

# 12<sup>th</sup> GECCO Workshop on Blackbox Optimization Benchmarking (BBOB): Welcome and Introduction to COCO/BBOB

**The BBOBies**

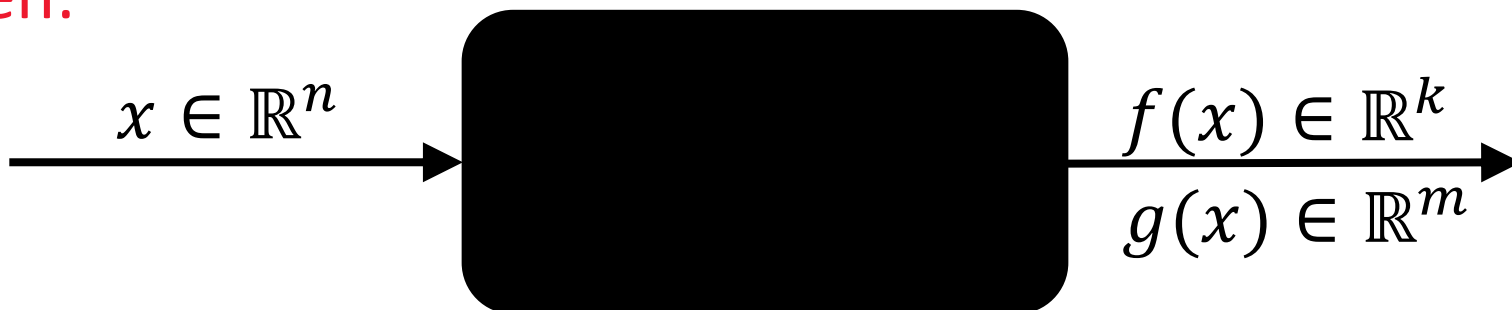
<https://github.com/numbbbo/coco>



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

# Practical Blackbox Optimization

Given:



Not clear:

which of the many algorithms should I use on my problem?

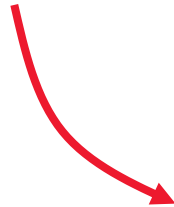
# Practical Need: Benchmarking

- understanding of algorithms
- algorithm selection/recommendation
- 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

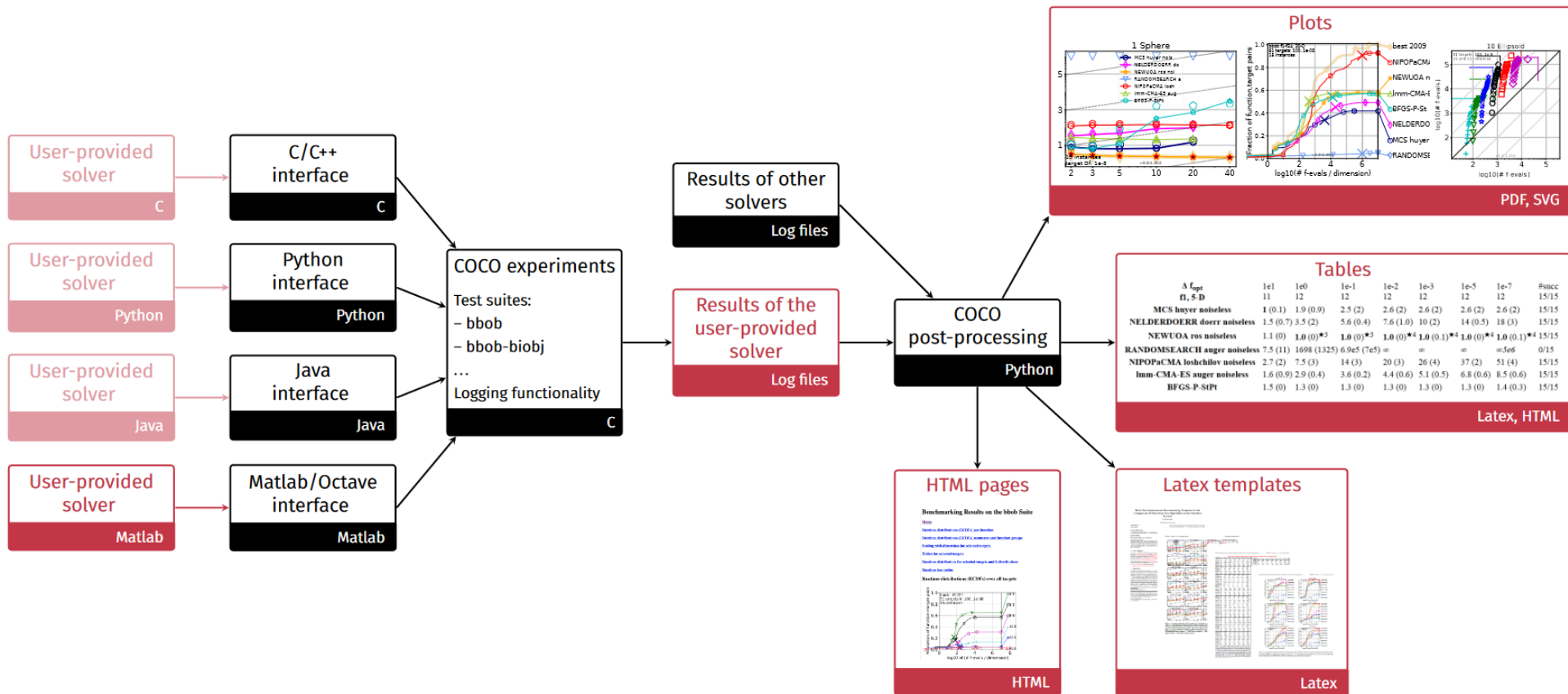


**Comparing Continuous Optimizers Platform**

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

**automatized benchmarking**

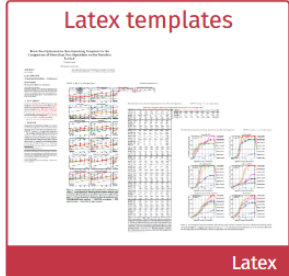
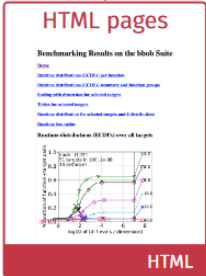
# Overview of COCO's Structure



