

10th GECCO Workshop on Blackbox Optimization Benchmarking (BBOB): Welcome and Introduction to COCO/BBOB

The BBOBies

<https://github.com/numbbbo/coco>

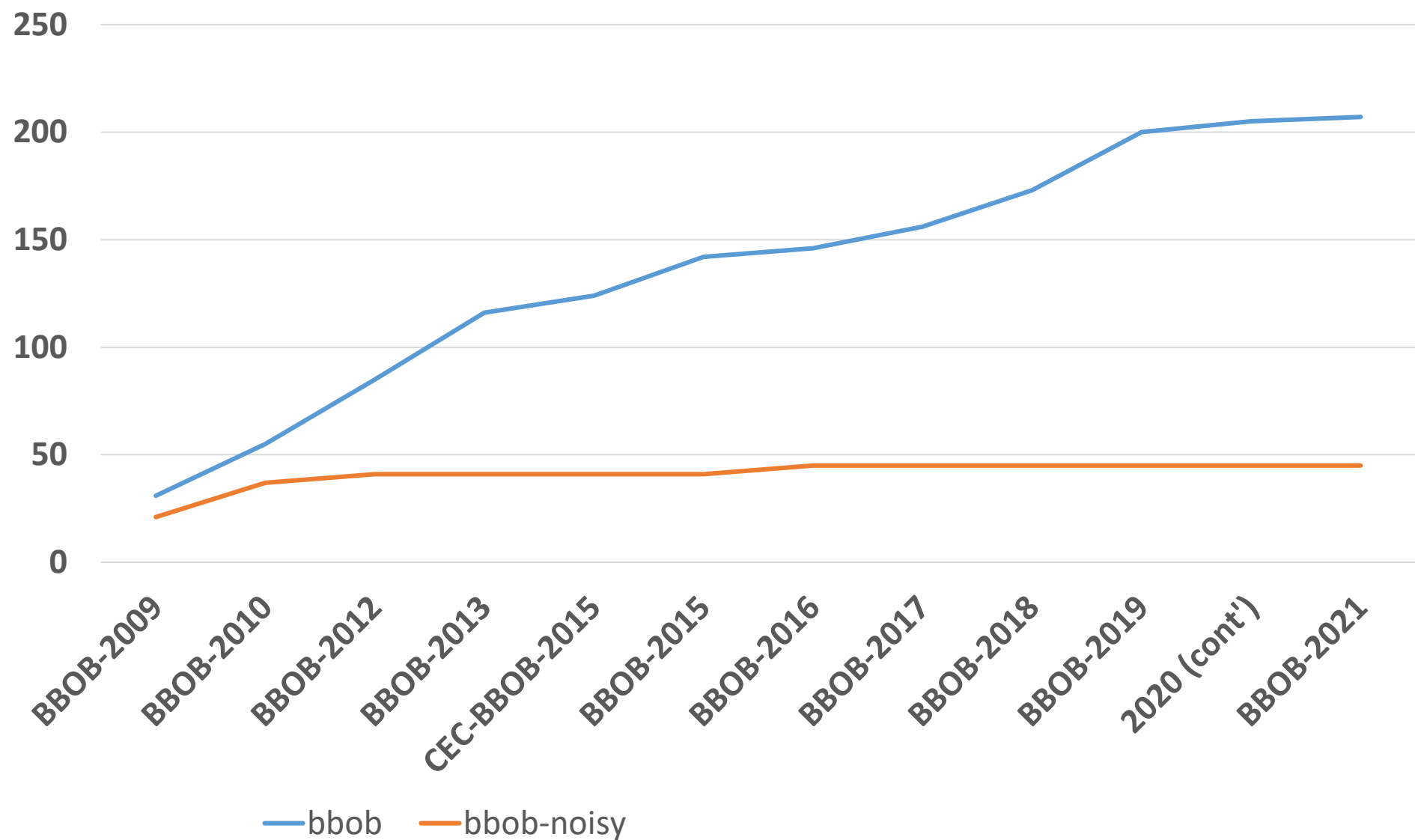


slides based on previous ones by A. Auger, N. Hansen, and D. Brockhoff

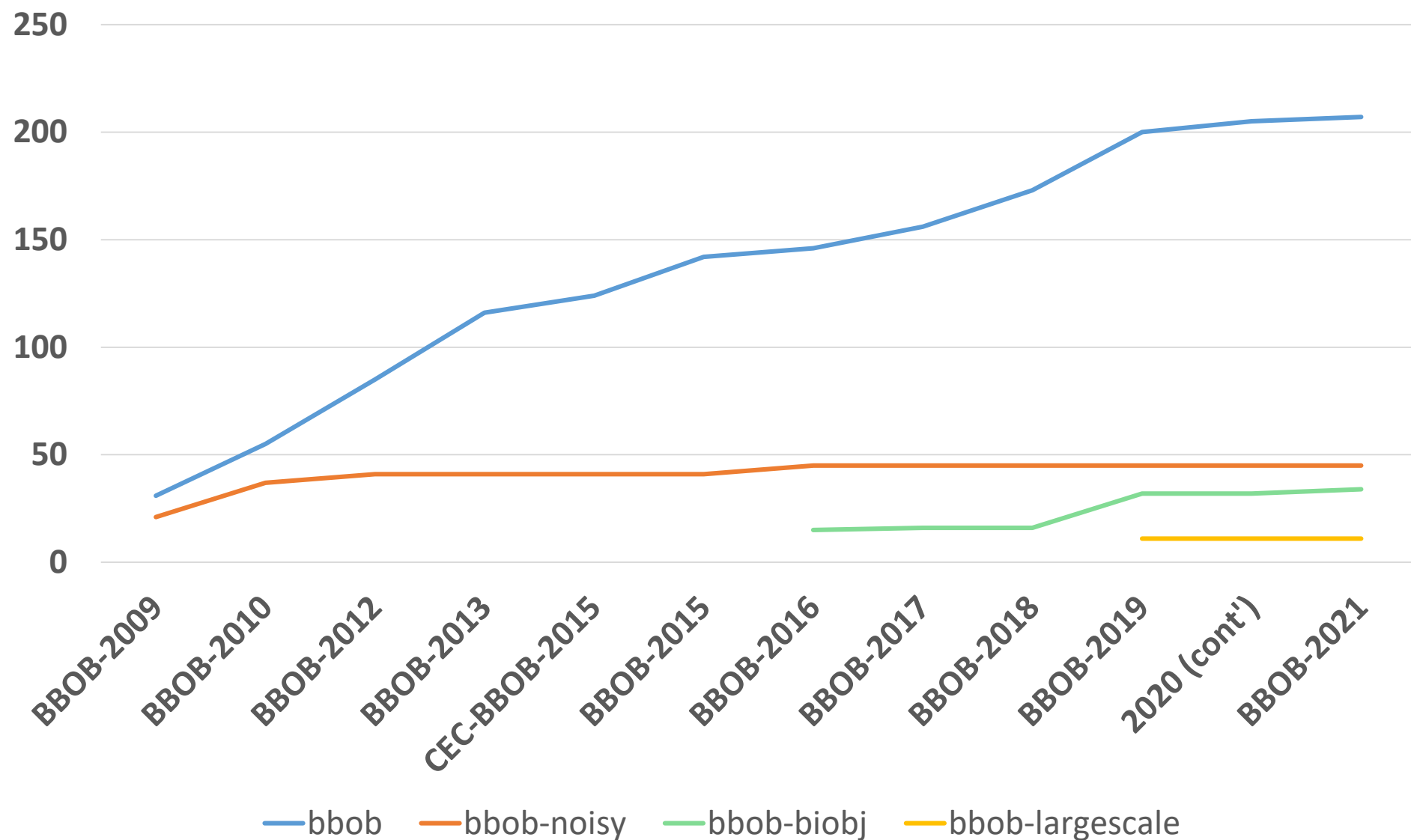
The BBOB Benchmarking Series

- all started at CEC'2005 special session
organized by P. N. Suganthan, N. Hansen, J. J. Liang, K. Deb, Y.-P. Chen, A. Auger and S. Tiwari
- split soon thereafter into the CEC and GECCO “schools”
- CEC: many topics, many test suites, competitions
- BBOB:
 - focus on a few test suites
 - 2 of them unchanged since 2009
 - assisted by the COCO platform: (semi-)automated benchmarking
- recently even more interest in benchmarking

Submitted COCO Data Sets (cumulated)

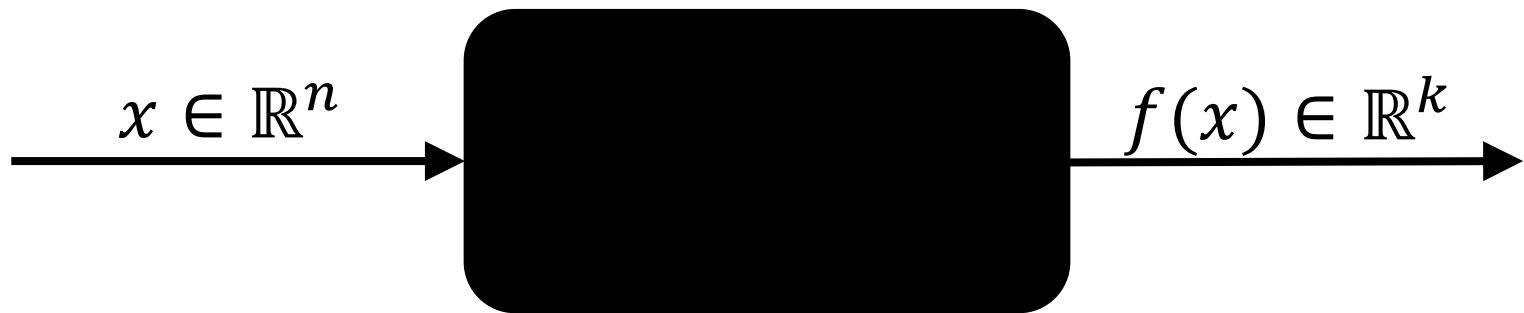


Submitted COCO Data Sets (cumulated)



Numerical Blackbox Optimization

Optimize $f: \Omega \subset \mathbb{R}^n \mapsto \mathbb{R}^k$



derivatives not available or not useful

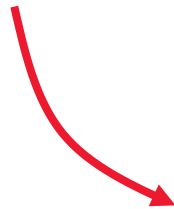
Need: Benchmarking

- understanding of algorithms
- algorithm selection
- putting algorithms to a standardized test
 - simplify judgement
 - simplify comparison
 - regression test under algorithm changes

Kind of everybody has to do it (and it is tedious):

- choosing (and implementing) problems, performance measures, visualization, stat. tests, ...
- running a set of algorithms

