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

The BBOBies
https://github.com/numbbo/coco

INVENTORS FOR THE DIGITAL WORLD

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

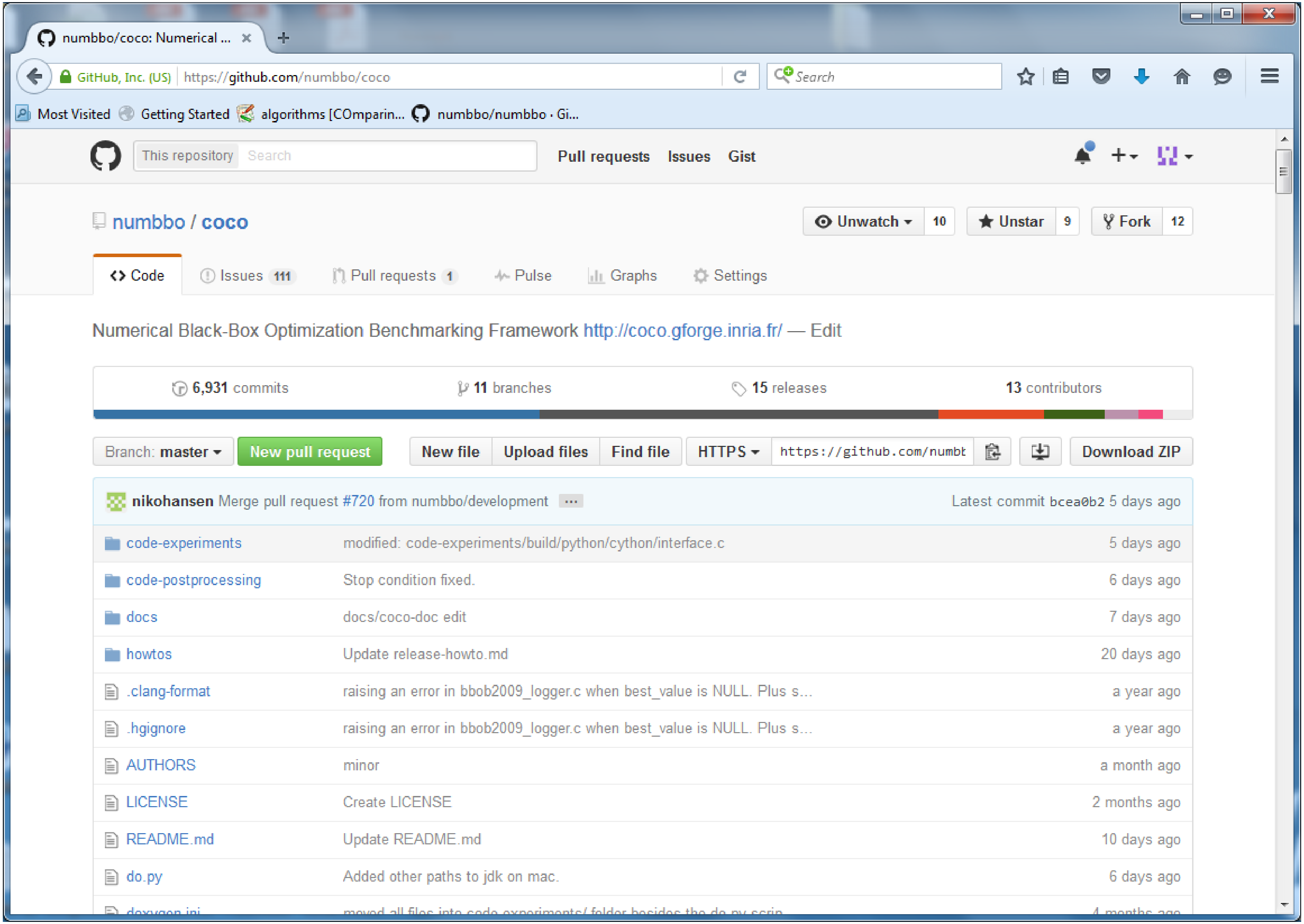
that's where COCO and BBOB come into play

Comparing Continuous Optimizers Platform

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

automatized benchmarking

https://github.com/numbbo/coco



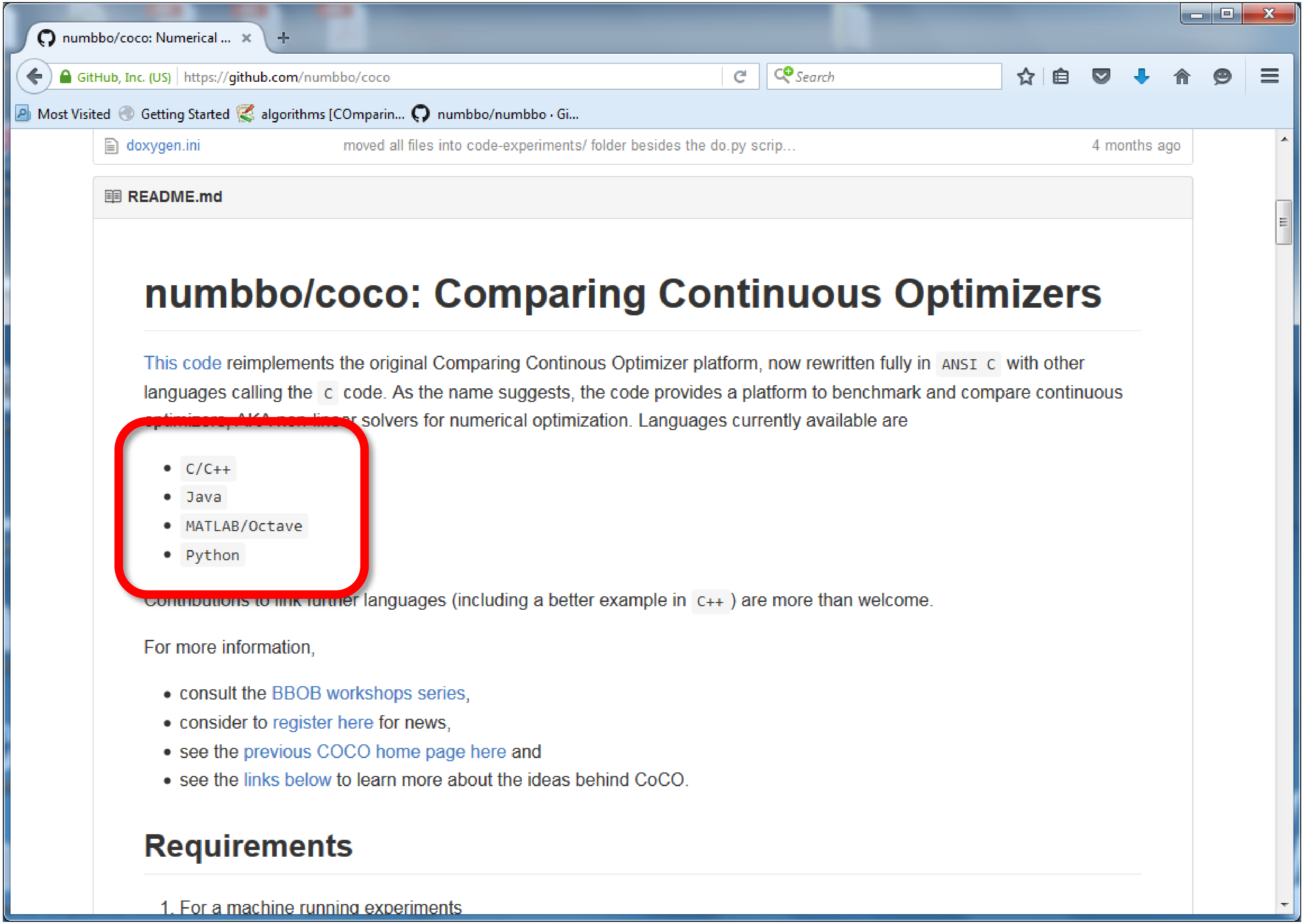
Numerical Black-Box Optimization Benchmarking Framework http://coco.gforge.inria.fr/ — Edit

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.

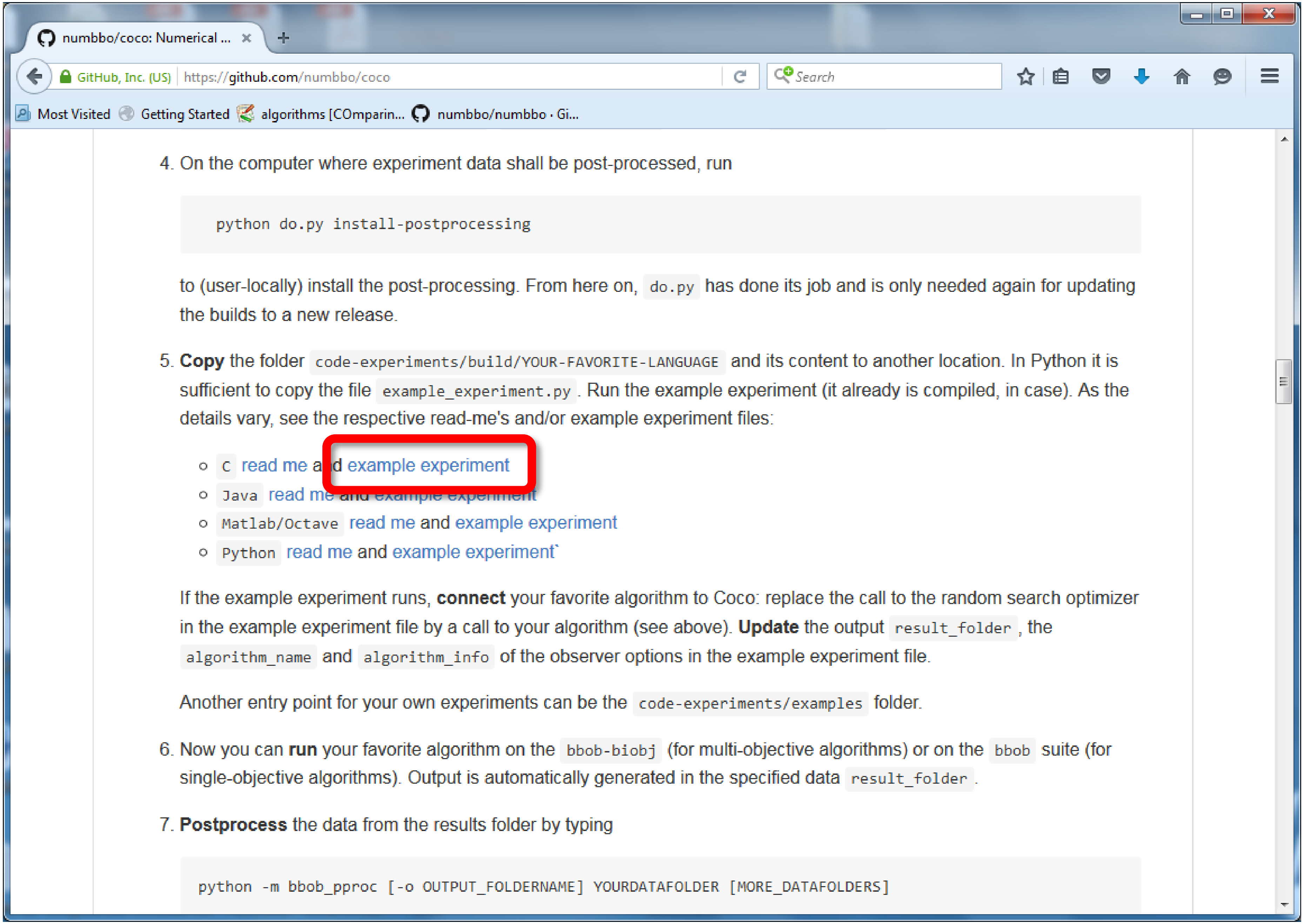
For more information,

- 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.

