6th GECCO Workshop on Blackbox Optimization Benchmarking (BBOB): Turbo Intro to COCO/BBOB

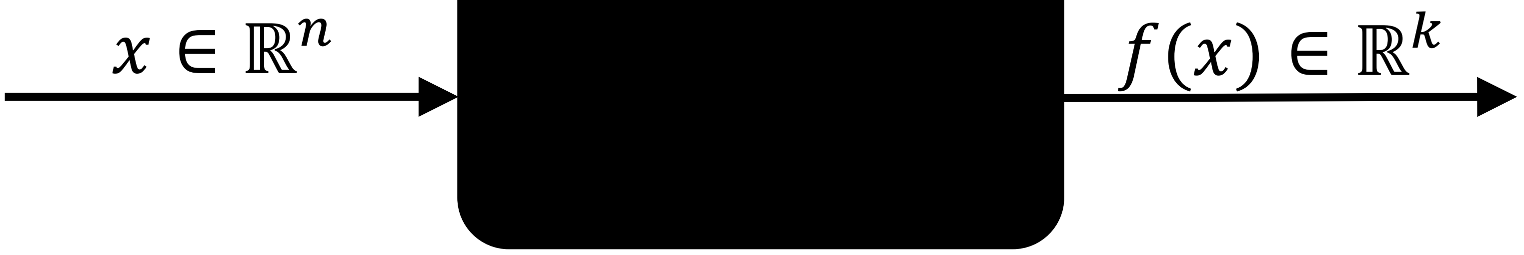
The BBOBies

https://github.com/numbbo/coco

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

Numerical Blackbox Optimization

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



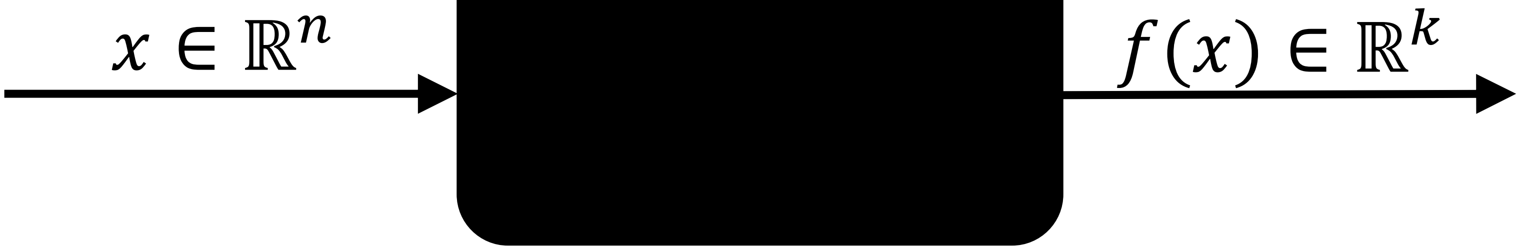
$x \in \mathbb{R}^n$

$f(x) \in \mathbb{R}^k$

derivatives not available or not useful

Practical Blackbox Optimization

Given:



Not clear:

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

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

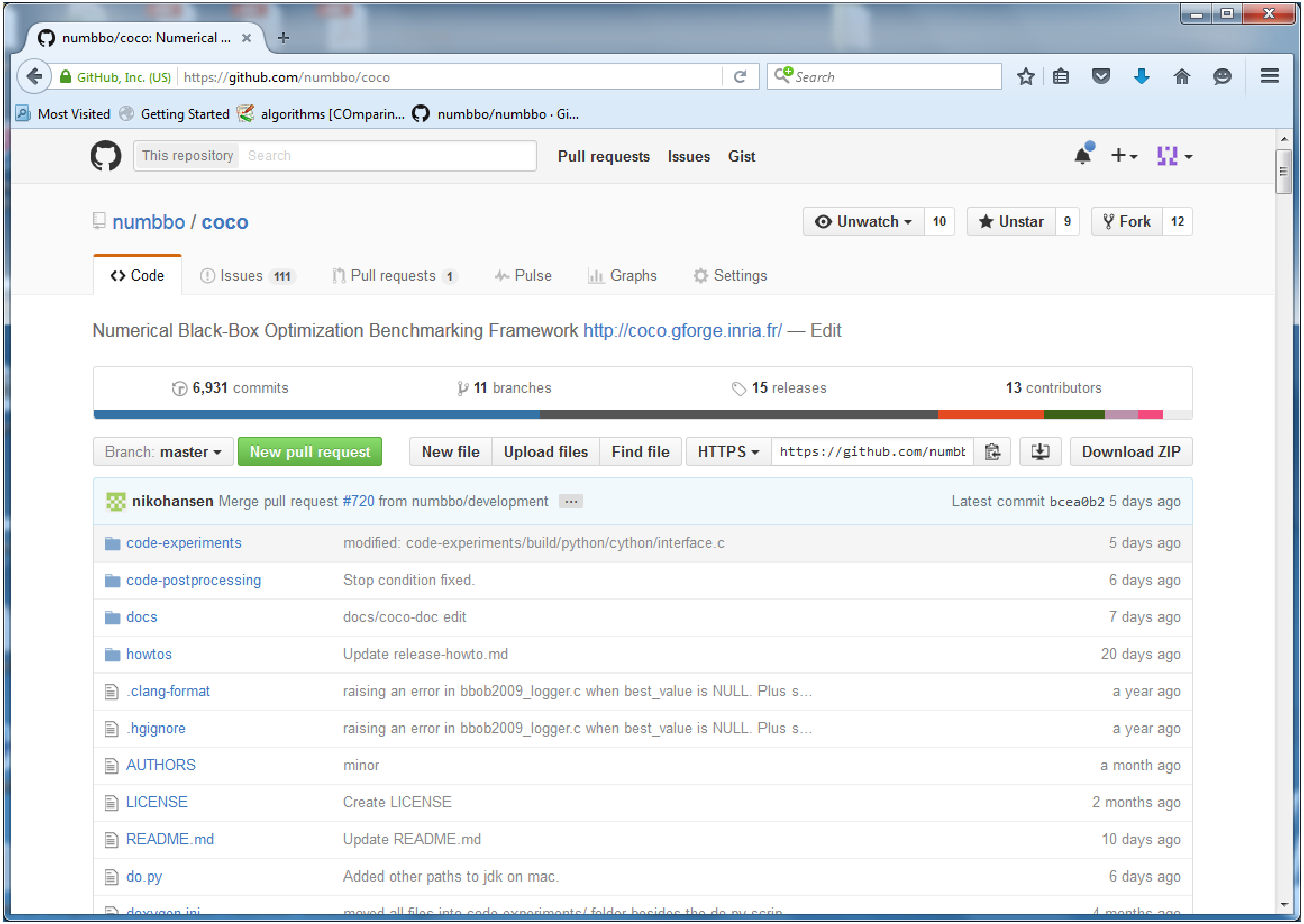
that's where COCO and BBOB come into play

Comparing Continuous Optimizers Platform

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

automatized benchmarking

https://github.com/numbbo/coco



numbbo / coco

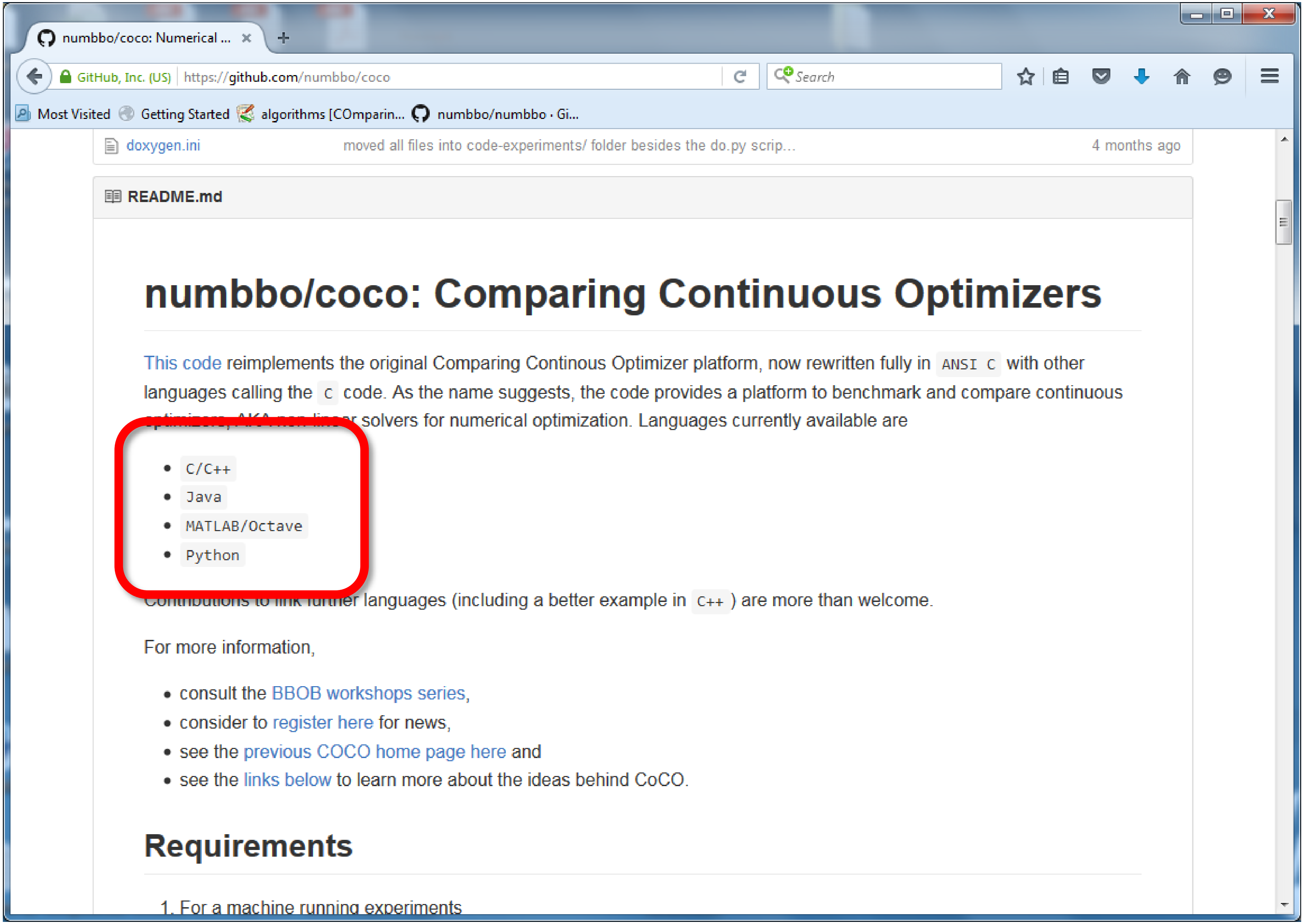
Numerical Black-Box Optimization Benchmarking Framework http://coco.gforge.inria.fr/ — Edit

6,931 commits | 11 branches | 15 releases | 13 contributors

nikohansen Merge pull request #720 from numbbo/development ... Latest commit bcea0b2 5 days ago

code-experiments	modified: code-experiments/build/python/cython/interface.c	5 days ago
code-postprocessing	Stop condition fixed.	6 days ago
docs	docs/coco-doc edit	7 days ago
howtos	Update release-howto.md	20 days ago
.clang-format	raising an error in bbob2009_logger.c when best_value is NULL. Plus s...	a year ago
.hgignore	raising an error in bbob2009_logger.c when best_value is NULL. Plus s...	a year ago
AUTHORS	minor	a month ago
LICENSE	Create LICENSE	2 months ago
README.md	Update README.md	10 days ago
do.py	Added other paths to jdk on mac.	6 days ago
doxygen.ini	moved all files into code-experiments/ folder besides the do.py scrip	4 months ago

https://github.com/numbbo/coco



doxygen.ini	moved all files into code-experiments/ folder besides the do.py scrip...	4 months ago

README.md

numbbo/coco: Comparing Continuous Optimizers

This code reimplements the original Comparing Continous Optimizer platform, now rewritten fully in `ANSI C` with other languages calling the `C` code. As the name suggests, the code provides a platform to benchmark and compare continuous optimizers, AKA non-linear solvers for numerical optimization. Languages currently available are

- `C/C++`
- `Java`
- `MATLAB/Octave`
- `Python`

Contributions to link further languages (including a better example in `C++`) are more than welcome.