that's where COCO and BBOB come into play

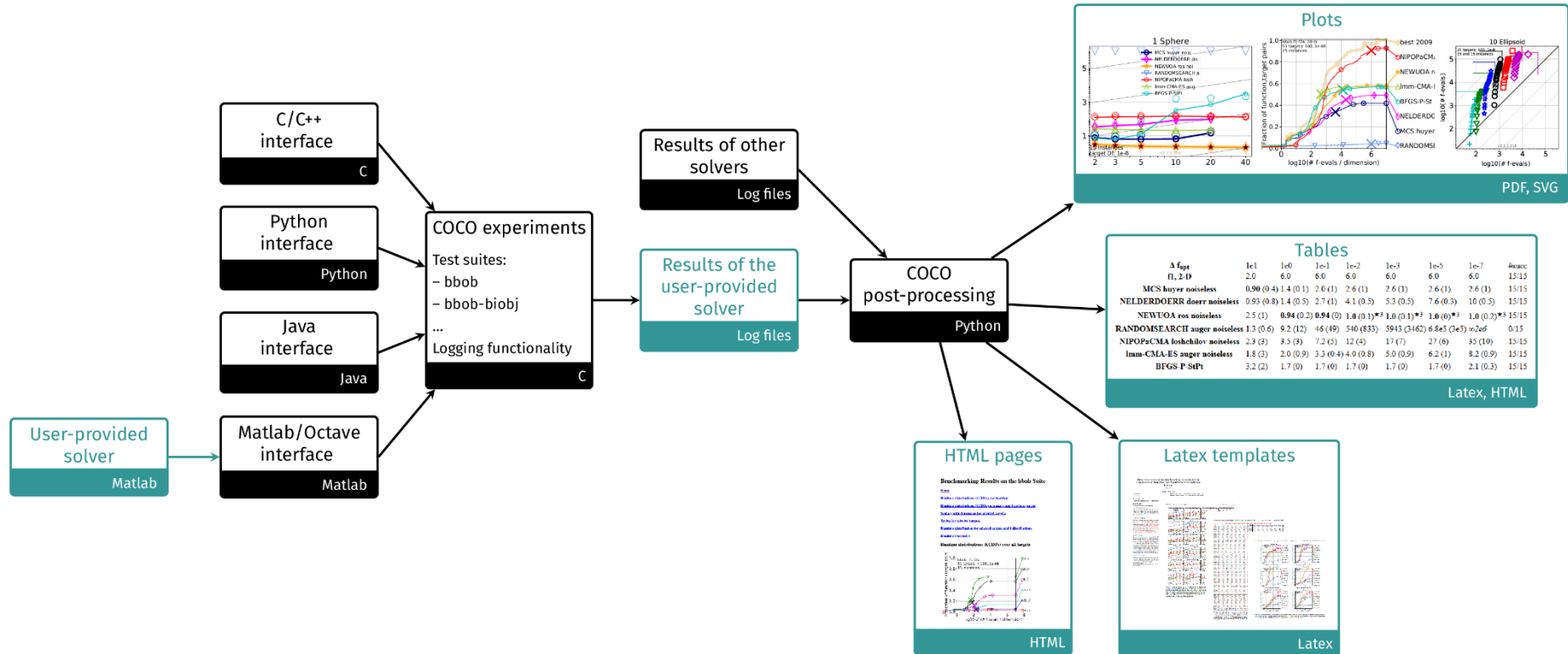


Comparing Continuous Optimizers Platform

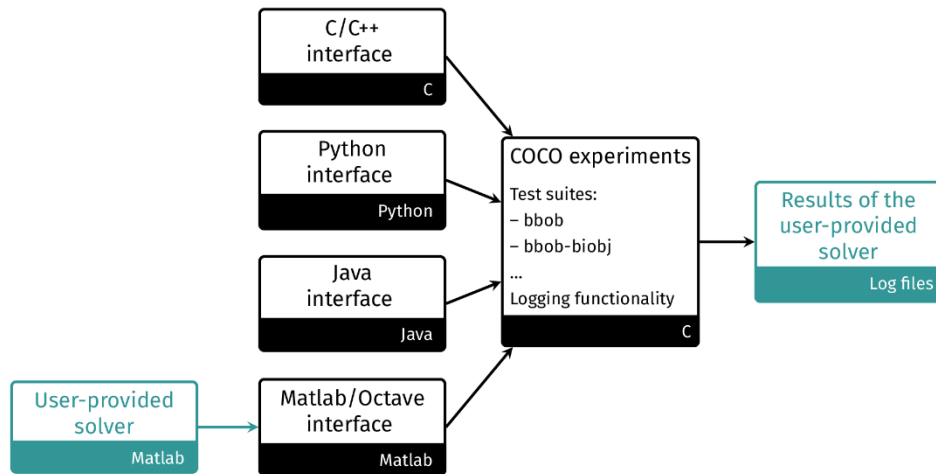
`https://github.com/numbbo/coco`

automatized benchmarking

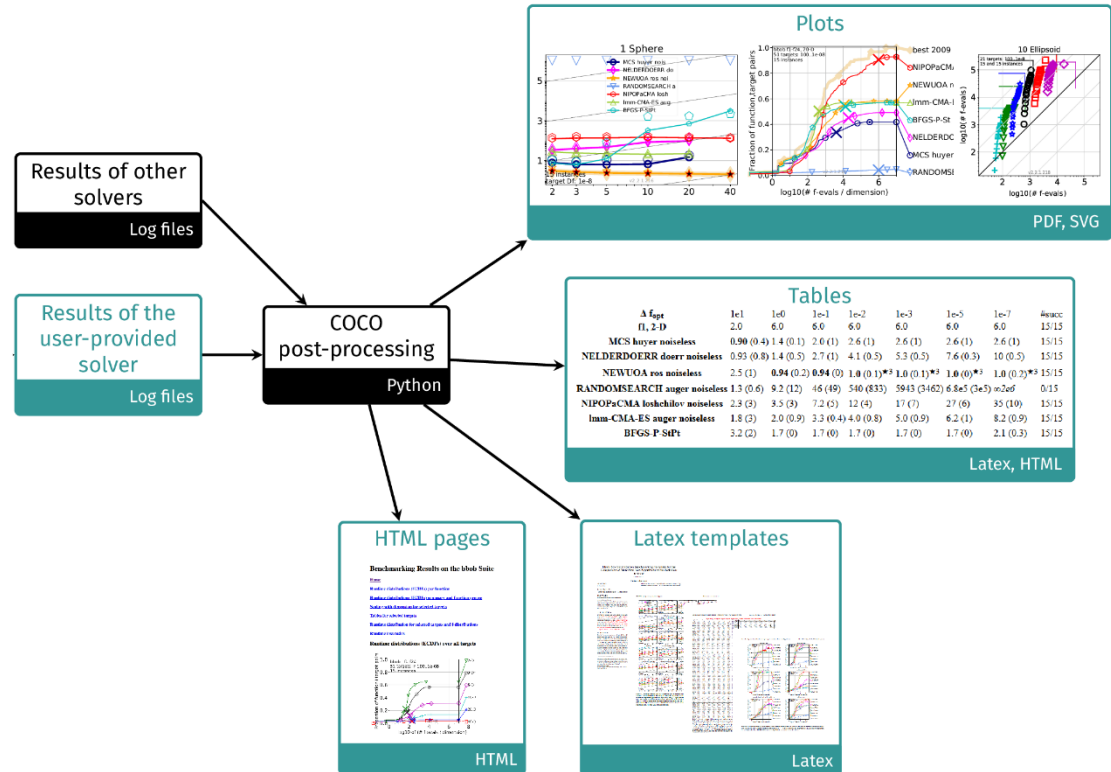
Overview of COCO's Structure



Overview of COCO's Structure



Overview of COCO's Structure



Is Benchmarking Not Trivial?

- ① Choose a set of algorithms
- ② Choose a set of (test) functions
- ③ Run the algorithms and compare the results!

the devil is in the details...

hence, COCO implements a
reasonable, well-founded, and
well-documented
pre-chosen methodology

Measuring Performance

On

- **real world problems**
 - expensive
 - comparison typically limited to certain domains
 - experts have limited interest to publish
- **"artificial" benchmark functions**
 - cheap
 - controlled
 - data acquisition is comparatively easy
 - **problem of representativeness**

Test Functions

- define the "scientific question"

the relevance can hardly be overestimated

- should represent "reality"
- are often too simple?

remind separability

- account for **invariance properties**

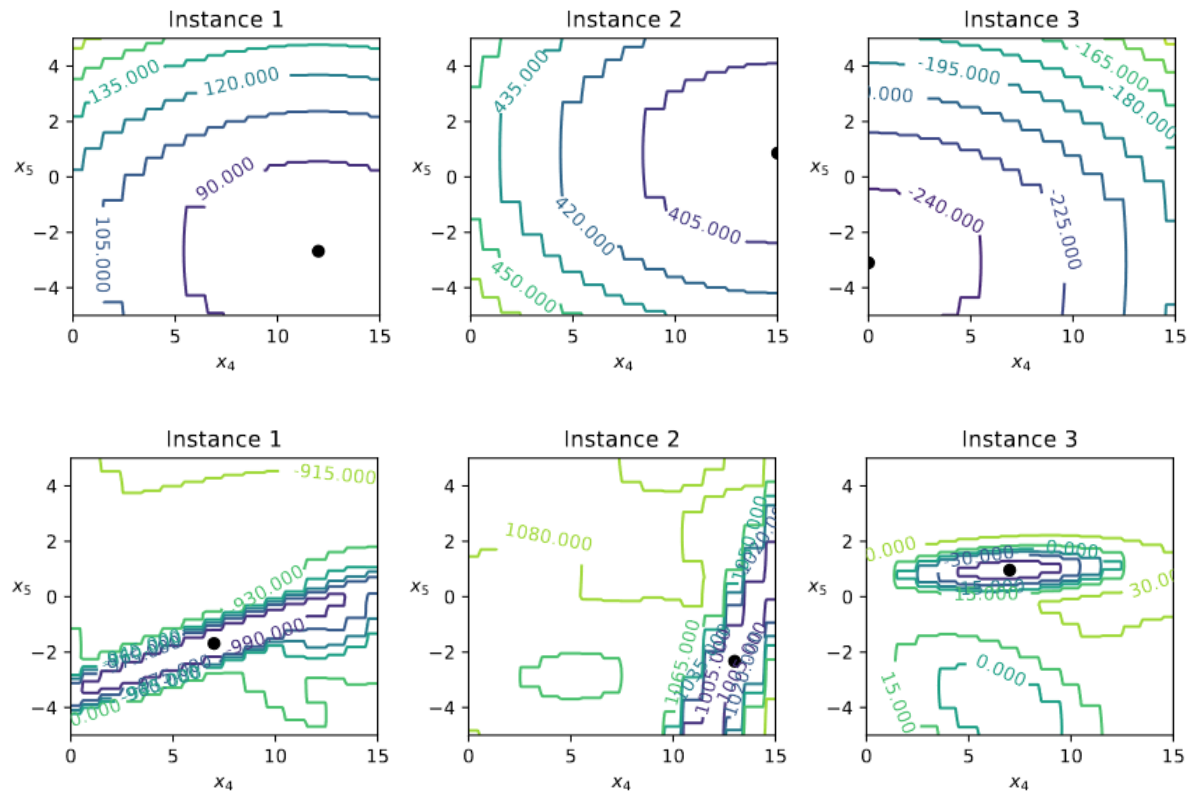
prediction of performance is based on “similarity”,
ideally equivalence classes of functions

Notion of Instances

- All COCO problems come in form of instances
 - e.g. as translated/rotated versions of the same function

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Notion of Instances

- All COCO problems come in form of instances
 - e.g. as translated/rotated versions of the same function
- Prescribed instances typically change from year to year
 - avoid overfitting
 - 5 instances are always kept the same

Plus:

- the bbob functions are locally perturbed by non-linear transformations

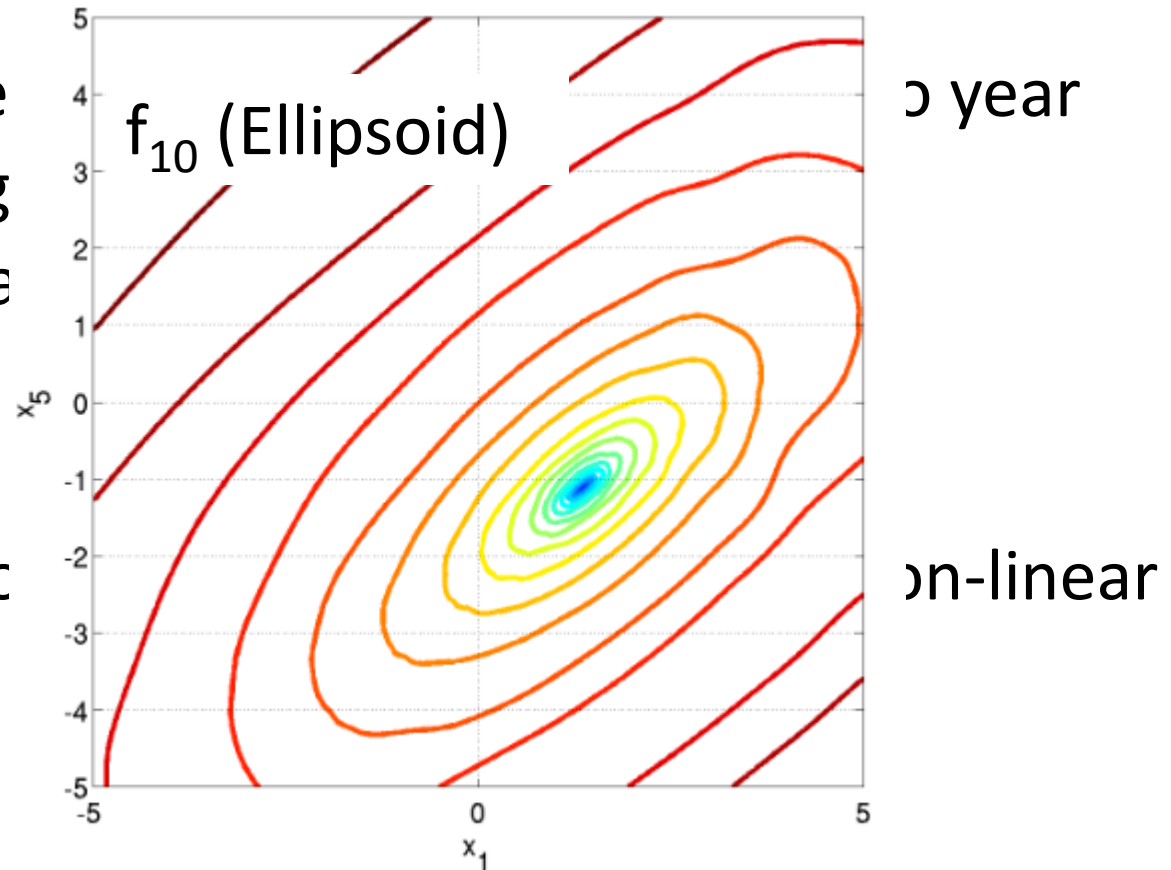
Notion of Instances

- All COCO problems come in form of instances
 - e.g. as translated/rotated version f_{15} (Rastrigin) or linear function

- Prescribed instance
 - avoid overfitting
 - 5 instances are a

Plus:

- the bbob function transformations



Available Test Suites in COCO

bbob (2009–)	24 noiseless fcts	200+ data sets
bbob-noisy (2009–)	30 noisy fcts	40+ data sets
bbob-biobj (2016–)	55 bi-objective fcts	30+ data sets
bbob-largescale (2019–)	24 noiseless fcts	11 data sets
bbob-mixint (2019–)	24 noiseless fcts	4 data sets
bbob-biobj-mixint (2019–)	92 bi-objective fcts	-

Easy Data Access

```
import cocopp  
cocopp.main('BIPOP')
```

```
[...]
```

ValueError: 'BIPOP' has multiple matches in the data archive:

```
2009/BIPOP-CMA-ES_hansen_noiseless.tgz
```

```
2012/BIPOPcCMA_loshchilov_noiseless.tgz
```

```
[...]
```

```
2017/KL-BIPOP-CMA-ES-Yamaguchi.tgz
```

Either pick a single match, or use the `get_all` or `get_first` method,

or use the ! (first) or * (all) marker and try again.

```
cocopp.main('BIPOP! BFGS! SLSQP-11')
```

[data access also available via command line]

How Do We Measure Performance?

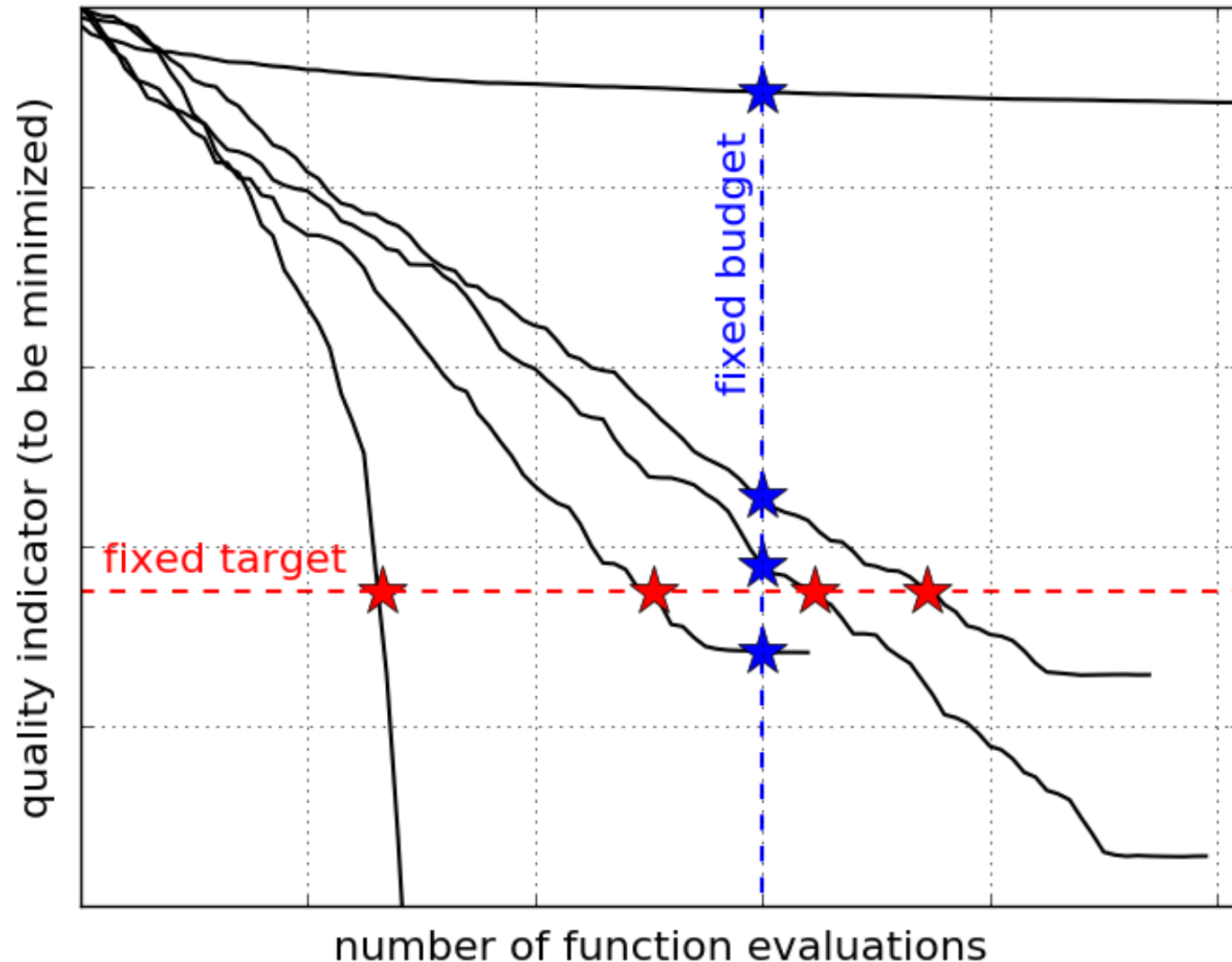
Meaningful quantitative measure

- quantitative on the ratio scale (highest possible)
 - "algo A is two *times* better than algo B" is a meaningful statement
- assume a wide range of values
- meaningful (interpretable) with regard to the real world
 - possible to transfer from benchmarking to real world

runtime or first hitting time is the prime candidate
(we don't have many choices anyway)