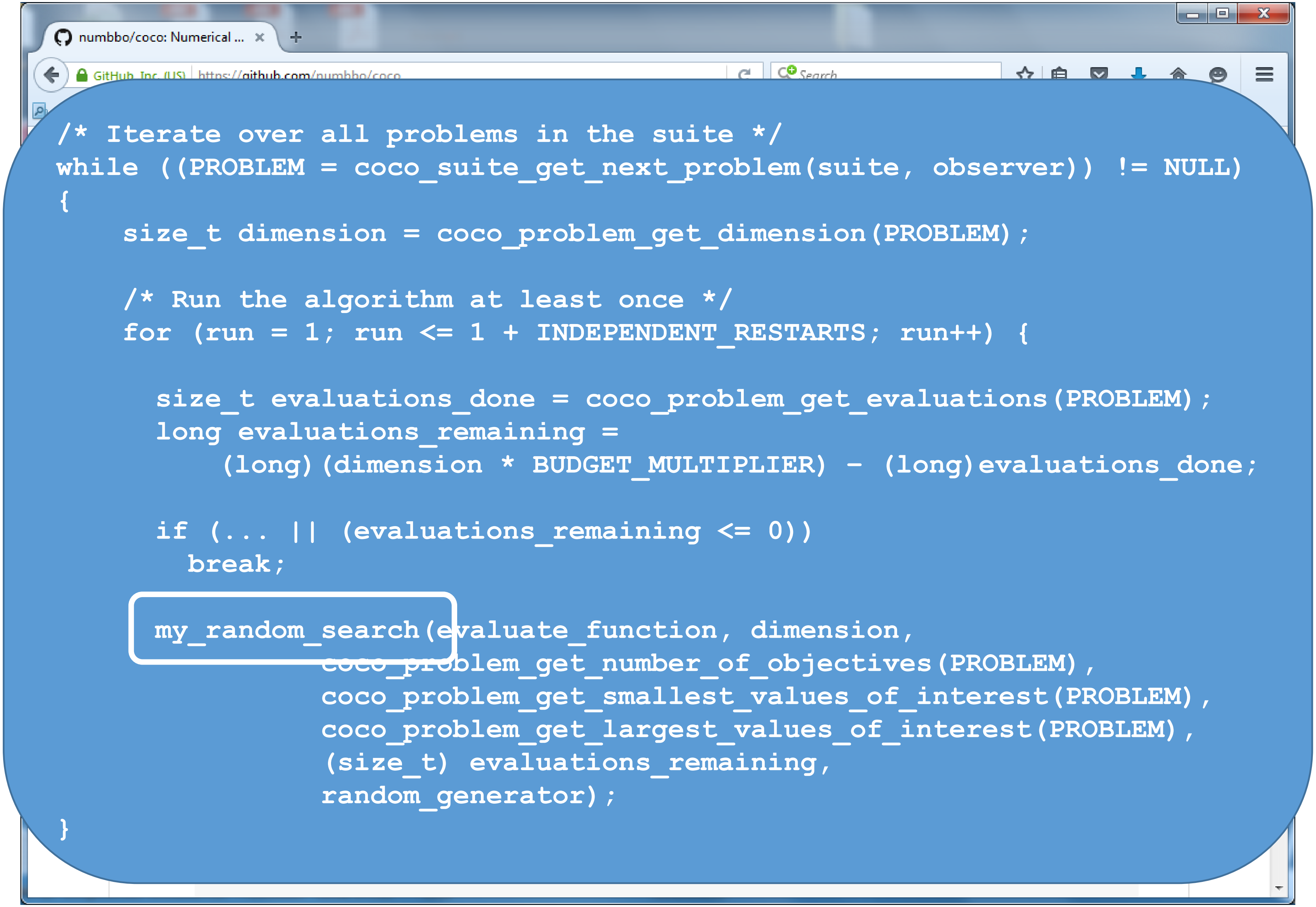
    Another entry point for your own experiments can be the `code-experiments/examples` folder.

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

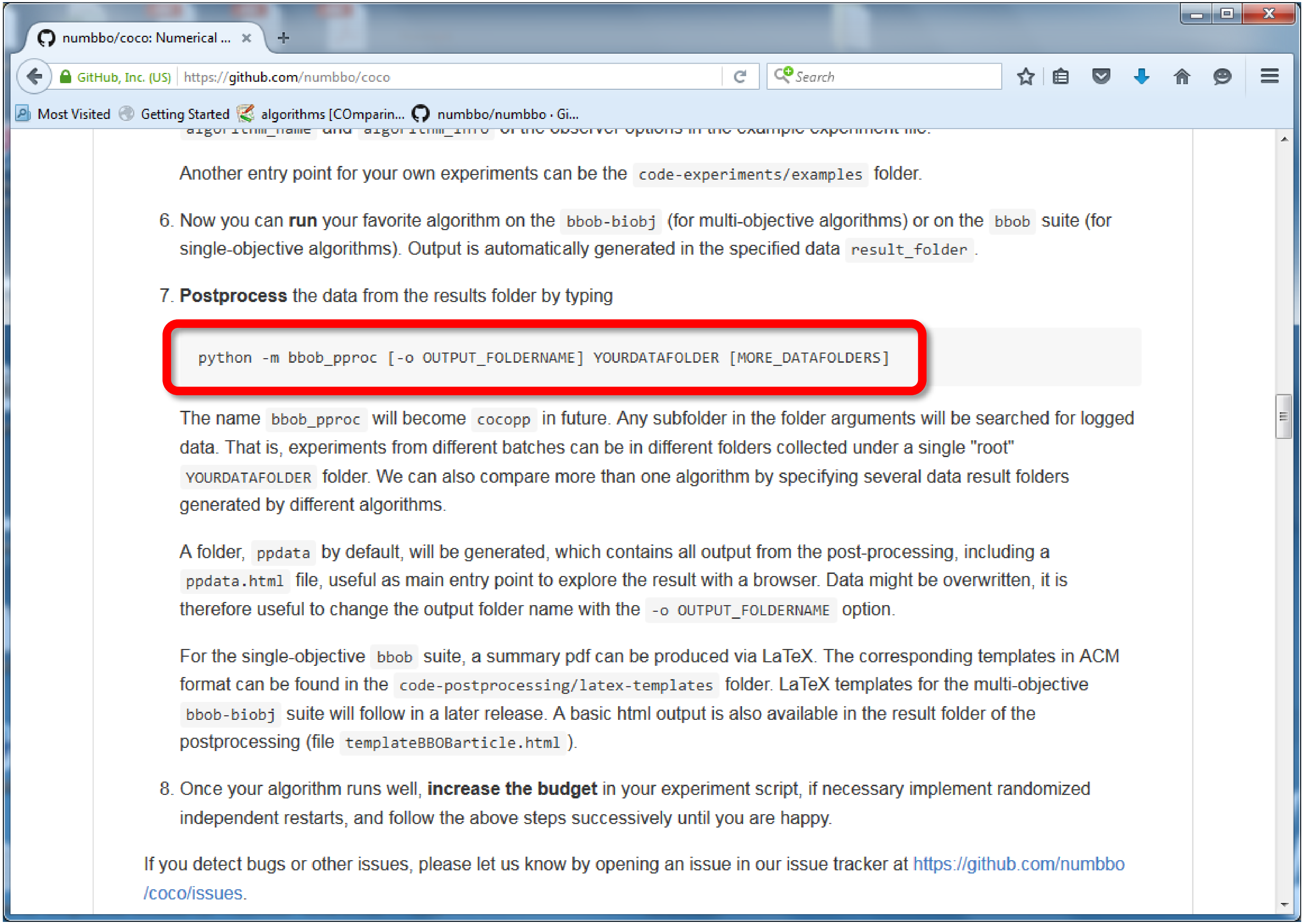
```
python -m bbob_pproc [-o OUTPUT_FOLDERNAME] YOURDATAFOLDER [MORE_DATAFOLDERS]
```

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`.

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```
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.

