performance on a benchmark can be very context-dependent
- To a large extent influenced by the specific requirements of the user
- As such, flexibility is key




DEMO
IOHanalyzer

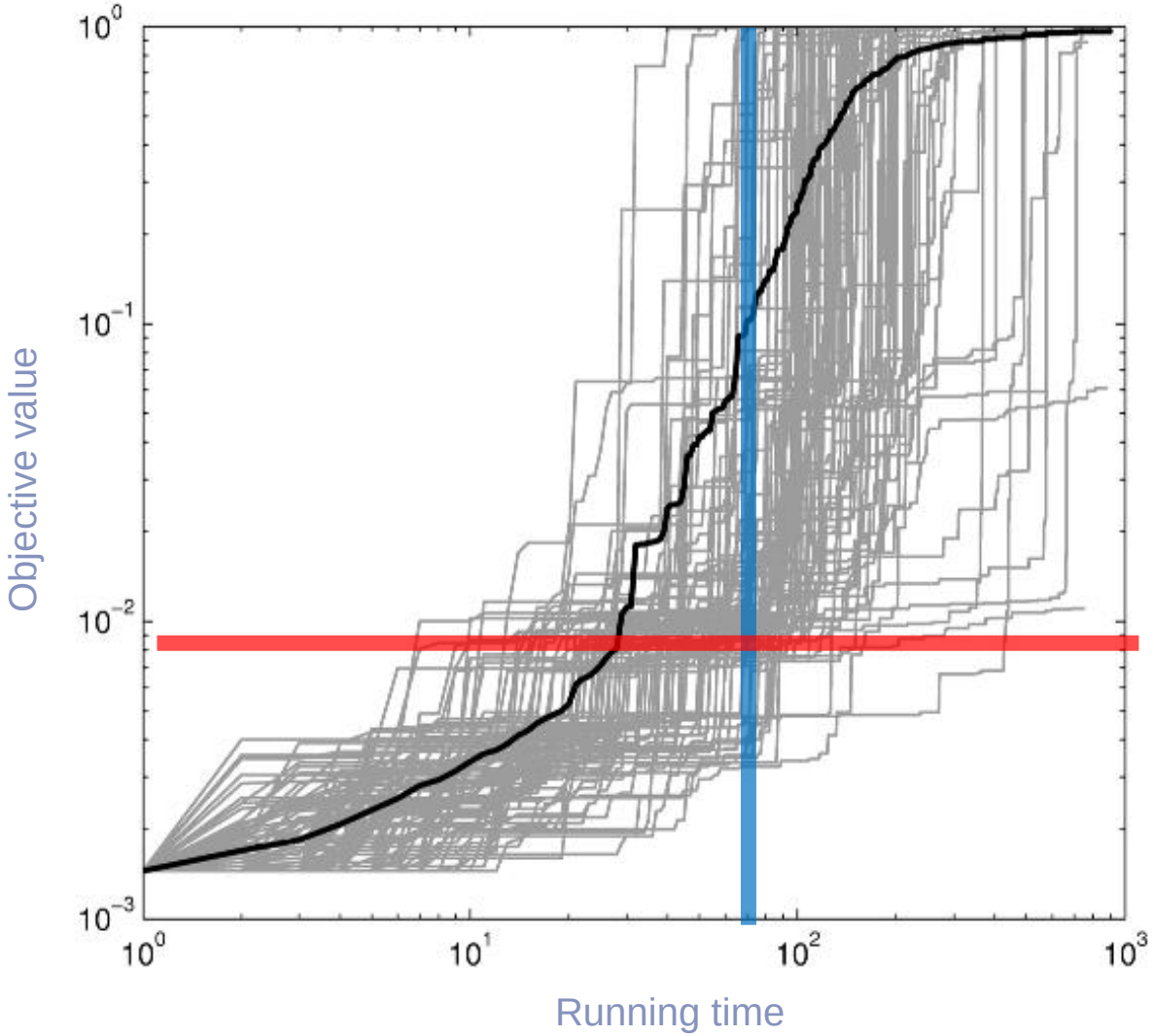
IOHanalyzer overview

- What perspective to consider?

Fixed-budget:
objective samples given runtime budget

Fixed-target: runtime samples given target value

Success rate: some runs might not hit this line



Fixed-target Analysis

- Running time – random variable
  - Parameterized by *a target value*

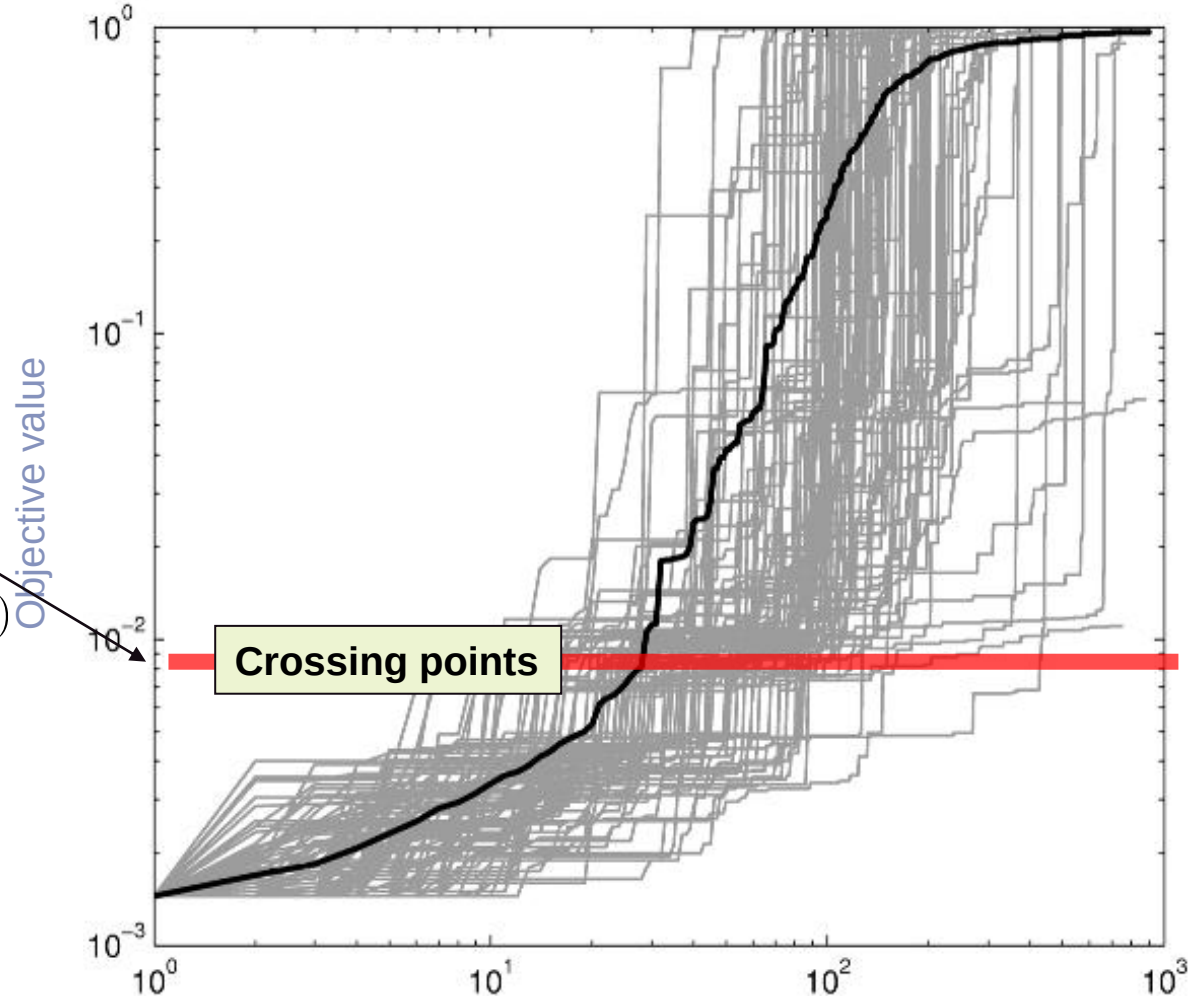
$$T(f_{\text{target}}) \in \mathbb{N}_{>0}$$