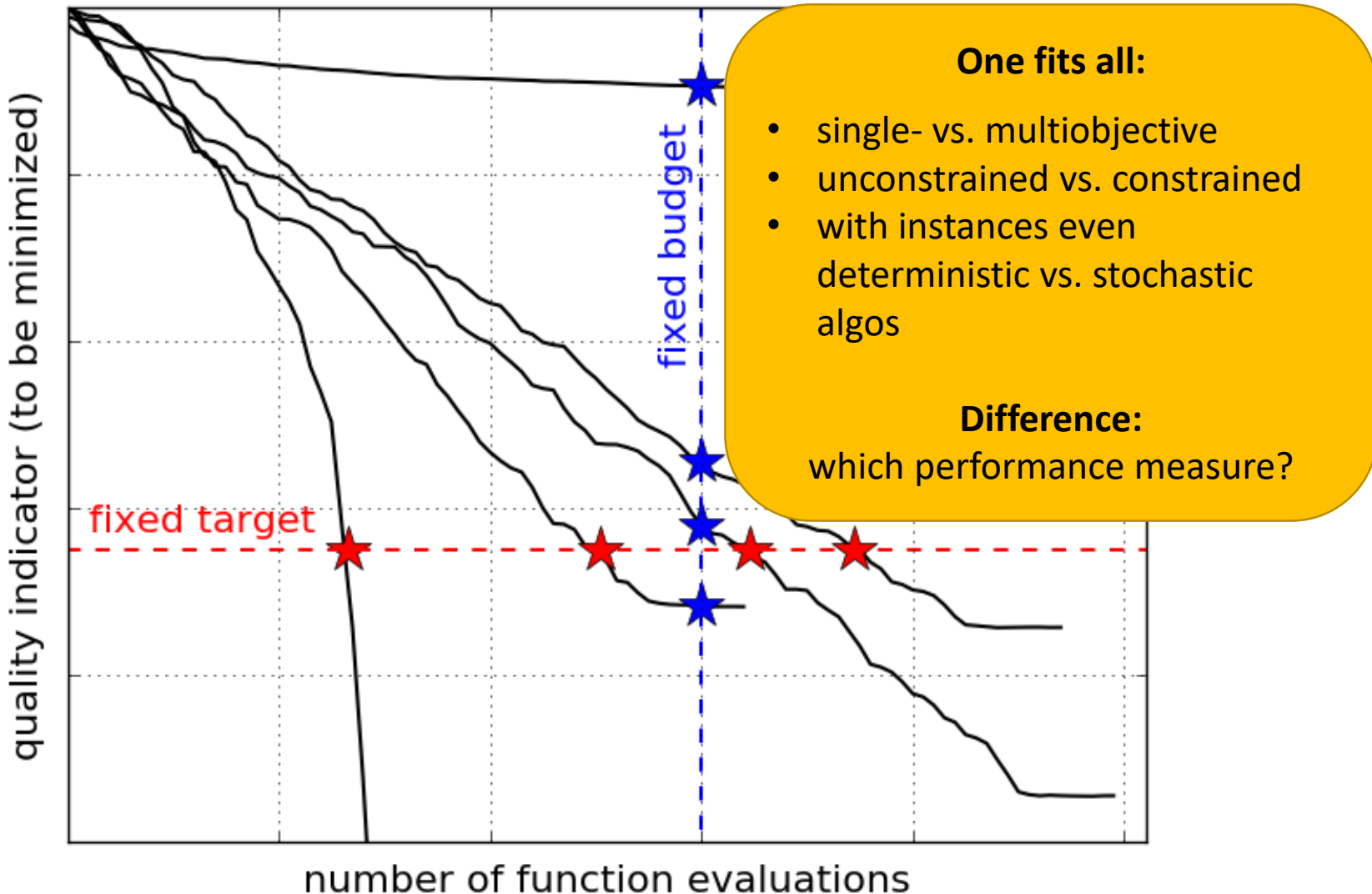
Measuring Performance Empirically

convergence graphs is all we have to start with...



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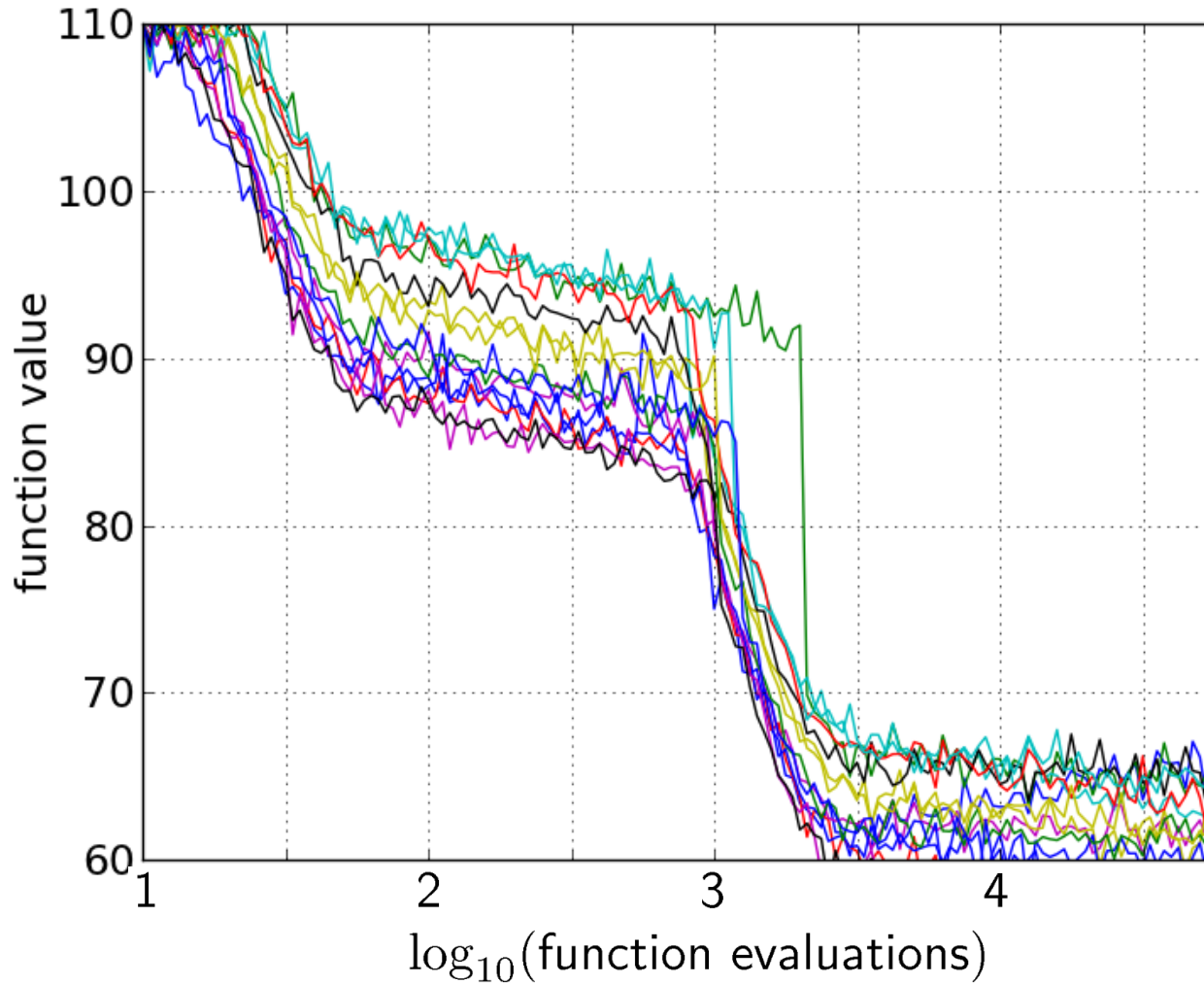
Main Performance Visualization:

Empirical Runtime Distributions

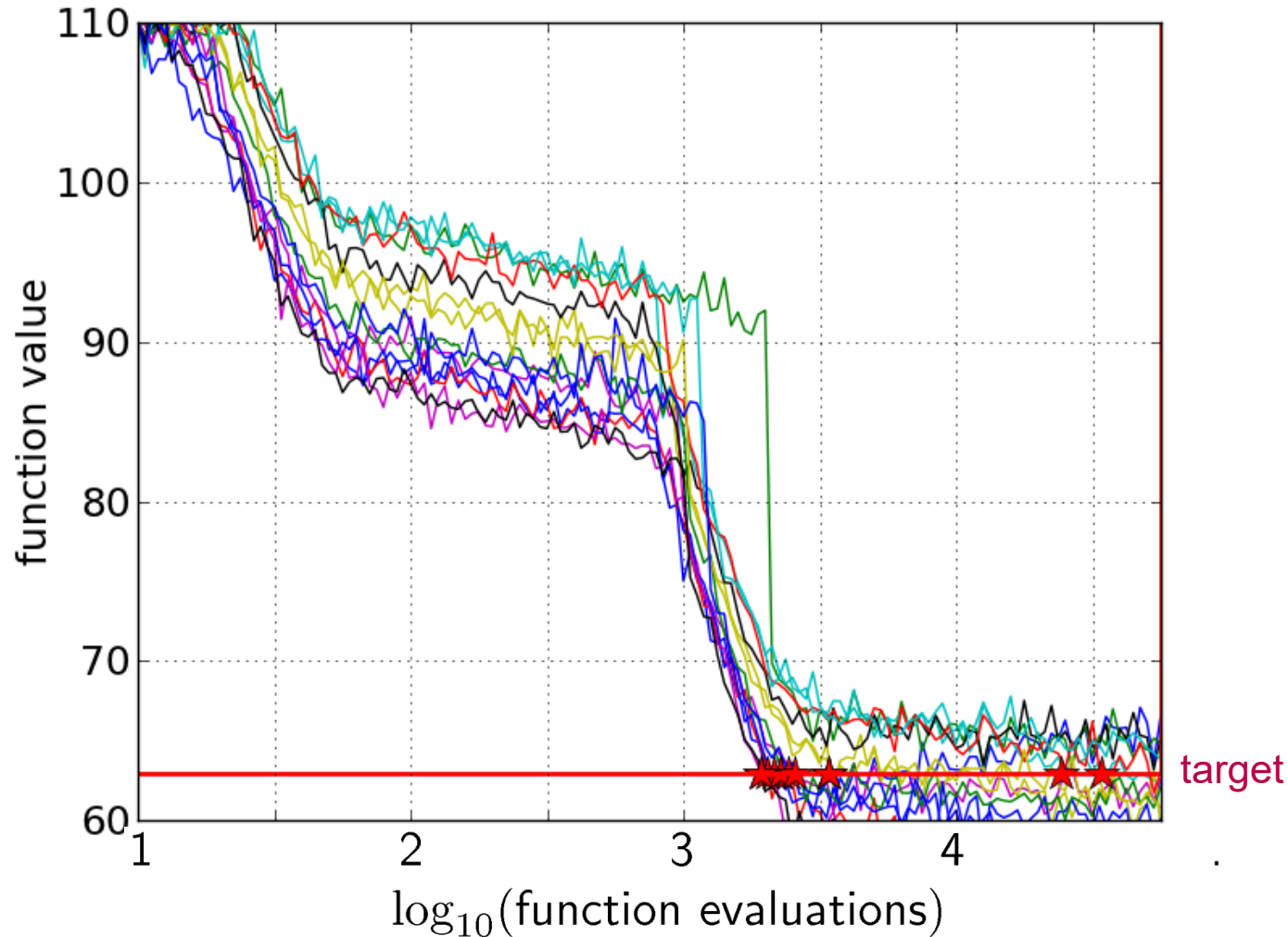
[aka Empirical Cumulative Distribution Function (ECDF) of the Runtime]

[similar to data profiles]