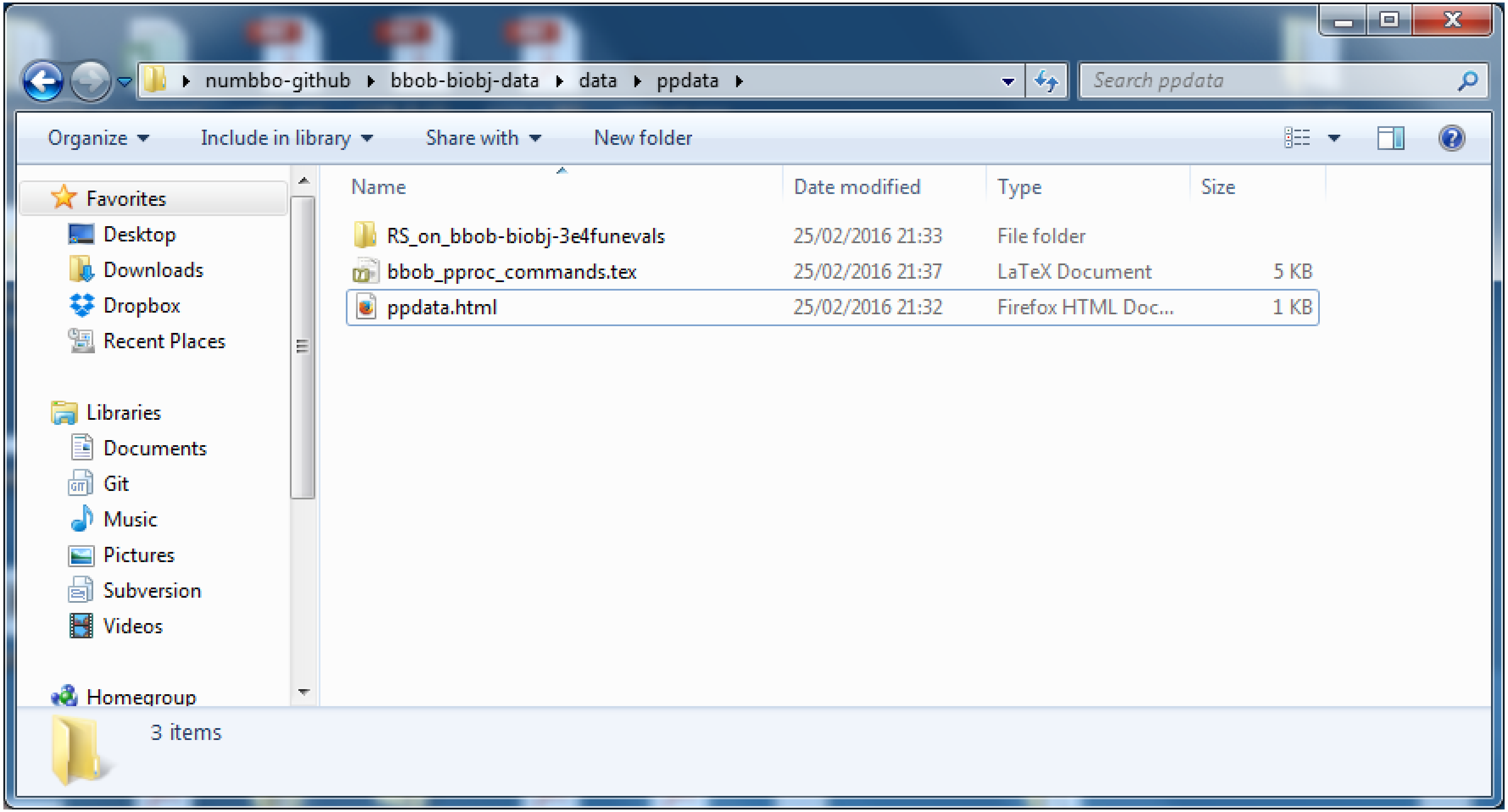
A folder, `ppdata` by default, will be generated, which contains all output from the post-processing, including a `ppdata.html` file, useful as main entry point to explore the result with a browser. Data might be overwritten, it is therefore useful to change the output folder name with the `-o OUTPUT_FOLDERNAME`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

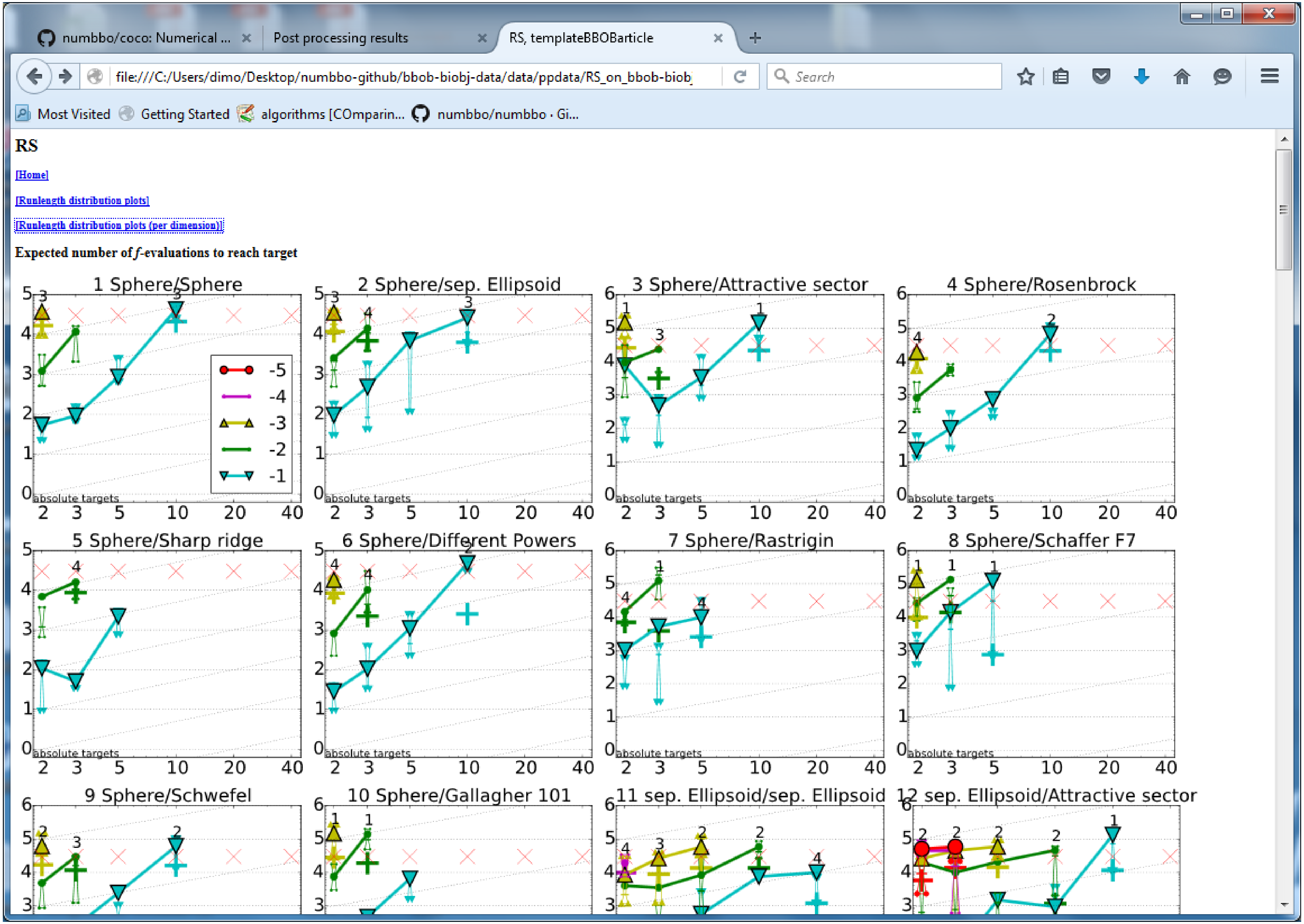
result folder



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

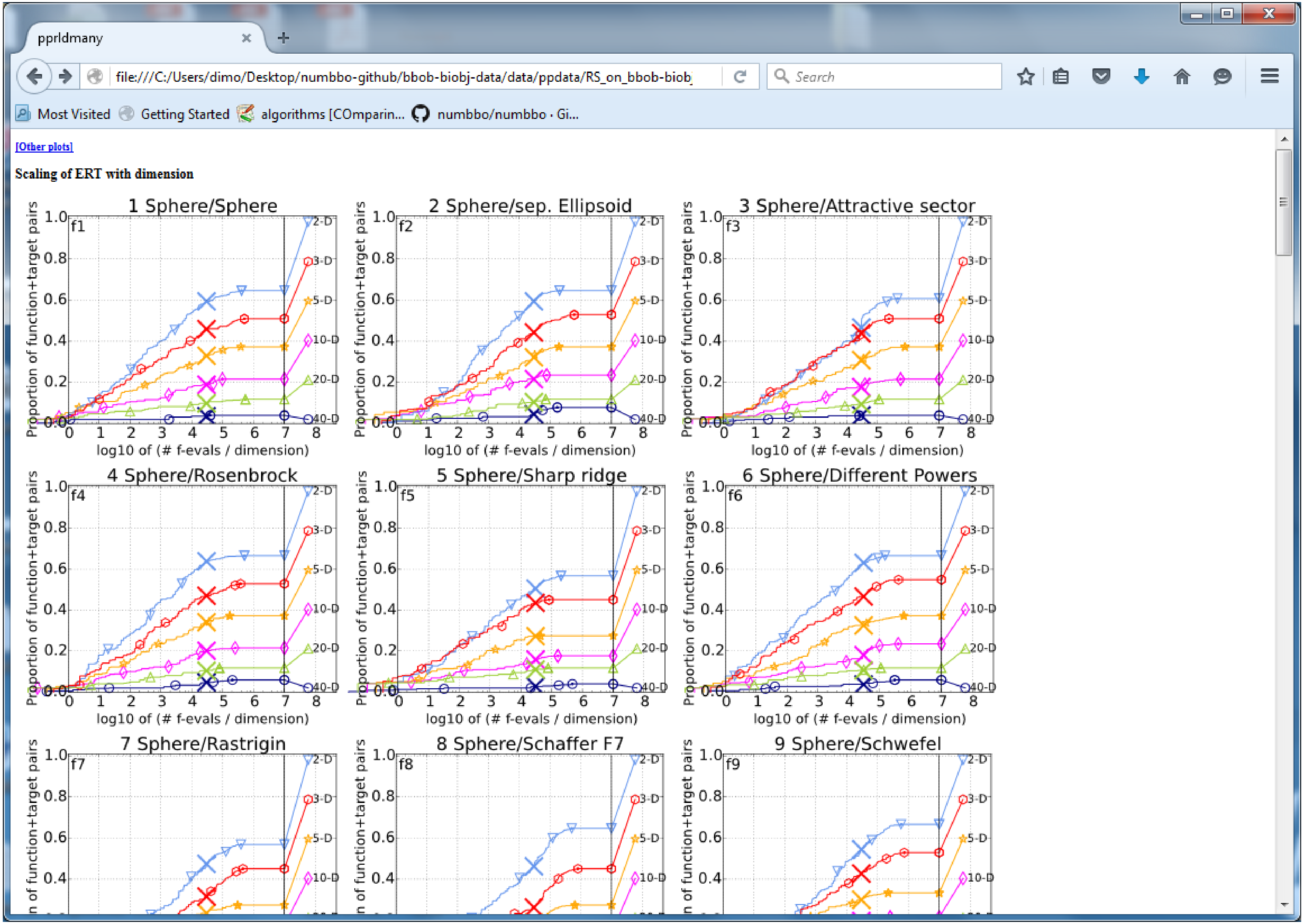
[Home]

[Runlength distribution plots]

[Runlength distribution plots (per dimension)]

Expected number of *f*-evaluations to reach target

automatically generated results



[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)