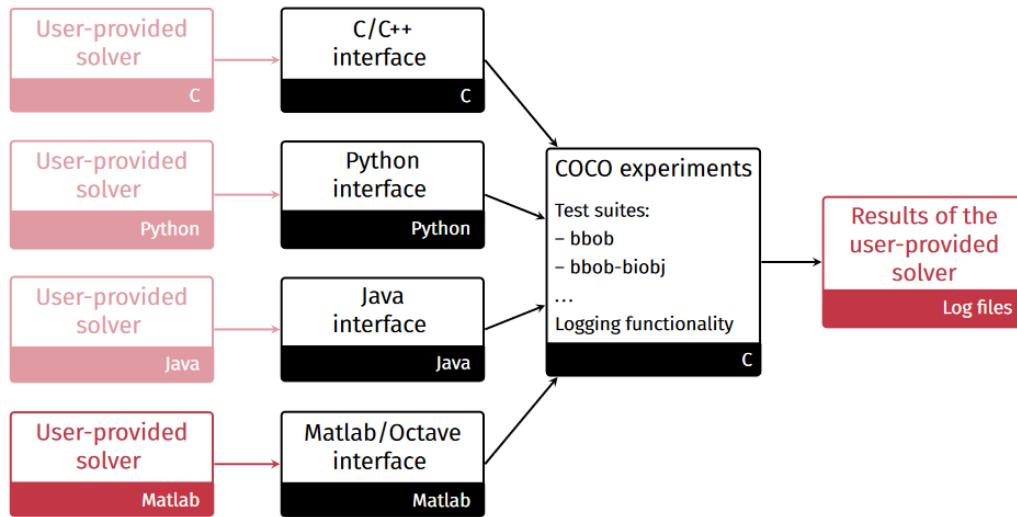
**Tables**

	$\Delta \epsilon_{opt}$	1e1	1e0	1e-1	1e-2	1e-3	1e-5	1e-7	#succ
MCS buyer noiseless	1 (0.1)	1.9 (0.9)	2.5 (2)	2.6 (2)	2.6 (2)	2.6 (2)	2.6 (2)	2.6 (2)	15/15
NELDERDOERR doerr noiseless	1.5 (0.7)	3.5 (2)	5.6 (0.4)	7.6 (1.0)	10 (2)	14 (0.5)	18 (3)	15/15	15/15
NEWUOA ros noiseless	1.1 (0)	1.0 (0)*3	1.0 (0)*3	1.0 (0)*4	1.0 (0.1)*4	1.0 (0.1)*4	1.0 (0.1)*4	1.0 (0.1)*4	15/15
RANDOMSEARCH angier noiseless	7.5 (11)	1698 (1325)	6.9e5 (7e5)	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	0/15
NIPOPaCMA loschilov noiseless	2.7 (2)	7.5 (3)	14 (3)	20 (3)	26 (4)	37 (2)	51 (4)	51 (4)	15/15
Imm-CMA-ES angier noiseless	1.6 (0.9)	2.9 (0.4)	3.6 (0.2)	4.4 (0.6)	5.1 (0.5)	6.8 (0.6)	8.5 (0.6)	15/15	15/15
BFGS-P-SQP1	1.5 (0)	1.3 (0)	1.3 (0)	1.3 (0)	1.3 (0)	1.3 (0)	1.3 (0)	1.4 (0.3)	15/15

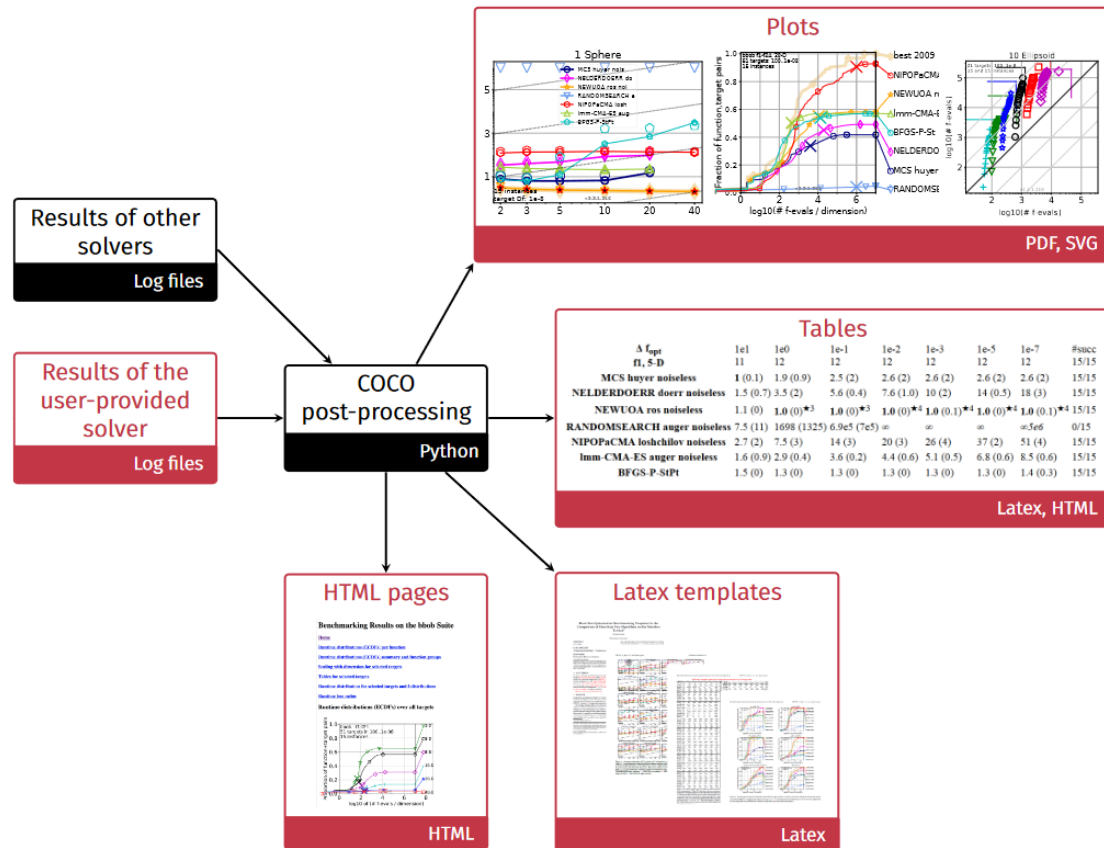
Latex, HTML



# Overview of COCO's Structure



# Overview of COCO's Structure



Results of other solvers

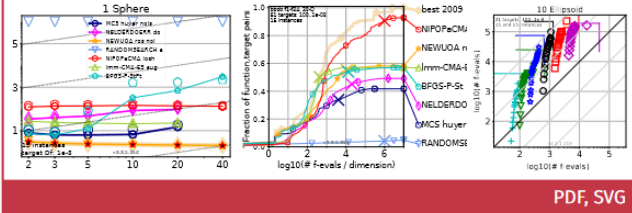
Log files

Results of the user-provided solver

Log files

COCO post-processing  
Python

Plots

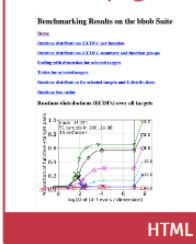


Tables

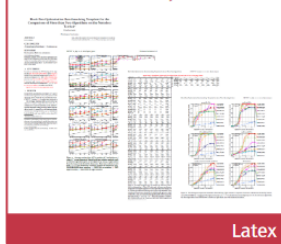
	$\Delta \epsilon_{opt}$	$n=1$	$n=2$	$n=3$	$n=5$	$n=7$	#succ
MCS buyei noiseless	1.0 (0.1)	1.9 (0.9)	2.5 (2)	2.6 (2)	2.6 (2)	2.6 (2)	15/15
NELDERDOERR doerr noiseless	1.5 (0.7)	3.5 (2)	5.6 (0.4)	7.6 (1.0)	10 (2)	14 (0.5)	18 (3)
NEWUOA ros noiseless	1.1 (0)	1.0 (0)*3	1.0 (0)*3	1.0 (0)*4	1.0 (0.1)*4	1.0 (0.1)*4	15/15
RANDOMSEARCH angier noiseless	7.5 (11)	1698 (1325)	6.9e5 (7e5)	$\infty$	$\infty$	$\infty$	0/15
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Imm-CMA-ES angier noiseless	1.6 (0.9)	2.9 (0.4)	3.6 (0.2)	4.4 (0.6)	5.1 (0.5)	6.8 (0.6)	8.5 (0.6)
BFGS-P-SPI	1.5 (0)	1.3 (0)	1.3 (0)	1.3 (0)	1.3 (0)	1.3 (0)	1.4 (0.3)