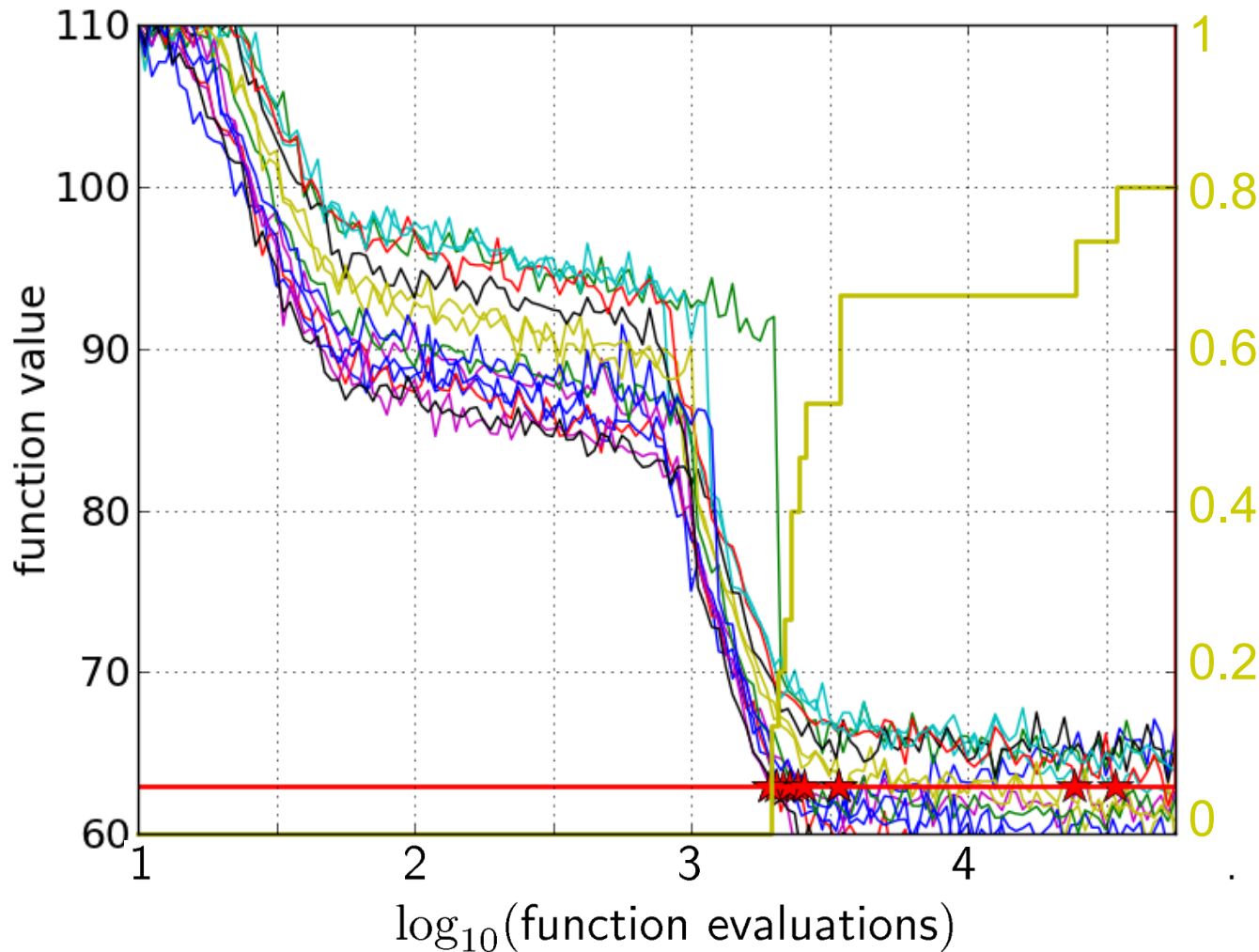
Convergence Graph of 15 Runs



15 Runs \leq 15 Runtime Data Points



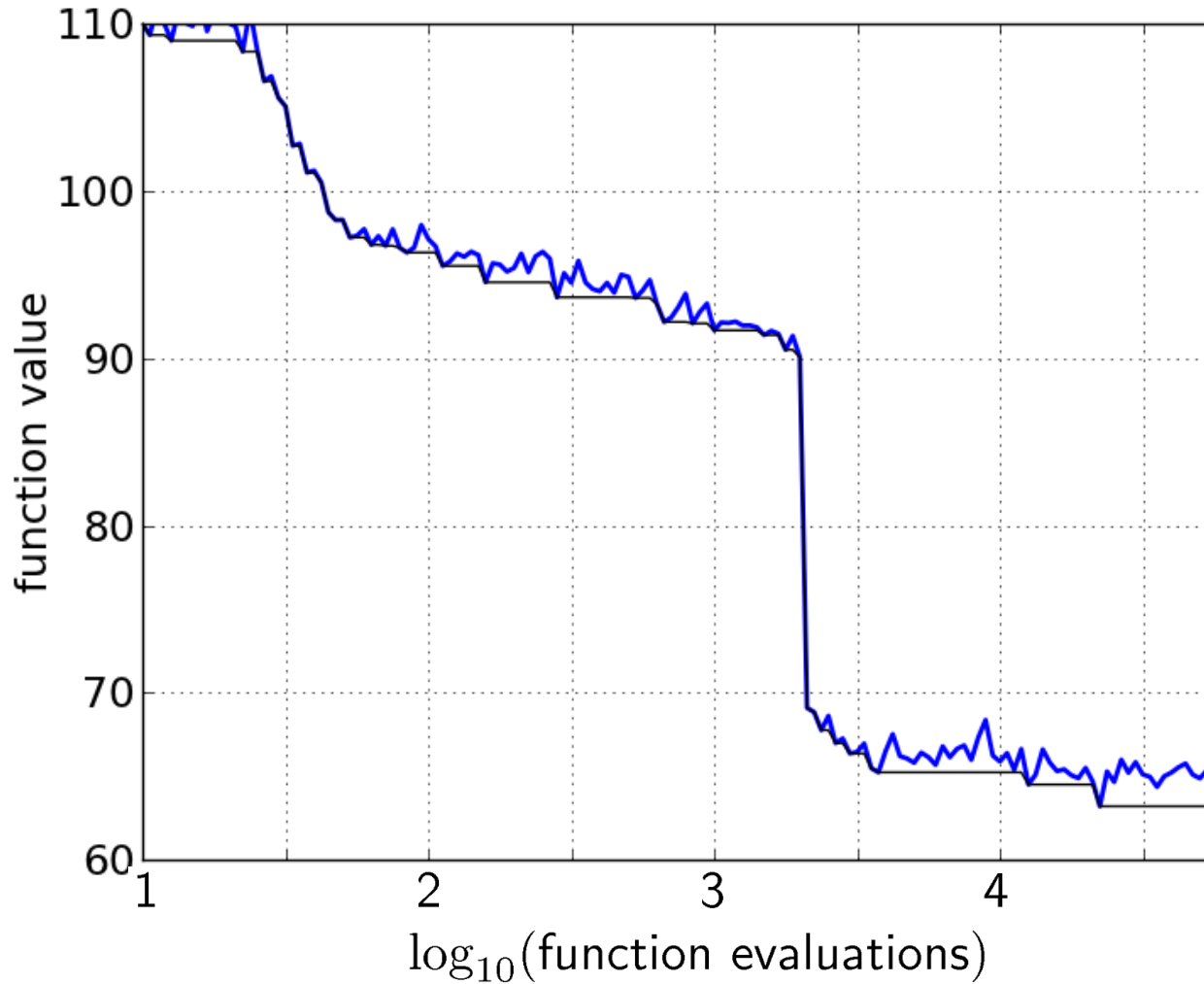
Empirical Cumulative Distribution



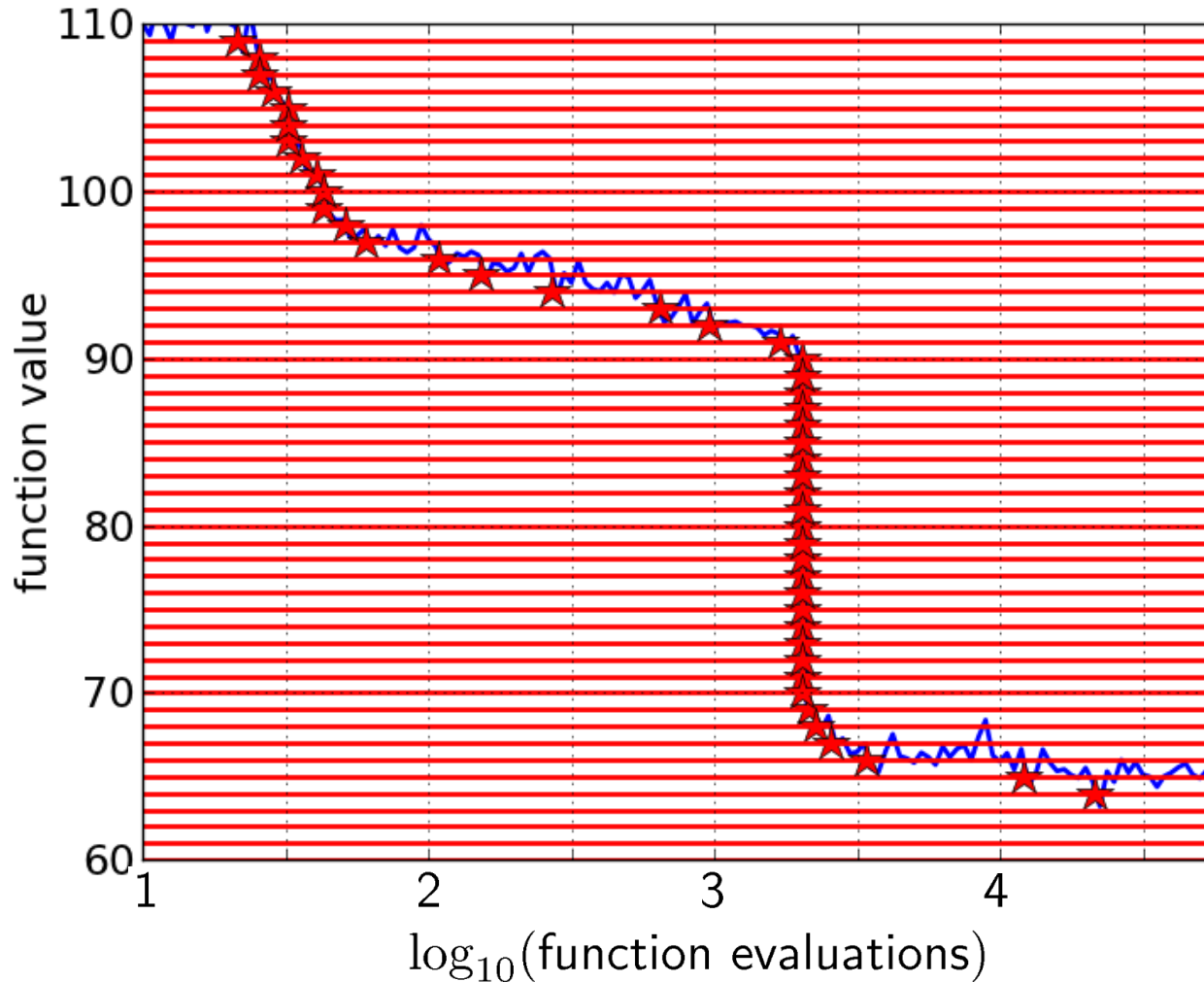
- 1 the **ECDF** of run lengths to reach the target
- has for each data point a **vertical step of constant size**
 - displays for each x-value (budget) the count of observations to the left (first hitting times)

e.g. 60% of the runs need between 2000 and 4000 evaluations
80% of the runs reached the target