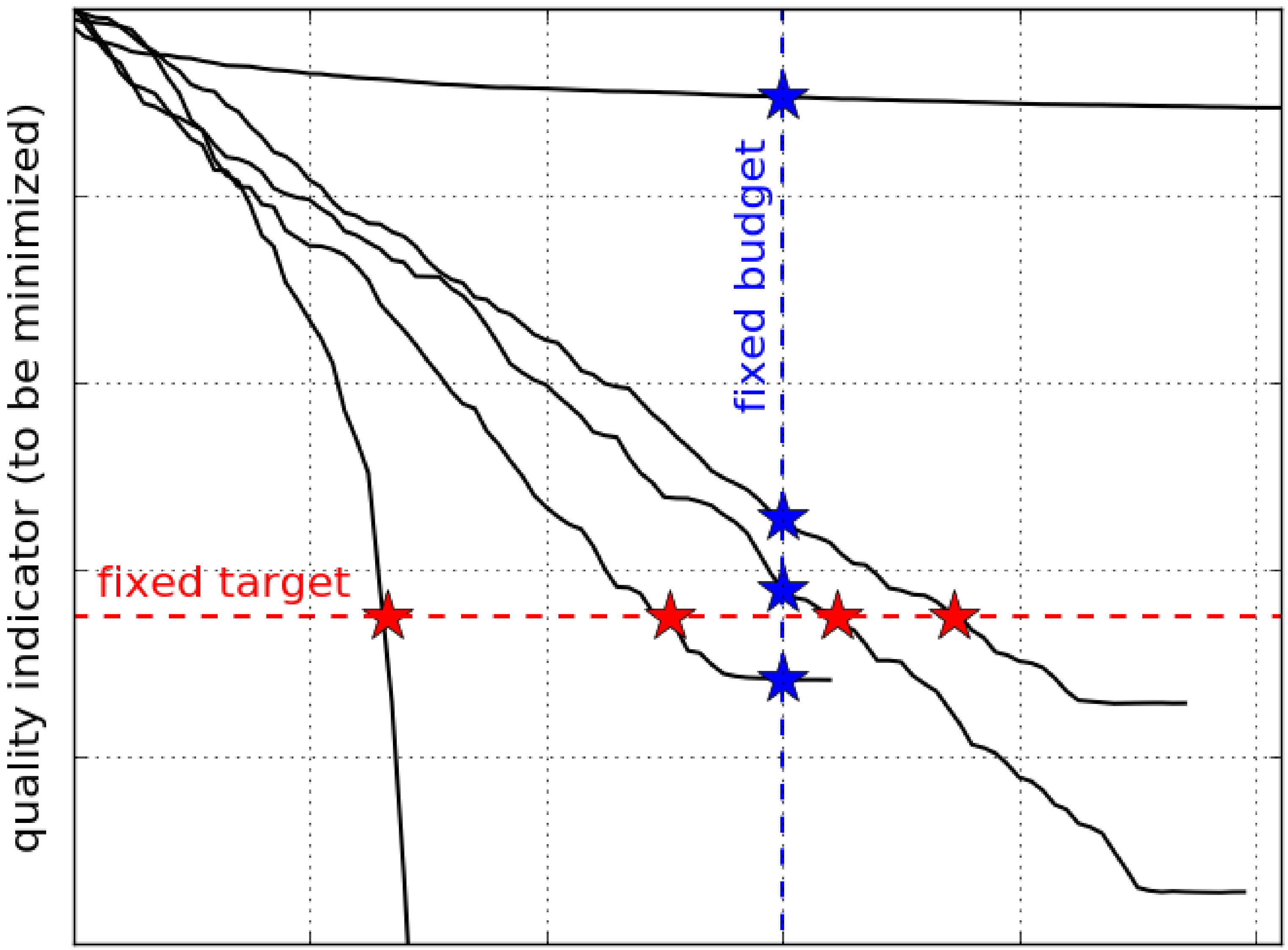
How Do We Measure Performance?

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

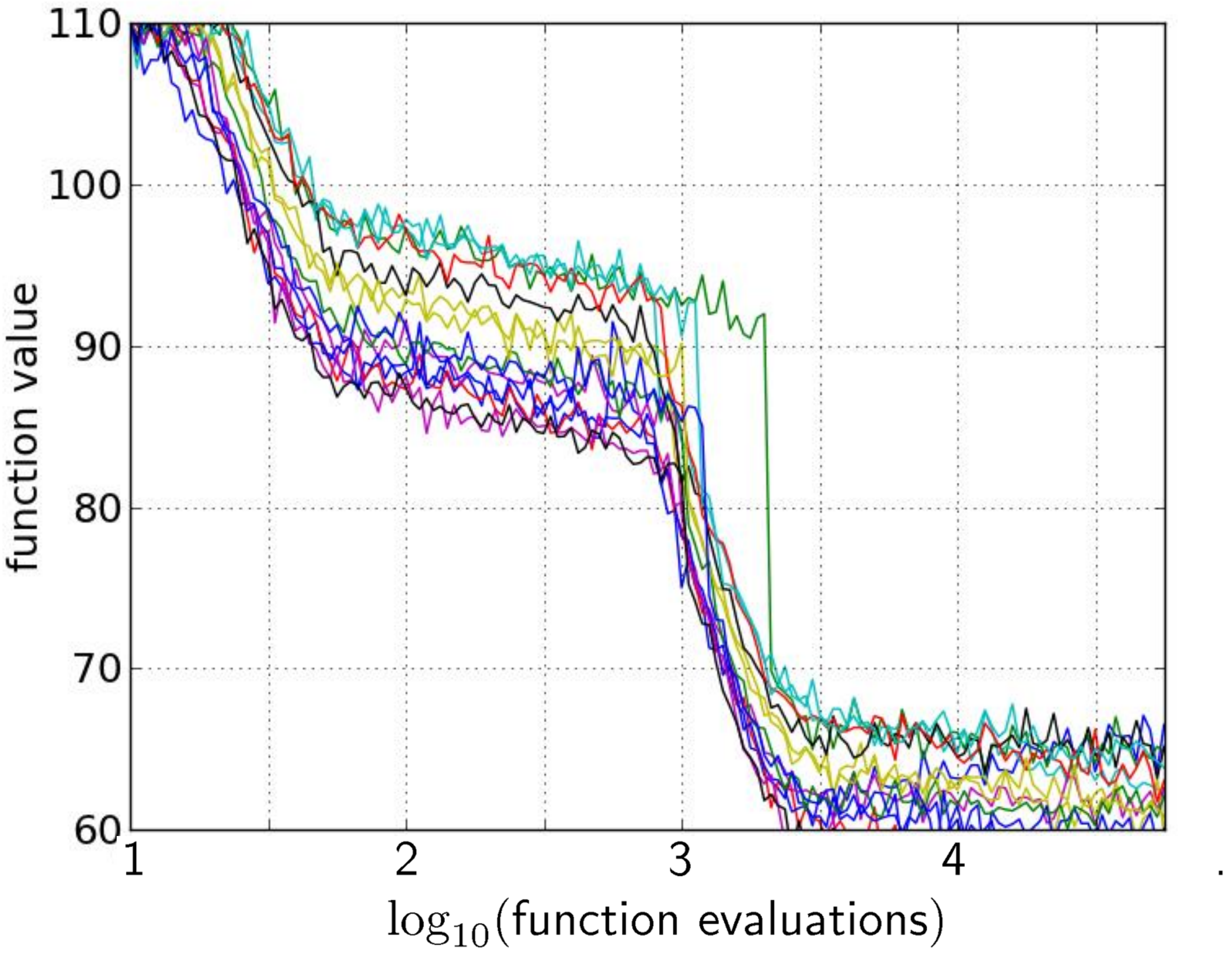


ECDF:

Empirical Cumulative Distribution Function of the Runtime

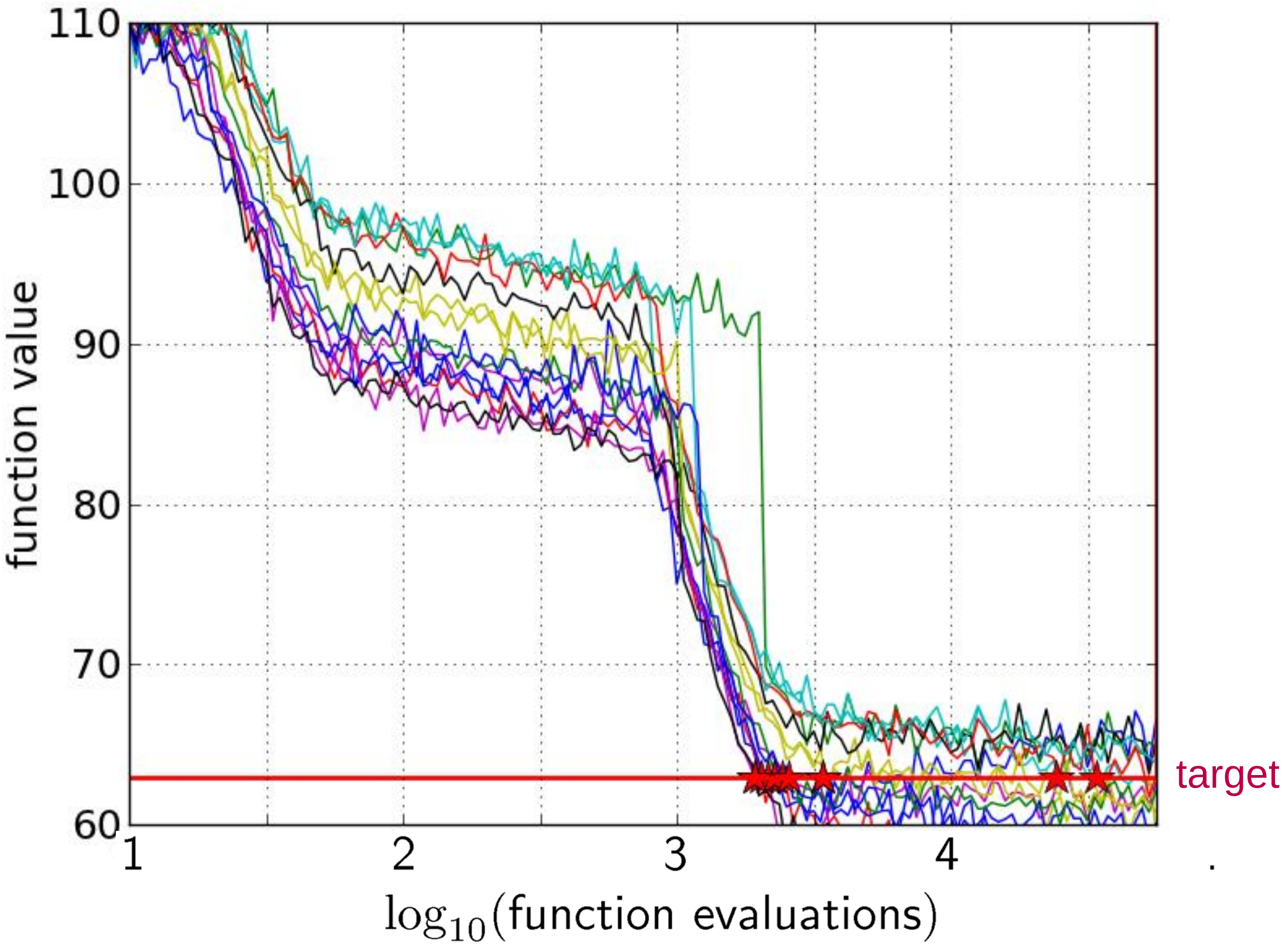
[aka data profile]