Latex, HTML

HTML pages



Latex templates



HTML

Latex



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

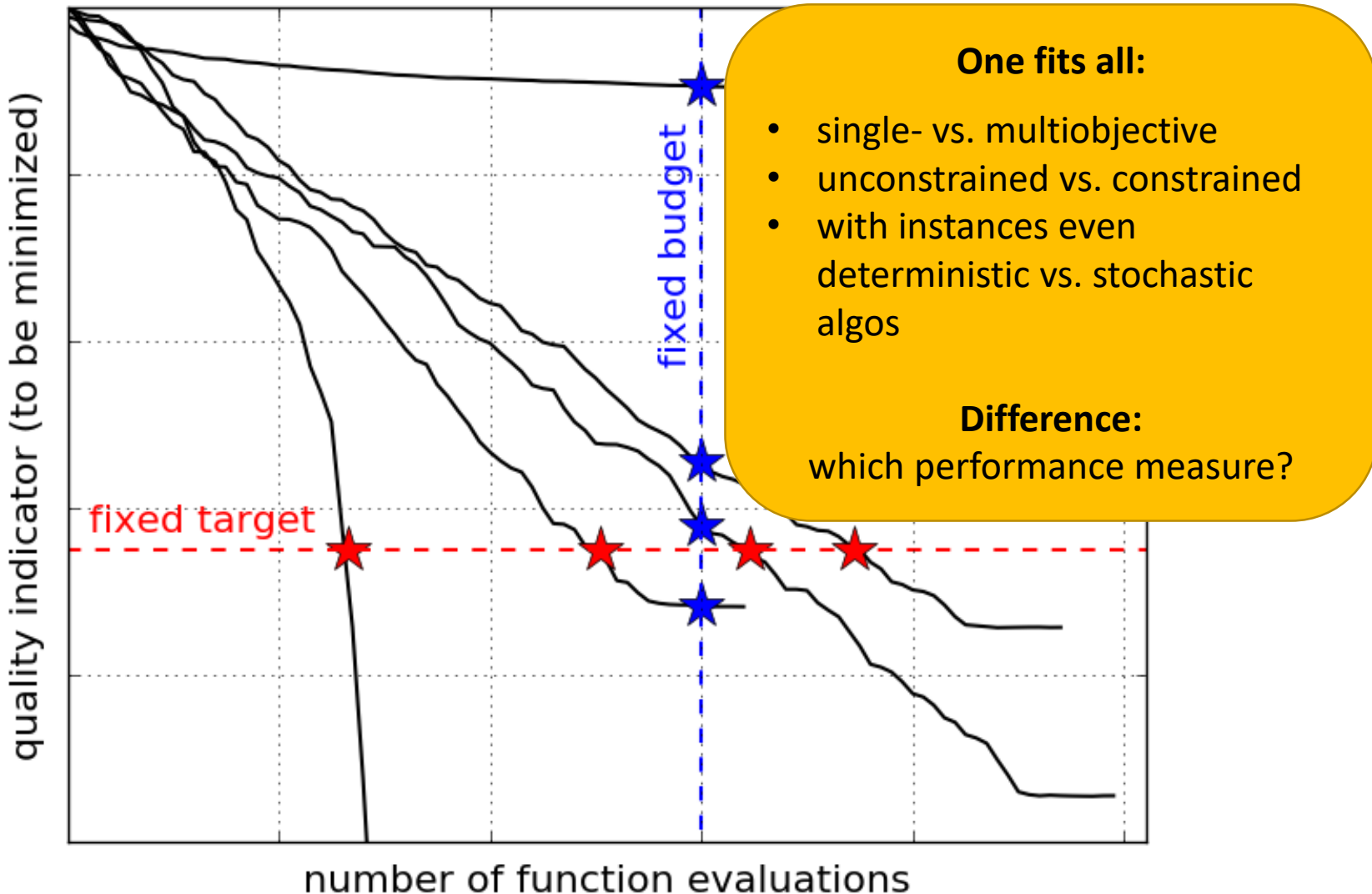
main performance measure:

