8th GECCO Workshop on Blackbox Optimization Benchmarking (BBOB): Welcome and Introduction to COCO/BBOB

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

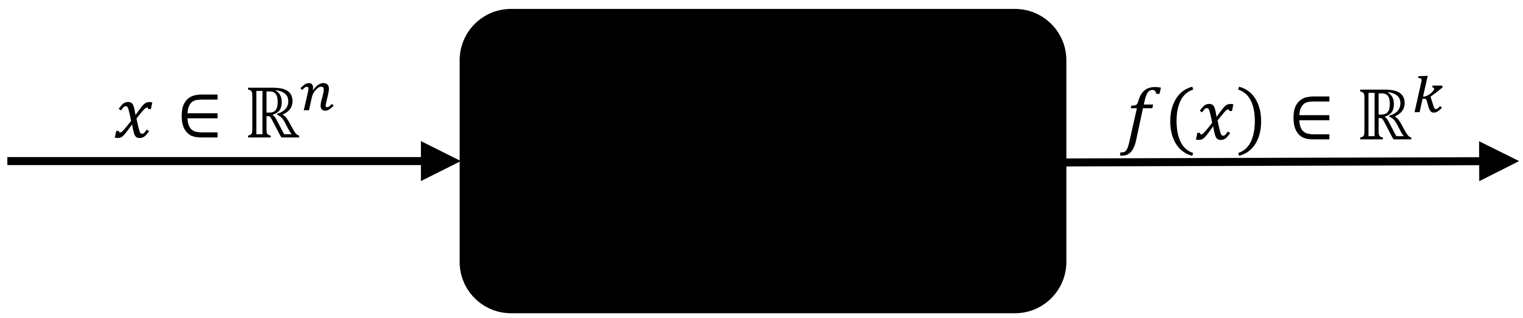
INVENTORS FOR THE DIGITAL WORLD

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

challenging optimization problems
appear in many
scientific, technological and industrial domains

Numerical Blackbox Optimization

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



derivatives not available or not useful

Practical Blackbox Optimization

Given:

Not clear:

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

Numerical Blackbox Optimizers

Deterministic algorithms

Quasi-Newton with estimation of gradient (BFGS) [Broyden et al. 1970]
Simplex downhill [Nelder & Mead 1965]
Pattern search [Hooke and Jeeves 1961]
Trust-region methods (NEWUOA, BOBYQA) [Powell 2006, 2009]

Stochastic (randomized) search methods

Evolutionary Algorithms (continuous domain)

- Differential Evolution [Storn & Price 1997]
- Particle Swarm Optimization [Kennedy & Eberhart 1995]
- **Evolution Strategies, CMA-ES** [Rechenberg 1965, Hansen & Ostermeier 2001]
- Estimation of Distribution Algorithms (EDAs) [Larrañaga, Lozano, 2002]
- Cross Entropy Method (same as EDA) [Rubinstein, Kroese, 2004]
- [Holland 1975, Goldberg 1989]

Simulated annealing [Kirkpatrick et al. 1983]
Simultaneous perturbation stochastic approx. (SPSA) [Spall 2000]

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- choice typically not immediately clear
- although practitioners have knowledge about which difficulties their problem has (e.g. multi-modality, non-separability, ...)