Reconstructing A Single Run

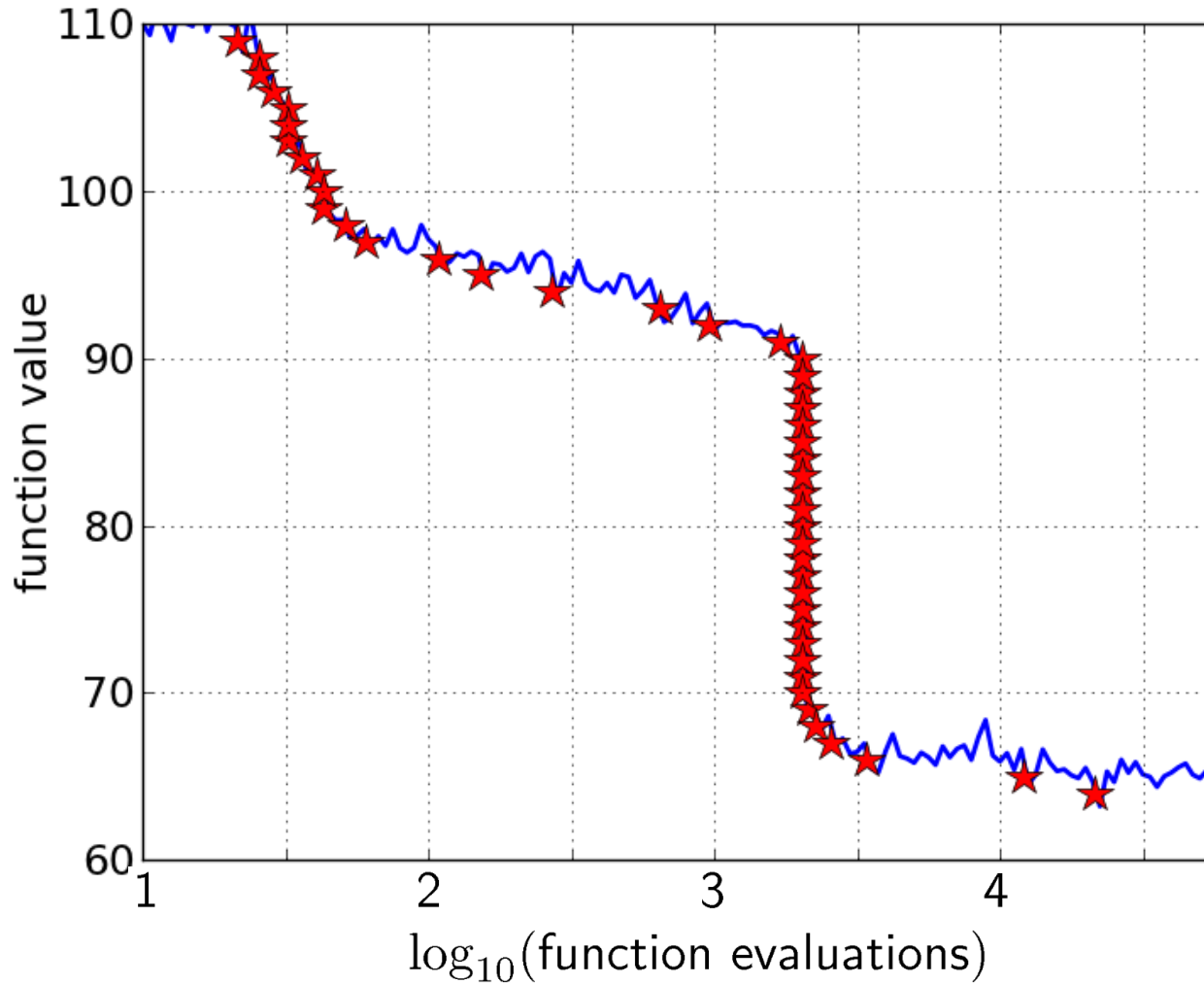


Reconstructing A Single Run

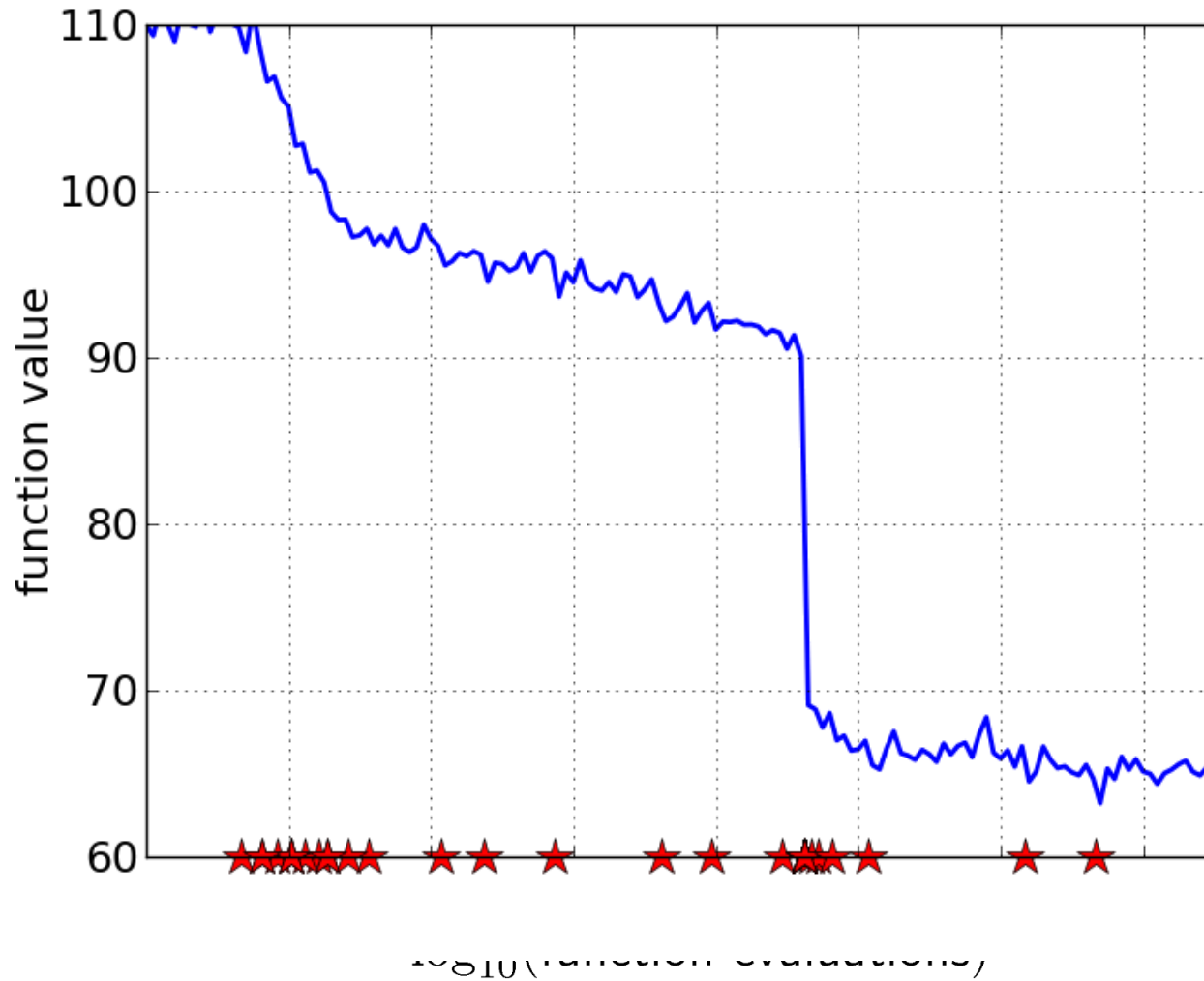


50 equally
spaced targets

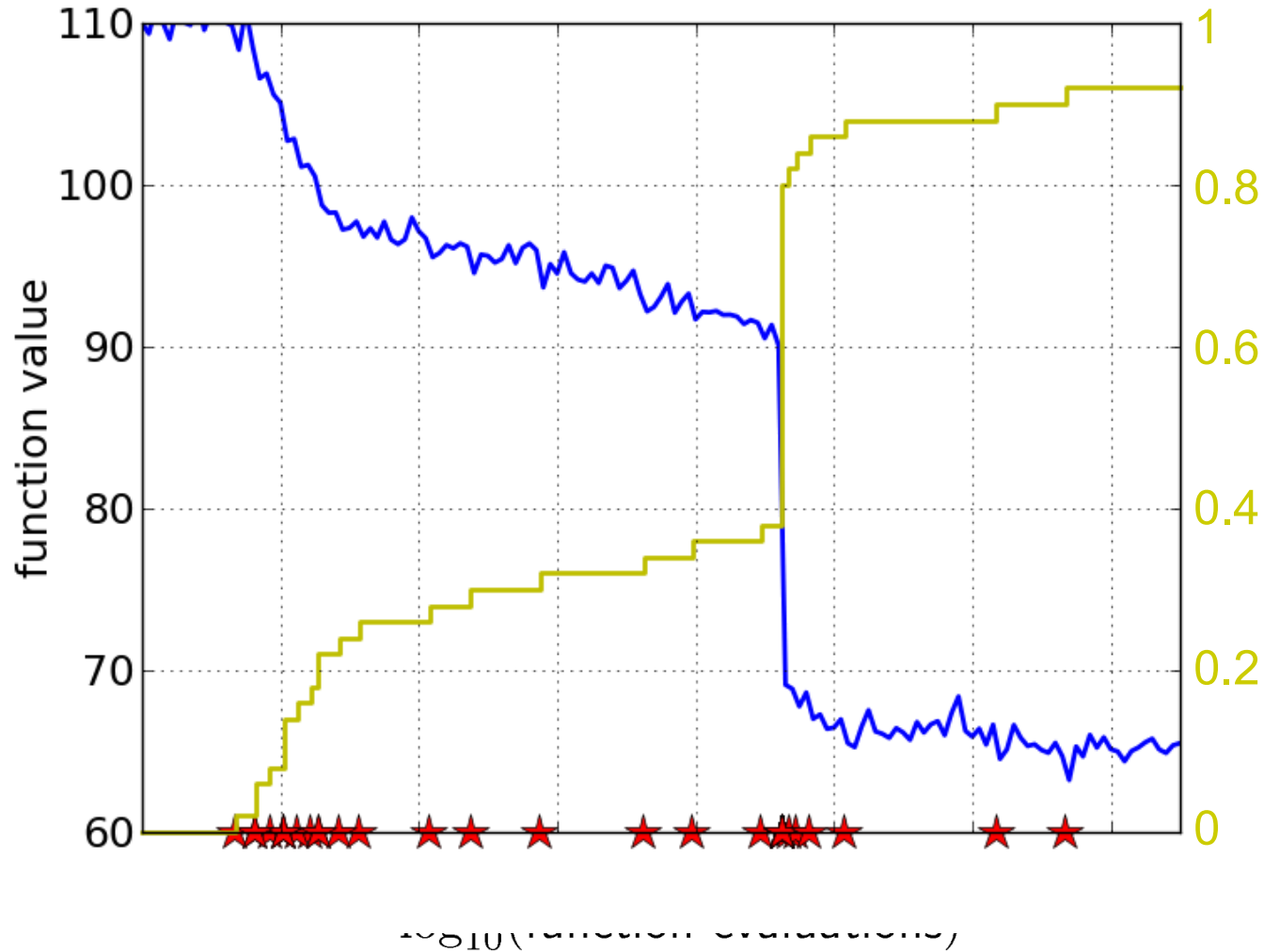
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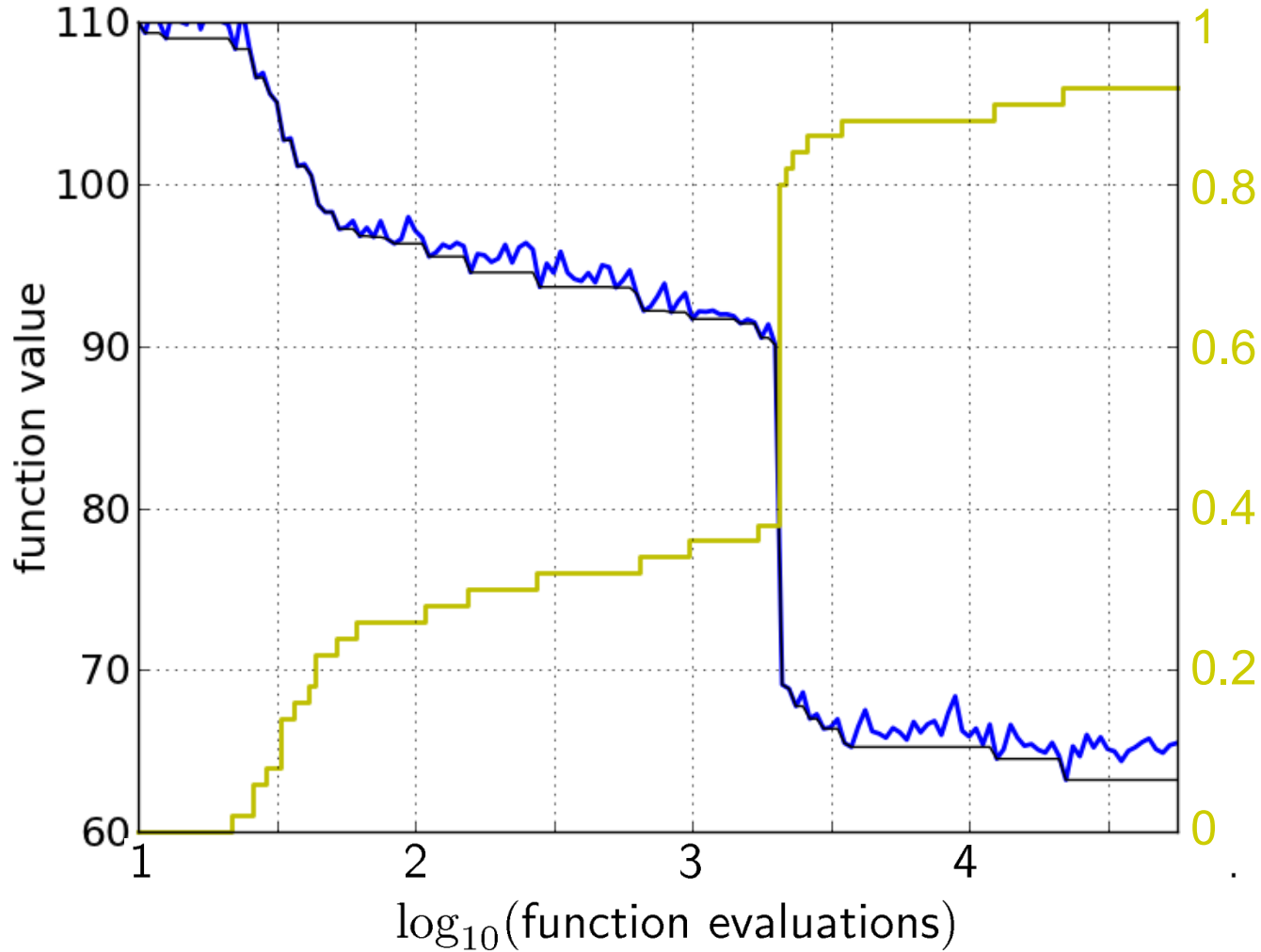


Reconstructing A Single Run



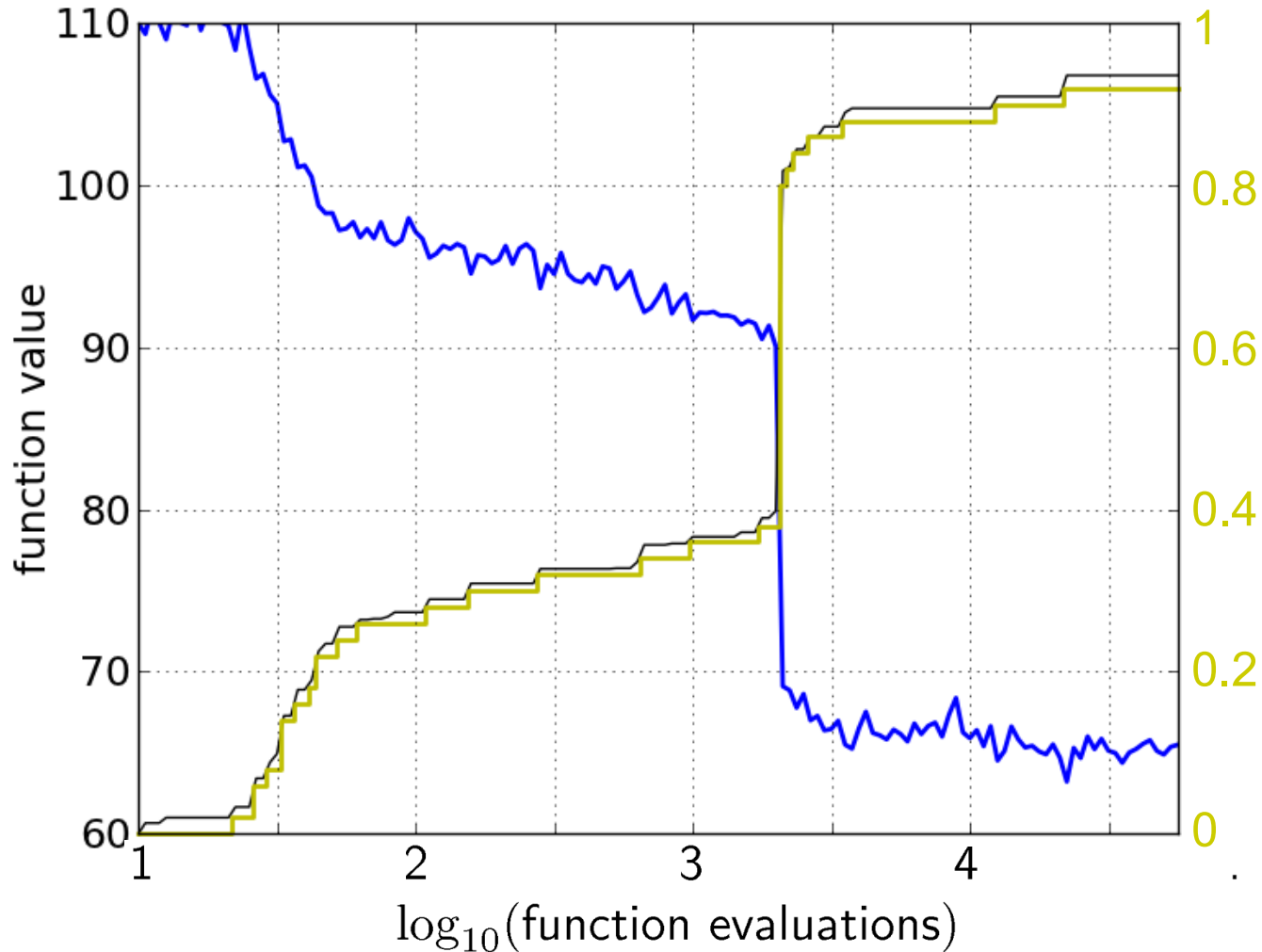
ie empirical CDF makes a step for each star, is monotonous and displays for each budget the fraction of targets achieved within the budget