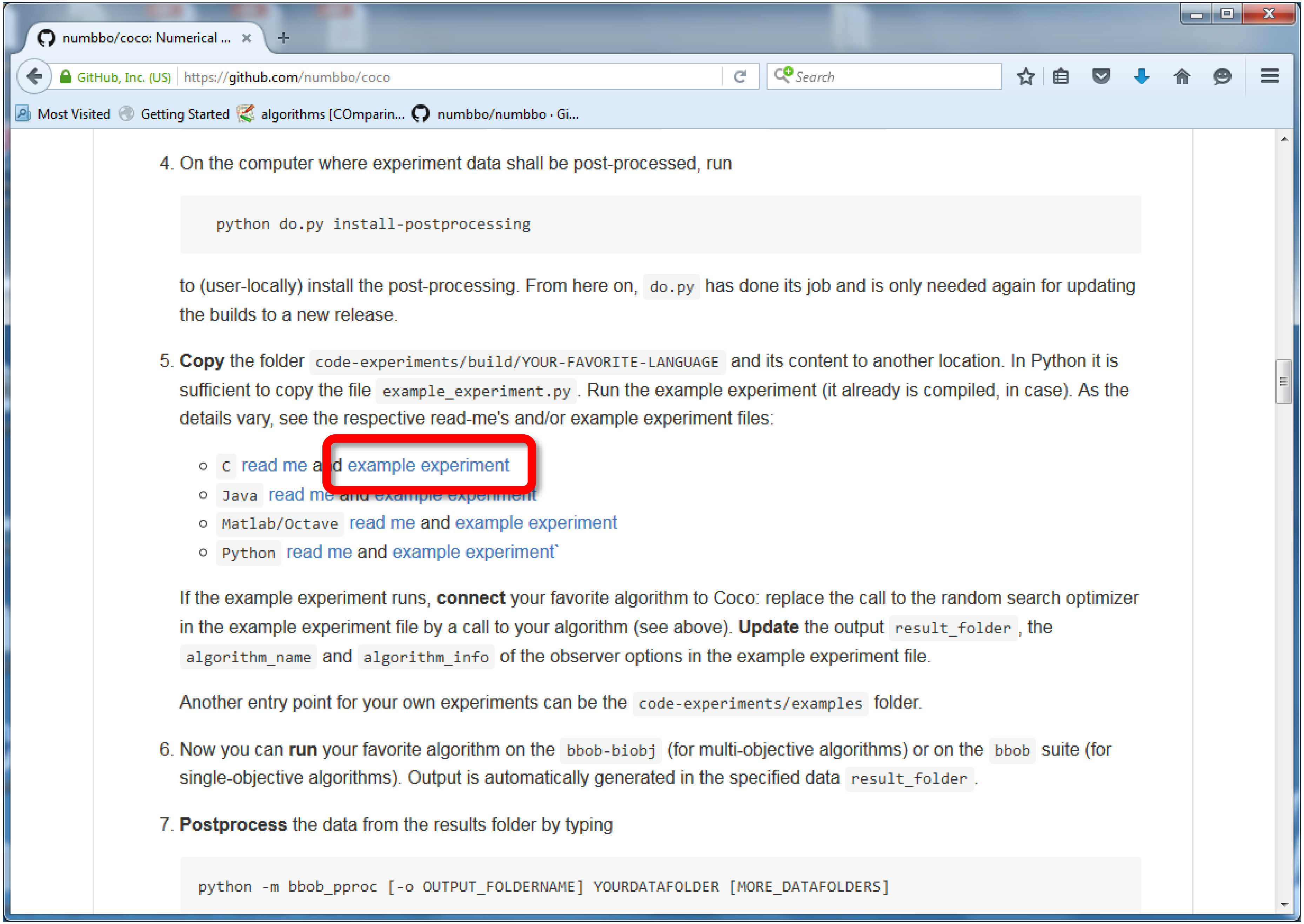
For more information,

- consult the BBOB workshops series,
- consider to register here for news,
- see the previous COCO home page here and
- see the links below to learn more about the ideas behind CoCO.

Requirements

1. For a machine running experiments

https://github.com/numbbo/coco



4. On the computer where experiment data shall be post-processed, run

```
python do.py install-postprocessing
```

to (user-locally) install the post-processing. From here on, `do.py` has done its job and is only needed again for updating the builds to a new release.

5. **Copy** the folder `code-experiments/build/YOUR-FAVORITE-LANGUAGE` and its content to another location. In Python it is sufficient to copy the file `example_experiment.py`. Run the example experiment (it already is compiled, in case). As the details vary, see the respective read-me's and/or example experiment files:

   - `C` read me and example experiment
   - `Java` read me and example experiment
   - `Matlab/Octave` read me and example experiment
   - `Python` read me and example experiment`

   If the example experiment runs, **connect** your favorite algorithm to Coco: replace the call to the random search optimizer in the example experiment file by a call to your algorithm (see above). **Update** the output `result_folder`, the `algorithm_name` and `algorithm_info` of the observer options in the example experiment file.

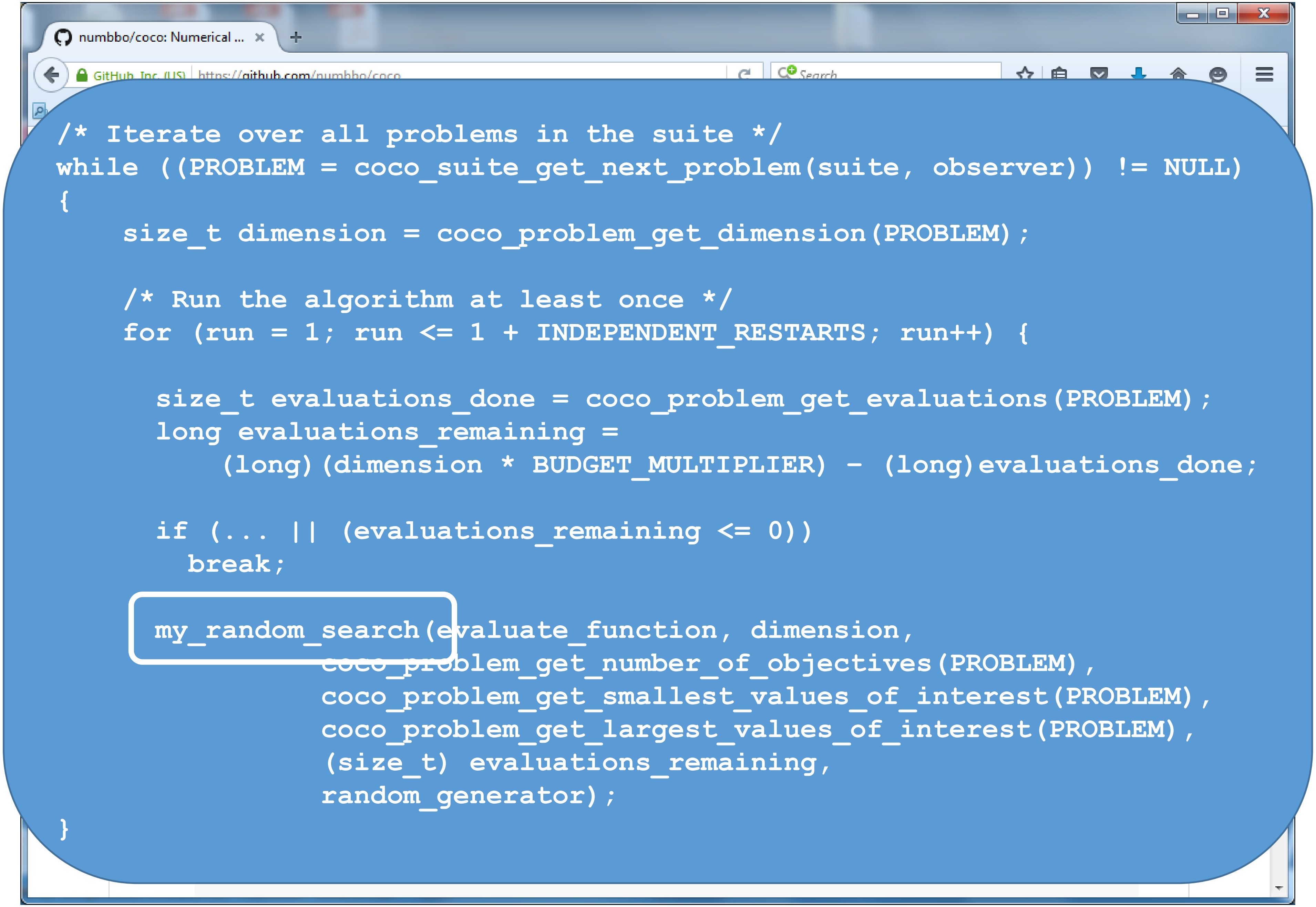
   Another entry point for your own experiments can be the `code-experiments/examples` folder.

6. Now you can **run** your favorite algorithm on the `bbob-biobj` (for multi-objective algorithms) or on the `bbob` suite (for single-objective algorithms). Output is automatically generated in the specified data `result_folder`.

7. **Postprocess** the data from the results folder by typing

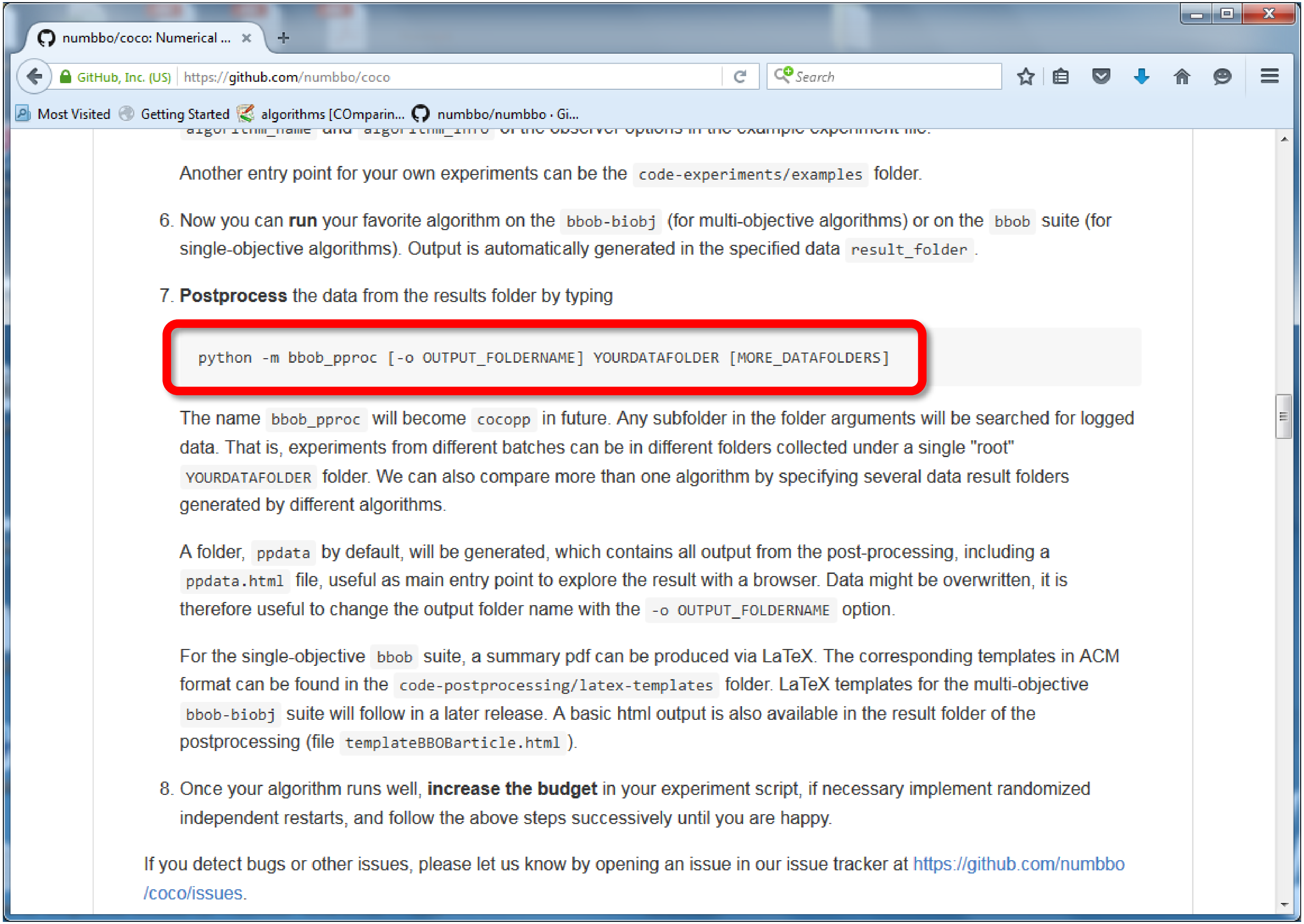
```
python -m bbob_pproc [-o OUTPUT_FOLDERNAME] YOURDATAFOLDER [MORE_DATAFOLDERS]
```