**runtime**

until a certain target difficulty is reached

# Measuring Performance Empirically

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



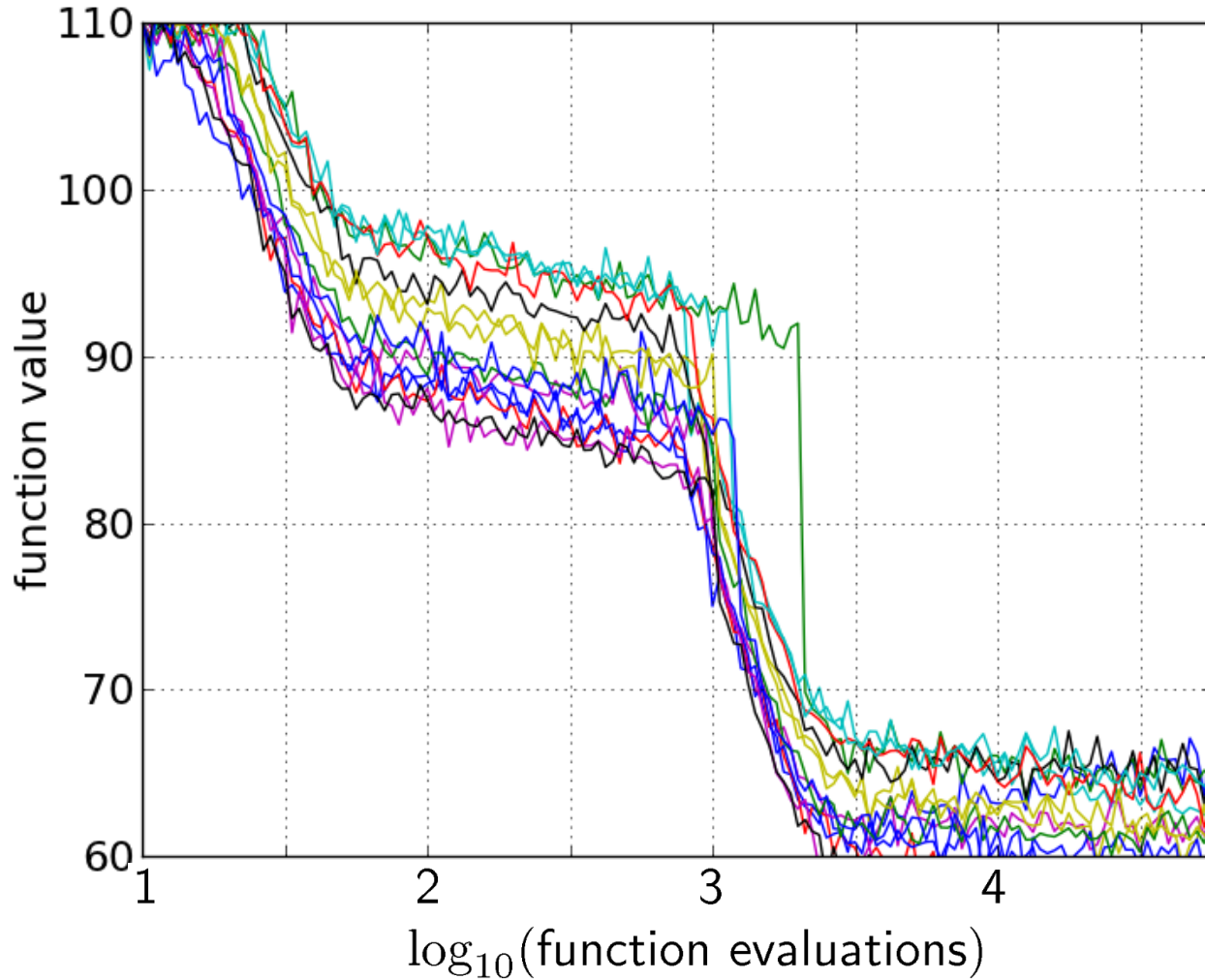
## **Main Performance Visualization:**

### Empirical Runtime Distributions

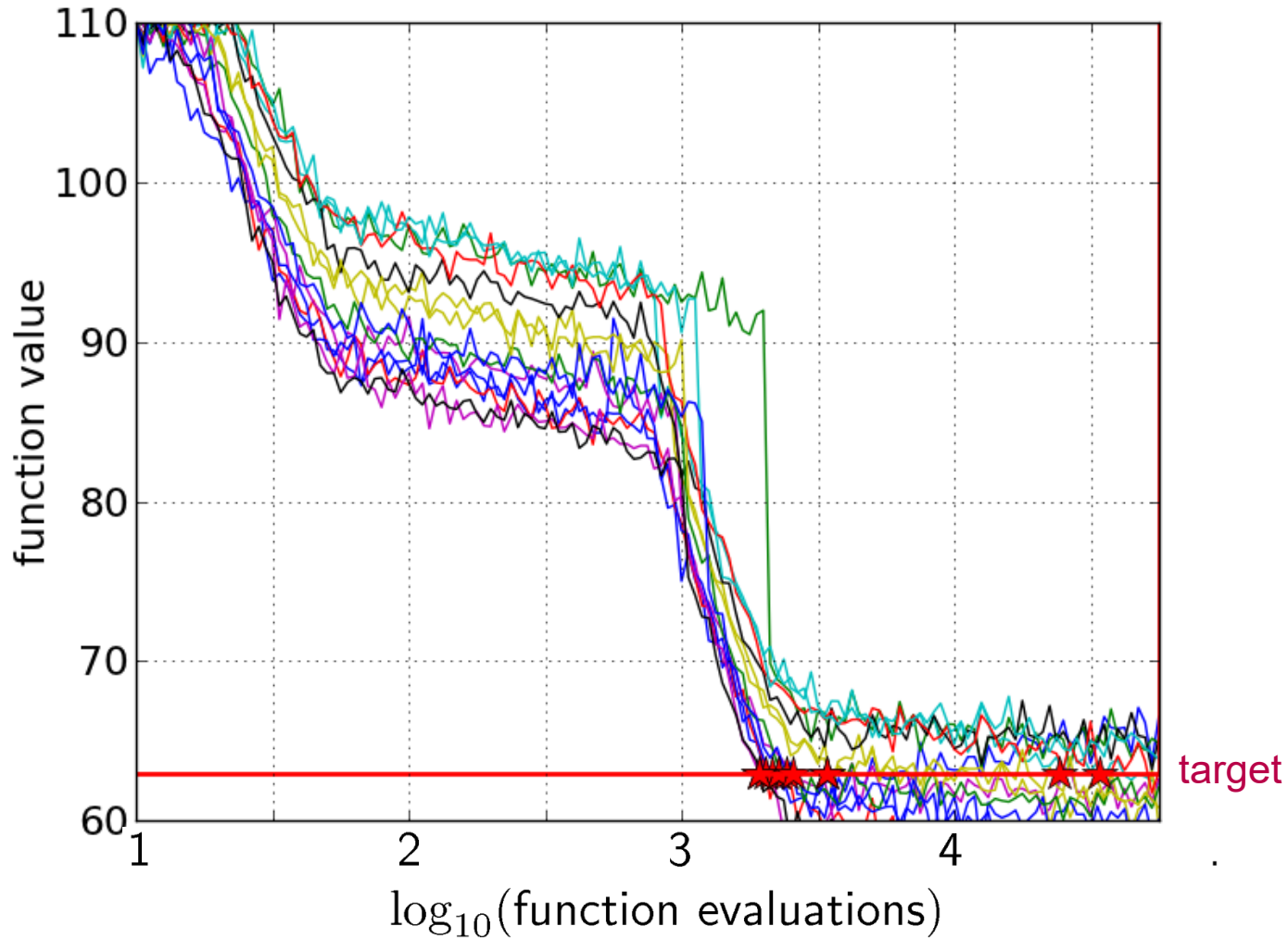
[aka Empirical Cumulative Distribution Function (ECDF) of the Runtime]

[aka data profile]