Reconstructing A Single Run



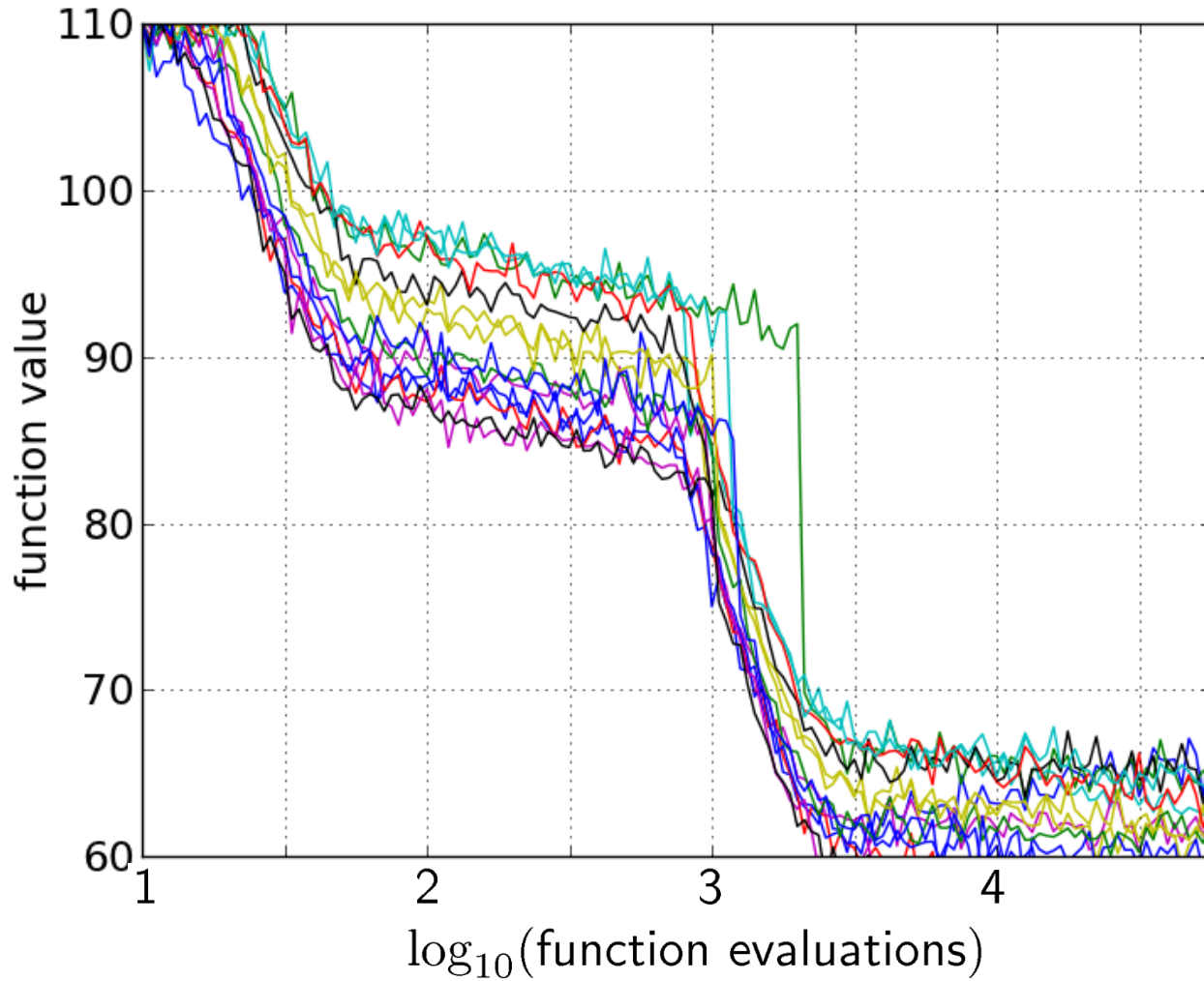
the ECDF recovers
the monotonous
graph,
discretised and
flipped

Reconstructing A Single Run



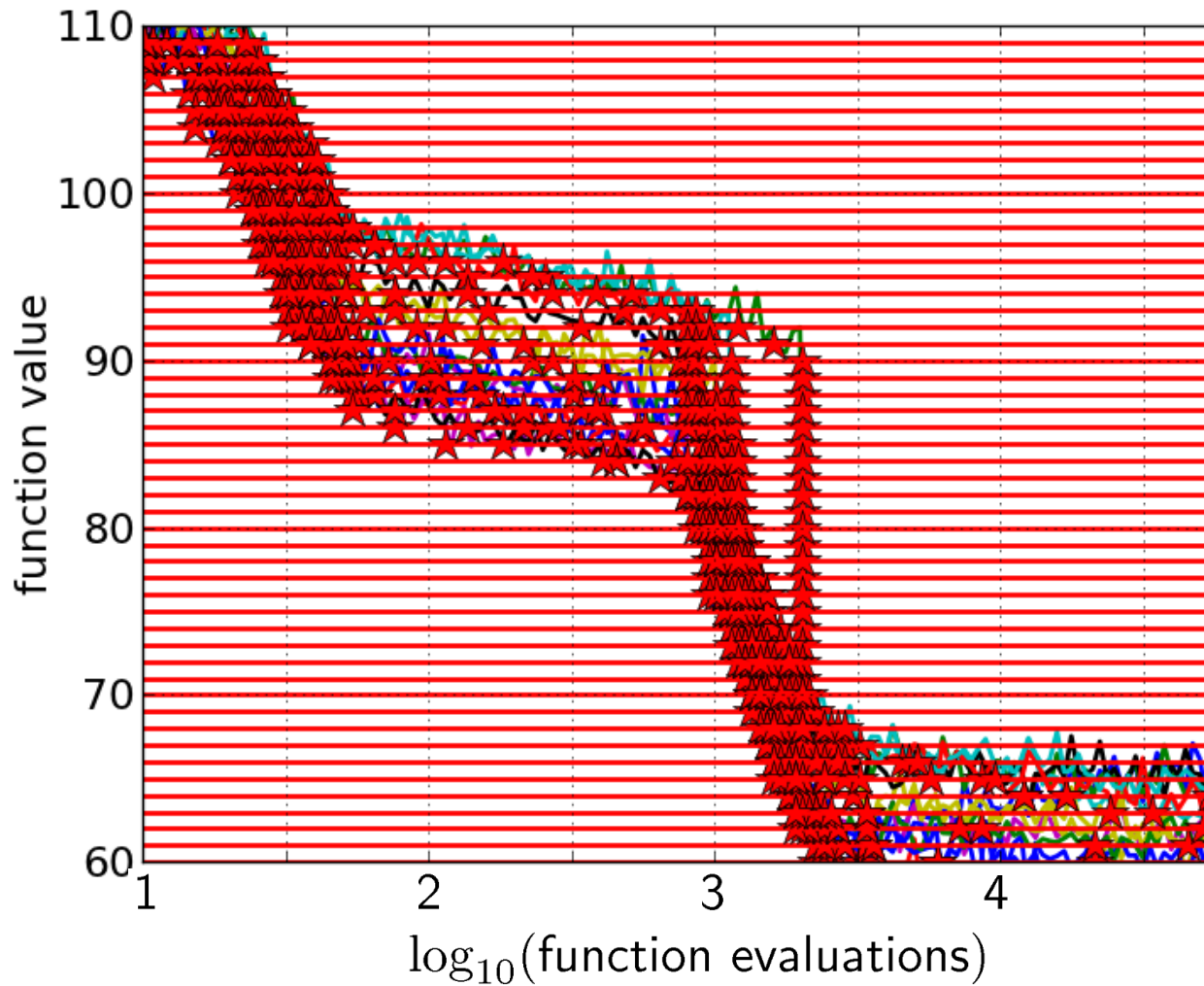
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Aggregation