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

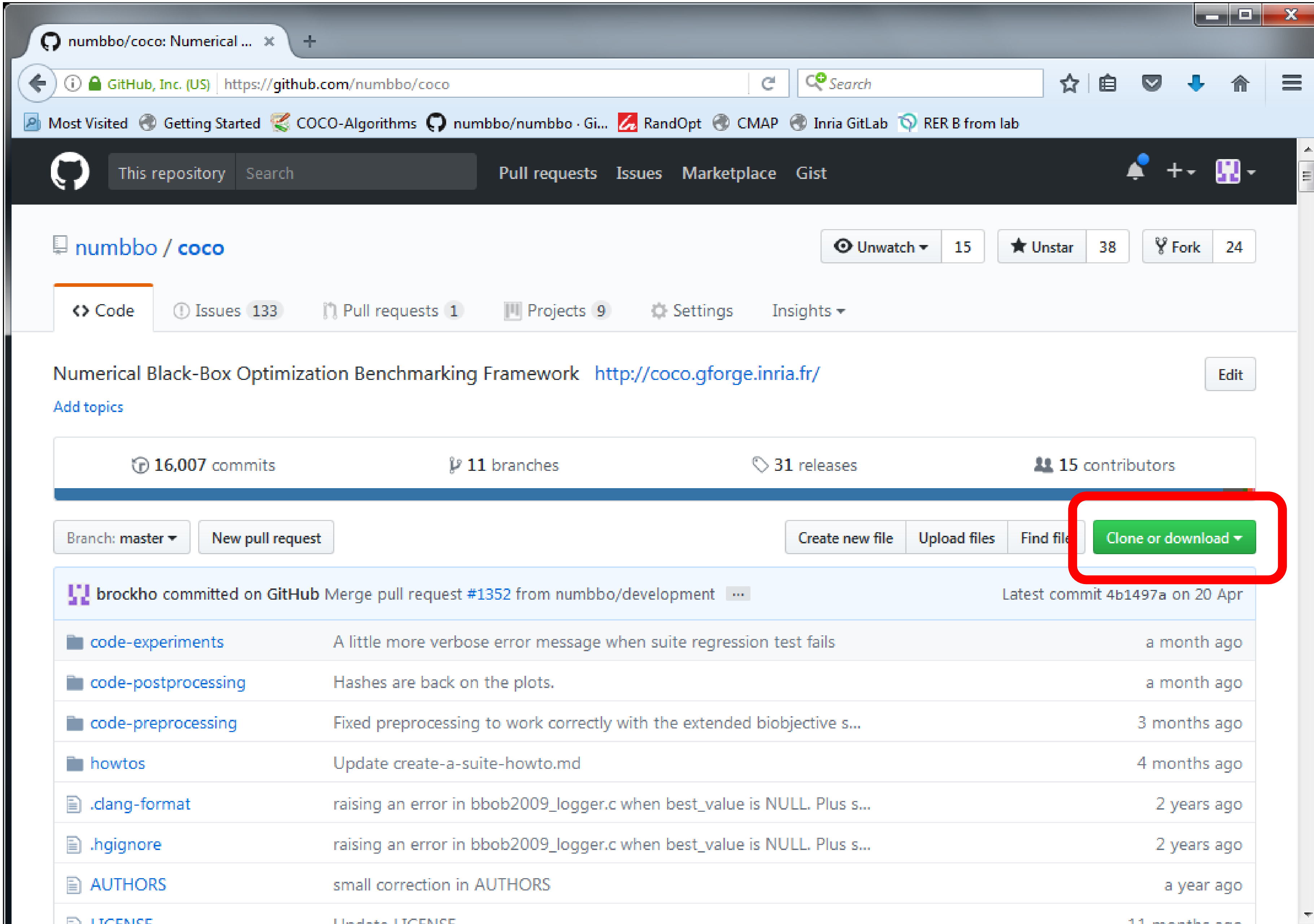
Comparing Continuous Optimizers Platform

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

automatized benchmarking

How to benchmark algorithms with COCO?

https://github.com/numbbo/coco



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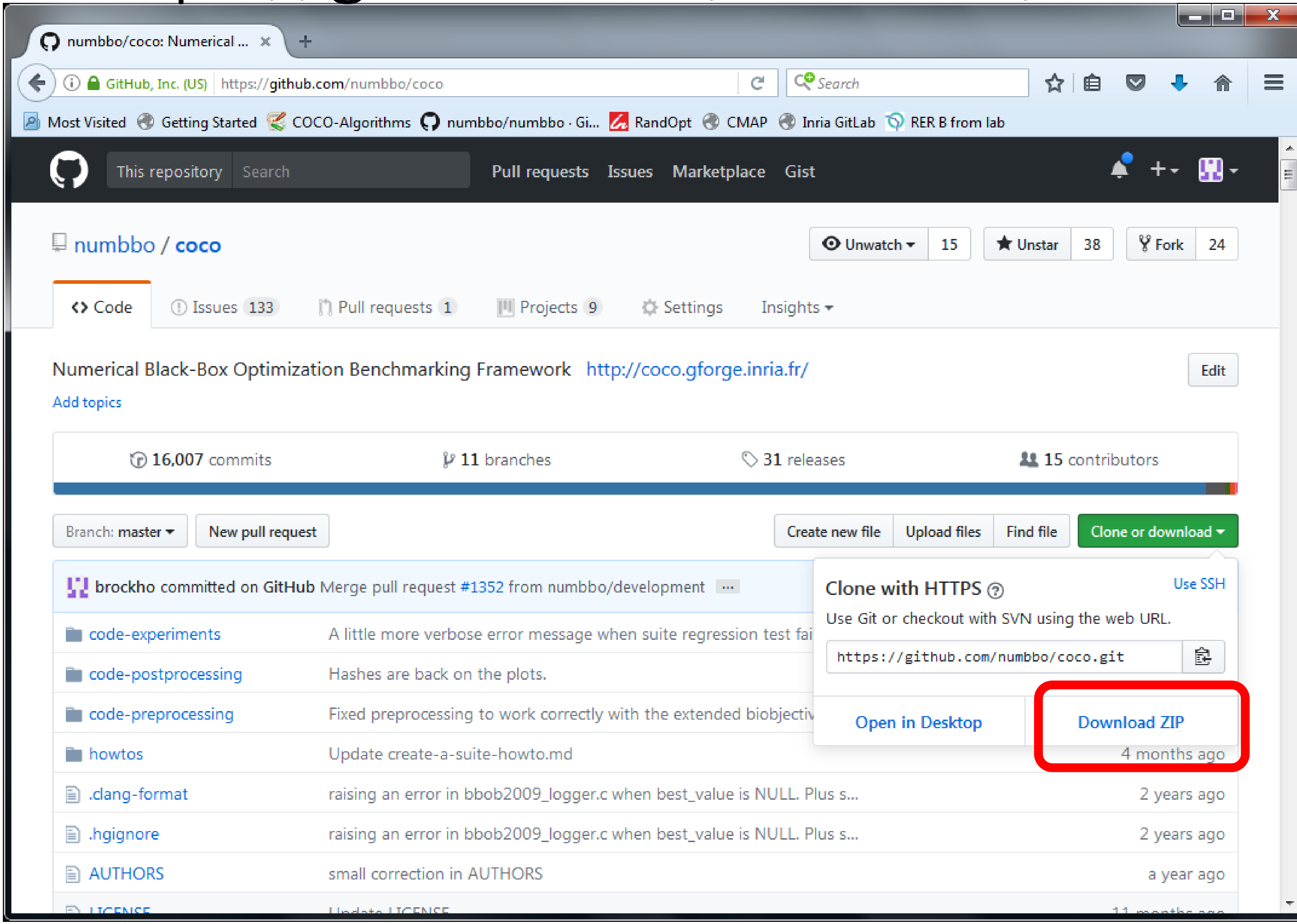