example_experiment.c



```
/* Iterate over all problems in the suite */
while ((PROBLEM = coco_suite_get_next_problem(suite, observer)) != NULL)
{
    size_t dimension = coco_problem_get_dimension(PROBLEM);

    /* Run the algorithm at least once */
    for (run = 1; run <= 1 + INDEPENDENT_RESTARTS; run++) {

      size_t evaluations_done = coco_problem_get_evaluations(PROBLEM);
      long evaluations_remaining =
          (long)(dimension * BUDGET_MULTIPLIER) - (long)evaluations_done;

      if (... || (evaluations_remaining <= 0))
        break;

      my_random_search(evaluate_function, dimension,
                coco_problem_get_number_of_objectives(PROBLEM),
                coco_problem_get_smallest_values_of_interest(PROBLEM),
                coco_problem_get_largest_values_of_interest(PROBLEM),
                (size_t) evaluations_remaining,
                random_generator);
}
```

https://github.com/numbbo/coco



`algorithm_name` and `algorithm_info` of the observer options in the example experiment file.

Another entry point for your own experiments can be the `code-experiments/examples` folder.

6. Now you can **run** your favorite algorithm on the `bbob-biobj` (for multi-objective algorithms) or on the `bbob` suite (for single-objective algorithms). Output is automatically generated in the specified data `result_folder`.

7. **Postprocess** the data from the results folder by typing

```
python -m bbob_pproc [-o OUTPUT_FOLDERNAME] YOURDATAFOLDER [MORE_DATAFOLDERS]
```

The name `bbob_pproc` will become `cocopp` in future. Any subfolder in the folder arguments will be searched for logged data. That is, experiments from different batches can be in different folders collected under a single "root" `YOURDATAFOLDER` folder. We can also compare more than one algorithm by specifying several data result folders generated by different algorithms.

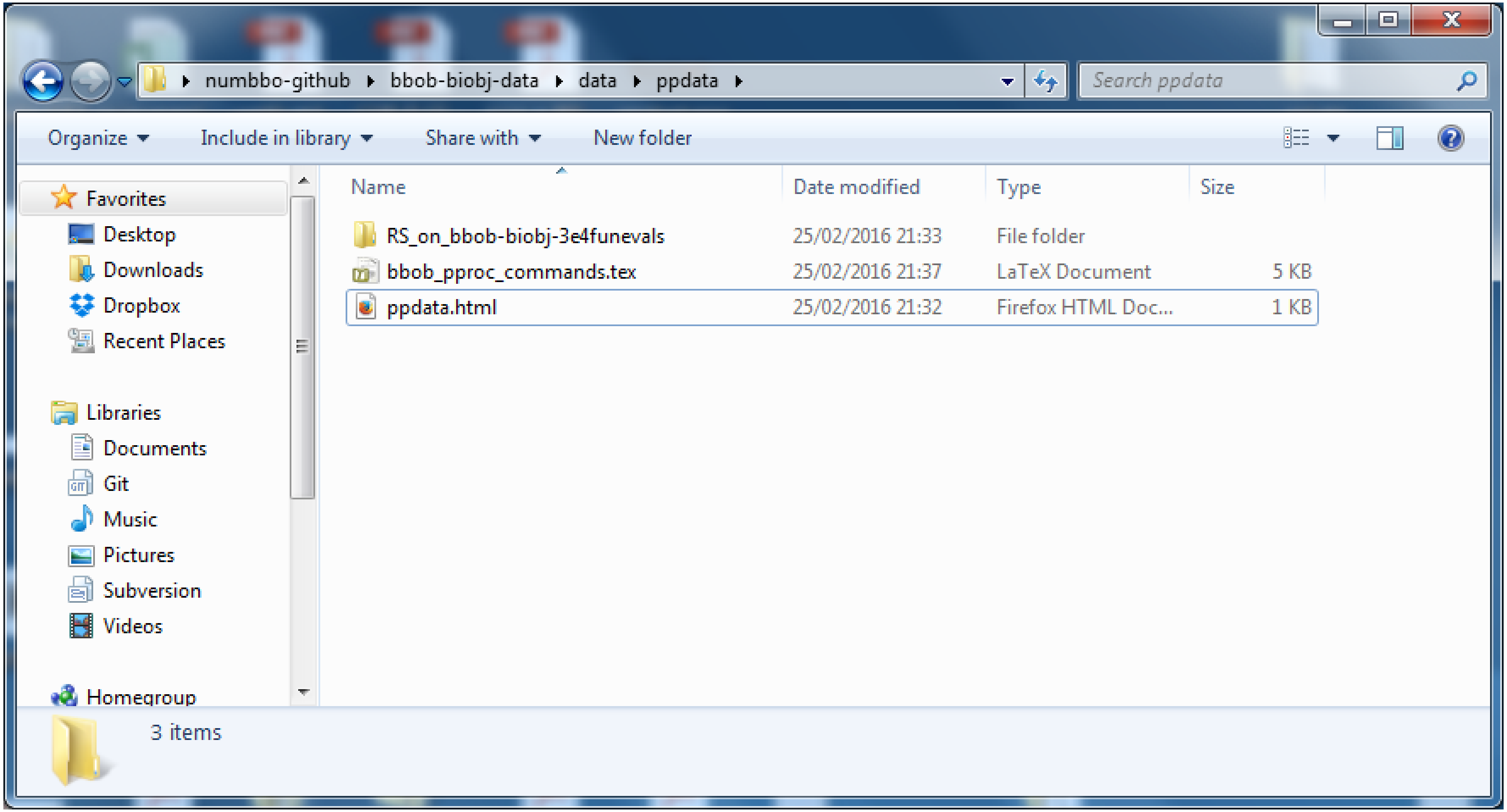
A folder, `ppdata` by default, will be generated, which contains all output from the post-processing, including a `ppdata.html` file, useful as main entry point to explore the result with a browser. Data might be overwritten, it is therefore useful to change the output folder name with the `-o OUTPUT_FOLDERNAME` option.

For the single-objective `bbob` suite, a summary pdf can be produced via LaTeX. The corresponding templates in ACM format can be found in the `code-postprocessing/latex-templates` folder. LaTeX templates for the multi-objective `bbob-biobj` suite will follow in a later release. A basic html output is also available in the result folder of the postprocessing (file `templateBBOBarticle.html`).

8. Once your algorithm runs well, **increase the budget** in your experiment script, if necessary implement randomized independent restarts, and follow the above steps successively until you are happy.

If you detect bugs or other issues, please let us know by opening an issue in our issue tracker at https://github.com/numbbo/coco/issues.

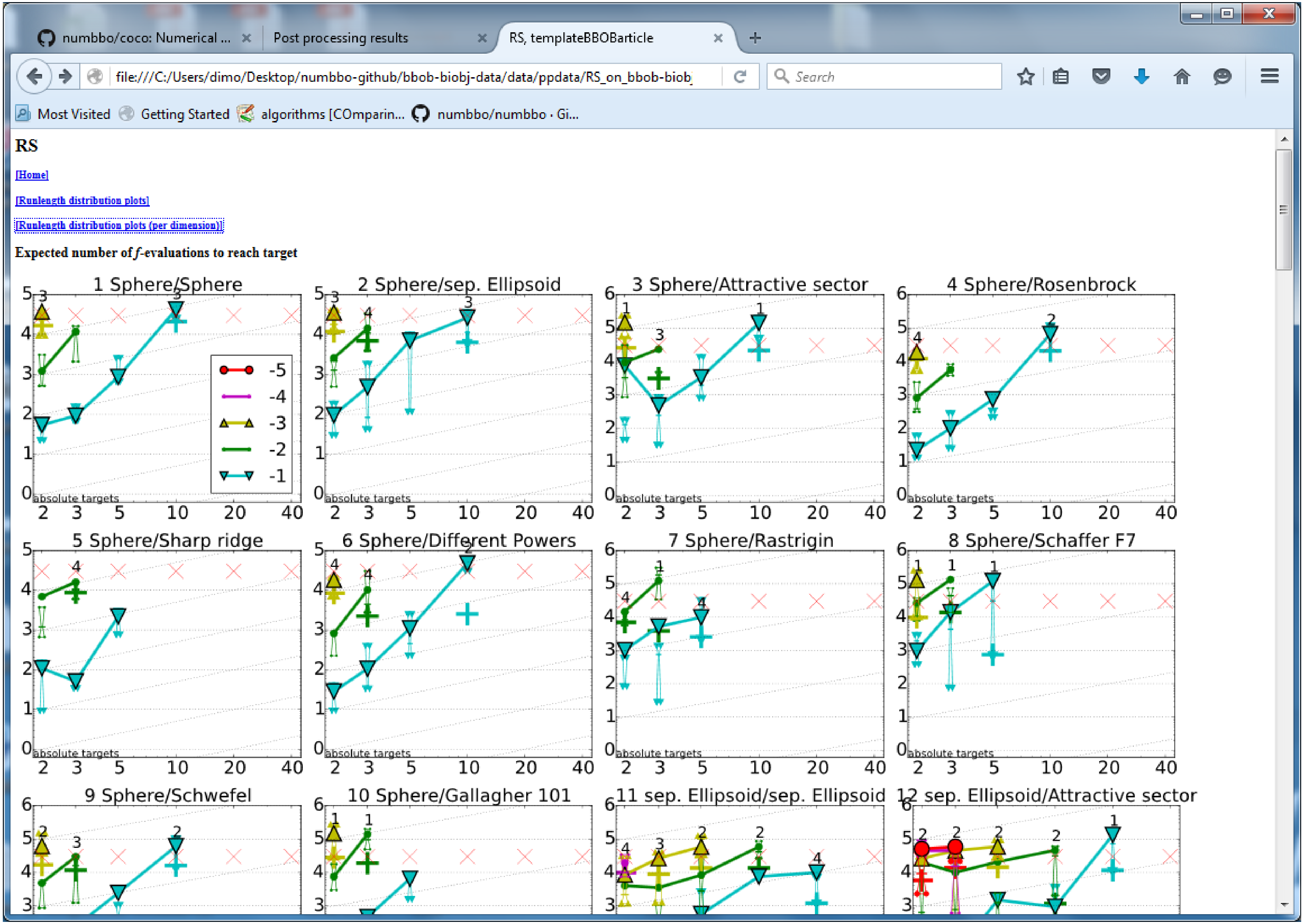
result folder



Name	Date modified	Type	Size
RS_on_bbob-biobj-3e4funevals	25/02/2016 21:33	File folder	
bbob_pproc_commands.tex	25/02/2016 21:37	LaTeX Document	5 KB
ppdata.html	25/02/2016 21:32	Firefox HTML Doc...	1 KB