15 Runs



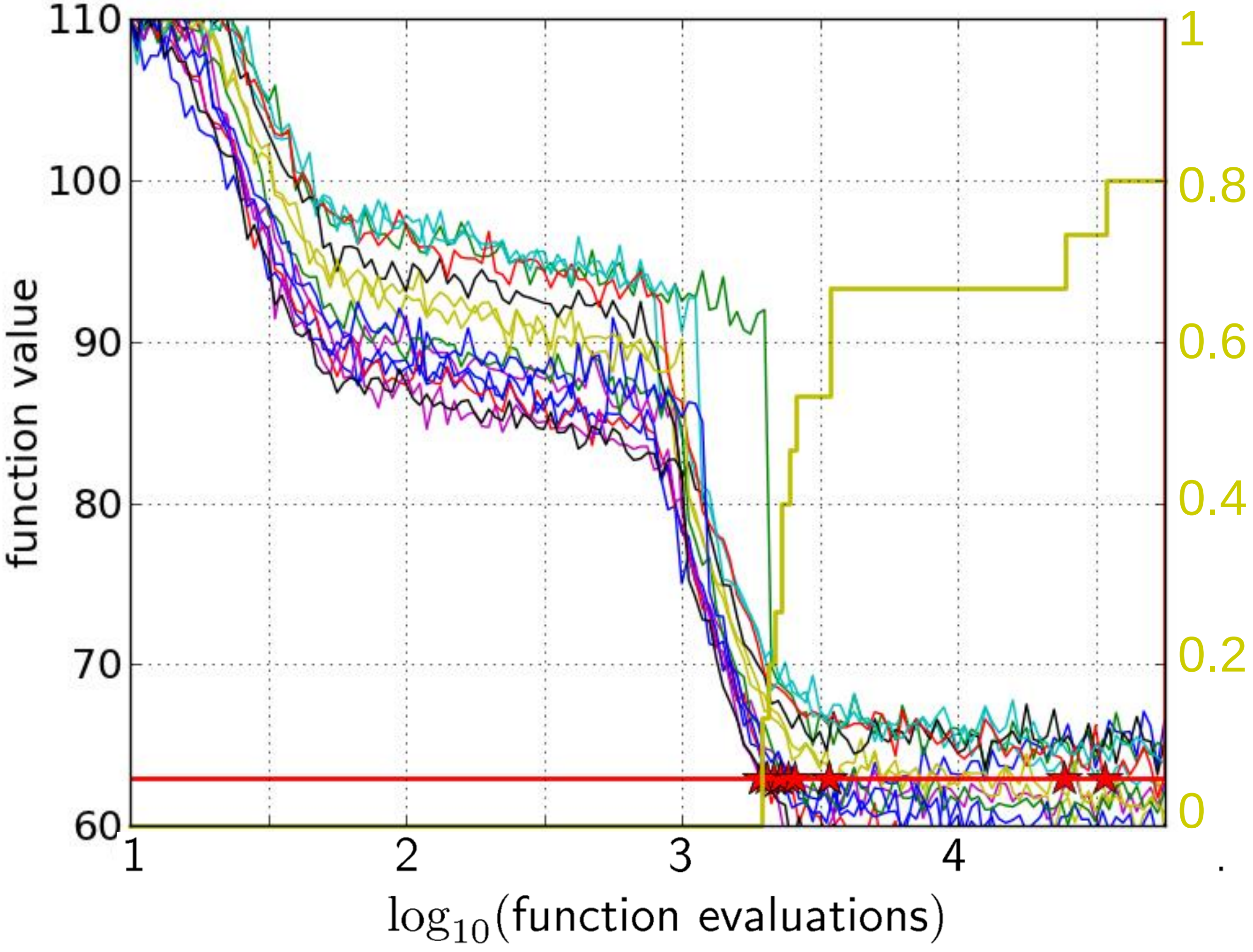
110
100
90
80
70
60
function value
1
2
3
4
log$_{10}$(function evaluations)

15 Runs ≤ 15 Runtime Data Points



.