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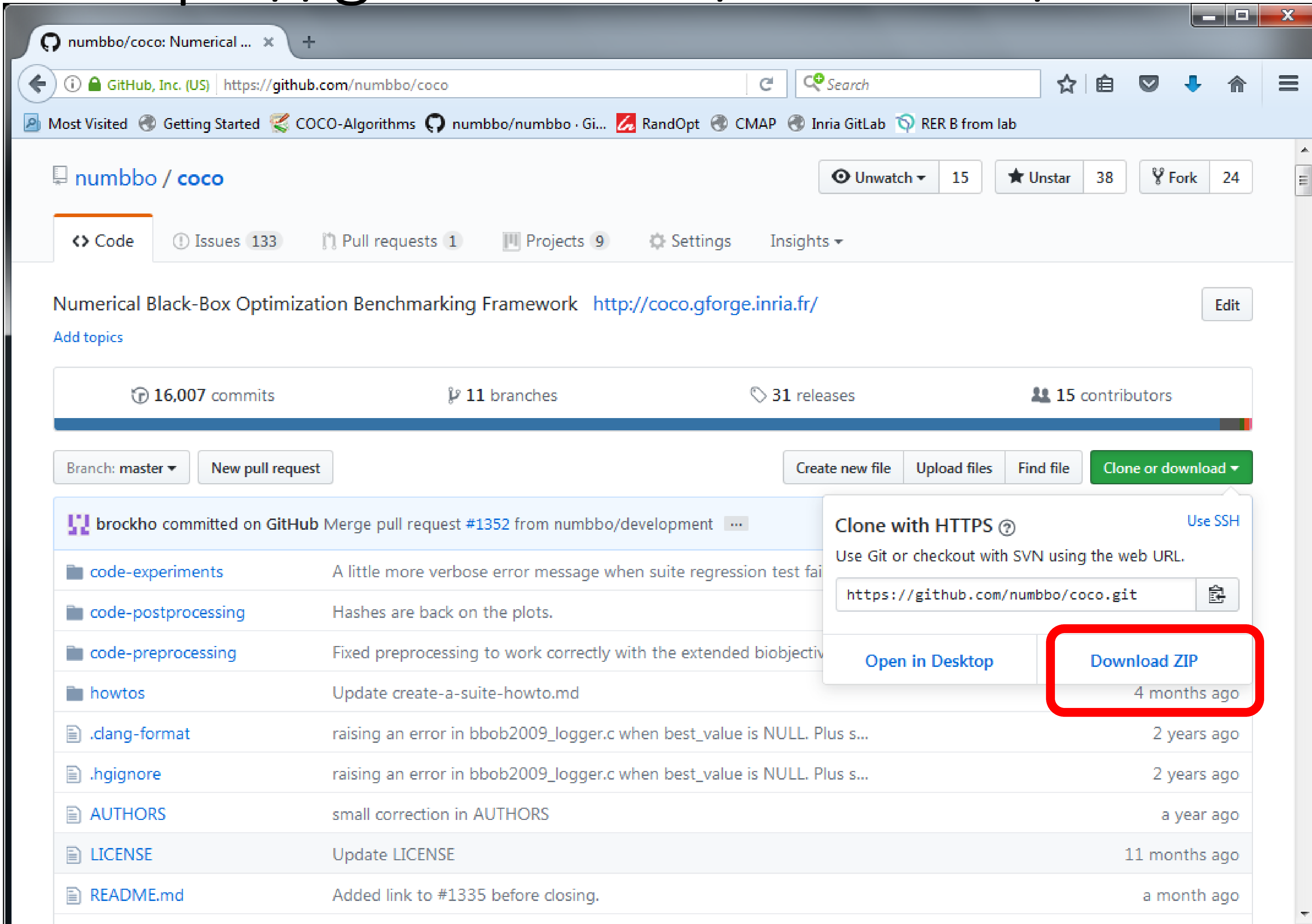