3 items

automatically generated results



RS

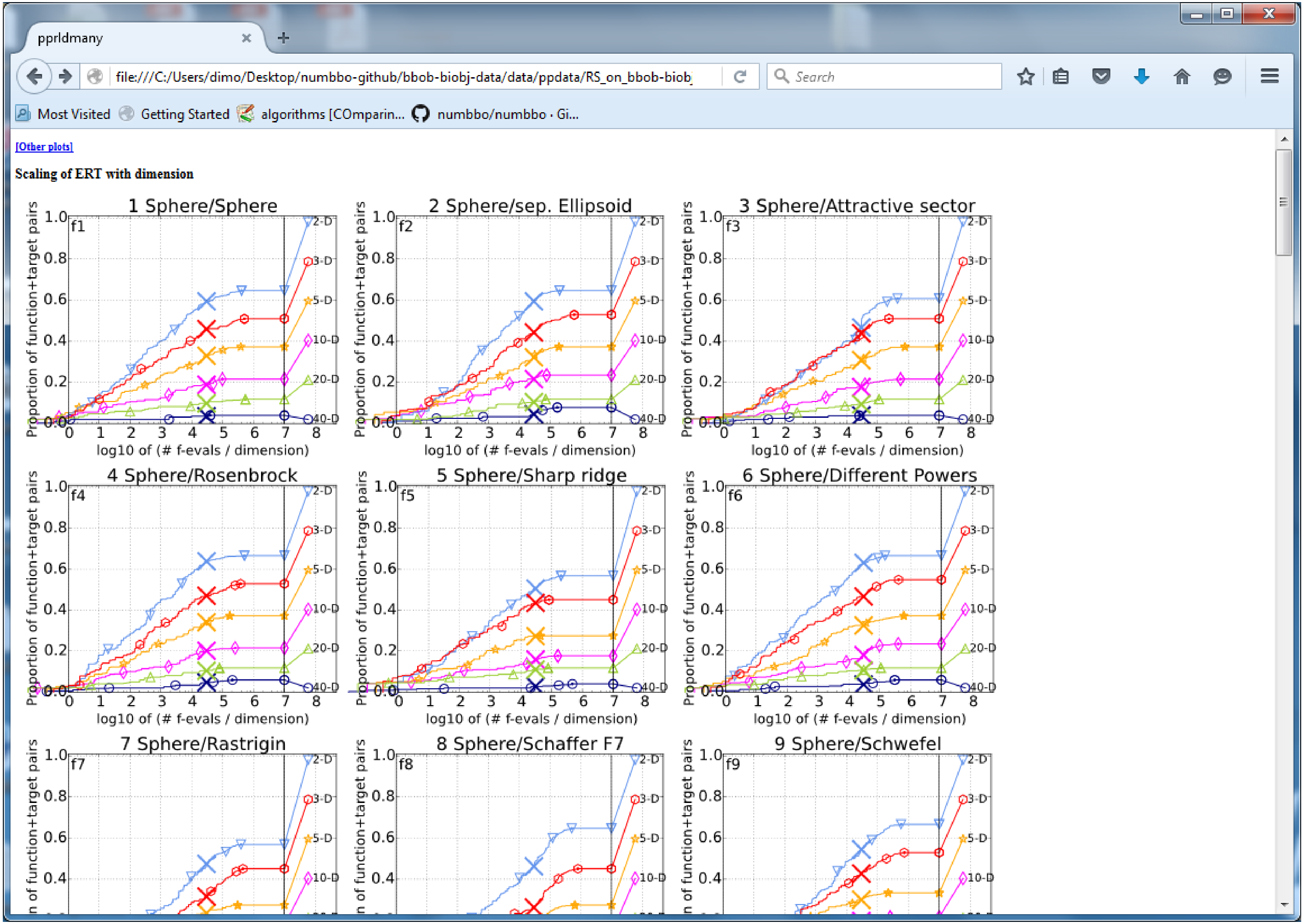
[Home]

[Runlength distribution plots]

[Runlength distribution plots (per dimension)]

Expected number of *f*-evaluations to reach target

automatically generated results


pprldmany
file:///C:/Users/dimo/Desktop/numbbo-github/bbob-biobj-data/data/ppdata/RS_on_bbob-biob
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[Other plots]

Scaling of ERT with dimension

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

COCO/BBOB

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

Available Test Suites in COCO

• bbob	24 noiseless fcts	140+ algo data sets
• bbob-noisy	30 noisy fcts	40+ algo data sets
• bbob-biobj	55 bi-objective fcts	new in 2016 15 algo data sets

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)

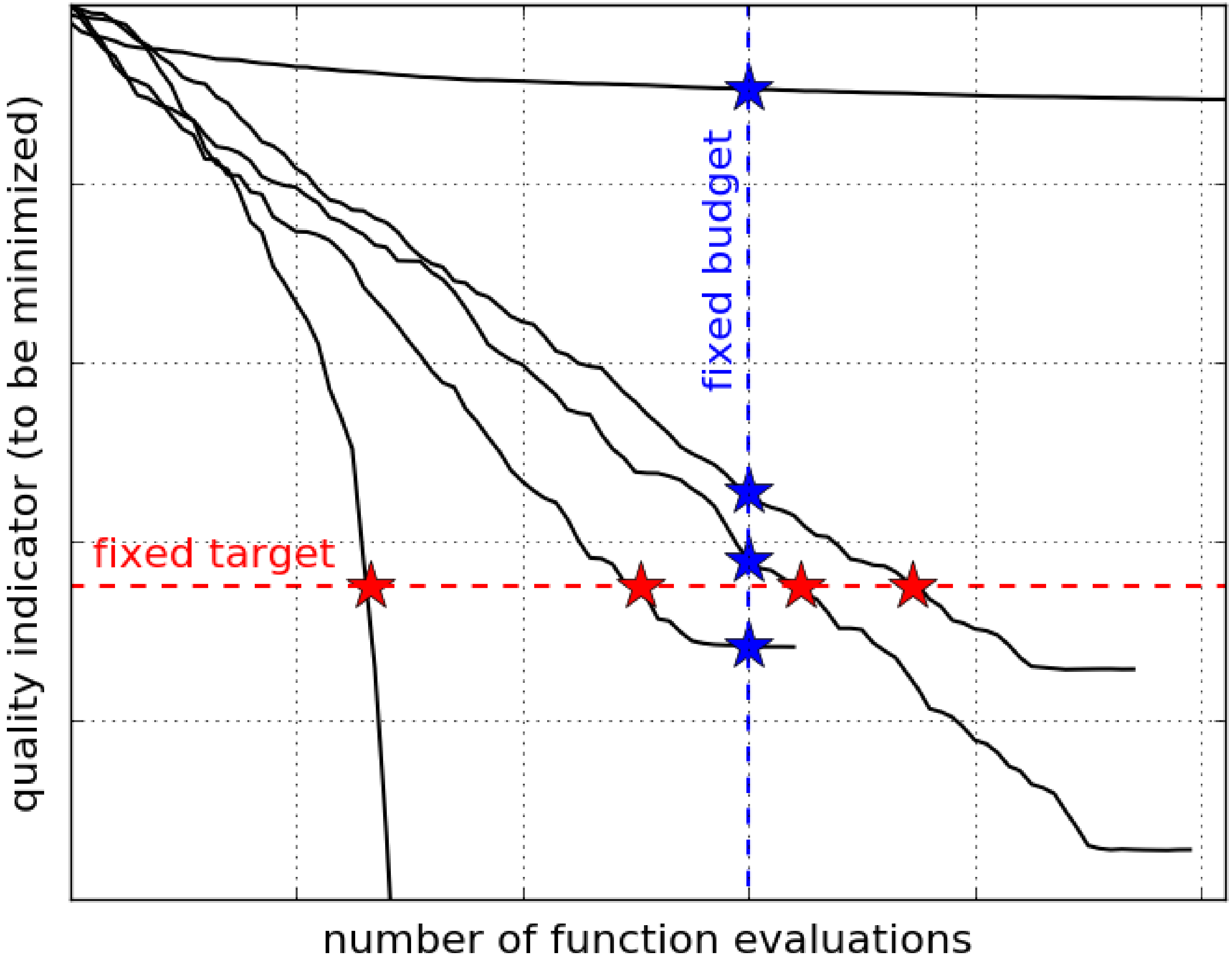
How Do We Measure Performance?

Two objectives:

- Find solution with small(est possible) function/indicator value
- With the least possible search costs (number of function evaluations)

For measuring performance: fix one and measure the other

Measuring Performance Empirically

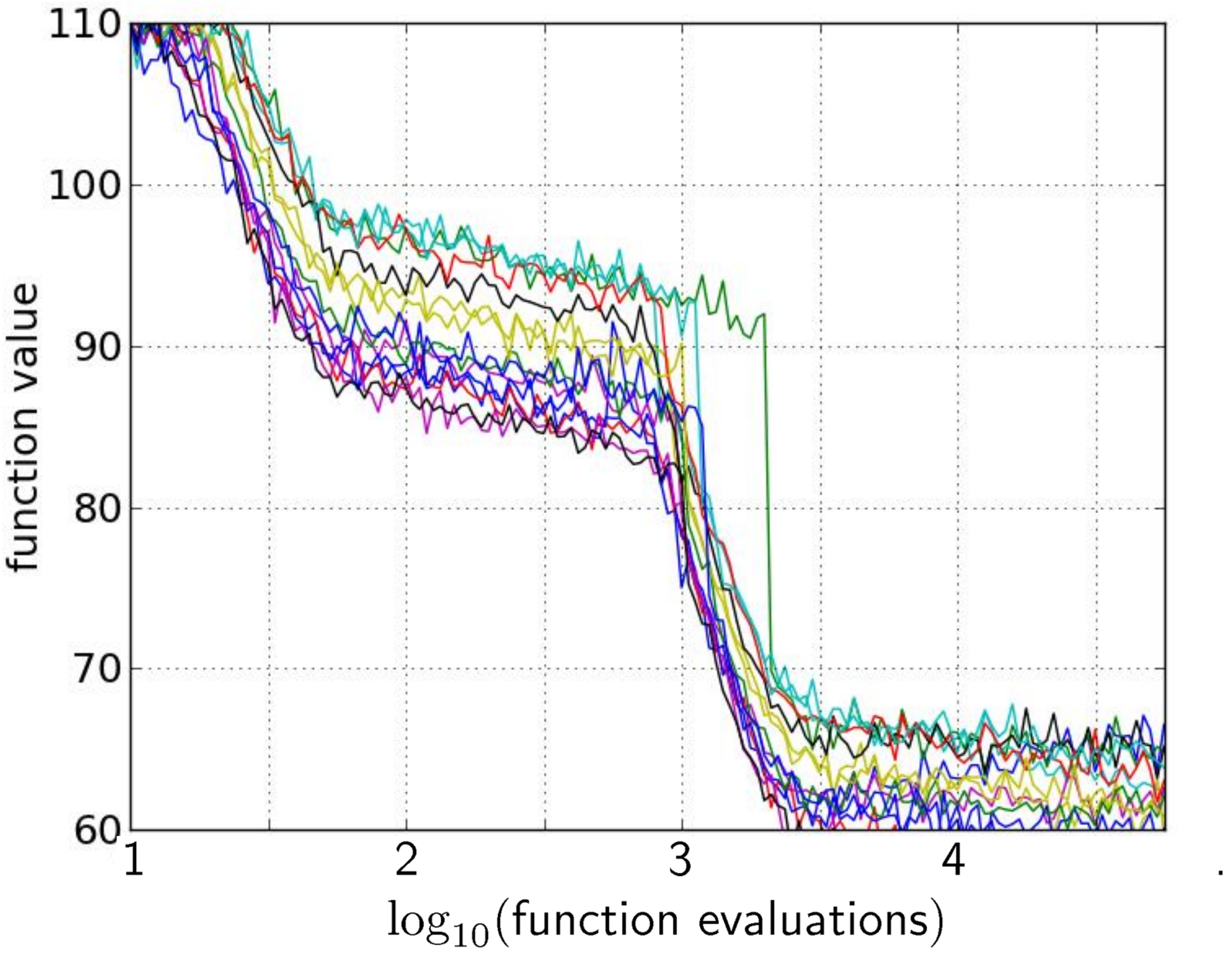


ECDF:

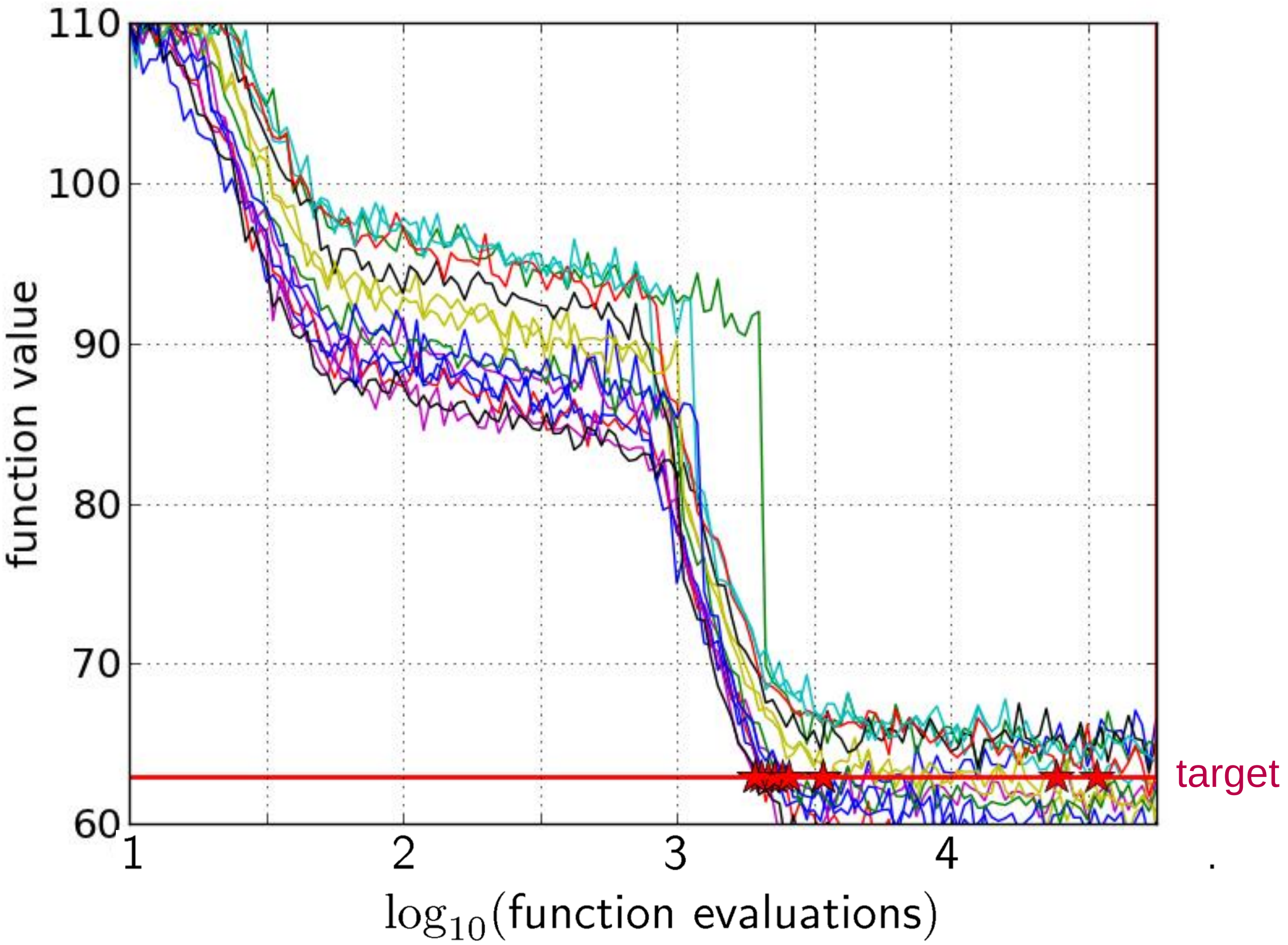
Empirical Cumulative Distribution Function of the Runtime

[aka data profile]

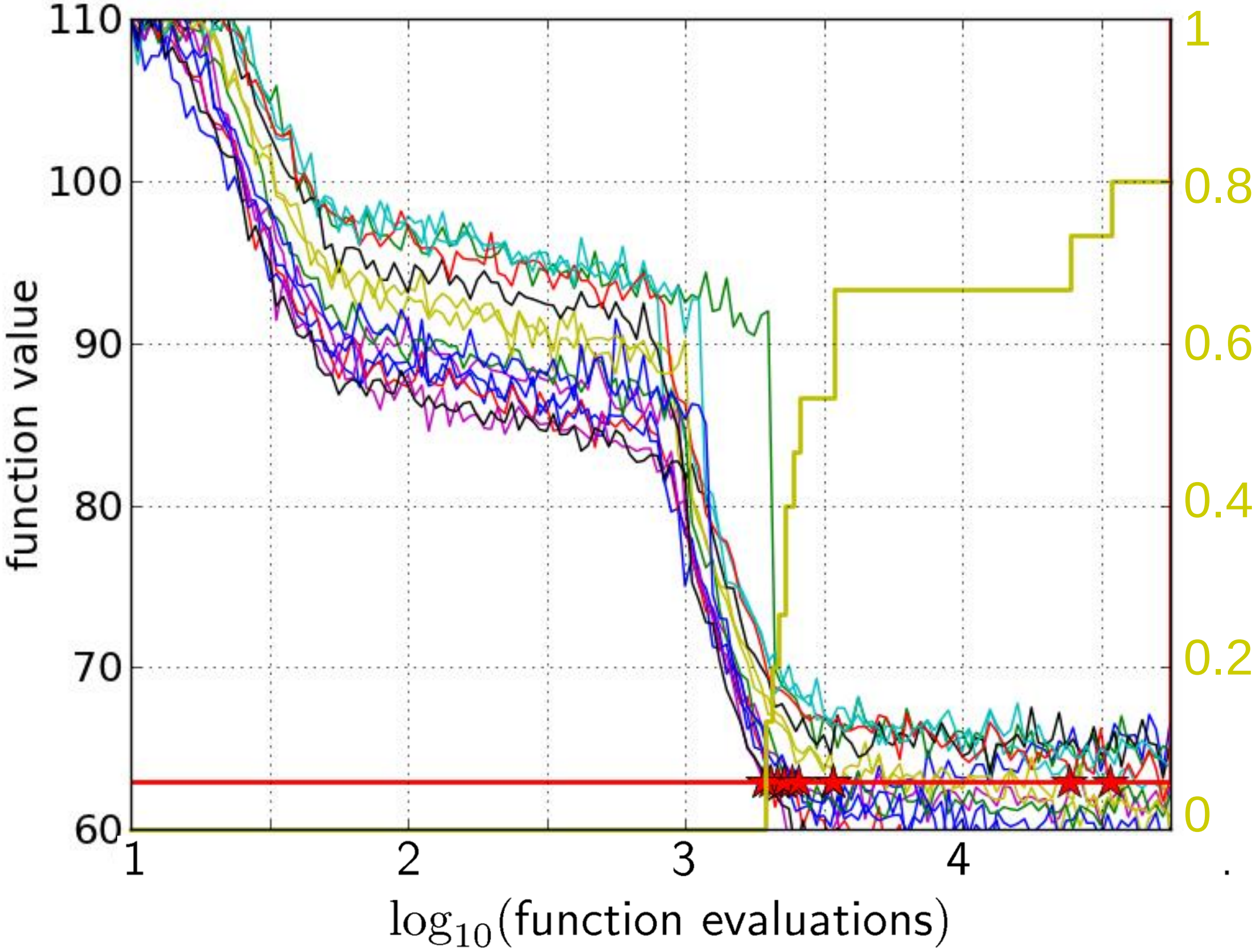
15 Runs


110
100
90
80
70
60
function value
1
2
3
4
.
$\log_{10}$(function evaluations)