15 runs

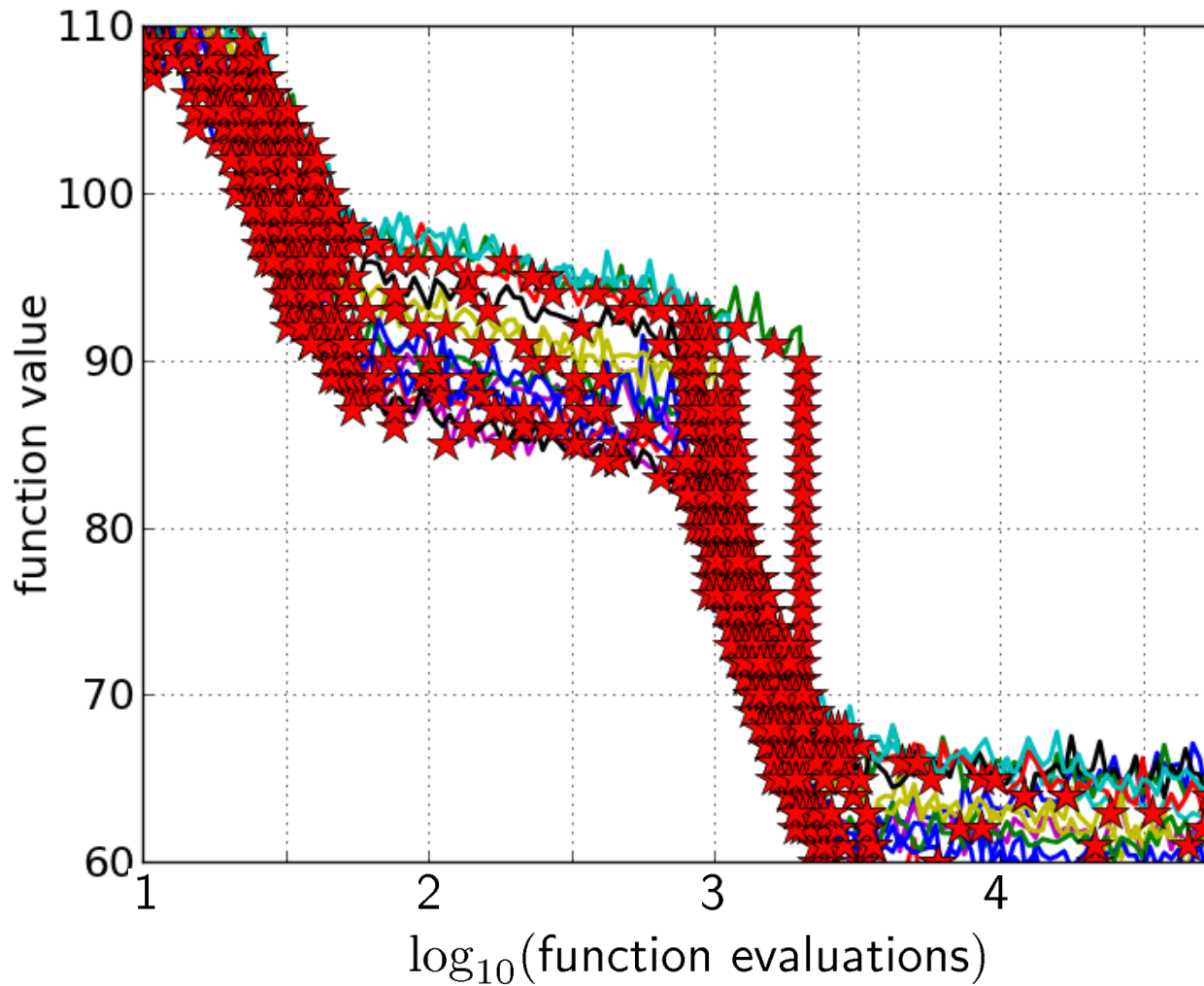
Aggregation



15 runs

50 targets

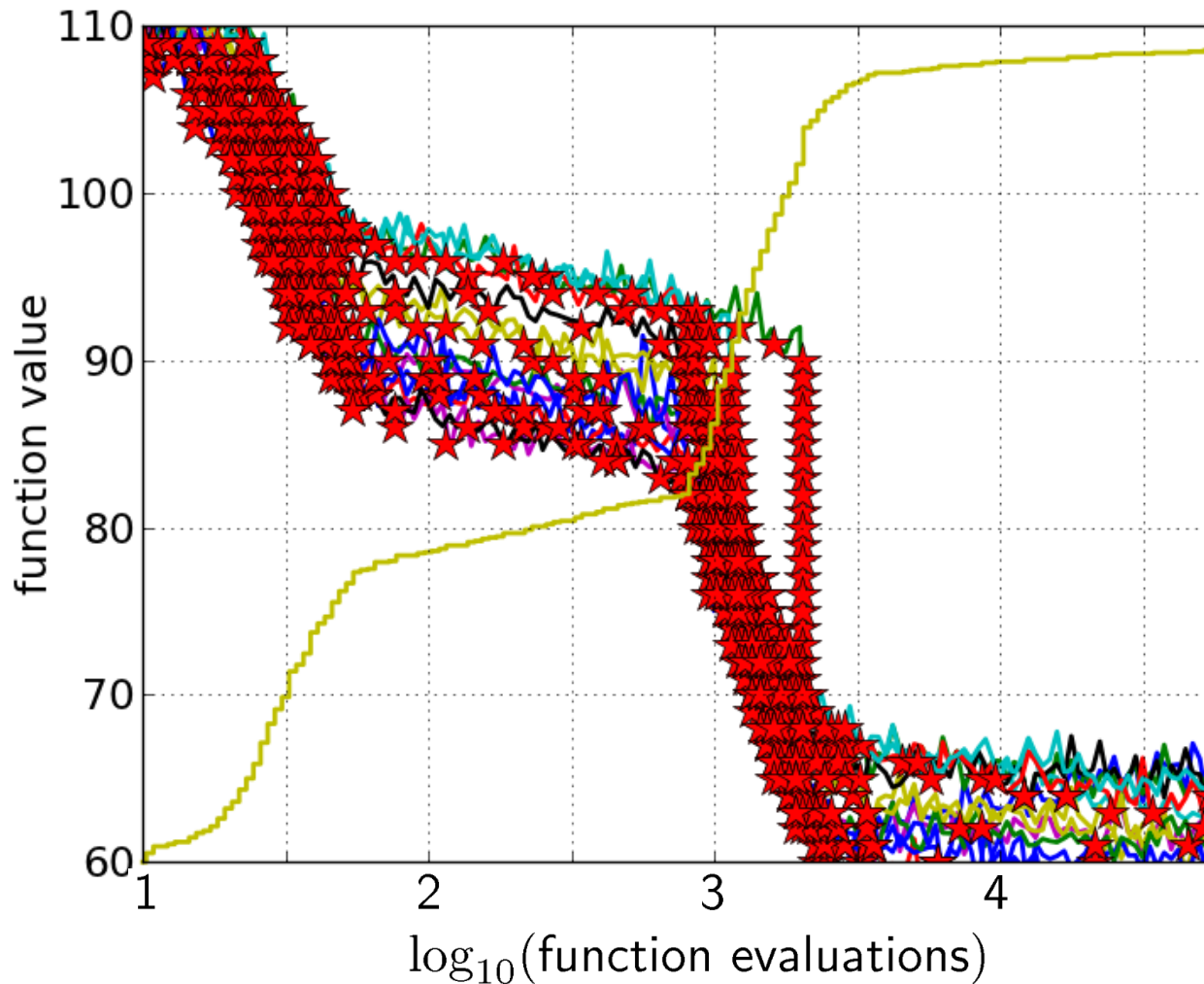
Aggregation



15 runs

50 targets

Aggregation

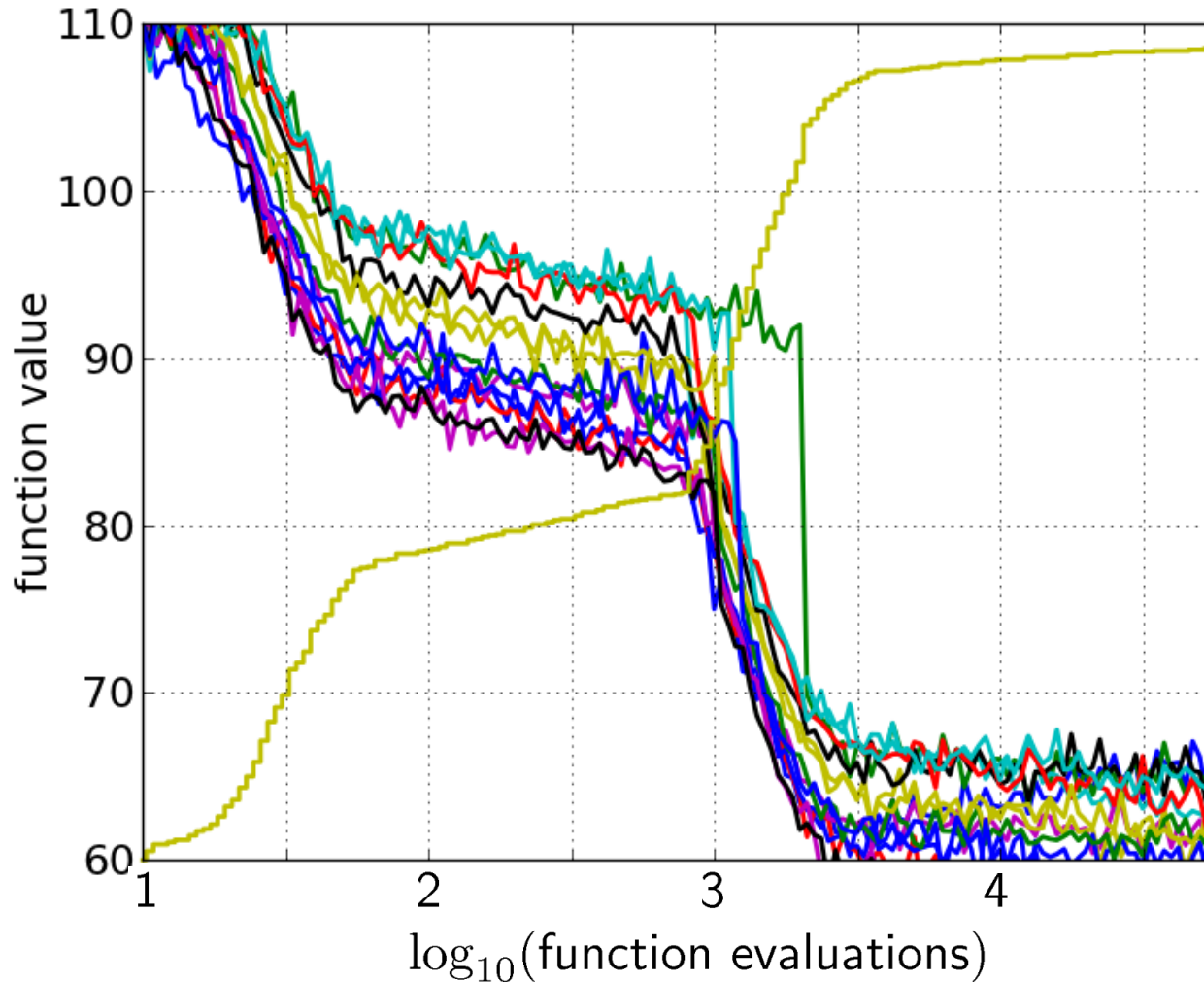


15 runs

50 targets

ECDF with 750
steps

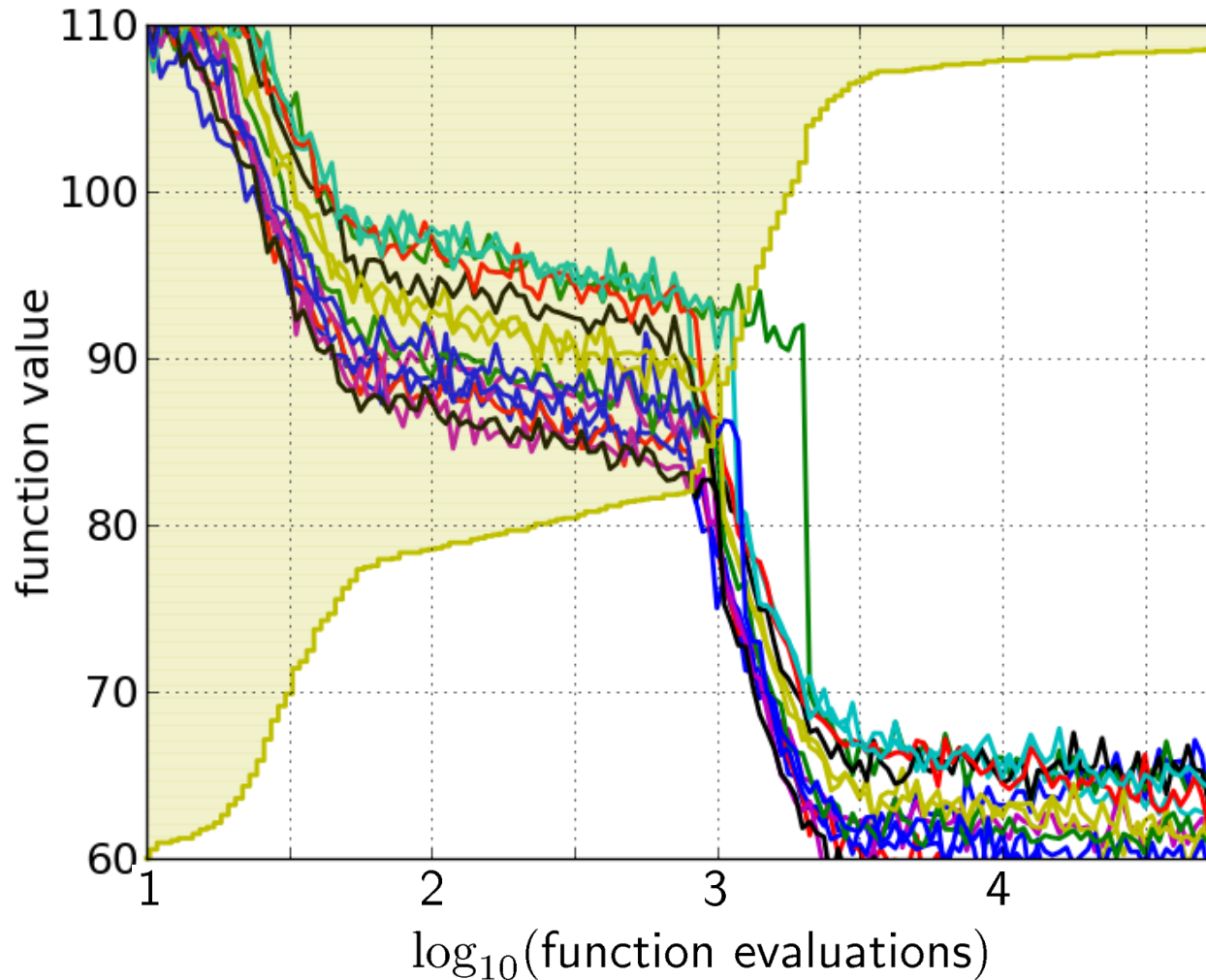
Aggregation



50 targets from
15 runs

...integrated in a
single graph

Interpretation



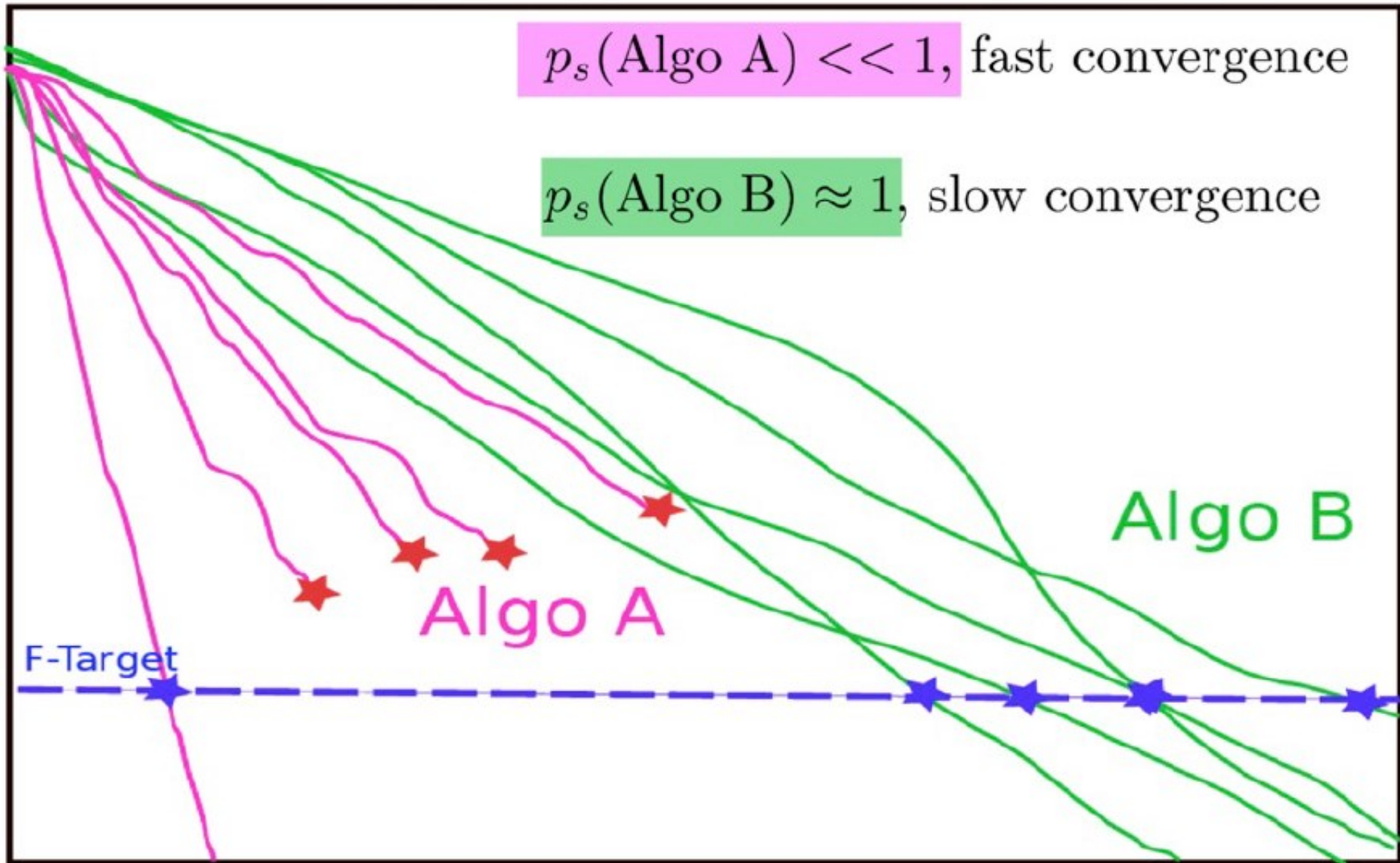
50 targets from
15 runs
integrated in a
single graph

area over the ECDF
curve

=

average log runtime
(or geometric avg.
runtime) over all
targets (difficult and
easy) and all runs

Fixed-target: Measuring Runtime

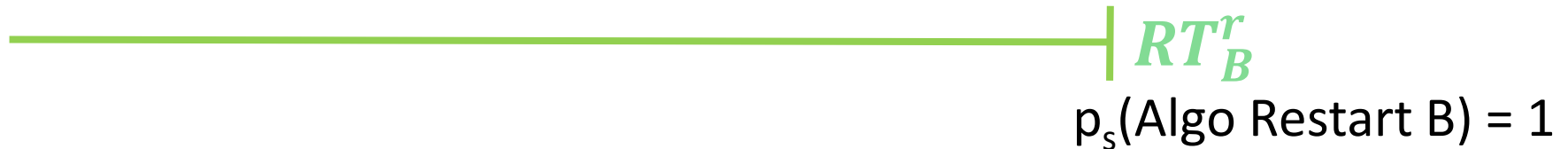


Fixed-target: Measuring Runtime

- Algo Restart A:



- Algo Restart B:



Fixed-target: Measuring Runtime

- Expected running time of the restarted algorithm:

$$E[RT^r] = \frac{1 - p_s}{p_s} E[RT_{unsuccessful}] + E[RT_{successful}]$$

- Estimator average running time (aRT):

$$\hat{p}_s = \frac{\text{\#successes}}{\text{\#runs}}$$

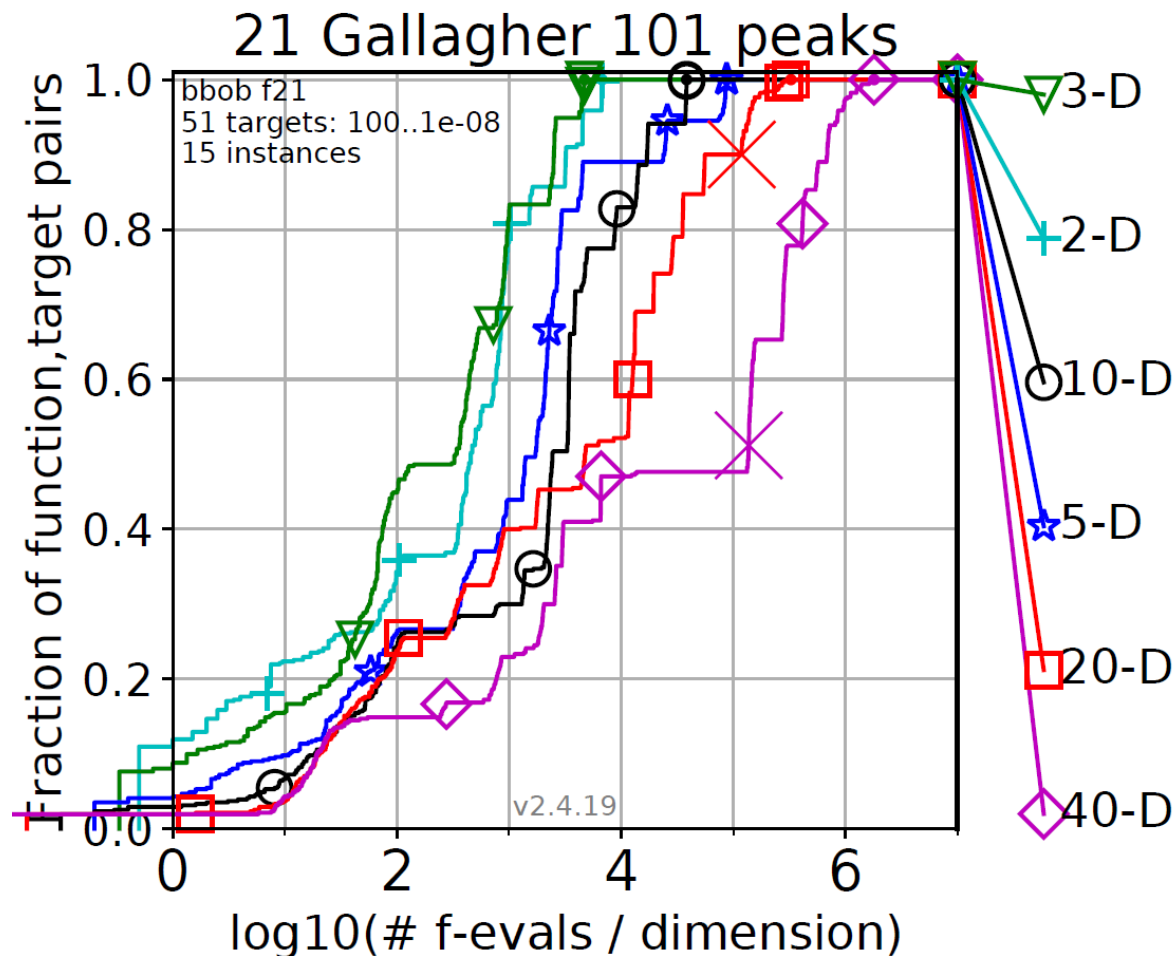
$\widehat{RT_{unsucc}}$ = Average evals of unsuccessful runs