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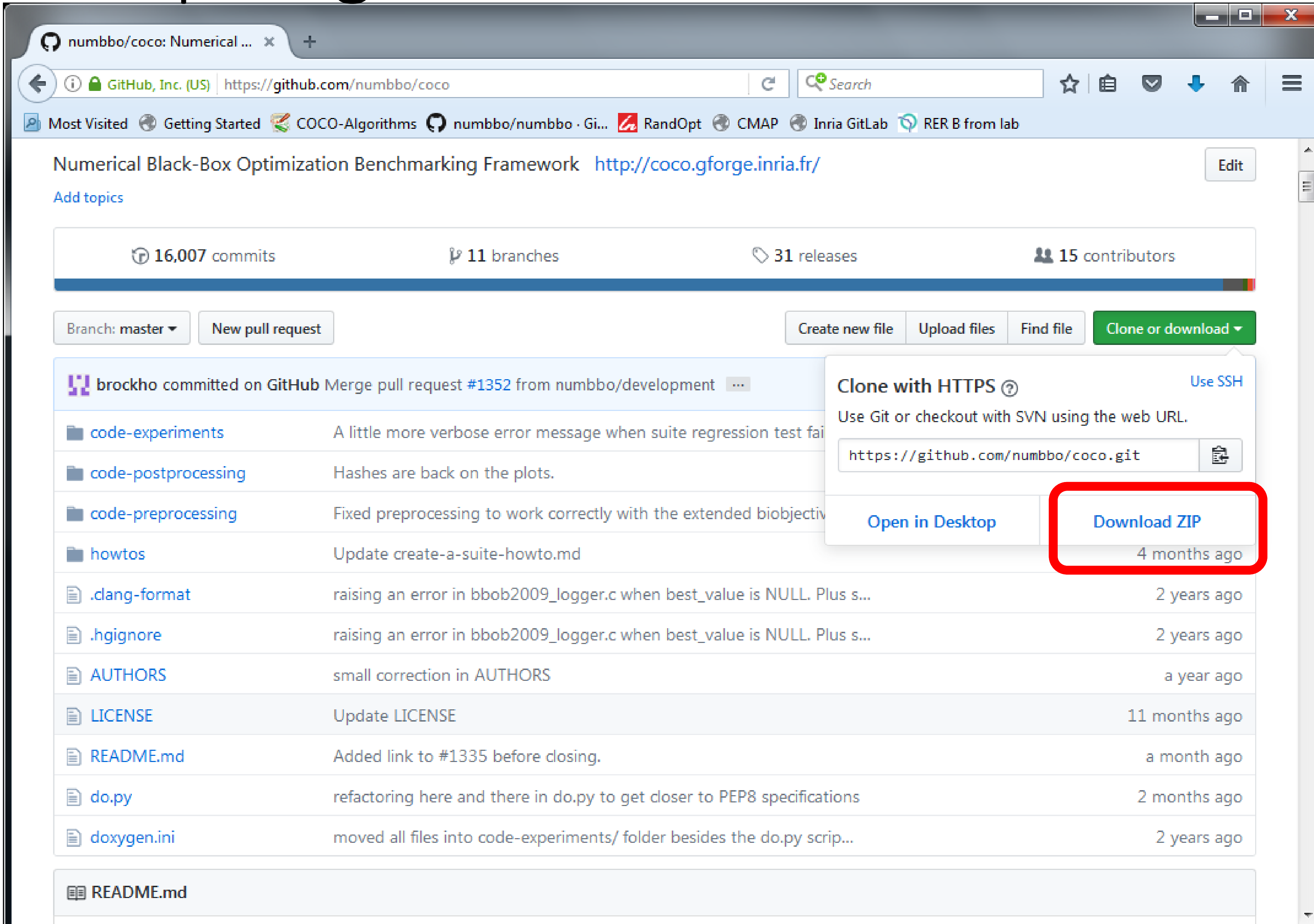