15 Runs ≤ 15 Runtime Data Points



Empirical Cumulative Distribution

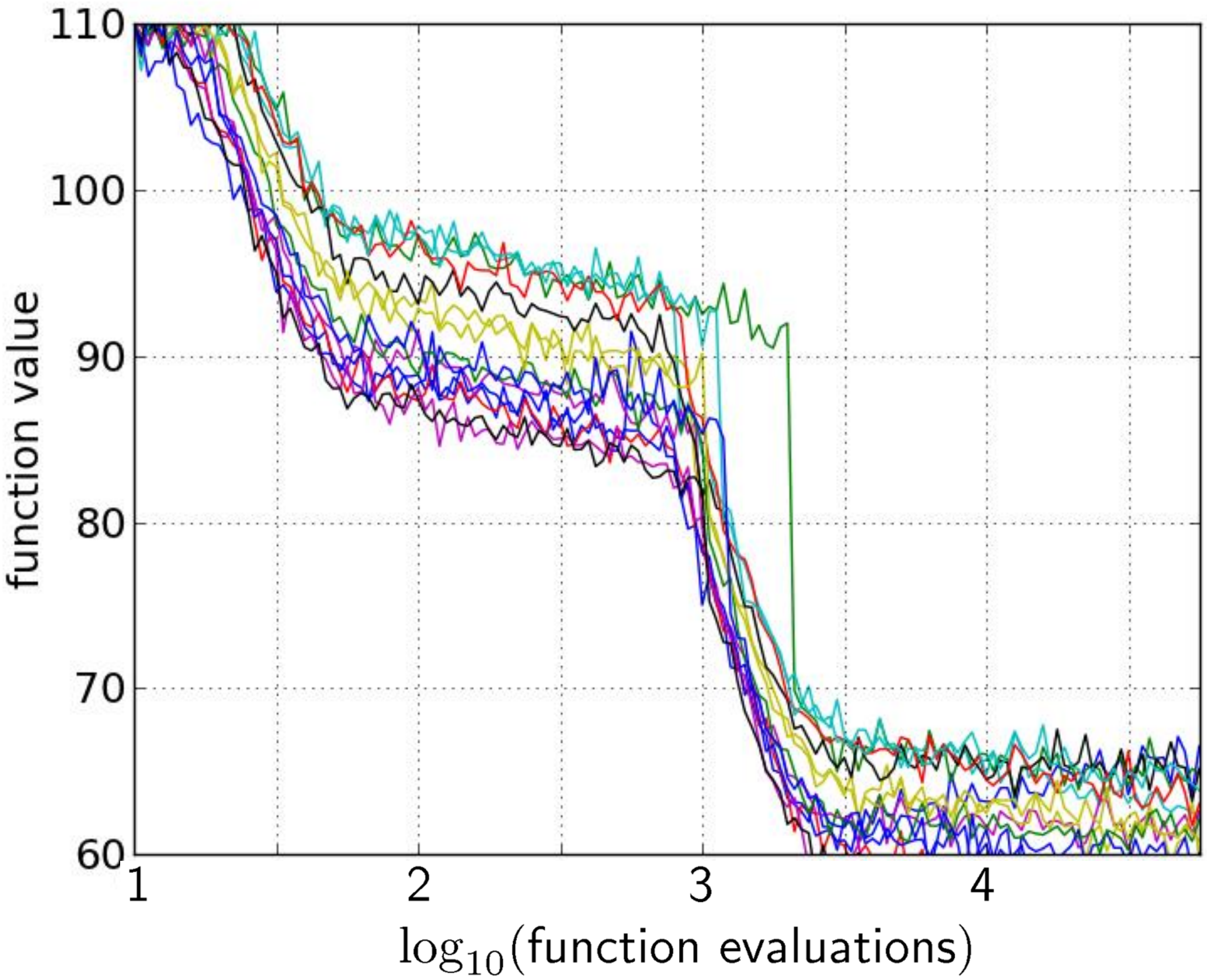


the ECDF of run lengths to reach the target

- 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

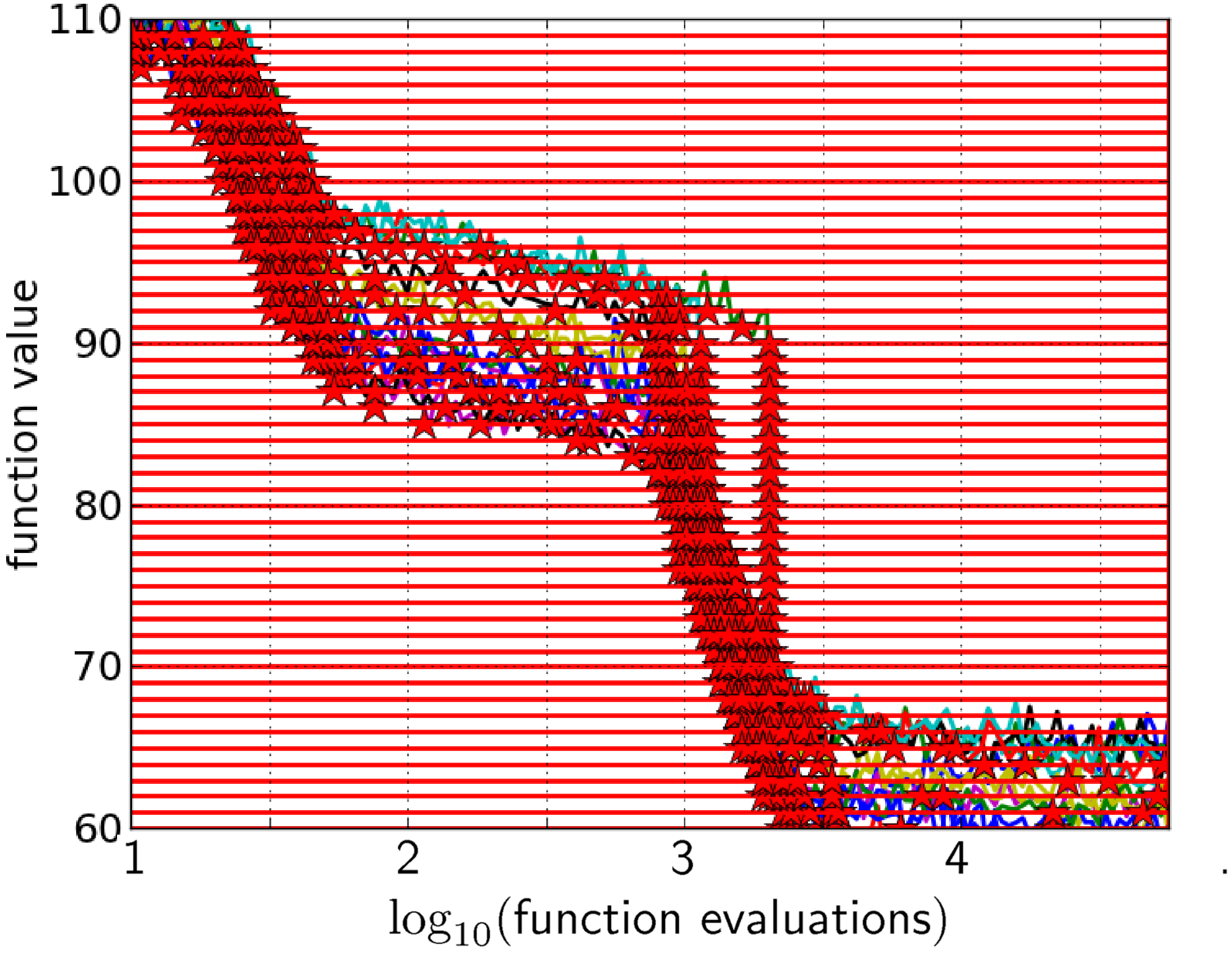
Aggregation



15 runs

.