- The number of runs – r

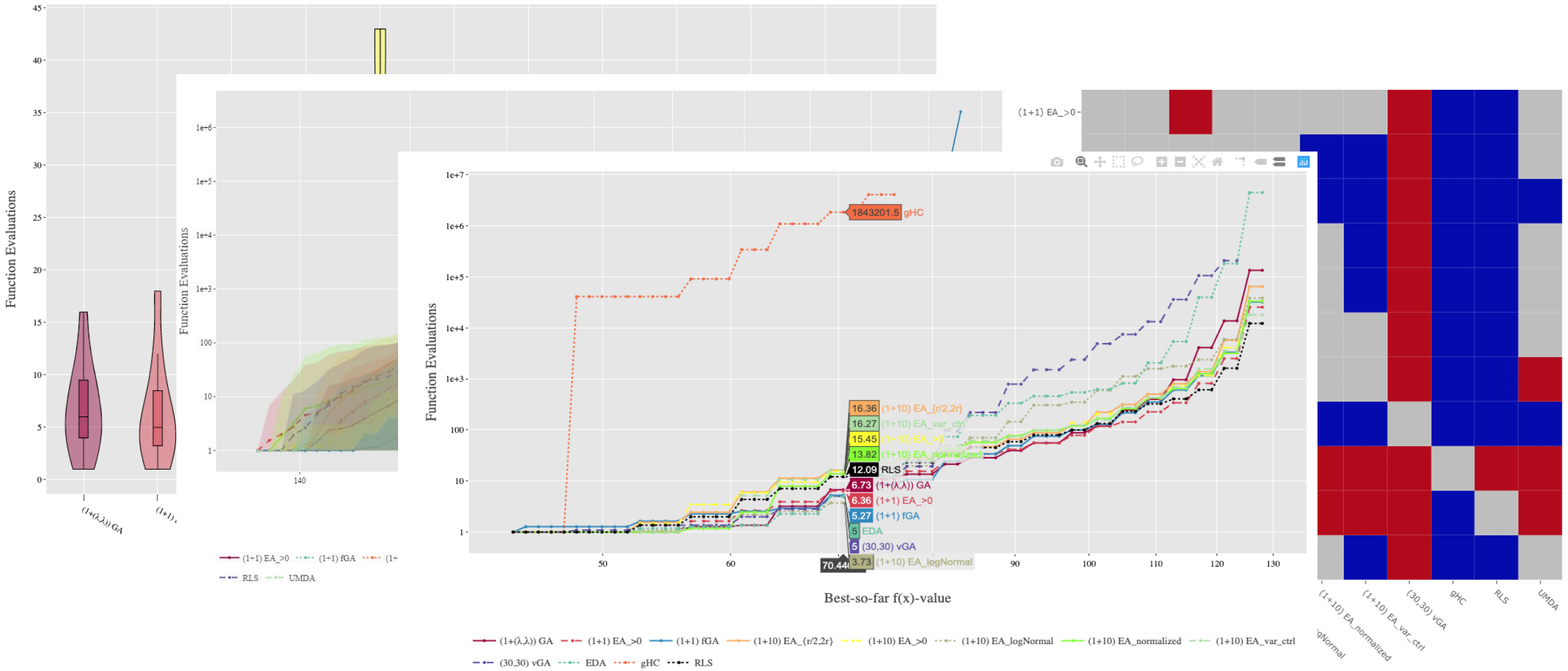
$$\{t_1(f_{\text{target}}), \ldots, t_r(f_{\text{target}})\}$$

- Successful? $t_i(f_{\text{target}}) < \infty$
- Unsuccessful? $t_i(f_{\text{target}}) = \infty$
- Number of successes $N_{\text{succ}} = \sum_{i=1}^{r} \mathbf{1}(t_i(f_{\text{target}}) < \infty)$

- Performance measures:
  - Expected Running Time
  - Penalized Average Running Time
  - Average Hitting time
  - Confidence intervals of hitting time
  - …