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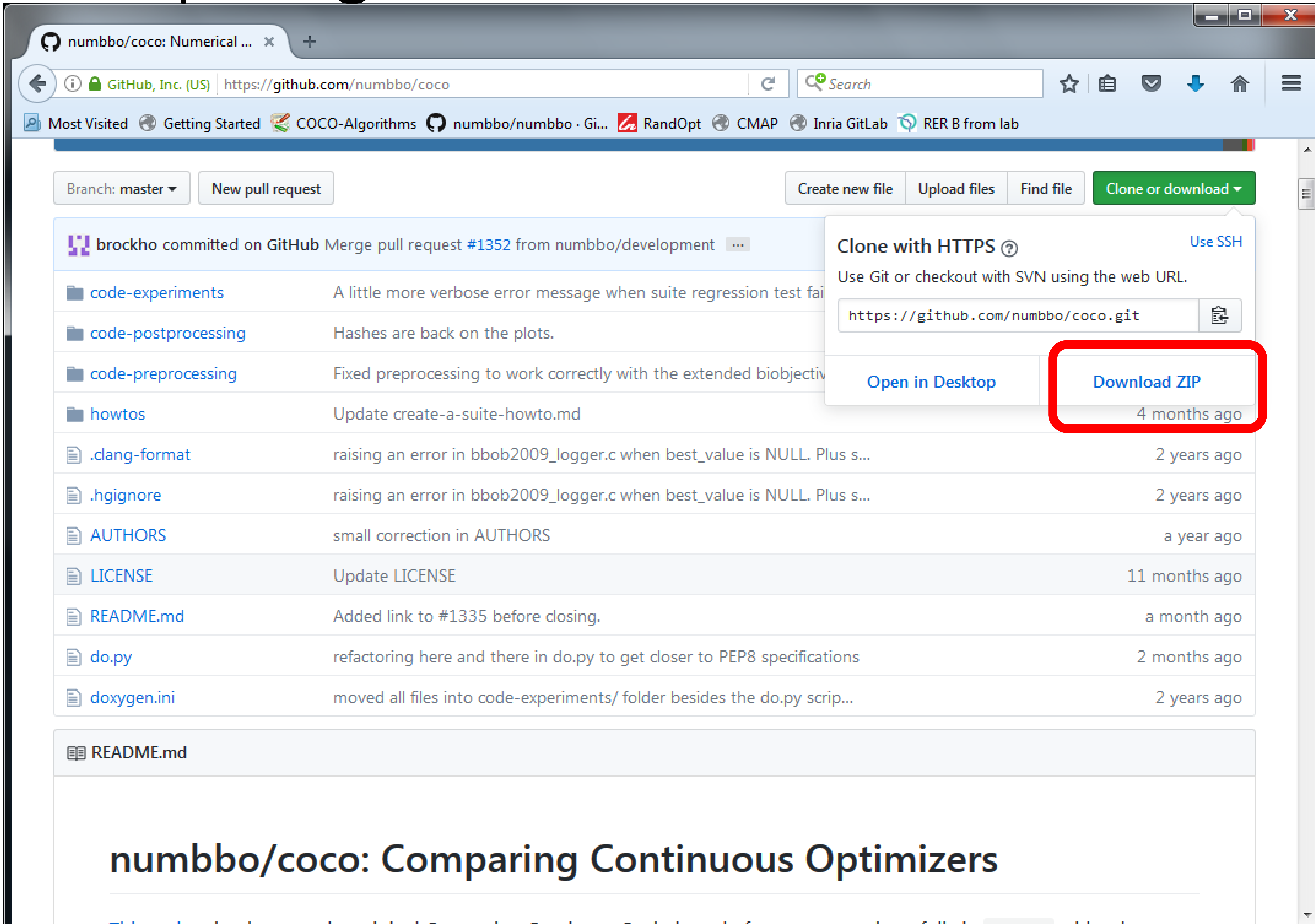