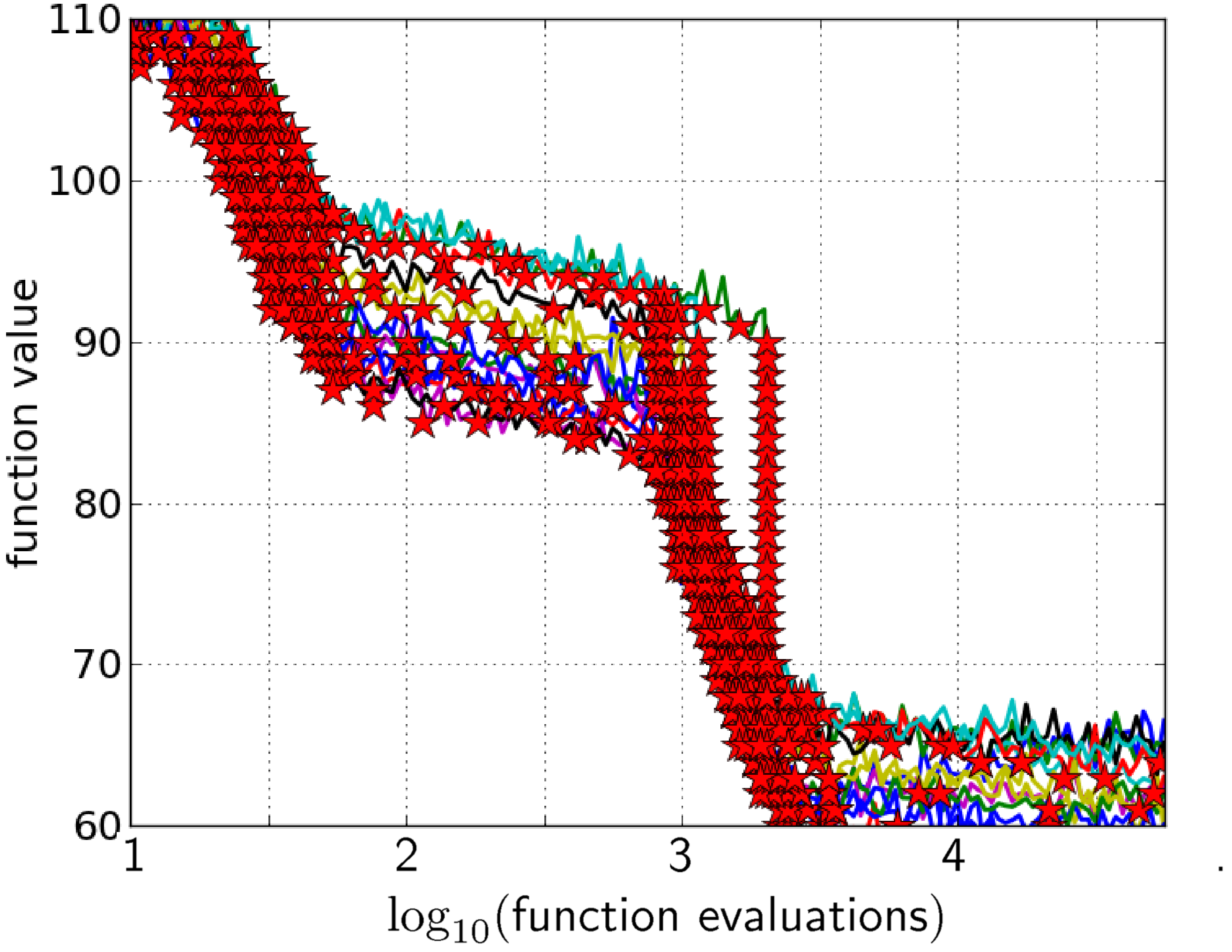
Aggregation



15 runs

50 targets

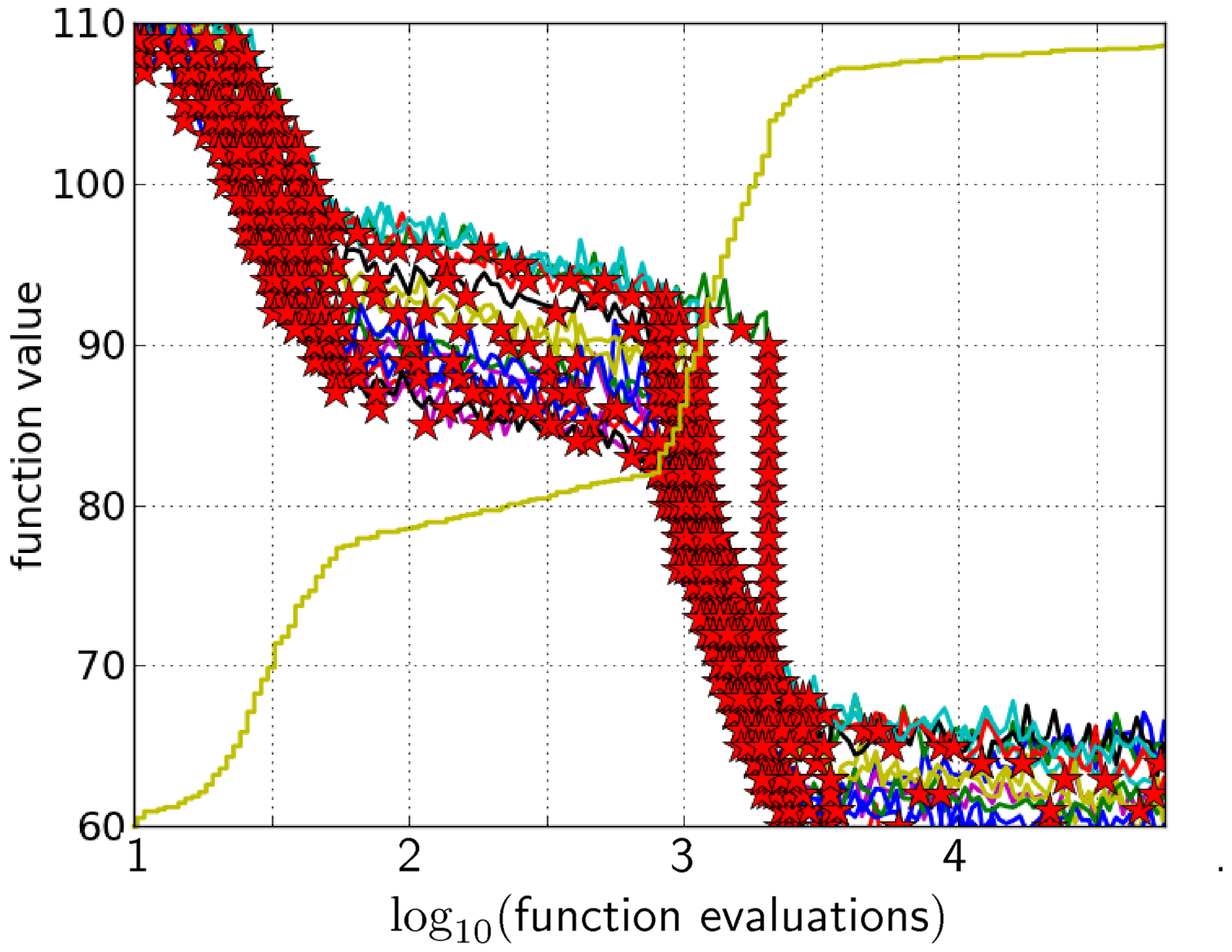
Aggregation



15 runs

50 targets

Aggregation

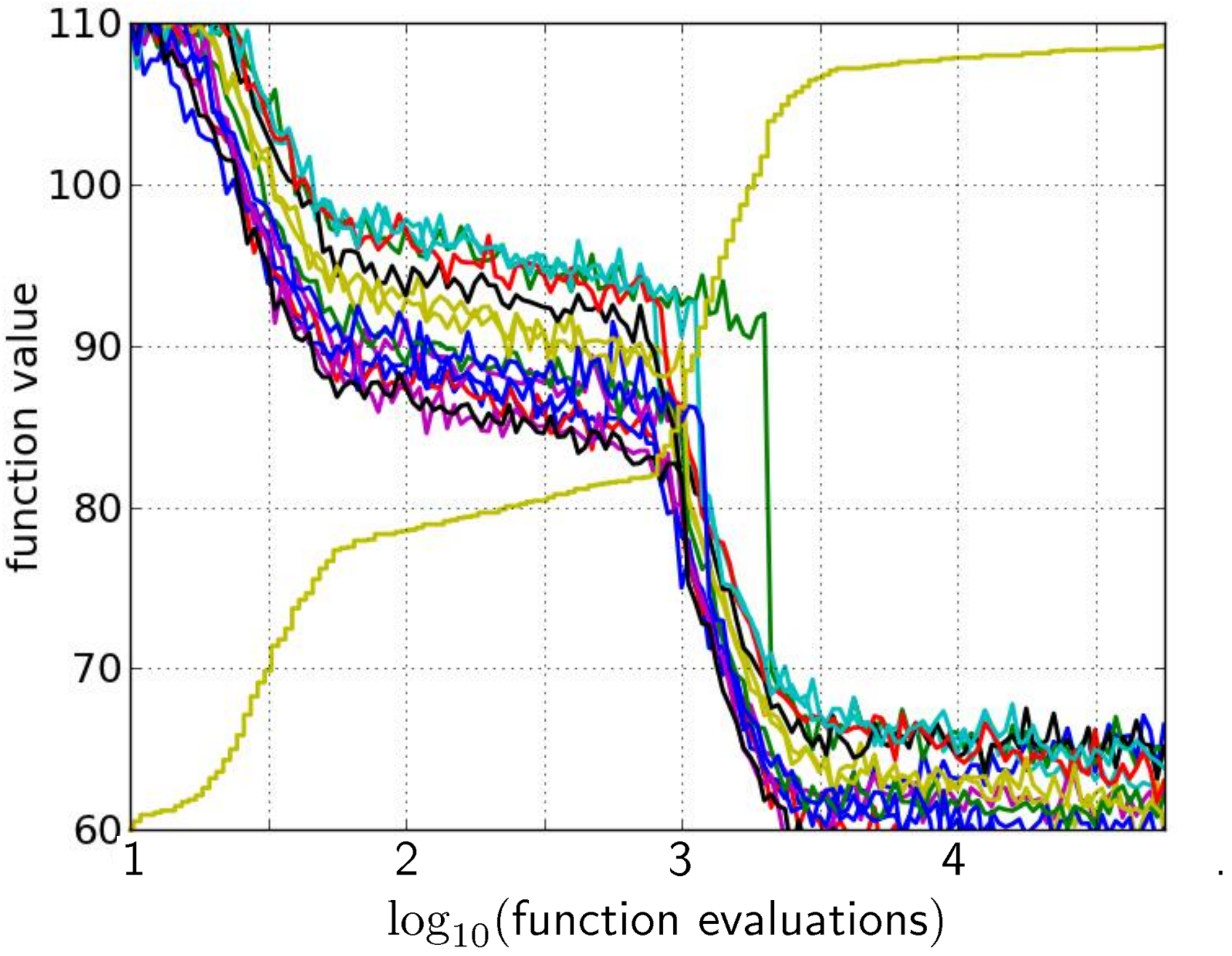


15 runs

50 targets

ECDF with 750 steps

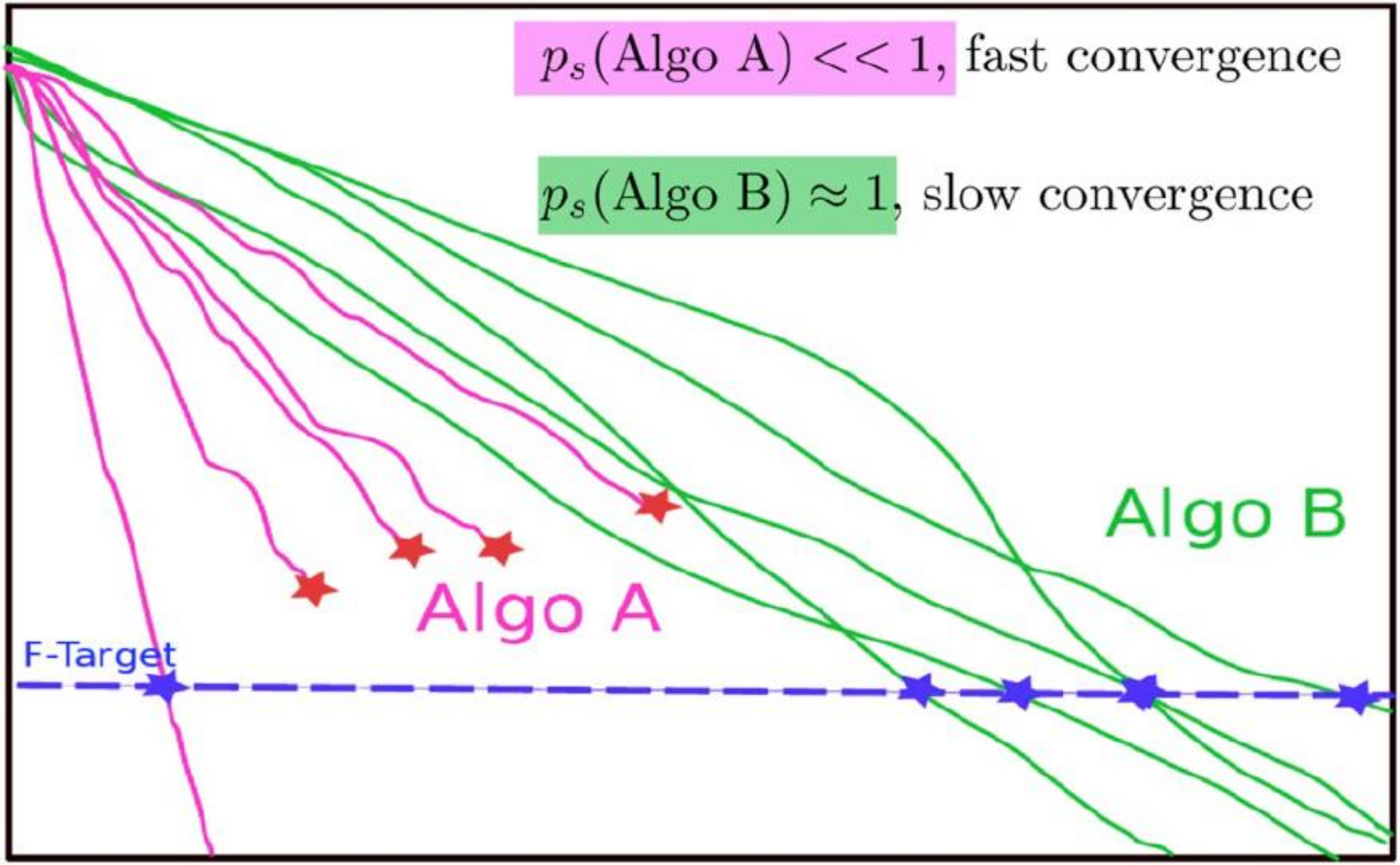
Aggregation



50 targets from
15 runs

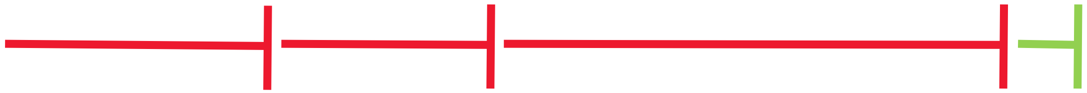
...integrated in a
single graph

Fixed-target: Measuring Runtime


$p_s(\text{Algo A}) << 1$, fast convergence
$p_s(\text{Algo B}) \approx 1$, slow convergence
Algo B
Algo A
F-Target

Fixed-target: Measuring Runtime

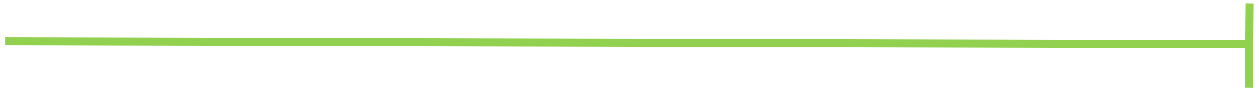
- Algo Restart A:



RT^r_A

p_s(Algo Restart A) = 1

- Algo Restart B:



RT^r_B

p_s(Algo Restart A) = 1

Fixed-target: Measuring Runtime

- Expected running time of the restarted algorithm:

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

- Estimator average running time (aRT):

$$\widehat{p_s} = \frac{\text{\#successes}}{\text{\#runs}}$$

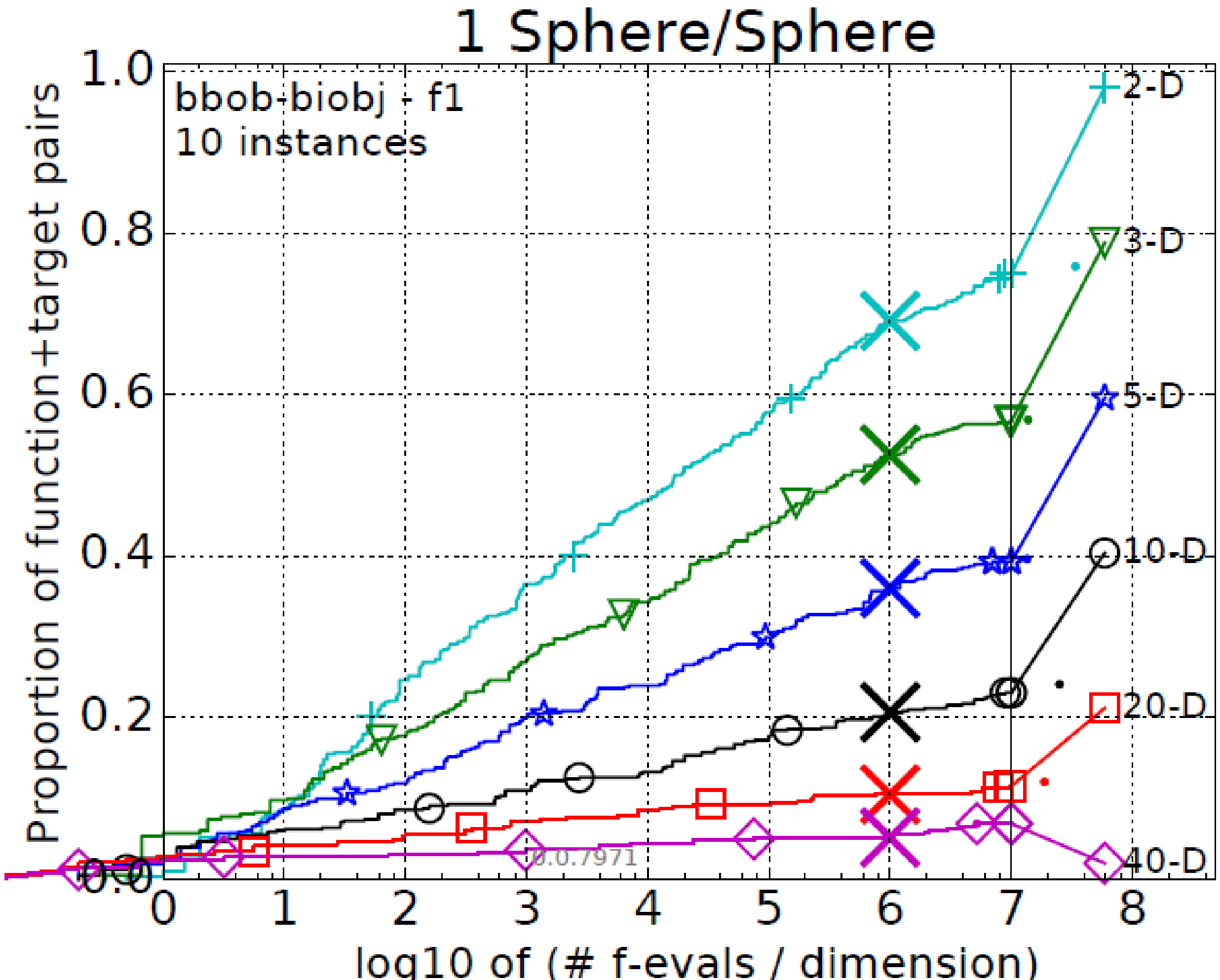
$$\widehat{RT_{unsucc}} = \text{Average evals of unsuccessful runs}$$

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

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

ECDFs with Simulated Restarts

What we typically plot are ECDFs of the simulated restarted algorithms:



Worth to Note: ECDFs in COCO

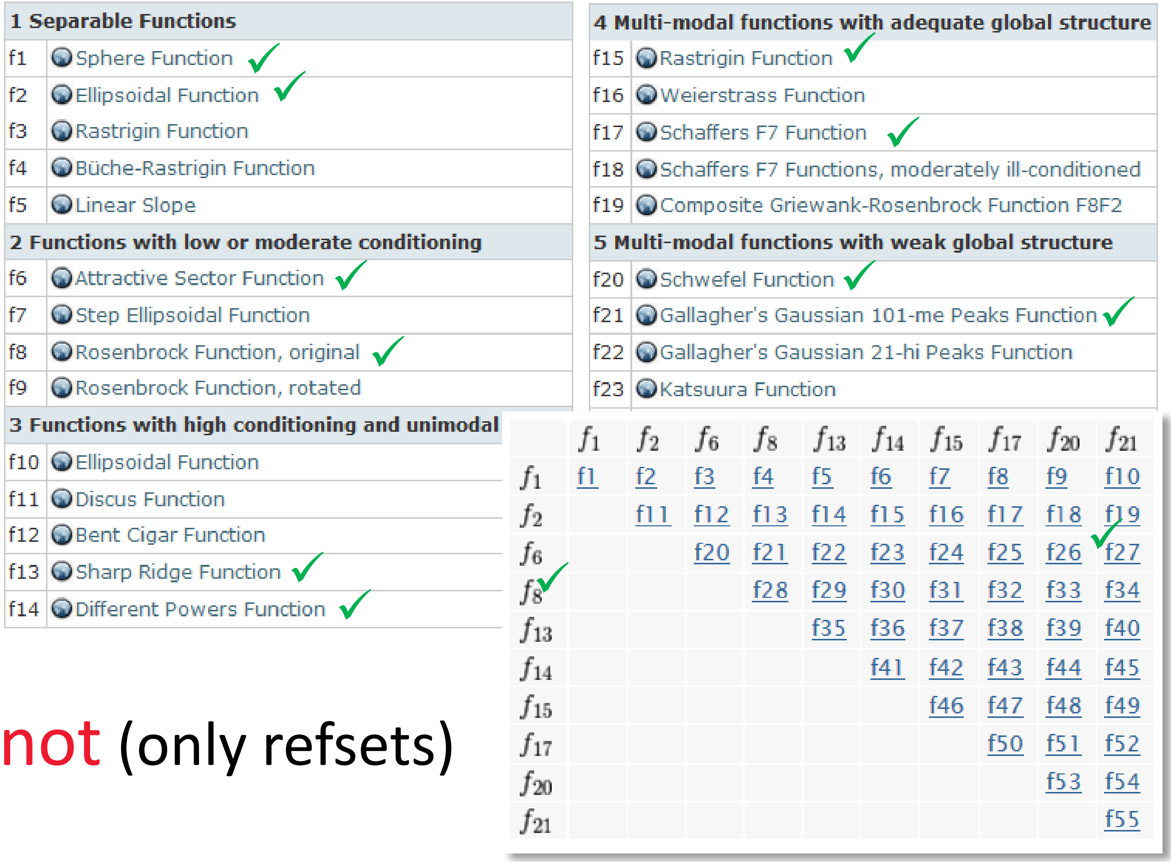
In COCO, ECDF graphs

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

the recent extension to multi-objective optimization

bbob-biobj Testbed (new in 2016)

- 55 functions, combining **bbob** functions
- 6 dimensions (2..40D)
- no normalization
- ideal/nadir known
- but Pareto set/front not (only refsets)



	1 Separable Functions
f1	Sphere Function ✓
f2	Ellipsoidal Function ✓
f3	Rastrigin Function
f4	Büche-Rastrigin Function
f5	Linear Slope
	2 Functions with low or moderate conditioning
f6	Attractive Sector Function ✓
f7	Step Ellipsoidal Function
f8	Rosenbrock Function, original ✓
f9	Rosenbrock Function, rotated
	3 Functions with high conditioning and unimodal
f10	Ellipsoidal Function
f11	Discus Function
f12	Bent Cigar Function
f13	Sharp Ridge Function ✓
f14	Different Powers Function ✓

	4 Multi-modal functions with adequate global structure
f15	Rastrigin Function ✓
f16	Weierstrass Function
f17	Schaffers F7 Function ✓
f18	Schaffers F7 Functions, moderately ill-conditioned
f19	Composite Griewank-Rosenbrock Function F8F2
	5 Multi-modal functions with weak global structure
f20	Schwefel Function ✓
f21	Gallagher's Gaussian 101-me Peaks Function ✓
f22	Gallagher's Gaussian 21-hi Peaks Function
f23	Katsuura Function

	f_1	f_2	f_6	f_8	f_{13}	f_{14}	f_{15}	f_{17}	f_{20}	f_{21}
f_1	f1	f2	f3	f4	f5	f6	f7	f8	f9	f10
f_2		f11	f12	f13	f14	f15	f16	f17	f18	f19
f_6			f20	f21	f22	f23	f24	f25	f26	✓ f27
f_8 ✓				f28	f29	f30	f31	f32	f33	f34
f_{13}					f35	f36	f37	f38	f39	f40
f_{14}						f41	f42	f43	f44	f45
f_{15}							f46	f47	f48	f49
f_{17}								f50	f51	f52
f_{20}									f53	f54
f_{21}										f55

Bi-objective Performance Assessment

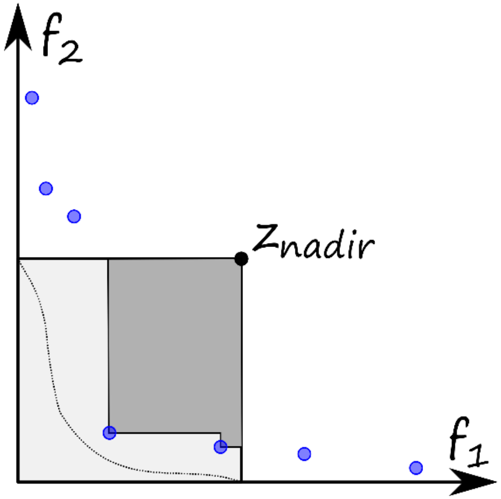
algorithm quality =

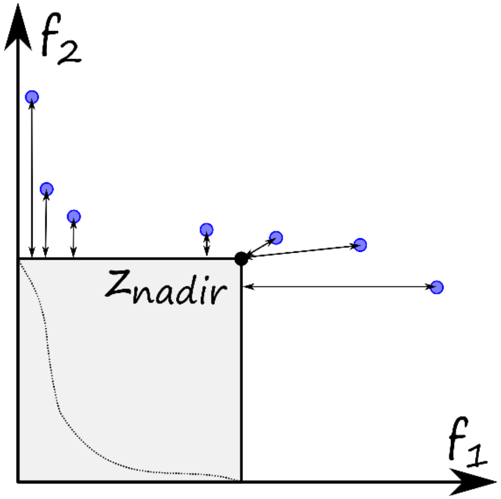
normalized* hypervolume (HV) of all non-dominated solutions

if a point dominates nadir

closest normalized* negative distance to region of interest $[0,1]^2$

if no point dominates nadir





* such that ideal=[0,0] and nadir=[1,1]

Bi-objective Performance Assessment

We measure runtimes to reach (HV indicator) targets:

- relative to a reference set, given as the best Pareto front approximation known (since exact Pareto set not known)
  - for the workshop: `before_workshop` values
  - from now on: updated `current_best` values incl. all non-dominated points found by the 15 workshop algos:
    will be available soon and hopefully fixed for some time
- actual absolute hypervolume targets used are

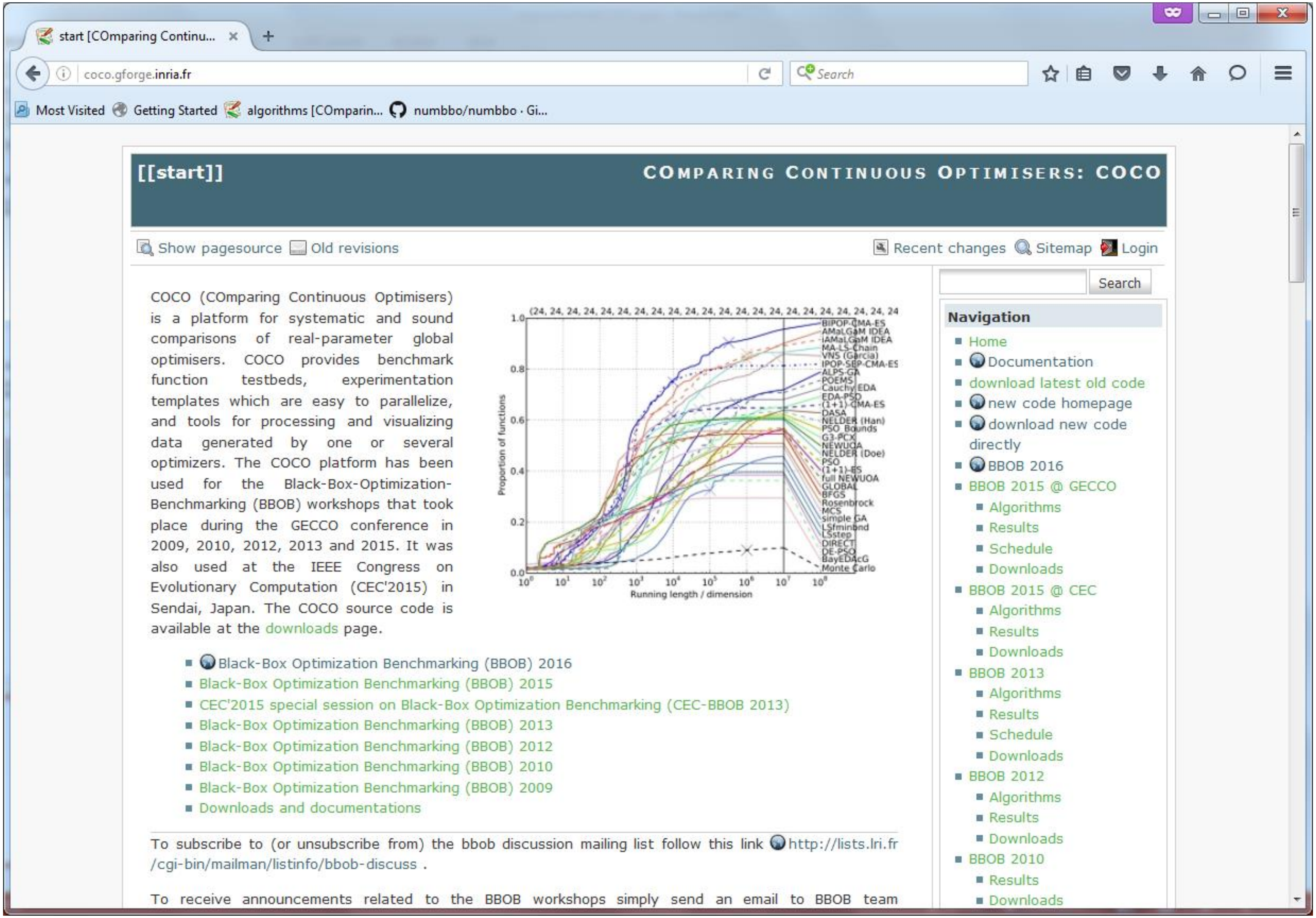
  HV(refset) – targetprecision

with 58 fixed targetprecisions between 1 and -10^{-4} (same for all functions, dimensions, and instances) in the displays

BBOB-2016 Session II

10:40 - 10:55	The BBOBies: Session Introduction
10:55 - 11:20	Cheryl Wong*, Abdullah Al-Dujaili, and Suresh Sundaram: Hypervolume-based DIRECT for Multi-Objective Optimisation
11:20 - 11:45	Abdullah Al-Dujaili* and Suresh Sundaram: A MATLAB Toolbox for Surrogate-Assisted Multi-Objective Optimization: A Preliminary Study
11:45 - 12:10	Oswin Krause*, Tobias Glasmachers, Nikolaus Hansen, and Christian Igel: Unbounded Population MO-CMA-ES for the Bi-Objective BBOB Test Suite
12:10 - 12:30	The BBOBies: Session Wrap-up

http://coco.gforge.inria.fr/



[[start]] COMPARING CONTINUOUS OPTIMISERS: COCO

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COCO (COmparing Continuous Optimisers) is a platform for systematic and sound comparisons of real-parameter global optimisers. COCO provides benchmark function testbeds, experimentation templates which are easy to parallelize, and tools for processing and visualizing data generated by one or several optimizers. The COCO platform has been used for the Black-Box-Optimization-Benchmarking (BBOB) workshops that took place during the GECCO conference in 2009, 2010, 2012, 2013 and 2015. It was also used at the IEEE Congress on Evolutionary Computation (CEC'2015) in Sendai, Japan. The COCO source code is available at the downloads page.

- Black-Box Optimization Benchmarking (BBOB) 2016
- Black-Box Optimization Benchmarking (BBOB) 2015
- CEC'2015 special session on Black-Box Optimization Benchmarking (CEC-BBOB 2013)
- Black-Box Optimization Benchmarking (BBOB) 2013
- Black-Box Optimization Benchmarking (BBOB) 2012
- Black-Box Optimization Benchmarking (BBOB) 2010
- Black-Box Optimization Benchmarking (BBOB) 2009
- Downloads and documentations

To subscribe to (or unsubscribe from) the bbob discussion mailing list follow this link http://lists.lri.fr/cgi-bin/mailman/listinfo/bbob-discuss .

To receive announcements related to the BBOB workshops simply send an email to BBOB team

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