Empirical Cumulative Distribution

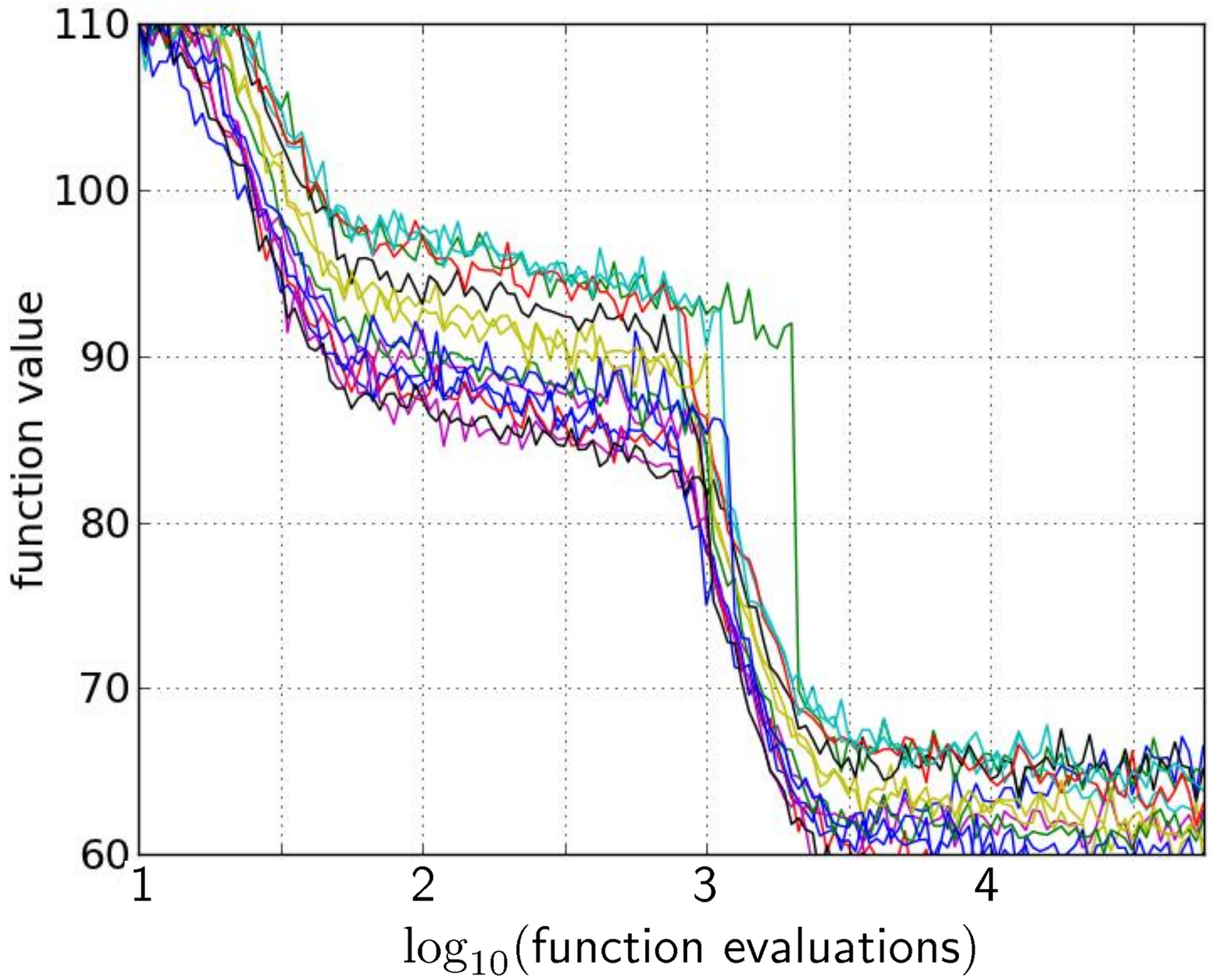


the ECDF of run lengths to reach the target

- 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

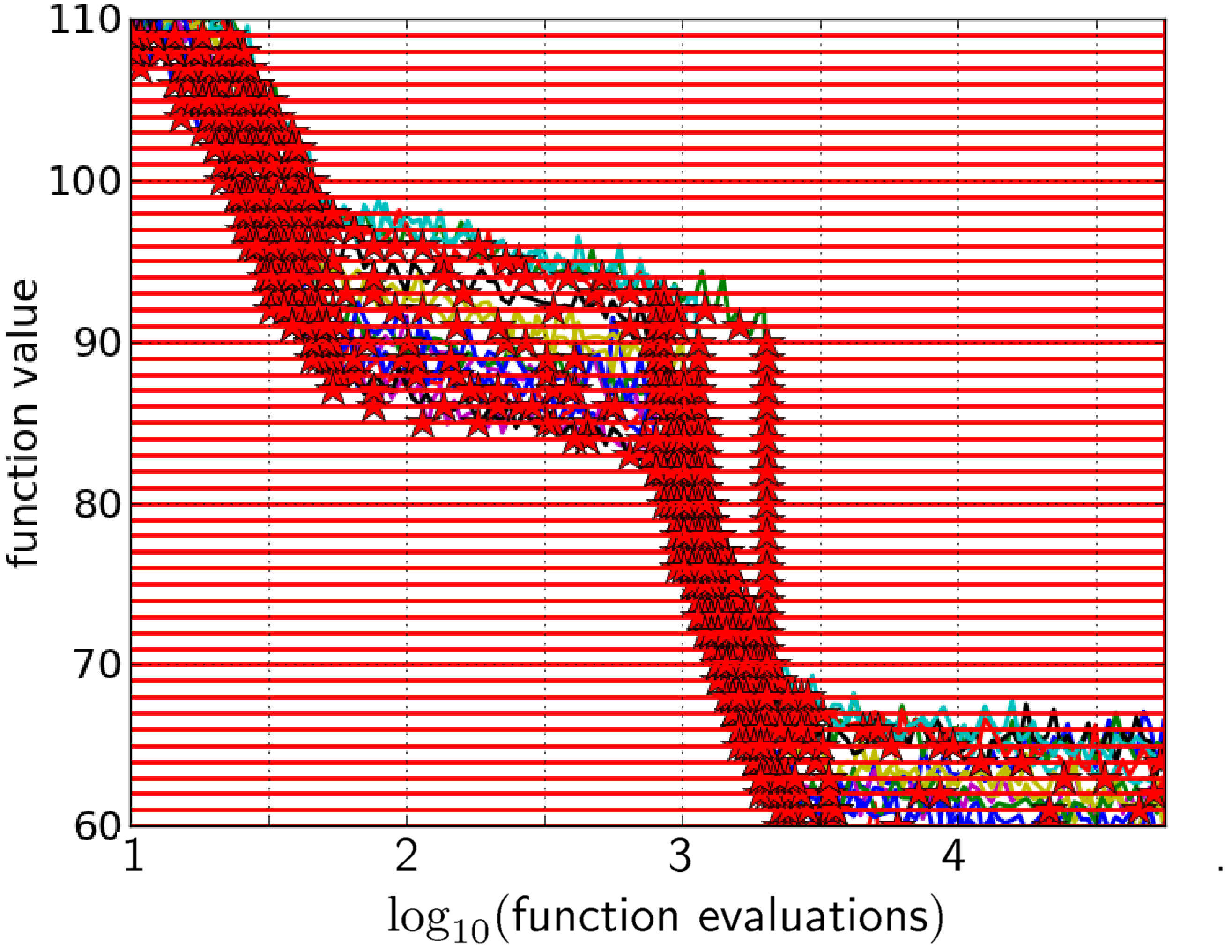
Aggregation



15 runs

.