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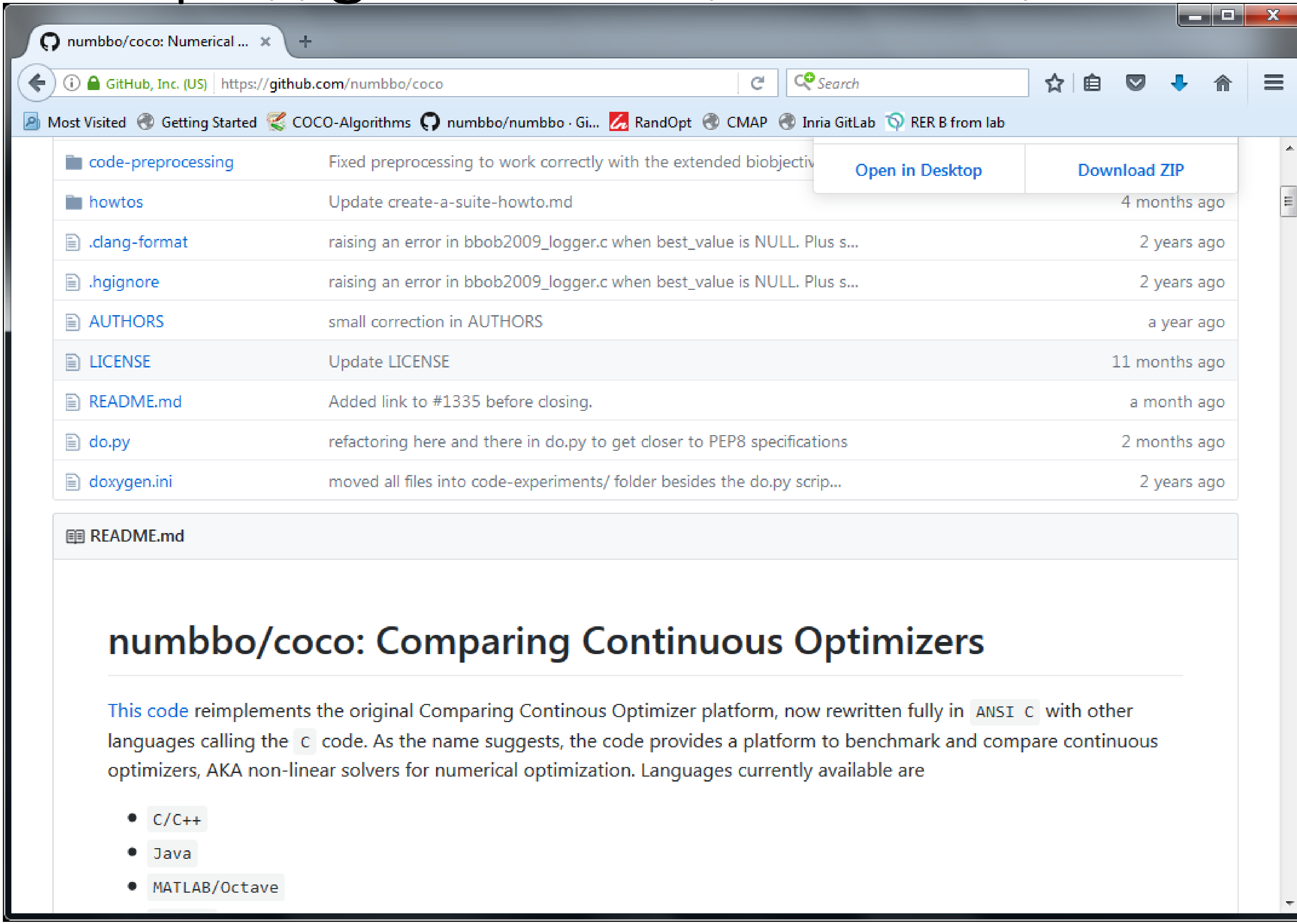