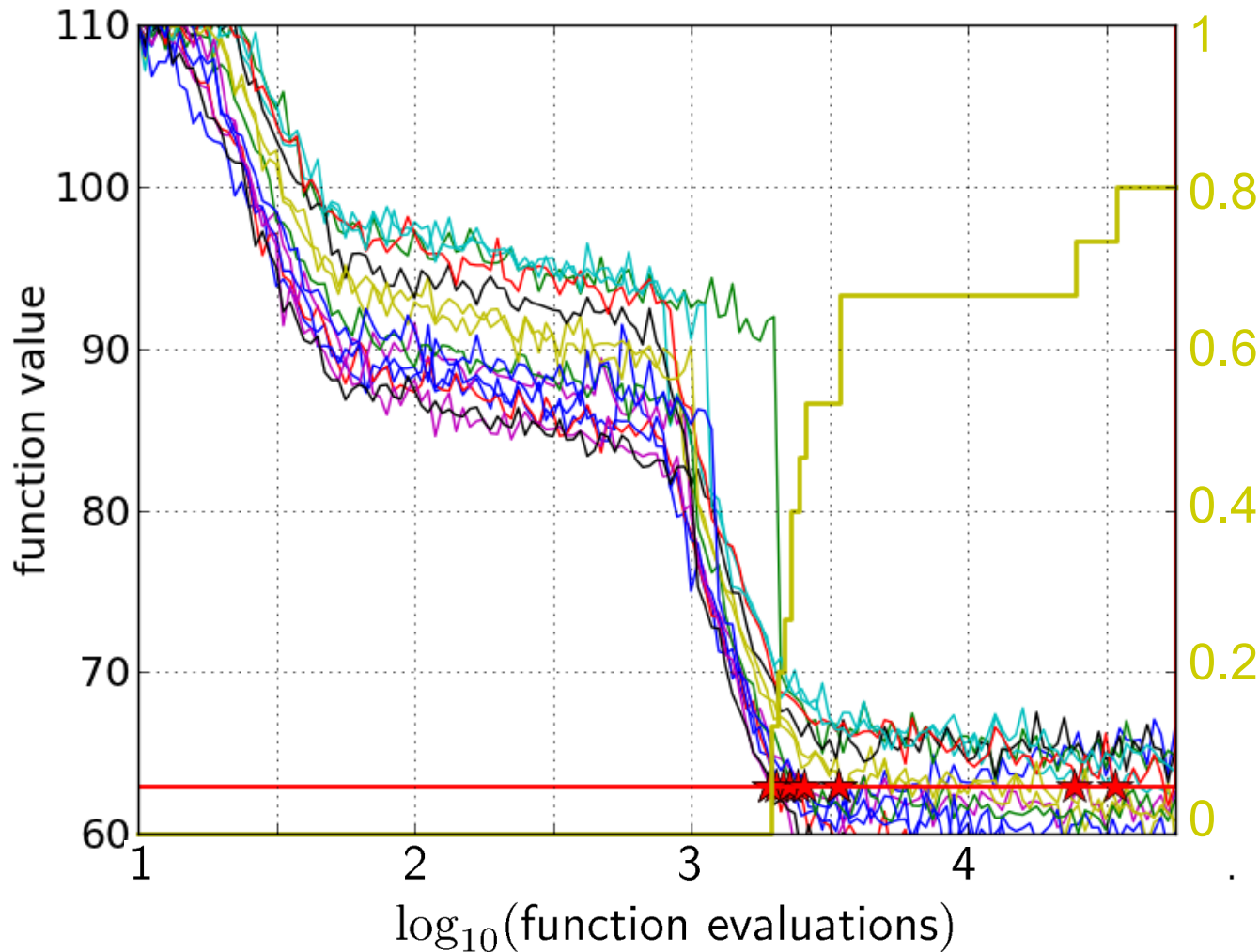
# Convergence Graph of 15 Runs



# 15 Runs $\leq$ 15 Runtime Data Points



# Empirical Cumulative Distribution

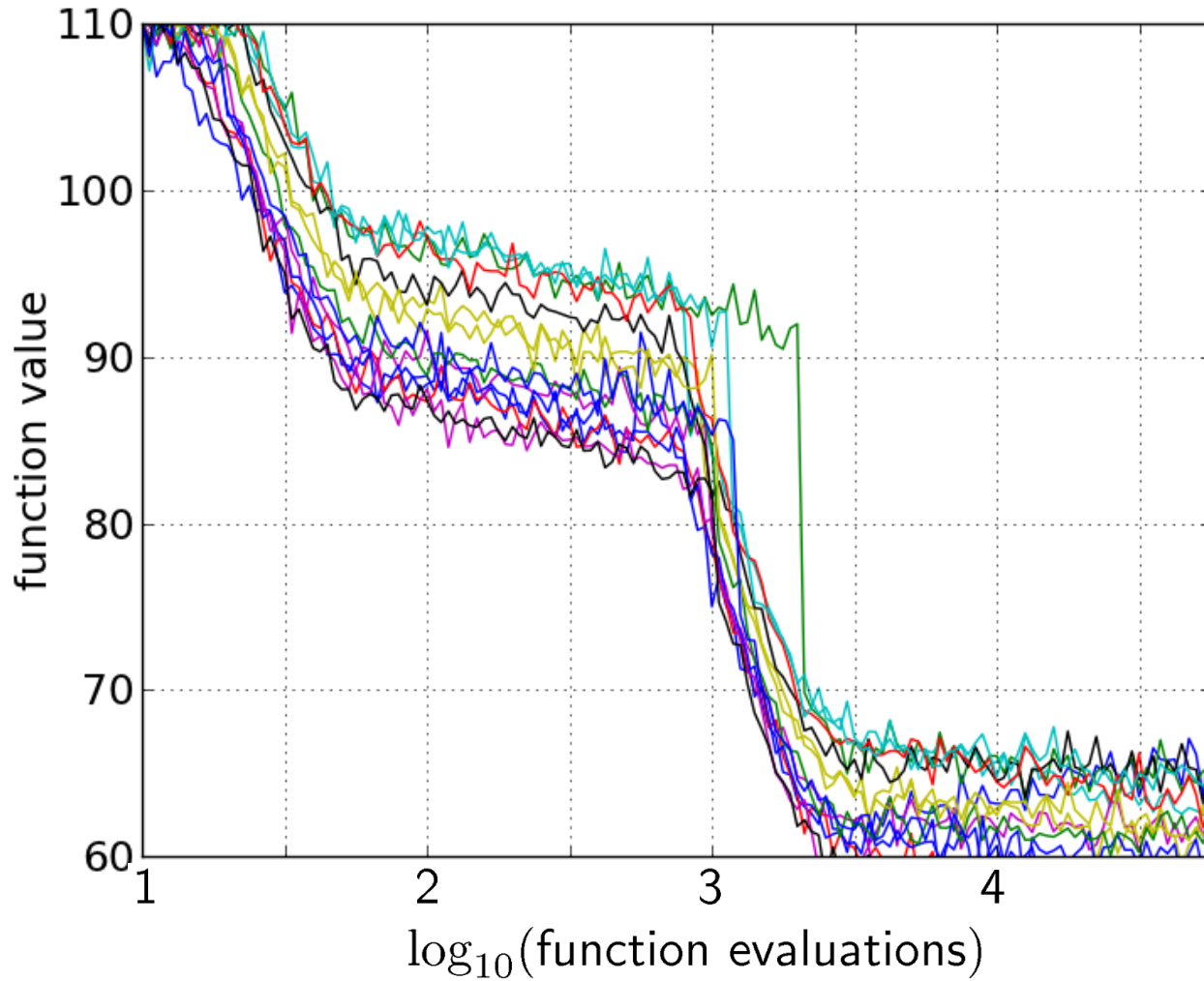


- 1 the **ECDF** of run lengths to reach the target
- has for each data point a **vertical step of constant size**
- displays for each x-value (budget) the count of observations to the left (first hitting times)