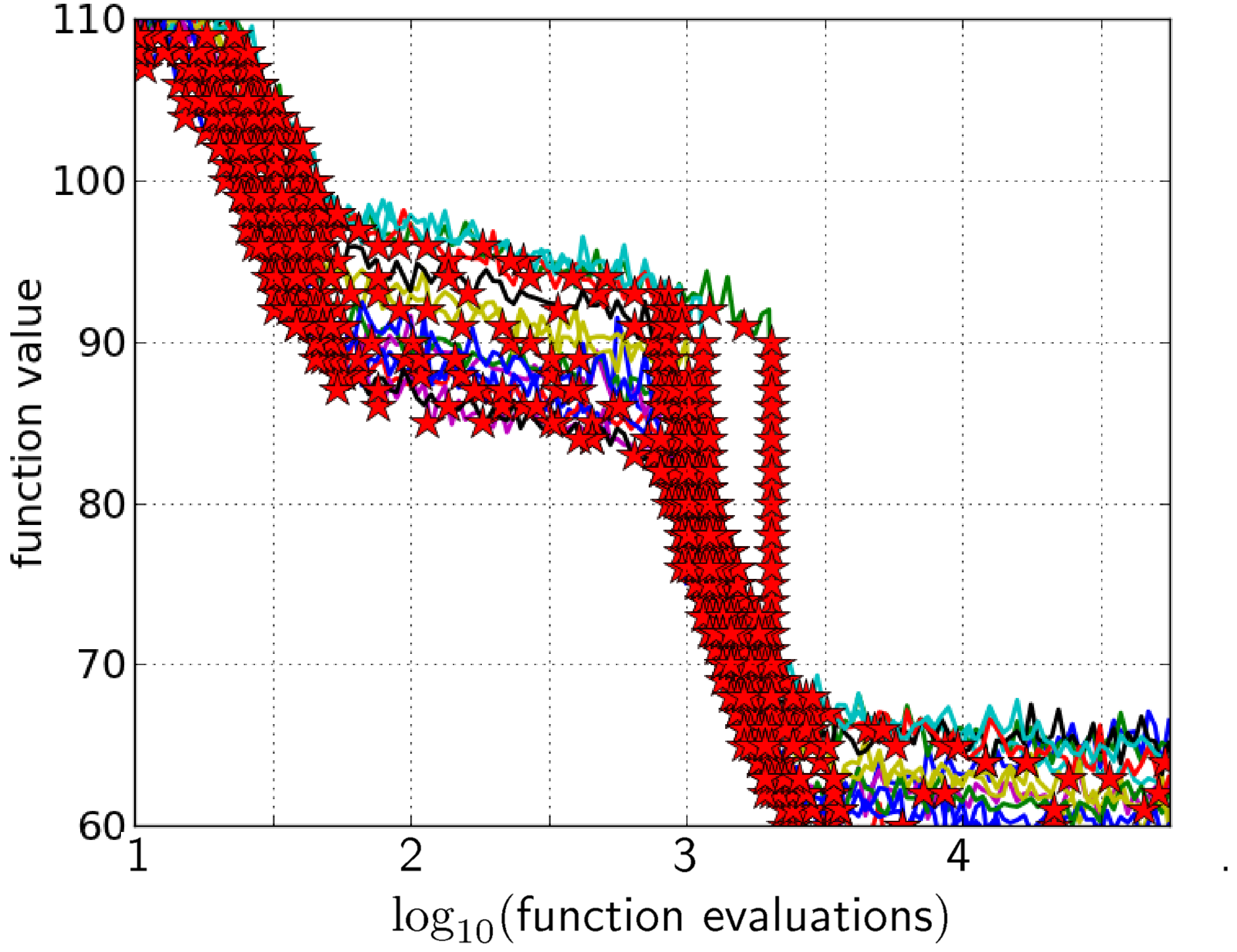
Aggregation



15 runs

50 targets

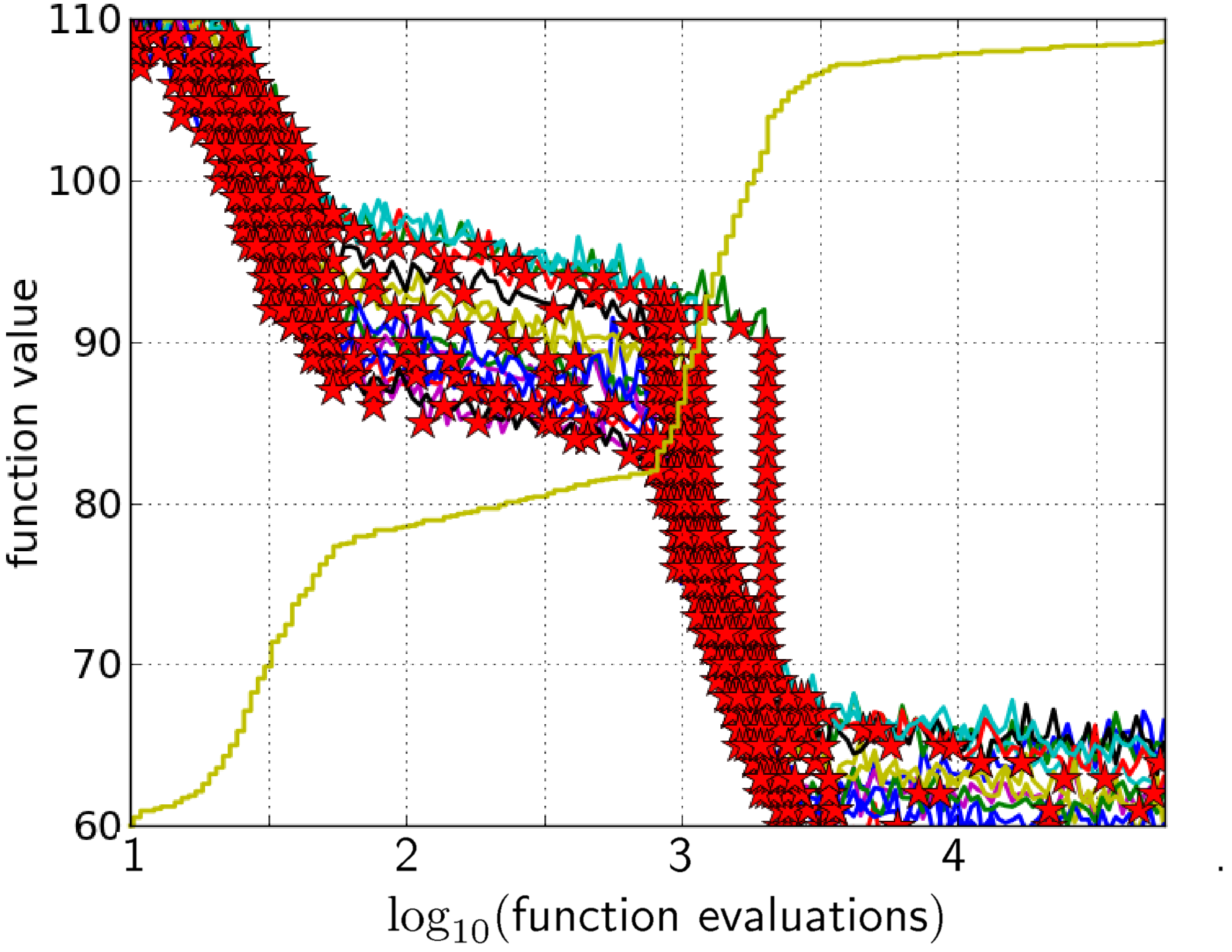
Aggregation



15 runs

50 targets

Aggregation

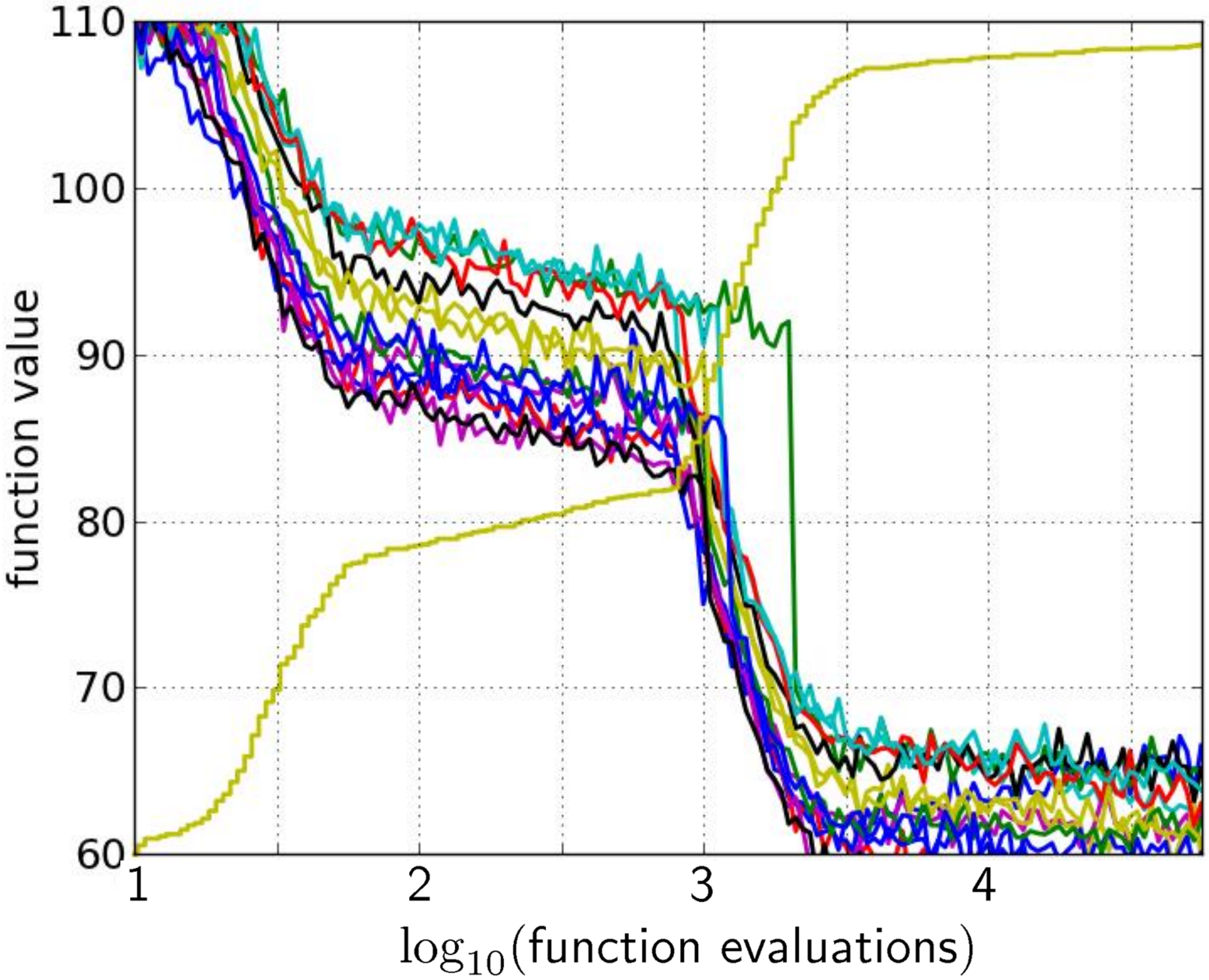


15 runs

50 targets

ECDF with 750 steps

Aggregation

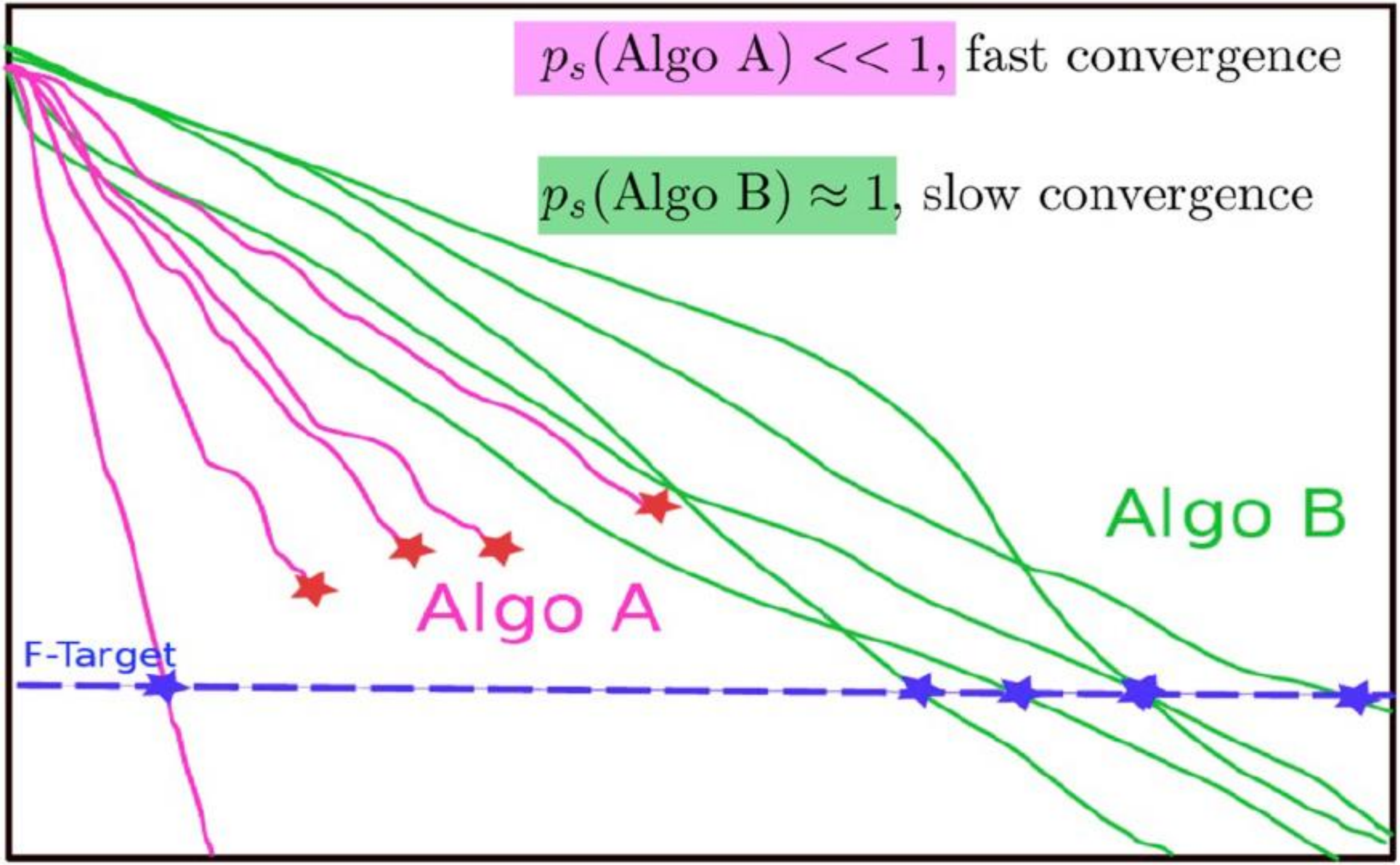


.

50 targets from
15 runs

...integrated in a
single graph

Fixed-target: Measuring Runtime



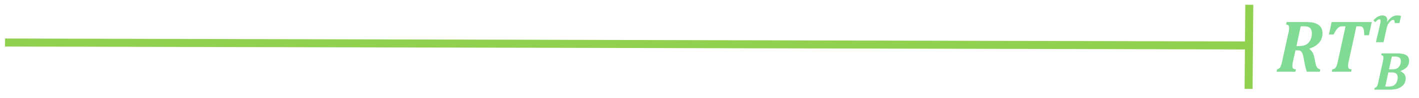
Fixed-target: Measuring Runtime

- 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):

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

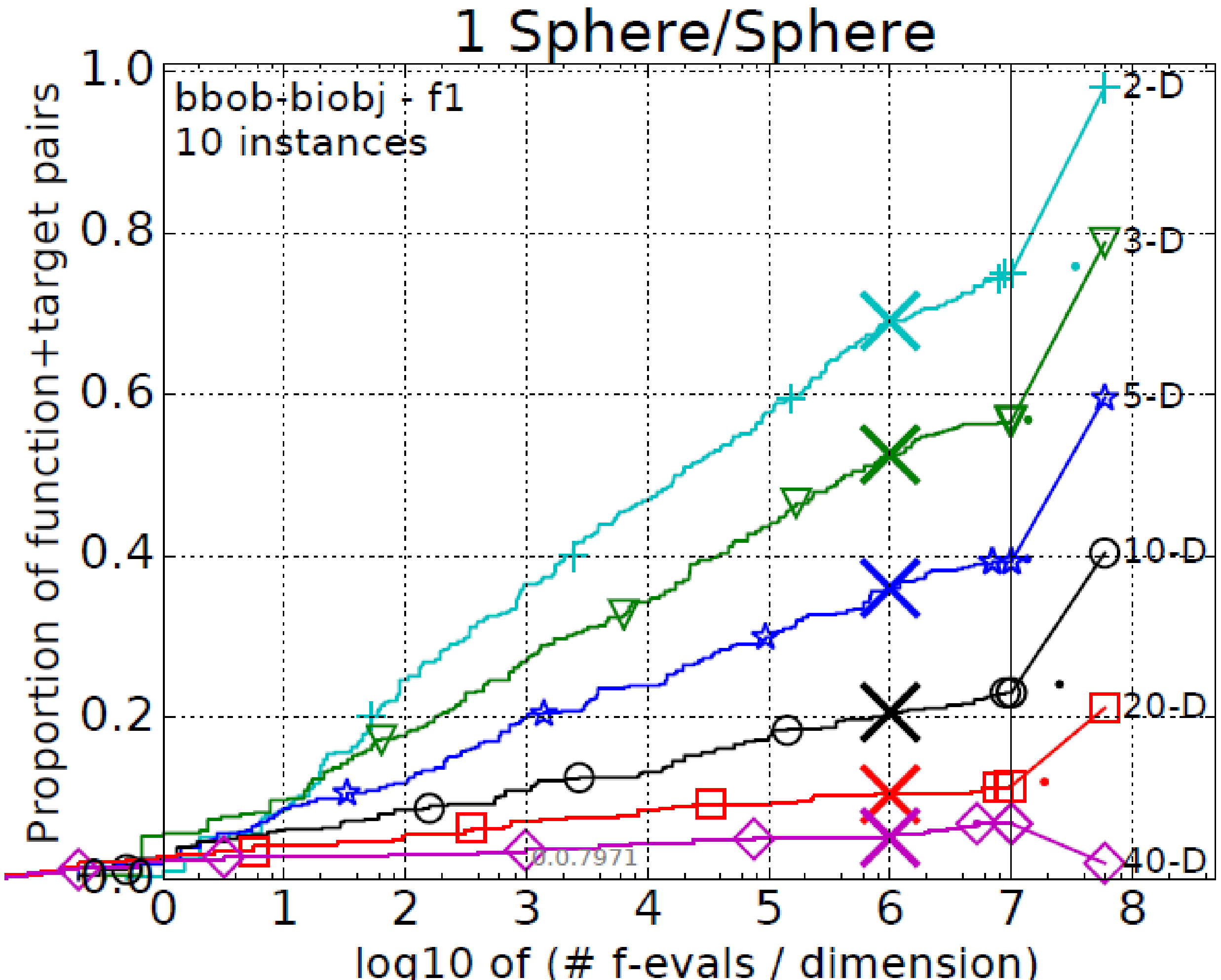
$$\widehat{RT_{unsucc}} = \text{Average evals of unsuccessful runs}$$