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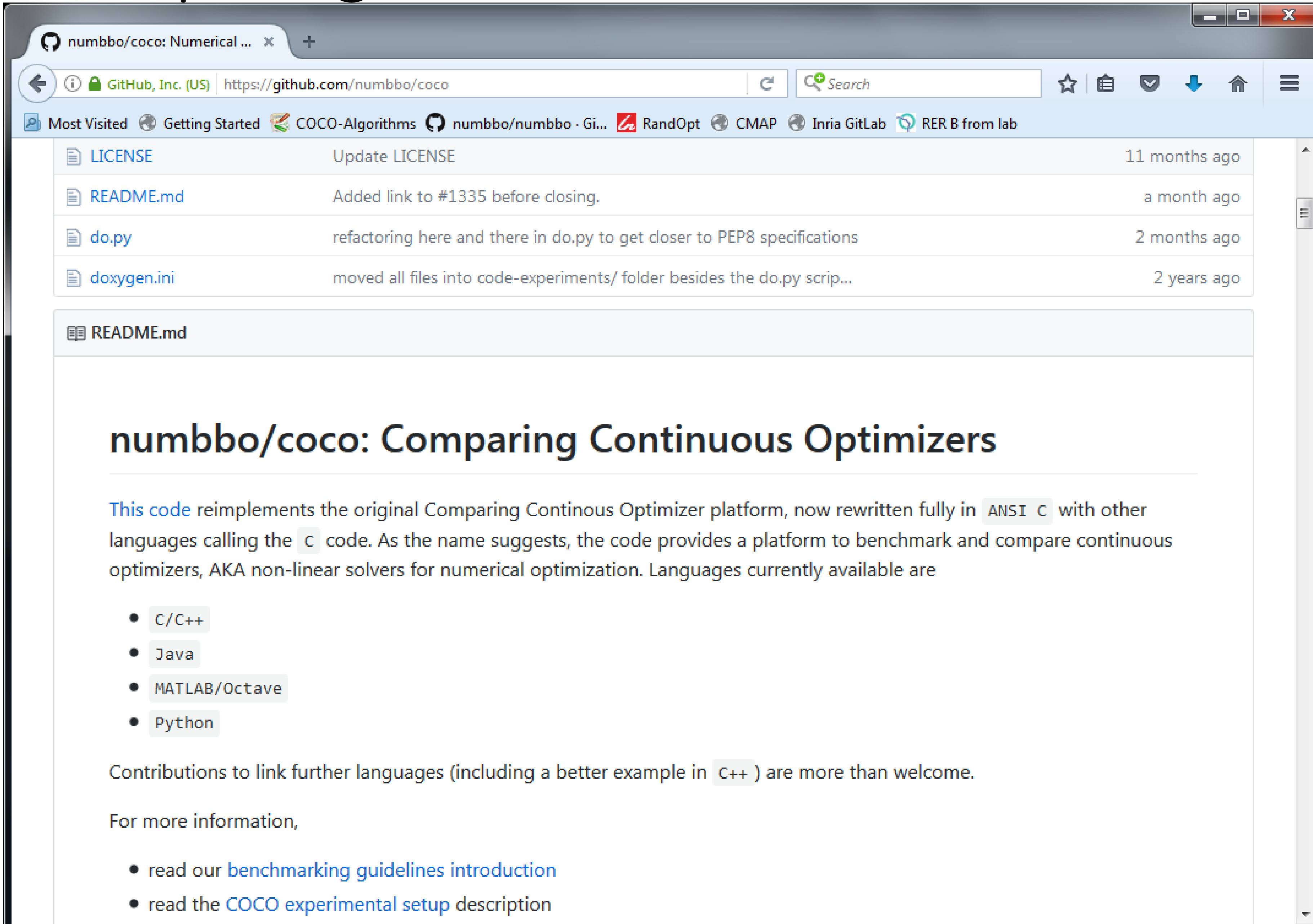

LICENSE	Update LICENSE	11 months ago
README.md	Added link to #1335 before closing.	a month ago
do.py	refactoring here and there in do.py to get closer to PEP8 specifications	2 months ago
doxygen.ini	moved all files into code-experiments/ folder besides the do.py scrip...	2 years ago

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,

- read our benchmarking guidelines introduction
- read the COCO experimental setup description

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- see the `bbob-biobj` and `bbob-biobj-ext` COCO multi-objective functions testbed documentation and the specificities of the performance assessment for the bi-objective testbeds.
- 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.

https://github.com/numbbo/coco

numbbo/coco: Numerical ...

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Getting Started

requirements & download

0. Check out the *Requirements* above.

1. **Download** the COCO framework code from github,

- either by clicking the Download ZIP button and unzip the `zip` file,
- or by typing `git clone https://github.com/numbbo/coco.git`. This way allows to remain up-to-date easily (but needs `git` to be installed). After cloning, `git pull` keeps the code up-to-date with the latest release.

The record of official releases can be found here. The latest release corresponds to the master branch as linked above.

2. In a system shell, **`cd` into** the `coco` or `coco-<version>` folder (framework root), where the file `do.py` can be found. Type, i.e. **execute**, one of the following commands once

```
python do.py run-c
python do.py run-java
python do.py run-matlab
python do.py run-octave
python do.py run-python
```

depending on which language shall be used to run the experiments. `run-*` will build the respective code and run the example experiment once. The build result and the example experiment code can be found under `code-experiments/build/<language>` (`<language>=matlab` for Octave). `python do.py` lists all available commands.

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

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

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installation I: experiments

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```
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```

installation II: 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.

4. **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). 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.

5. Now you can **run** your favorite algorithm on the `bbob` suite (for single-objective algorithms) or on the `bbob-biobj` and `bbob-biobj-ext` suites (for multi-objective algorithms). Output is automatically generated in the specified data `result_folder`. By now, more suites might be available, see below.