Fixed-target Analysis



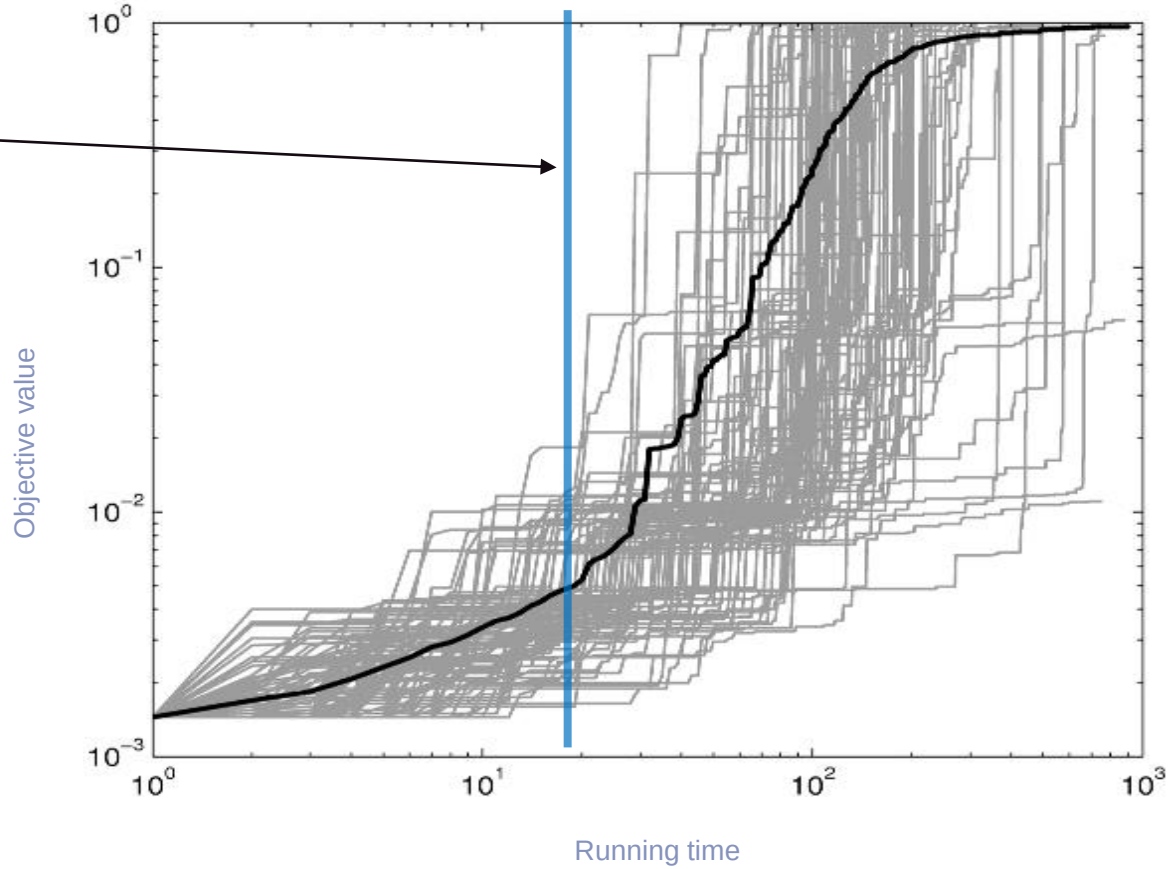
Fixed-budget analysis

- Function value – random variable
  - Parameterized by *a budget value*

$$V(b) \in \mathbb{R}, b \leq B$$

- The number of runs – r

$$\{v_1(b), \ldots, t_r(b)\}$$



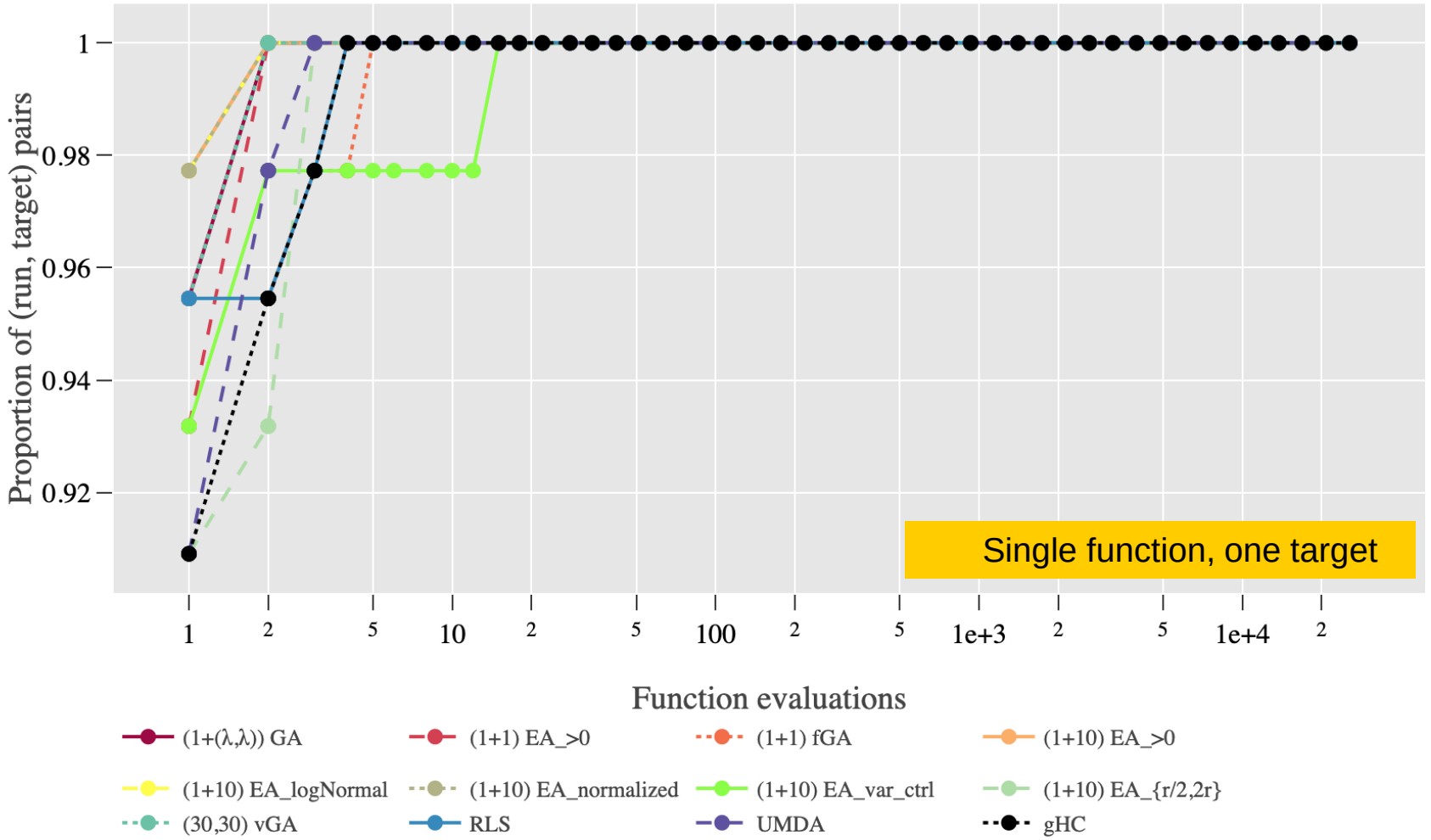
Single-function Analysis

	ID	runtime	runs	mean	median	sd	2%	5%	10%	25%	50%	75%	90%	95%	98%
	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All
1	(1+1) EA_>0	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
2	gHC	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
3	(1+10) EA_{r/2,2r}	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
4	(1+10) EA_>0	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
5	(1+10) EA_logNormal	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
6	(1+10) EA_normalized	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
7	(1+10) EA_var_ctrl	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
8	UMDA	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
9	(1+1) fGA	100000	11	312	312	0	312	312	312	312	312	312	312	312	312
10	(30,30) vGA	100000	11	293	293	3.81	287	288	289	291	293	294	297	298	299
11	RLS	100000	11	312	312	0	312	312	312	312	312	312	312	312	312