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

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

ECDFs with Simulated Restarts

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



Worth to Note: ECDFs in COCO

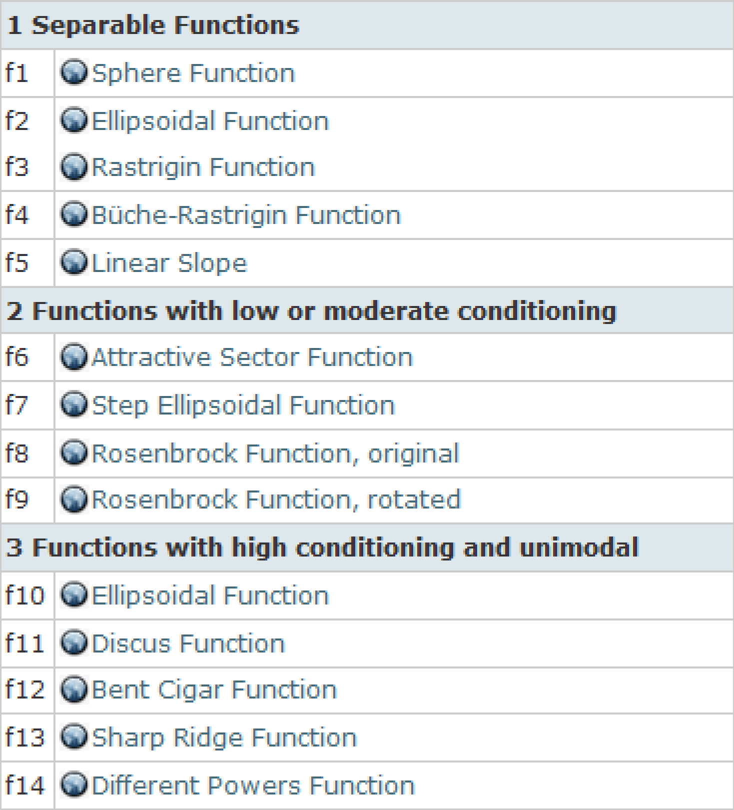
In COCO, ECDF graphs

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

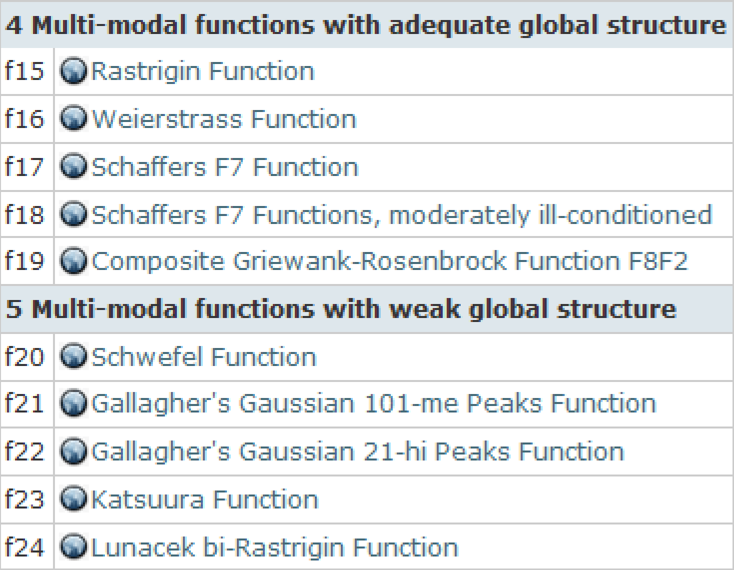
The single-objective BBOB functions

bbob Testbed

- 24 functions in 5 groups:



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
f24	Lunacek bi-Rastrigin Function

- 6 dimensions: 2, 3, 5, 10, 20, (40 optional)

Notion of Instances

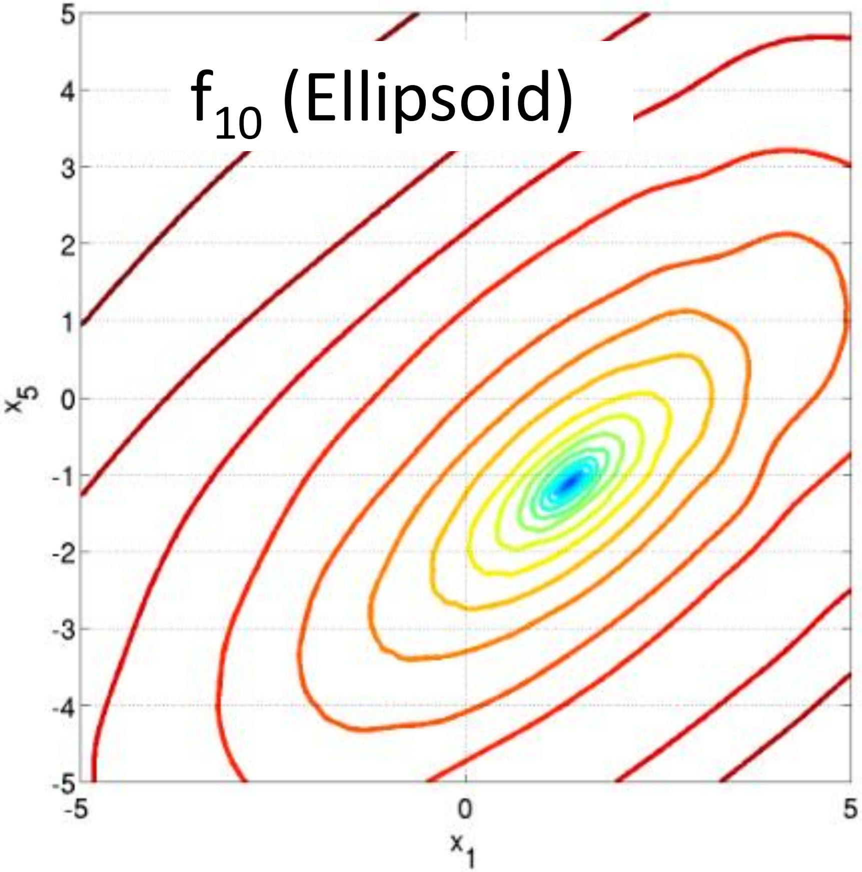
- All COCO problems come in form of instances
  - e.g. as translated/rotated versions of the same function
- Prescribed instances typically change from year to year
  - avoid overfitting
  - 5 instances are always kept the same

Plus:

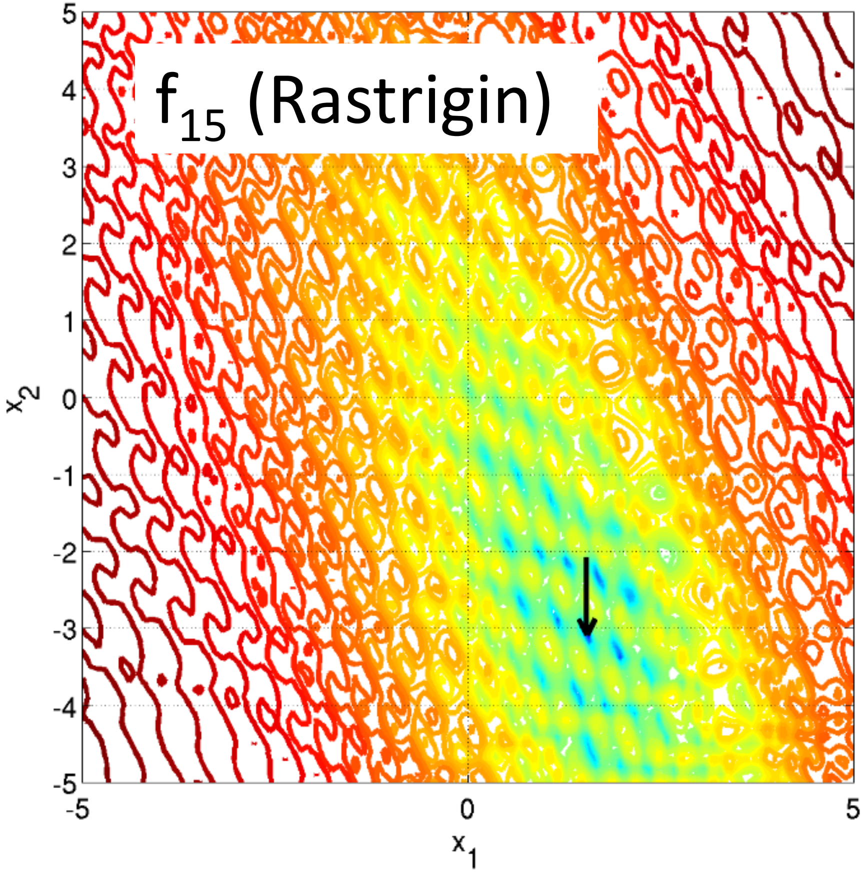
  - the bbob functions are locally perturbed by non-linear transformations

Notion of Instances

- All COCO problems come in form of instances



f_{10} (Ellipsoid)



f_{15} (Rastrigin)

r

`bbob-noisy` Testbed

- 30 functions with various kinds of noise types and strengths
  - 3 noise types: Gaussian, uniform, and seldom Cauchy
  - Functions with moderate noise
  - Functions with severe noise
  - Highly multi-modal functions with severe noise
  - `bbob` functions included: Sphere, Rosenbrock, Step ellipsoid, Ellipsoid, Different Powers, Schaffers' F7, Composite Griewank-Rosenbrock
- 6 dimensions: 2, 3, 5, 10, 20, (40 optional)

BBOB-2016 Session III

14:00 - 14:15	The BBOBies: Session Introduction
14:15 - 14:40	Kouhei Nishida* and Youhei Akimoto: Evaluating the Population Size Adaptation Mechanism for CMA-ES
14:40 - 15:05	The BBOBies: Wrap-up of all BBOB-2016 Results
15:05 - 15:30	Thomas Weise*: optimizationBenchmarking.org: An Introduction
15:30 - 15:50	Open Discussion