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

80% of the runs reached the target

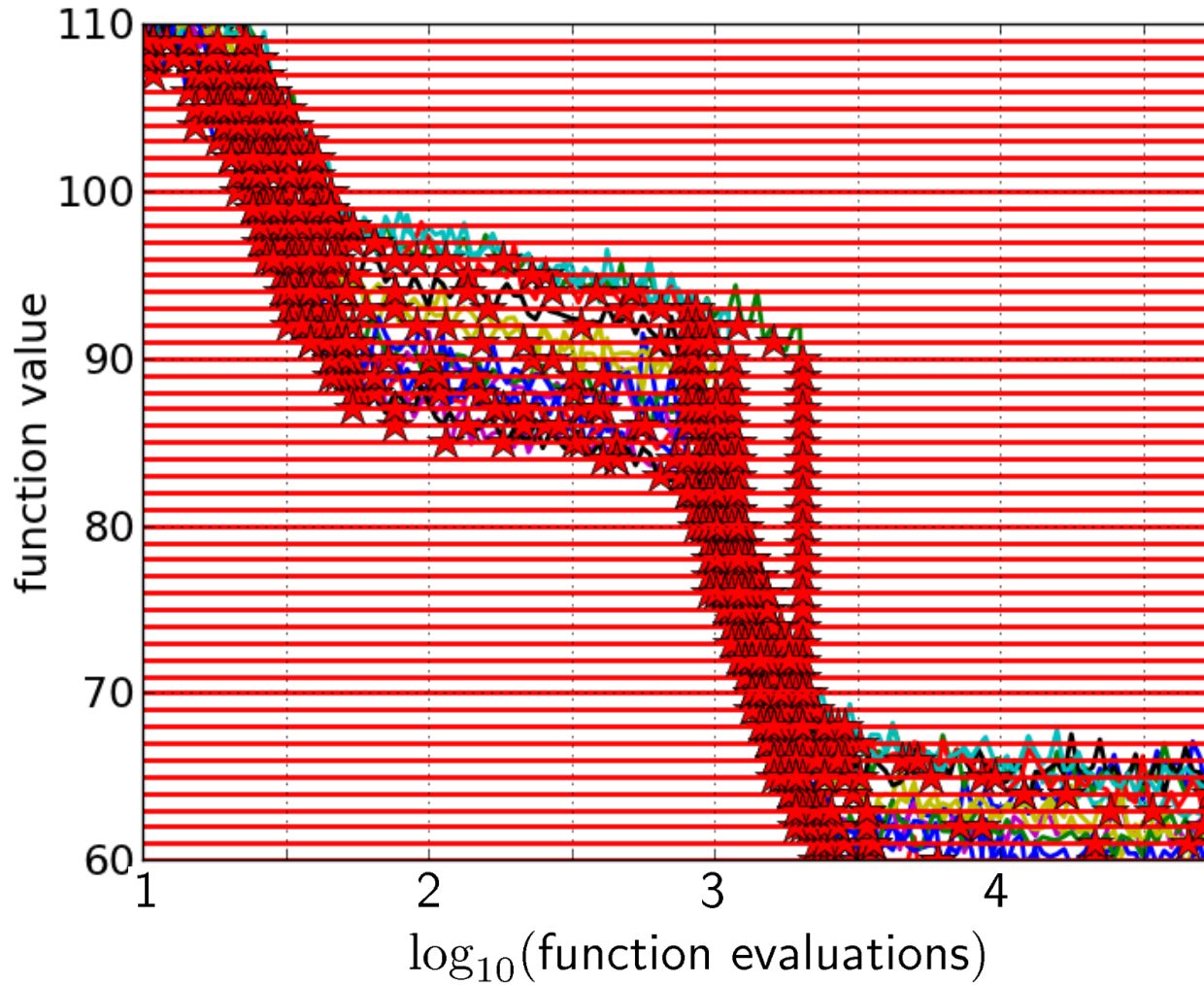
# Aggregation



15 runs



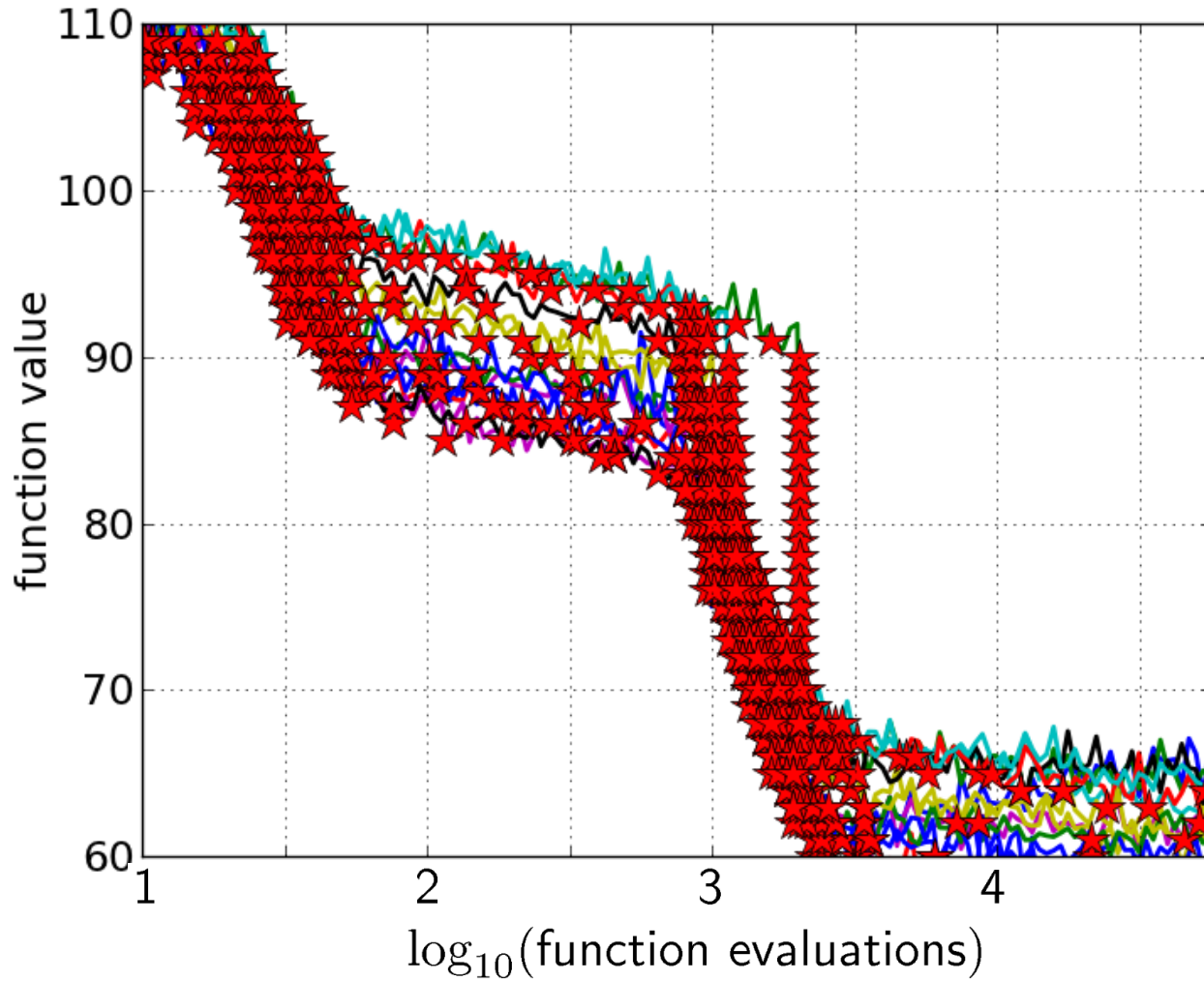
# Aggregation



15 runs

50 targets

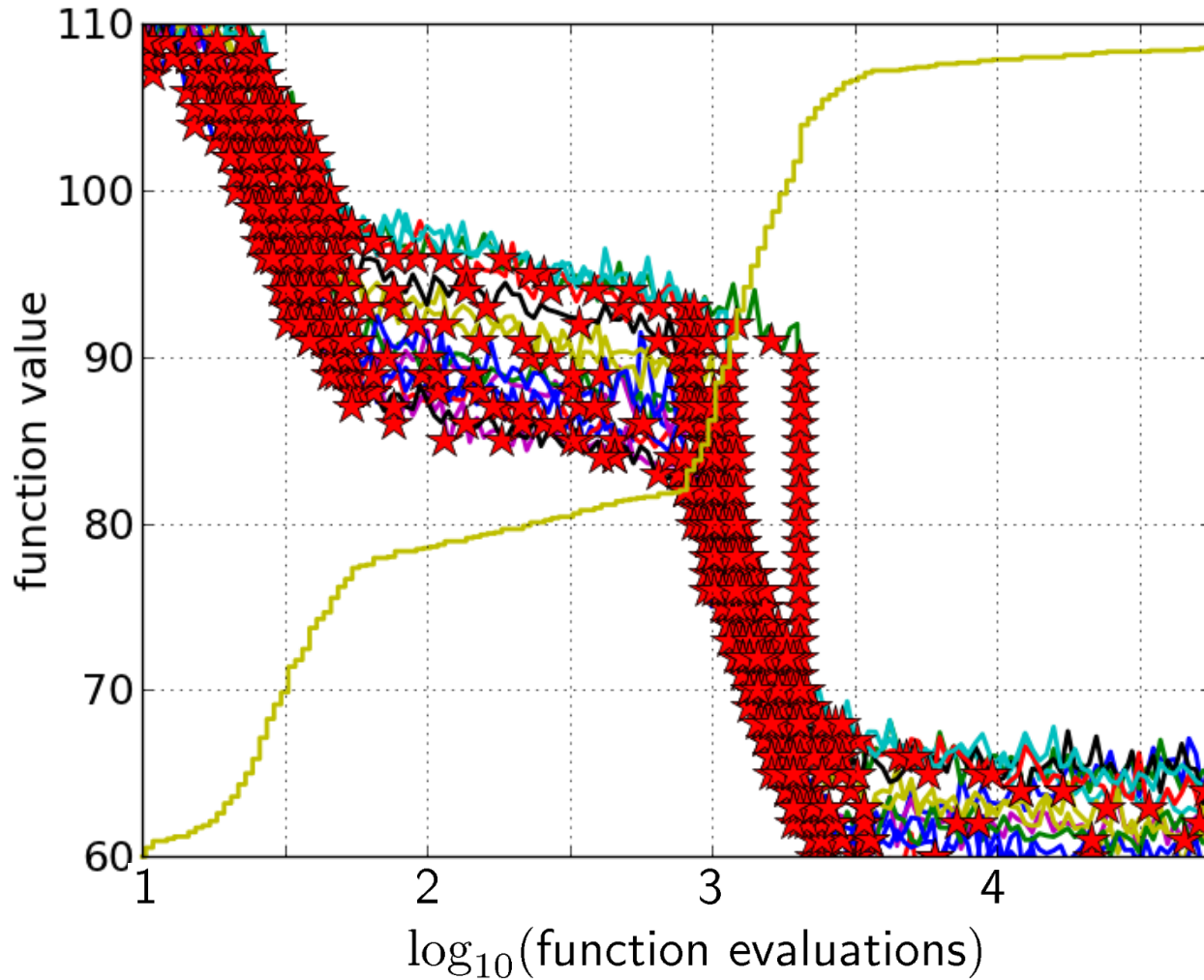
# Aggregation



15 runs

50 targets

# Aggregation

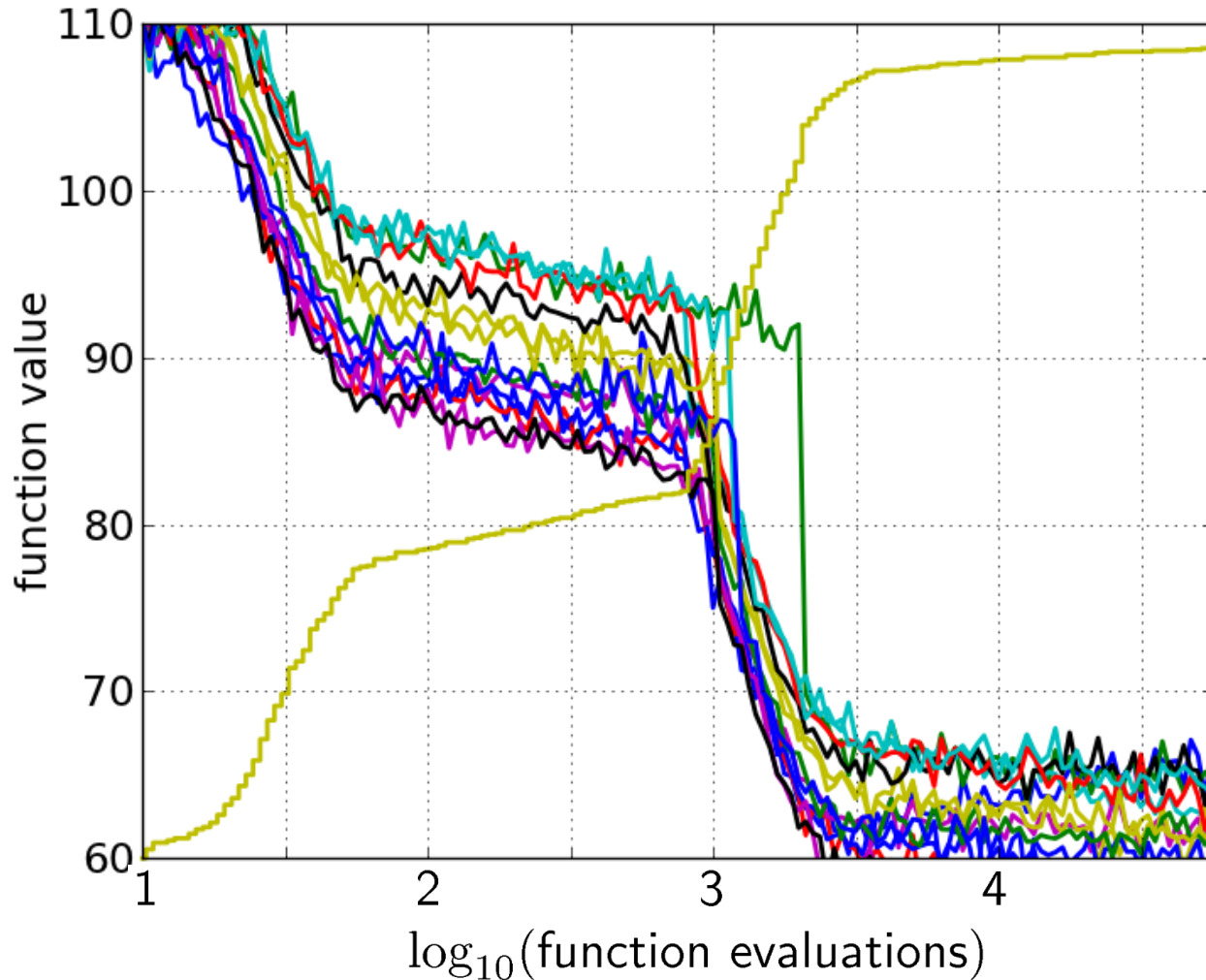


15 runs

50 targets

ECDF with 750  
steps

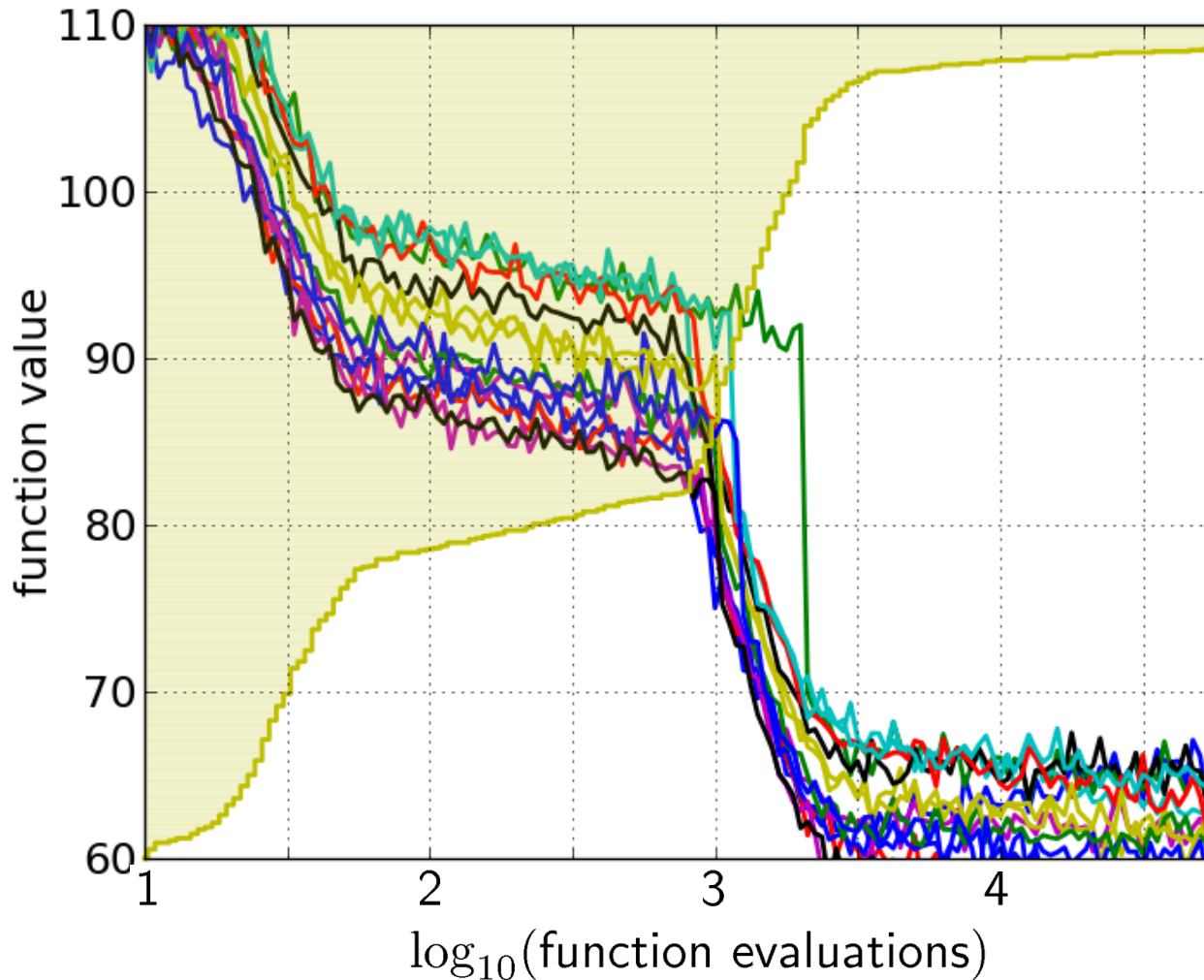
# Aggregation



50 targets from  
15 runs

...integrated in a  
single graph

# Interpretation



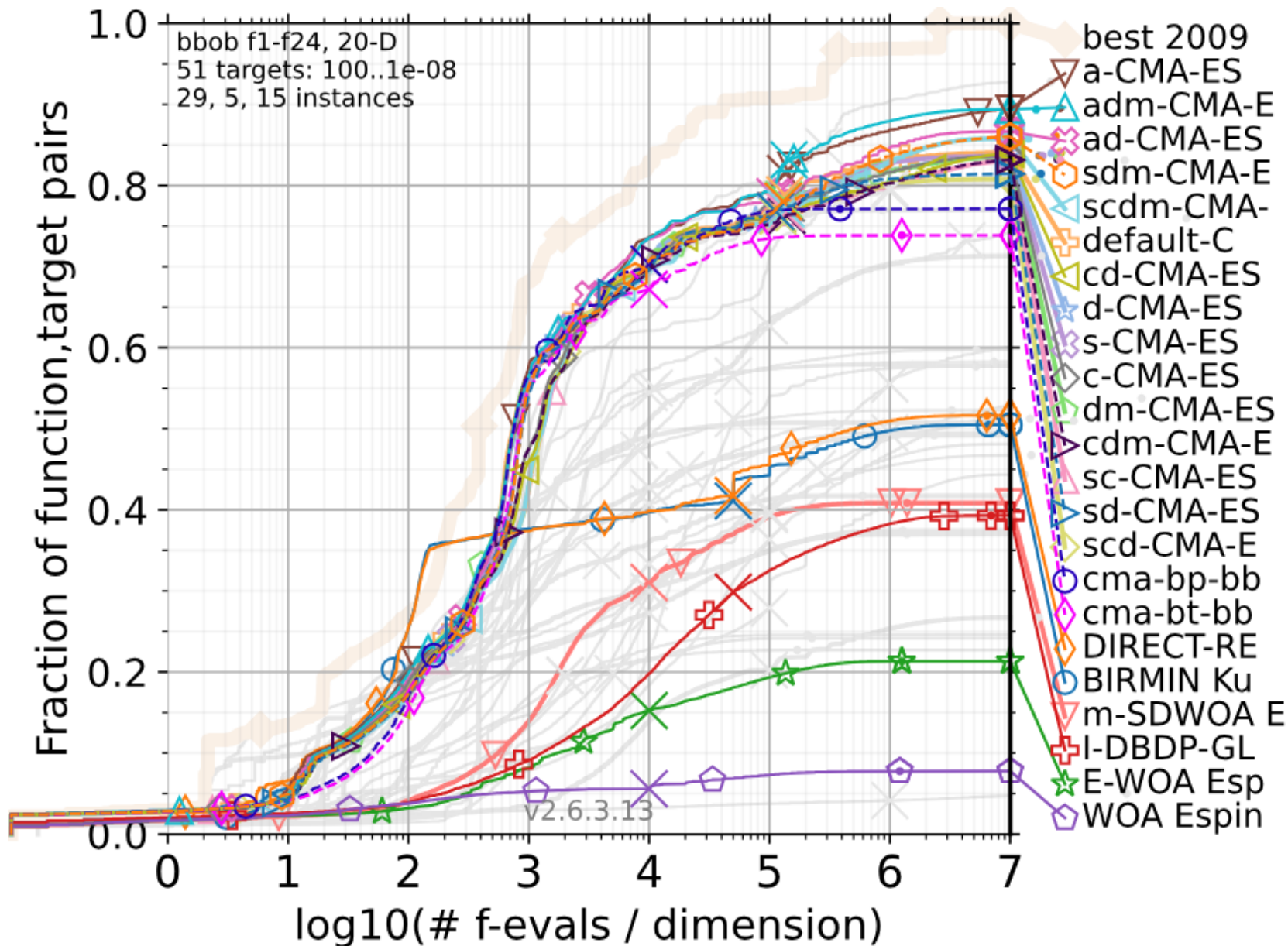
50 targets from  
15 runs  
integrated in a  
single graph

area over the ECDF  
curve

=

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

# Example



# Example

1.0

bbob f1-f24, 20-D

<https://numbbo.github.io/ppdata-archive/>

ppdata archive

Search ppdata archive

COCO code

data archive

postprocessed data

COCO Home

COCO postprocessed data archive

COCO (COmparing Continuous Optimizers) is a platform for systematic and sound comparisons of real-parameter global optimizers. Here, we provide postprocessed data from all 300+ officially supported algorithm data sets for the various available test suites. Due to the large amount of algorithms (and the limited space in the figures), we group algorithm data sets by year of publication.