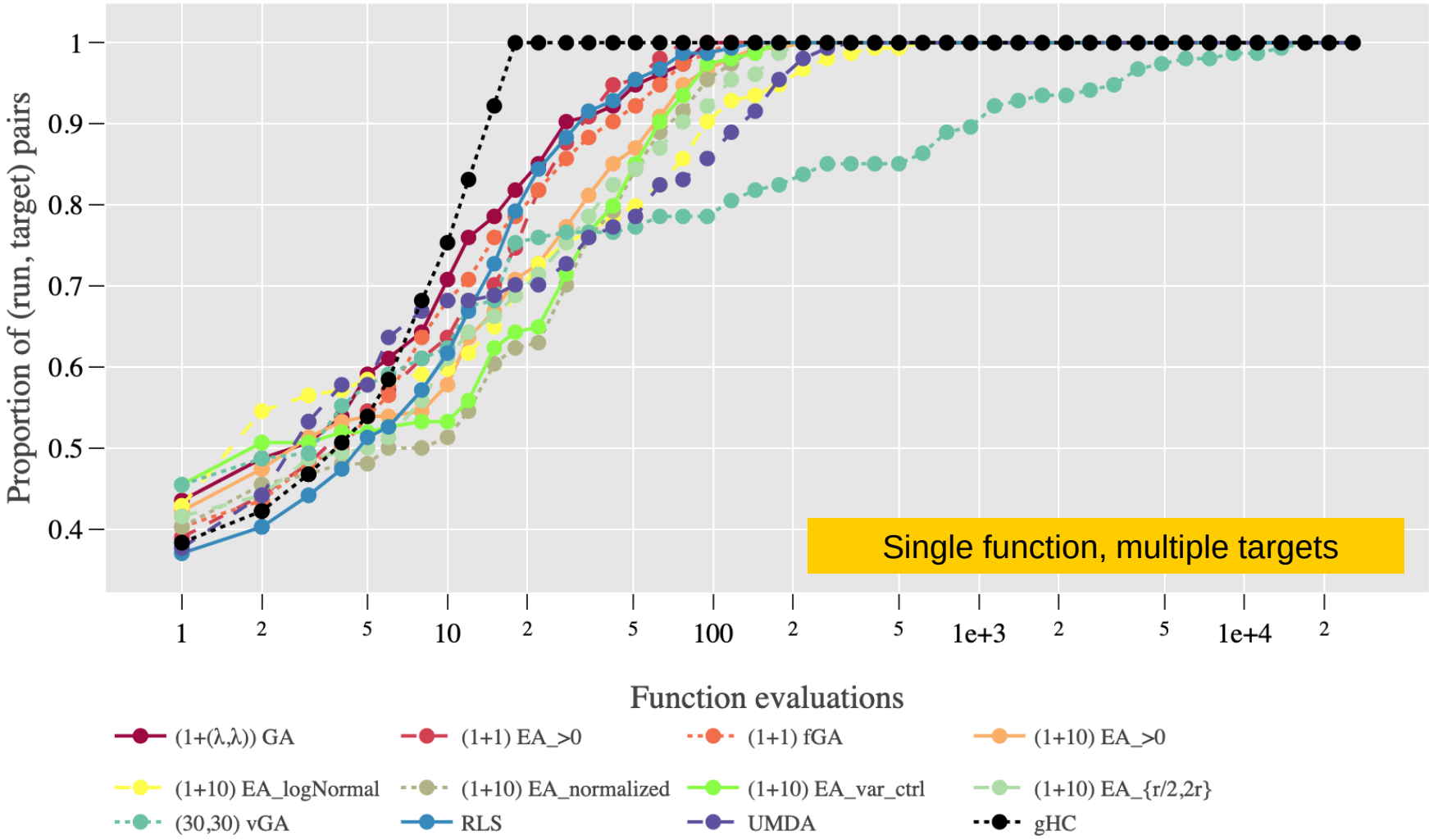
Showing 1 to 11 of 11 entries

Previous 1 Next

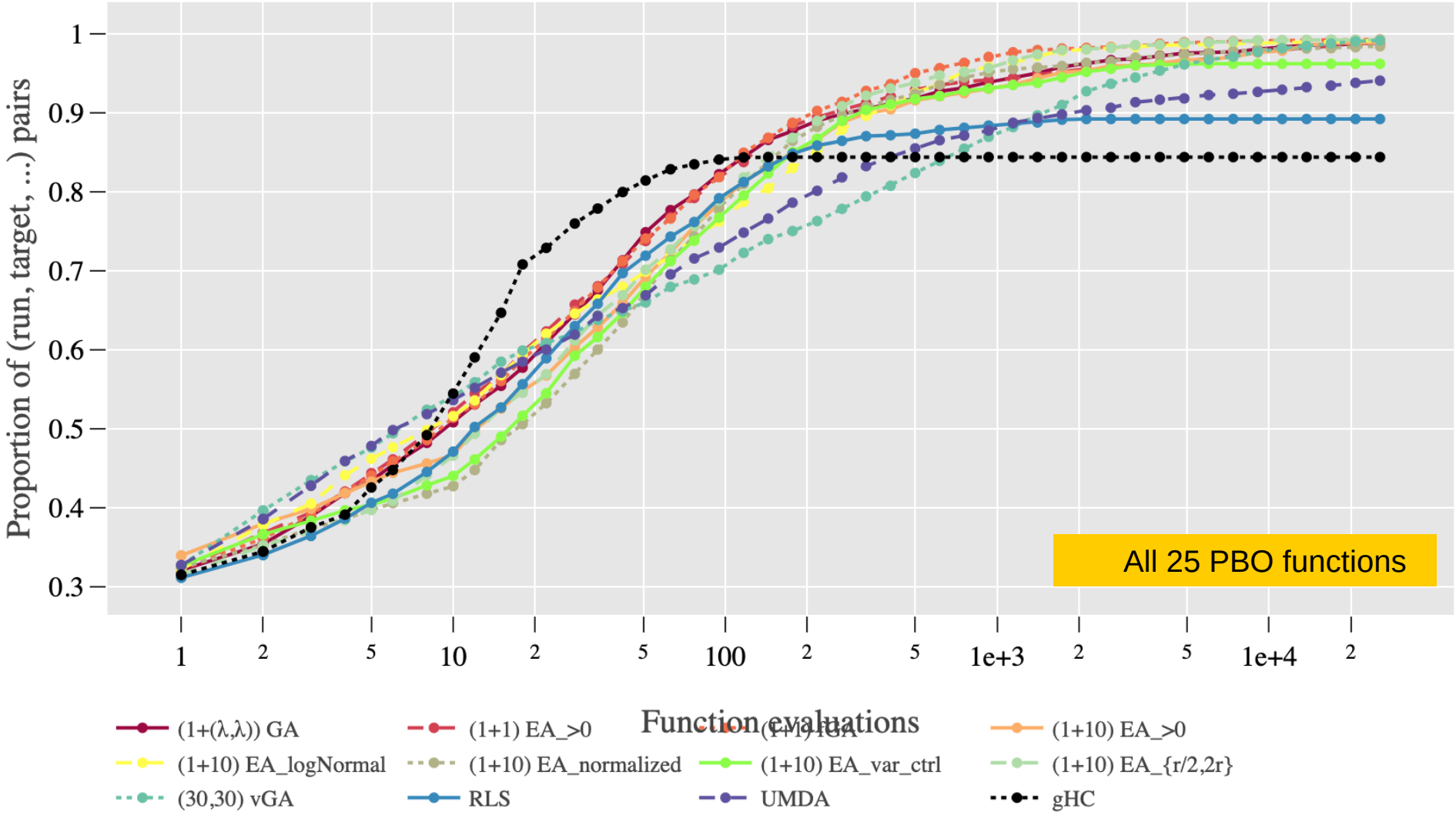
Empirical Cumulative Density Functions



Empirical Cumulative Density Functions

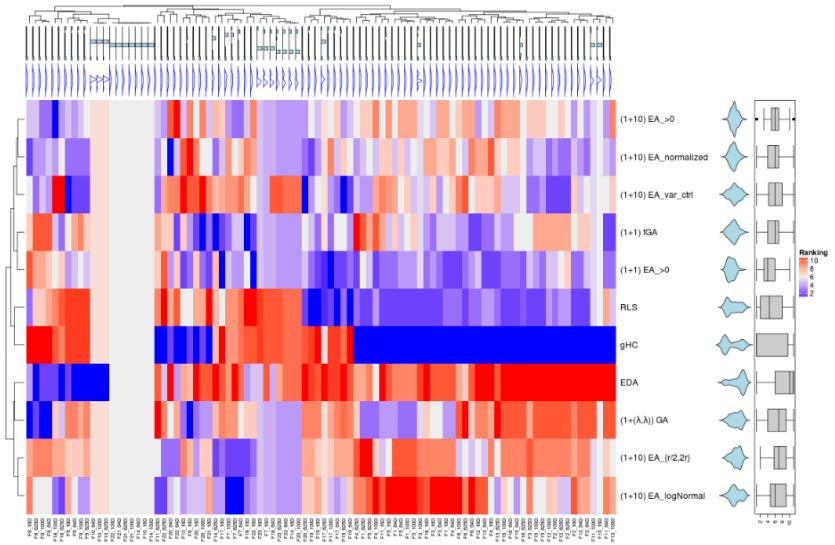


Empirical Cumulative Density Functions



Other functionality

- Aggregated rankings
  - Based on better mean per function
  - Glicko2 ranking based on per-run comparisons
- Portfolio contributions (Based on combined ECDF)
- Deep Statistical Comparison [1]
- Parameter Analysis



[1] Eftimov, T., Korošec, P., & Seljak, B. K. (2017). A novel approach to statistical comparison of meta-heuristic stochastic optimization algorithms using deep statistics. *Information Sciences*, *417*, 186-215.

IOHexperimenter overview

- The experimentation module of IOHprofiler
  - Easy to use, customizable and expandable

- Consists of **benchmark problems** and **loggers**
  - Benchmarks of discrete and continuous optimizations are available, and **customized** problems can be easily wrapped.
  - Default logger tracks algorithm performance and dynamic parameters by storing into csv files, and **customized** ones can be easily created for specific tasks.

- Current collaborations and extensions.
  - Algorithm frameworks: modular CMA-ES [2], DE [3] and modular GA [4]
  - More problems: submodular optimization competition [5], MK-Landscapes problems.
  - Other projects: integration with ParadisEO [6] and Nevergrad [7] for automated algorithm configuration.

[2] https://github.com/IOHprofiler/ModularCMAES
[3] https://github.com/Dvermetten/ModDE
[4] https://github.com/IOHprofiler/IOHalgorithm
[5] https://cs.adelaide.edu.au/~optlog/CompetitionESO2023.php
[6] https://github.com/nojhan/paradiseo
[7] https://github.com/facebookresearch/nevergrad


DEMO
IOHexperimenter

Benchmark Problems

- 25 Pseudo-Boolean optimization problems
  - OneMax
  - LeadingOnes
  - ….
- 24 BBOB continuous optimization problems
  - Sphere
  - …
- W-model extensions
  - Discrete optimization problems can be configured with customized properties.
- Submodular Problems (including constraints)
- MK-landscape problems
- Star-discrepancy problems (discrete and continuous formulations)
- Wrapper supporting any discrete or continuous problems