$\widehat{RT_{succ}}$ = Average evals of successful runs

$$aRT = \frac{\text{total \#evals}}{\text{\#successes}}$$

ECDFs with Simulated Restarts

What we typically plot are ECDFs of the simulated restarted algorithms (exception: multiobjective case)

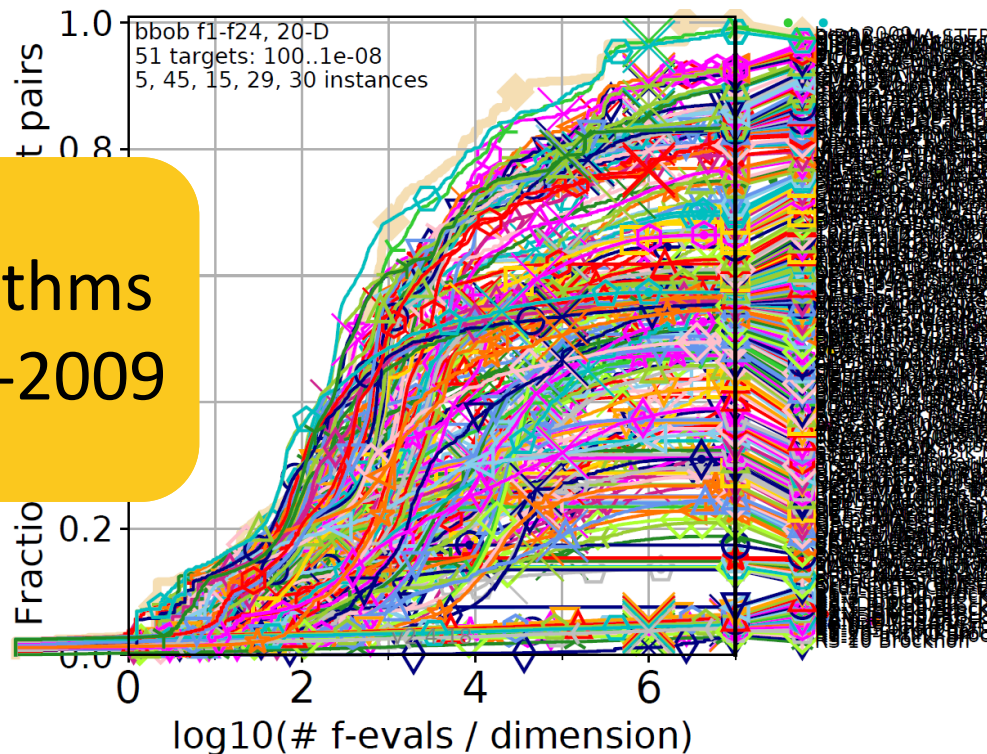


Worth to Note: ECDFs in COCO

In COCO, ECDF graphs

- never aggregate over dimension
 - but often over targets and functions
- can show data of more than 1 algorithm at a time

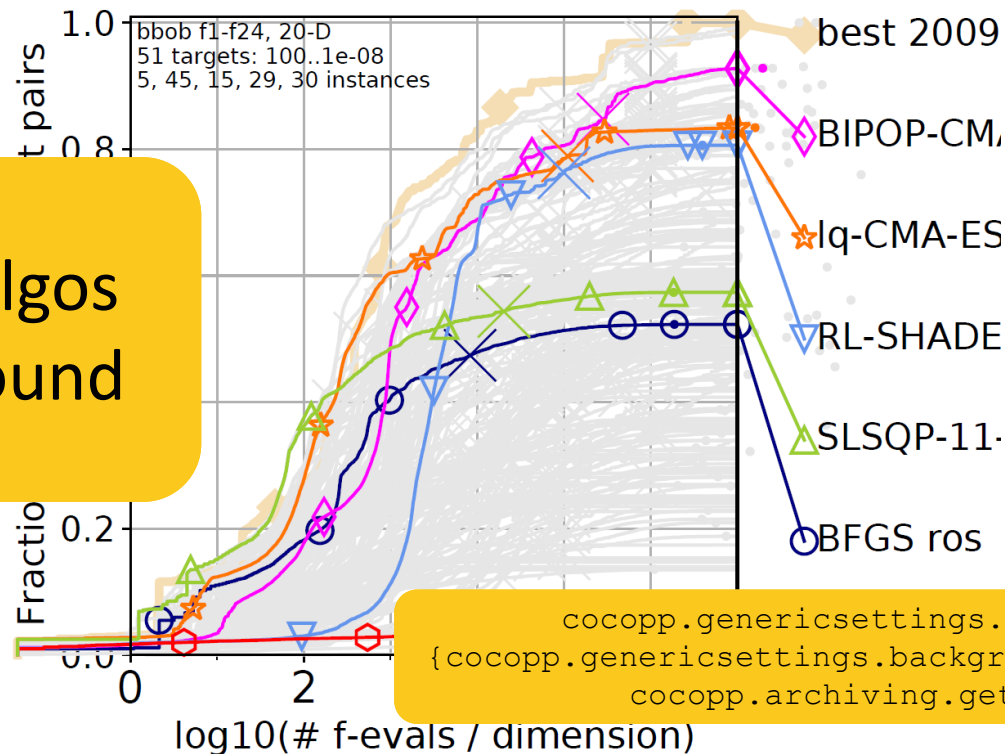
200+ algorithms
since BBOB-2009



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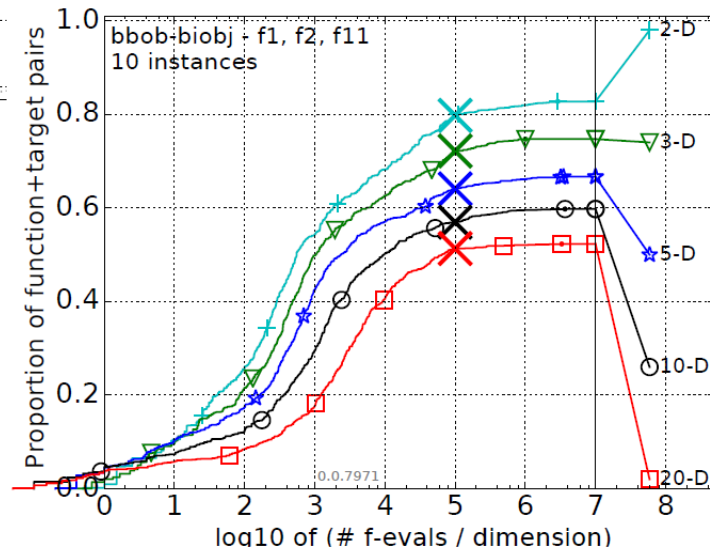
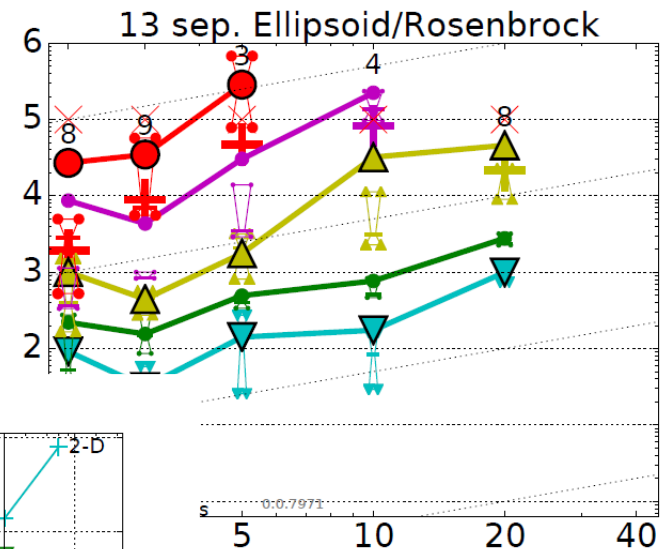
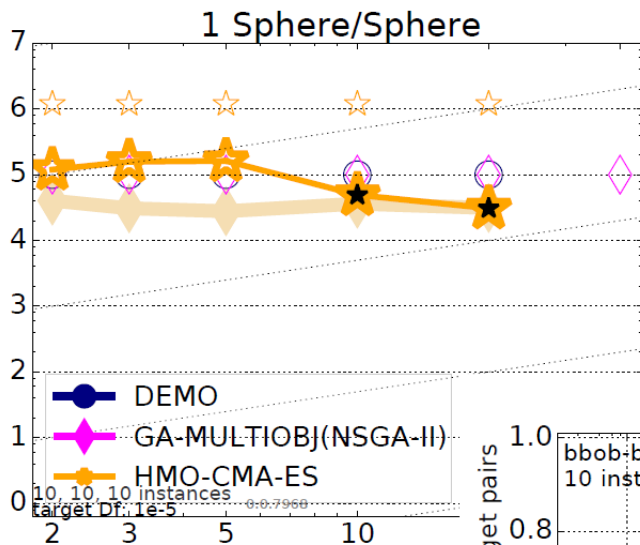


all but 6 algos
in background

```
cocopp.genericsettings.background =  
{cocopp.genericsettings.background_default_style:  
cocopp.archiving.get('bbob')}
```

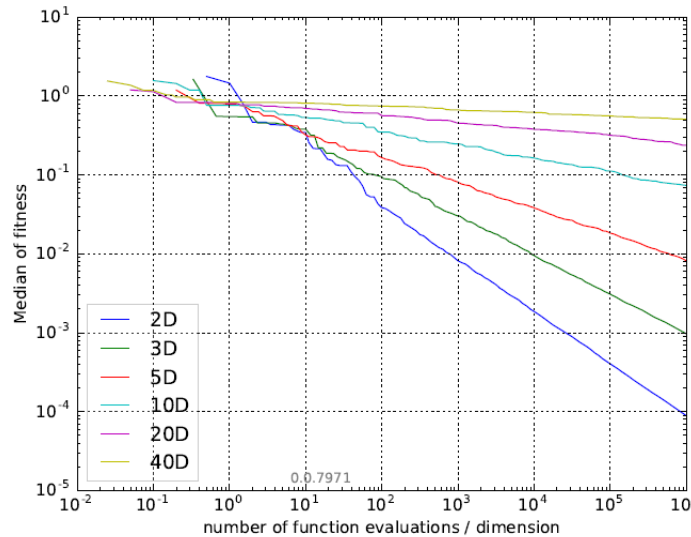
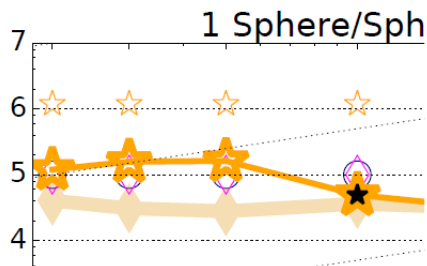

More Automated Plots...

...but no time to explain them here ☹️

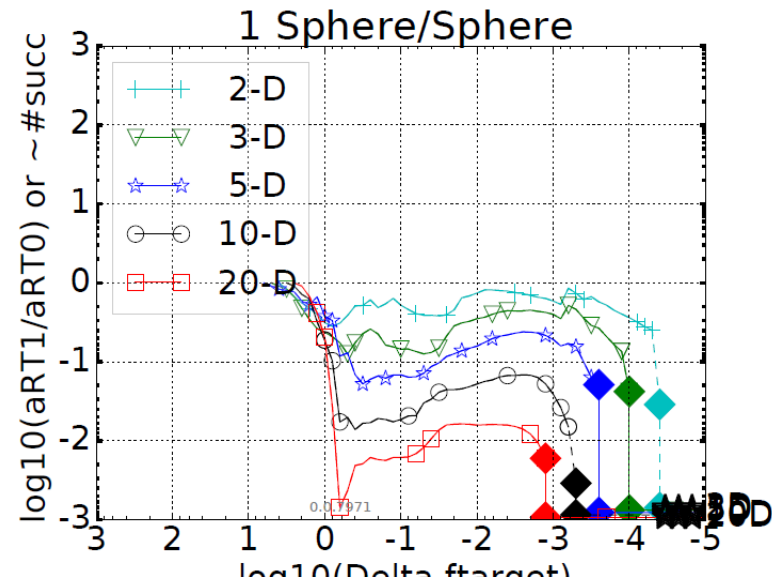
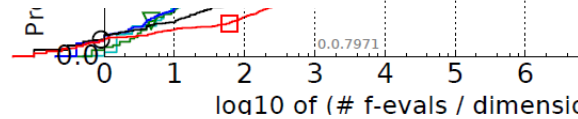
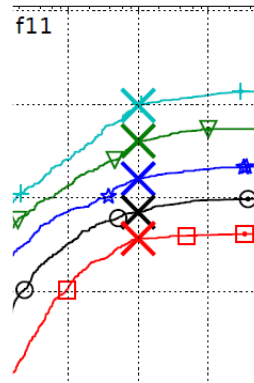
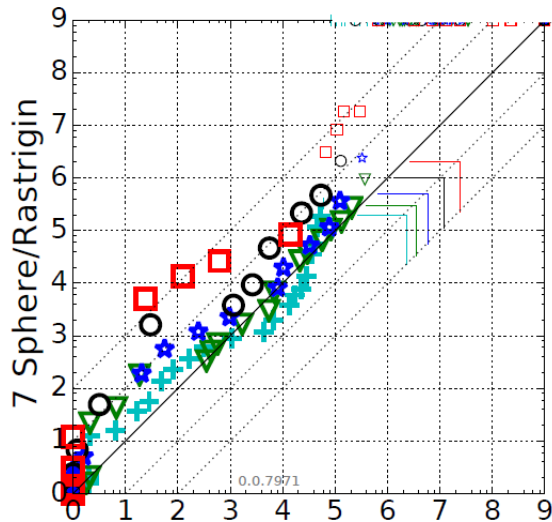
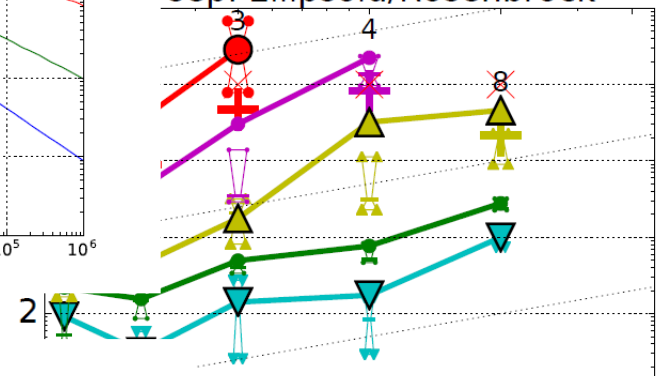


More Automated Plots...

...but no time t



sep. Ellipsoid/Rosenbrock



and now?

BBOB-2021

Session Saturday 10th of July, 2021

11:00 - 11:30	The BBOBies: A Short Introduction to COCO and BBOB
11:30 - 11:55	Michał Okulewicz, Mateusz Zaborski: Benchmarking SHADE algorithm enhanced with model based optimization on the BBOB noiseless testbed
11:55 - 12:20	Dimo Brockhoff, Baptiste Plaquevent-Jourdain, Anne Auger, and Nikolaus Hansen: DMS and MultiGLODS: Black-Box Optimization Benchmarking of Two Direct Search Methods on the Biobjective bbob-biobj Test Suite
12:20 – 12:50	Open Discussion