bbob	bbob-noisy	bbob-biobj	bbob-largescale	bbob-mixint	bbob-constrained
24 functions	30 functions	55 functions	24 bbob functions	24 functions	54 functions from 9 "raw" bbob

Fraction

0.2

0.0

0

1

2

3

4

5

6

7

$\log_{10}(\# \text{ f-evals} / \text{dimension})$

best 2009

a-CMA-ES

adm-CMA-E

ad-CMA-ES

sdm-CMA-E

scdm-CMA-

default-C

cd-CMA-ES

d-CMA-ES

s-CMA-ES

c-CMA-ES

dm-CMA-ES

cdm-CMA-E

sc-CMA-ES

sd-CMA-ES

scd-CMA-E

cma-bp-bb

cma-bt-bb

DIRECT-RE

BIRMIN Ku


m-SDWOA E

I-DBDP-GL

E-WOA Esp

WOA Espin

# Available Test Suites in COCO

bbob (since 2009)	24 noiseless fcts	250+ data sets
bbob-noisy (since 2009)	30 noisy fcts	40+ data sets
bbob-biobj (since 2016)	55 bi-obj. fcts	39 data sets
bbob-largescale (since 2019)	24 noiseless fcts	16 data sets
bbob-mixint (since 2019)	24 noiseless fcts	5 data sets
bbob-biobj-mixint (s. 2019)	92 bi-objective fcts	-
bbob-constrained (s. 2022)	54 constrained fcts	9 data sets
sbox-cost 	24 box-constr. fcts	2 data sets

<https://numbbo.github.io/data-archive/>