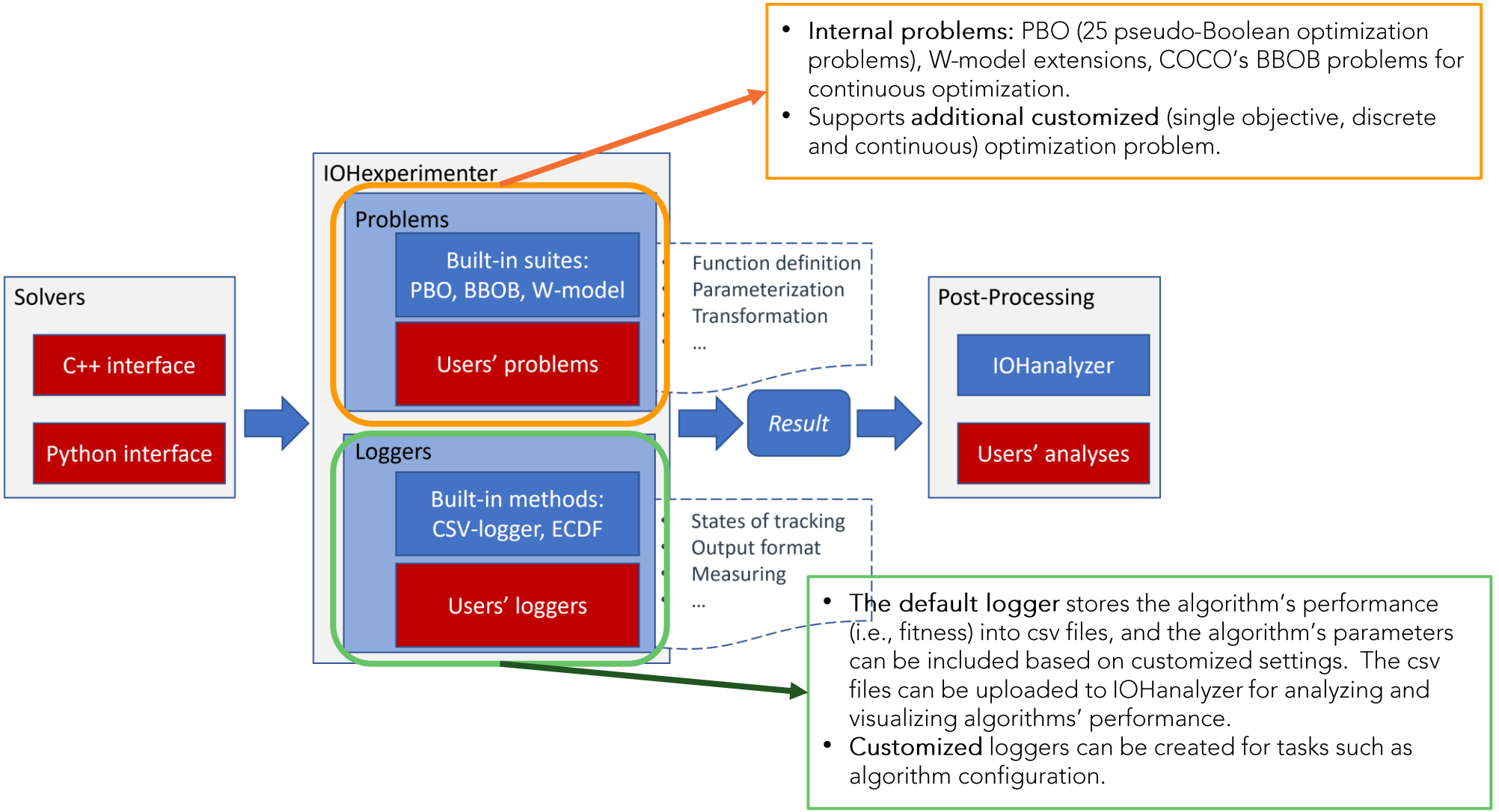
Logger

- Logger generating data that can be accessible by IOHanalyzer

- Modular design
  - Customized trigger to determine when to store the data
  - Tracking arbitrary parameters of the algorithm

- CSV logger
- In-memory
- Loggers computing statistics on the fly

Workflow of IOHexperimenter



What can I do with IOHexperimenter?

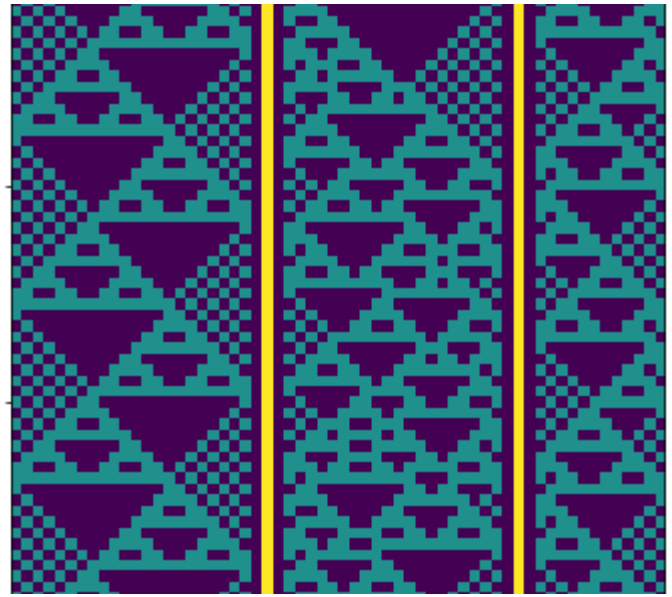
- I want to test my algorithms on IOHproblems without modifying much of the current implementation.
  - Include the IOH header files for C++ or import the IOH package for Python and replace your fitness functions with the ones defined in IOHexperimenter.
- I want to check how IOHalgorithms perform on my own benchmark problems.
  - Wrapper functions are available for C++ and Python. Define your problems following the examples and apply the existing algorithm implementations for the new problems by replacing the function evaluating fitness.
- I want to compare my algorithms to other state-of-the-art algorithms.
  - Implement your algorithms integrating with the *problem* and *logger* classes of IOHexperimenter and upload the generated data to IOHanalyzer, where data of many other algorithms are accessible for comparison.
- I want to use IOHanalyzer to analyze the performance of my algorithms.
  - Apply the logger of IOHexperimenter to track the performance of your algorithms by attaching the *logger* to the *problem* class. If you plan to test on your own problems, we suggest wrapping the problems into IOHexperimenter, which can be easily done.
- How do I contribute my work to IOHexperimenter?
  - Any contributions, e.g., reporting bugs, suggesting new problems, customized loggers, etc., are appreciated. A PR workflow is available on Github.

Teaching

- Benchmarking is a core component of any study of optimization algorithms
- So, should be accessible to students
- Introducing benchmarking concepts to students can be challenging
- IOHexperimenter helps by providing a fixed framework with pre-existing examples
- Interactivity of IOHanalyzer enables non-expert programmers to contribute to understanding of algorithm performance

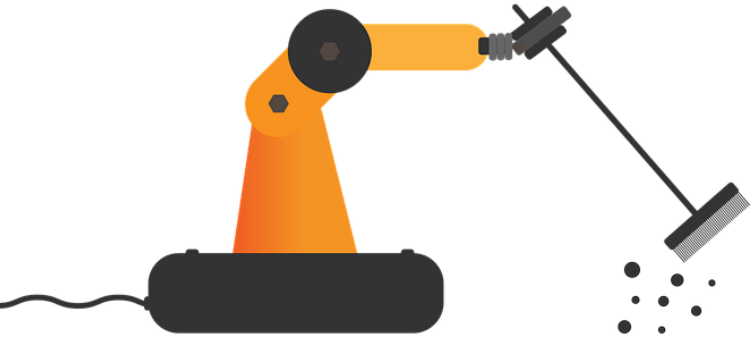
Teaching

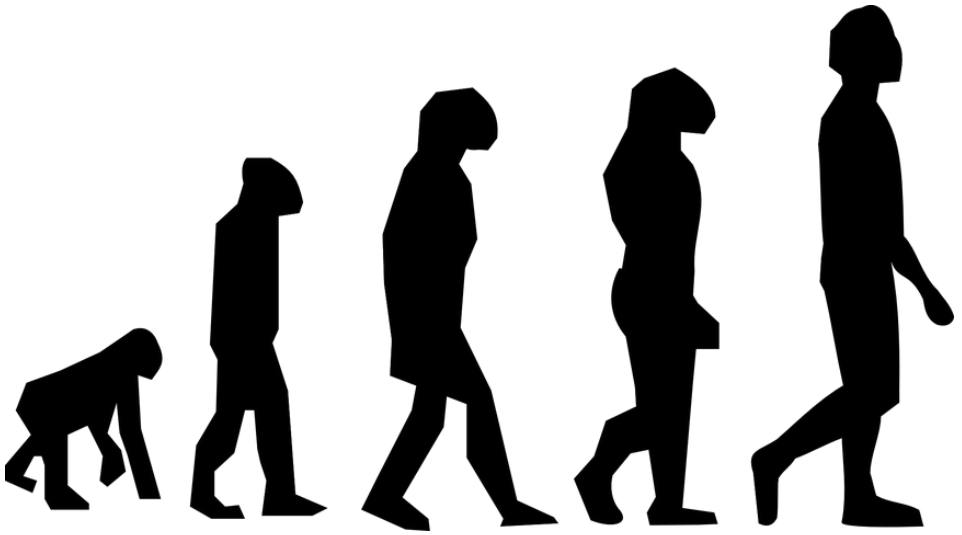
- Some examples of benefits we found while teaching:
  - Easily extending objective functions enables more wide variety of types of problems (e.g. inverting rules of cellular automata for a bachelor course on natural computing)
  - The common data format and many-algorithm analysis options enables for some degree of competitive algorithm design (e.g. a bonus point for the top 10% algorithms based on area under aggregated ECDF)
  - Common structure allows easy reproducibility of submissions + enables the creation of simple test-functions so students can check their algorithm for minimal acceptable performance



Student Projects

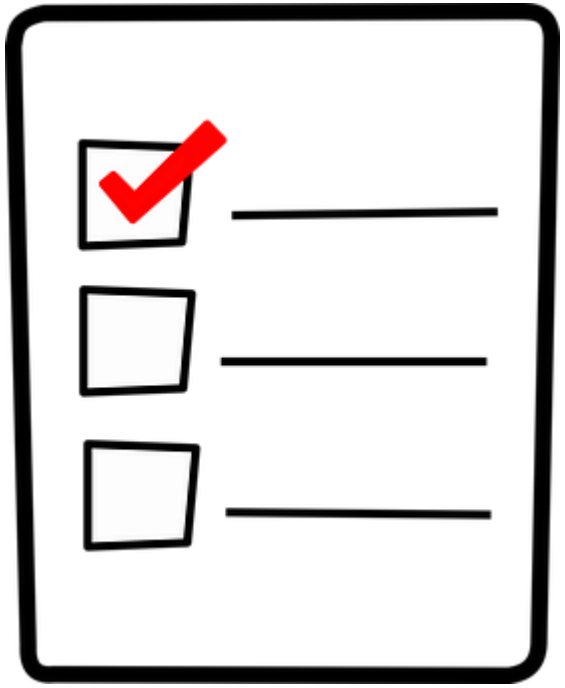
- Within our group, IOHprofiler is commonly used in both Bsc. and Msc. thesis projects
- Significantly reduces the overhead of setting up correct benchmarking practices and common visualizations
- Makes transitioning to scientific papers easier, since the benchmarking pipeline is correct





Research Benefits

- Straightforward data collection used in variety of contexts
- Algorithm selection: combine ioh and nevergrad to get data for 13 algorithms on 24 functions
- Dynamic Algorithm Selection: tracking of position information and dynamic attributes to determine switching points [9]
- Supporting algorithm development [10]:
  - Tables downloadable in LaTeX
  - Plots as pdf
  - Statistical testing

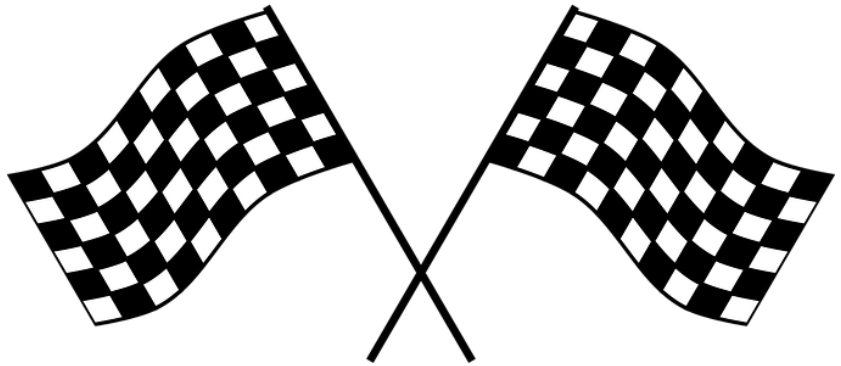


[9] Kostovska, A., Jankovic, A., Vermetten, D., de Nobel, J., Wang, H., Eftimov, T., & Doerr, C. (2022, August). Per-run algorithm selection with warm-starting using trajectory-based features. In Parallel Problem Solving from Nature–PPSN XVII: 17th International Conference, PPSN 2022
[10] Vermetten, D., Caraffini, F., Kononova, A. V., & Bäck, T. (2023). Modular Differential Evolution. arXiv preprint arXiv:2304.09524.

Competitions / Workshops

- Integrate problem in IOHexperiments:
  - Directly in the C++ backend
  - Using the wrapping functionality
- Make baselines directly available in IOHanalzyer
- Set up template for drop-in tables / figures
- Easy comparison of all combined results

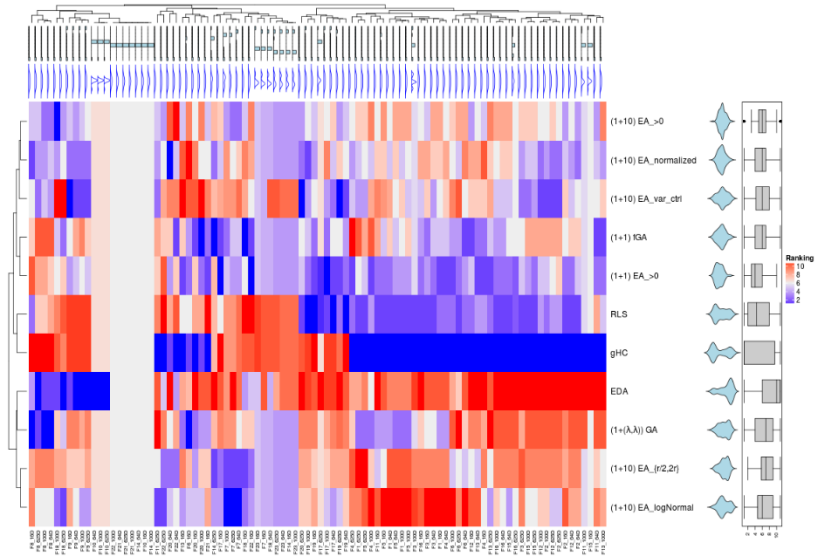
- Currently active:
  - Submodular Optimization Competition [11]
  - Star-discrepancy Optimization Competition [12]
  - Strict box-constrained optimization workshop [13]