# Easy Data Access

```
pip install cocopp
```

```
python -m cocopp exdata/myfolder BIPOP BFGS
```

# Easy Data Access

```
pip install cocopp
```

```
python -m cocopp exdata/myfolder BIPOP BFGS
```

```
[...]
```

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

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

```
2012/BIPOPcMA_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.

```
python -m cocopp exdata/myfolder BIPOP! BFGS!
```

[data access of course also available within `cocopp.main(...)`]

# Session 1: Mixint & Multiobjective Opt.

11:40 – 12:15 The BBOBies: "Introduction to BBOB"

↑  
mix-int

12:15 – 12:40 Tristan Marty, Yann Semet, Anne Auger, Sébastien Héron, Nikolaus Hansen: **Benchmarking CMA-ES with Basic Integer Handling on a Mixed-Integer Test Problem Suite**

↑

bbob-biobj

12:40 – 13:05 Dimo Brockhoff, Pascal Capetillo, Jonathan Hornewall, Raphael Walker: **Benchmarking the Borg algorithm on the Biobjective bbob-biobj Testbed**

↓

13:05 – 13:30 Victoria Johnson, João Duro, Visakan Kadiramanathan, Robin Purshouse: **A distributed multi-disciplinary design optimization benchmark test suite with constraints and multiple conflicting objectives**