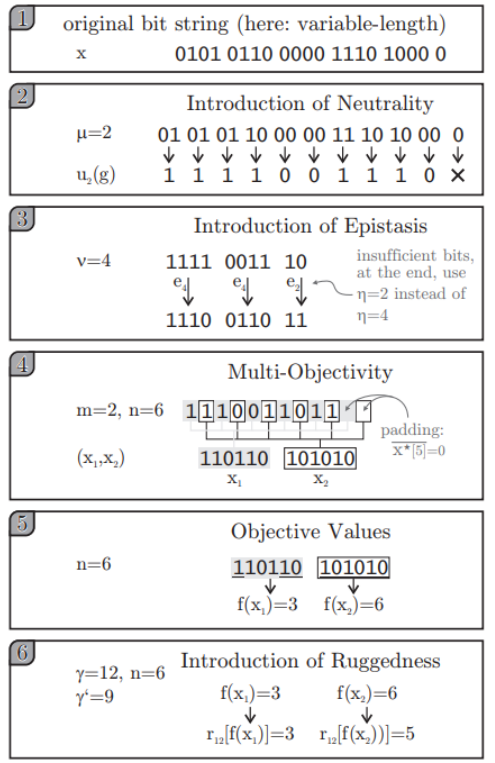


[11] Neumann, F., Neumann, A., Qian, C., Do, V. A., de Nobel, J., Vermetten, D., ... & Bäck, T. (2023). Benchmarking Algorithms for Submodular Optimization Problems Using IOHProfiler. arXiv preprint arXiv:2302.01464.
[12] Clement, F., Vermetten, D., de Nobel, J., Jesus, A., Paquete, L., & Doerr, C. Computing Star Discrepancies with Numerical Black-Box Optimization Algorithms.
[13] Kononova, A. et al. SBOX-COST — Strict box-constraint optimization studies Workshop, GECCO 2023

Collaborations

- Integration IOHexperimenter with ParadisEO (Johann Dréo)
- GUI for DSCtool in IOHanalyzer (Tome Eftimov)
- Implementation of W-model in IOHexperimenter (Thomas Weise)
- Integration of IOHexperimenter problems into Nevergrad
- We are always open to new collaborations!





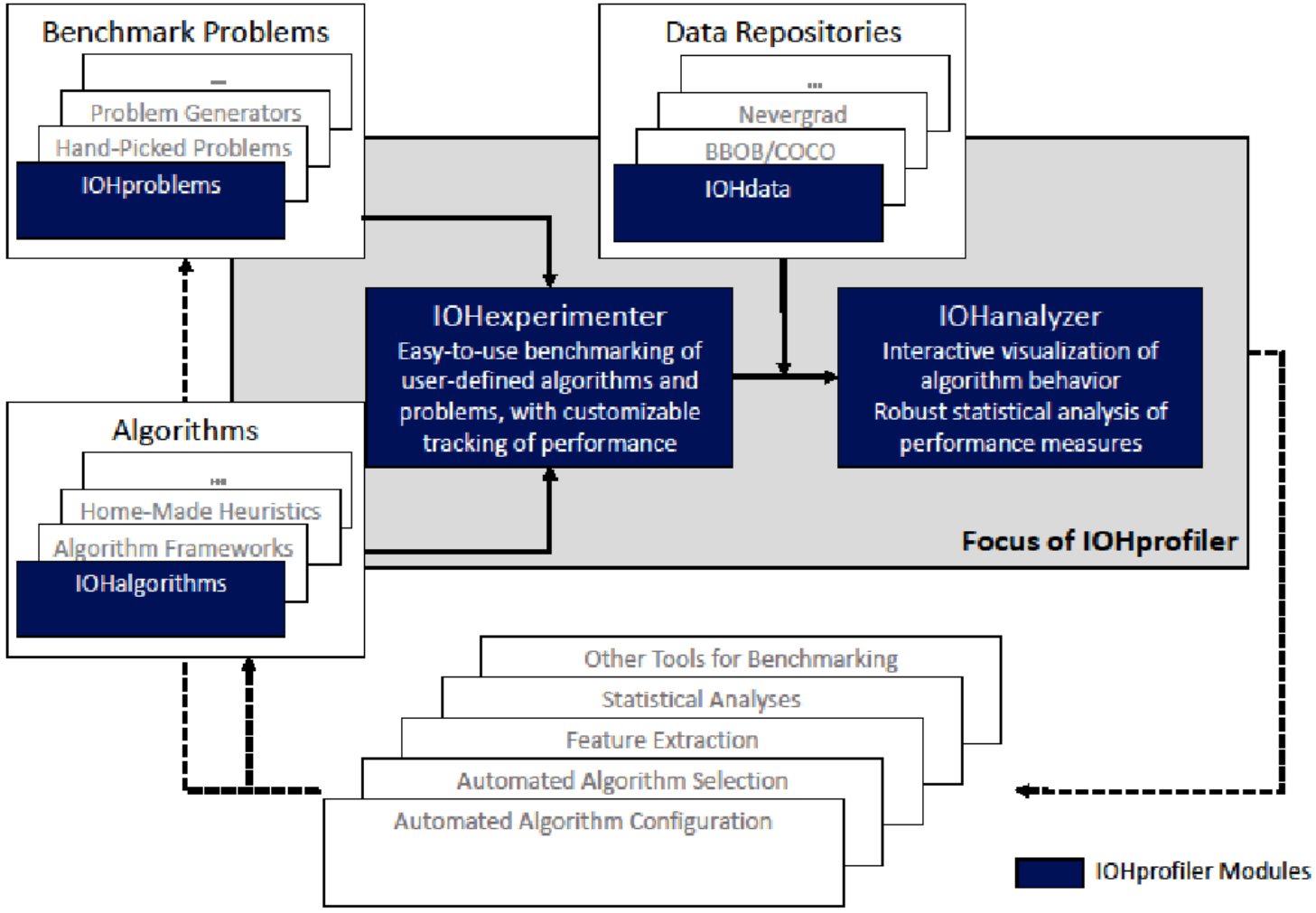
OPTION Ontology

- Benchmark data contains a lot of information
- But not always easy to extract
- Collaboration with OPTION: data ontology for iterative optimization [14]
- Annotated data supports wide variety of queries
- Current prototype interface enables loading data by study name
- Significant potential to implement many more easy to use query types

[14] A. Kostovska, D. Vermetten, C. Doerr, S. Džeroski, Panče Panov and T. Eftimov, "OPTION: OPTImization Algorithm Benchmarking ONtology," in IEEE Transactions on Evolutionary Computation, doi: 10.1109/TEVC.2022.3232844.

What is Next?

- Extend repository of algorithms + data
- Add interfaces to more tools
- Extensions to mixed-integer and multi-objective problems
- Add more benchmarks for constrained optimization
- More ways of analyzing the data



Discussion

- How can benchmarking tools like IOHprofiler aid in reproducibility?
- How can we make robust benchmarking easier to do?
- What features would make IOHprofiler fit your use-case better?
- How can we collaborate to make benchmarking as easy and useful as possible?