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coupling algo + COCO

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example_experiment.c (slightly simplified)

```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);
}
```

running the experiment

numbbo/coco at develop...

https://github.com/numbbo/coco/tree/development

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

```
python -m cocopp [-o OUTPUT_FOLDERNAME] YOURDAT
```

Any subfolder in the folder arguments will be searched fo ... n 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 an `index.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.

A summary pdf can be produced via LaTeX. The corresponding templates can be found in the `code-postprocessing/latex-templates` folder. Basic html output is also available in the result folder of the postprocessing (file `templateBBOBarticle.html`).

7. 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.

8. The experiments can be **parallelized** with any re-distribution of single problem instances to batches (see `example_experiment.py` for an example). Each batch must write in a different target folder (this should happen automatically). Results of each batch must be kept under their separate folder as is. These folders then must be

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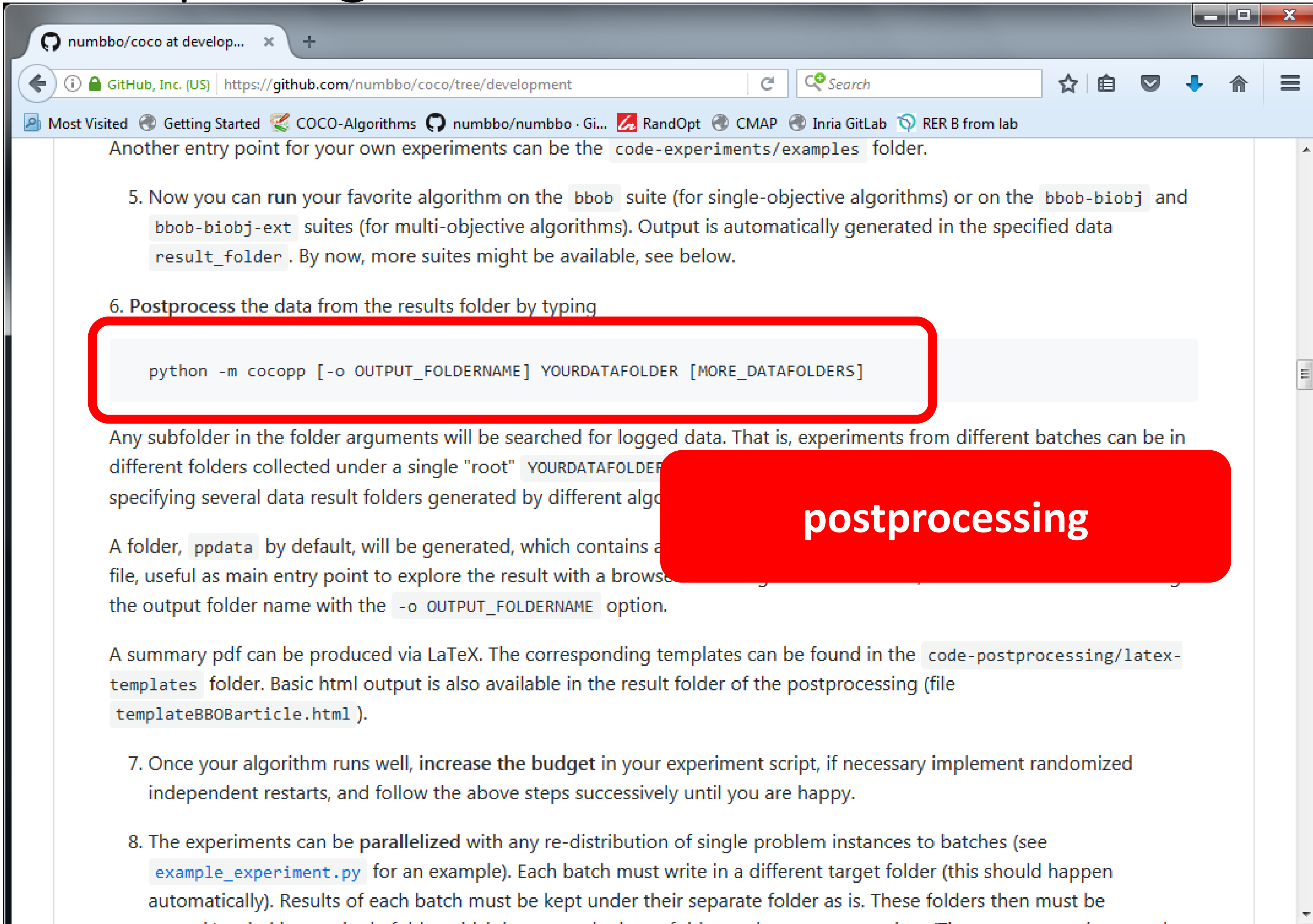

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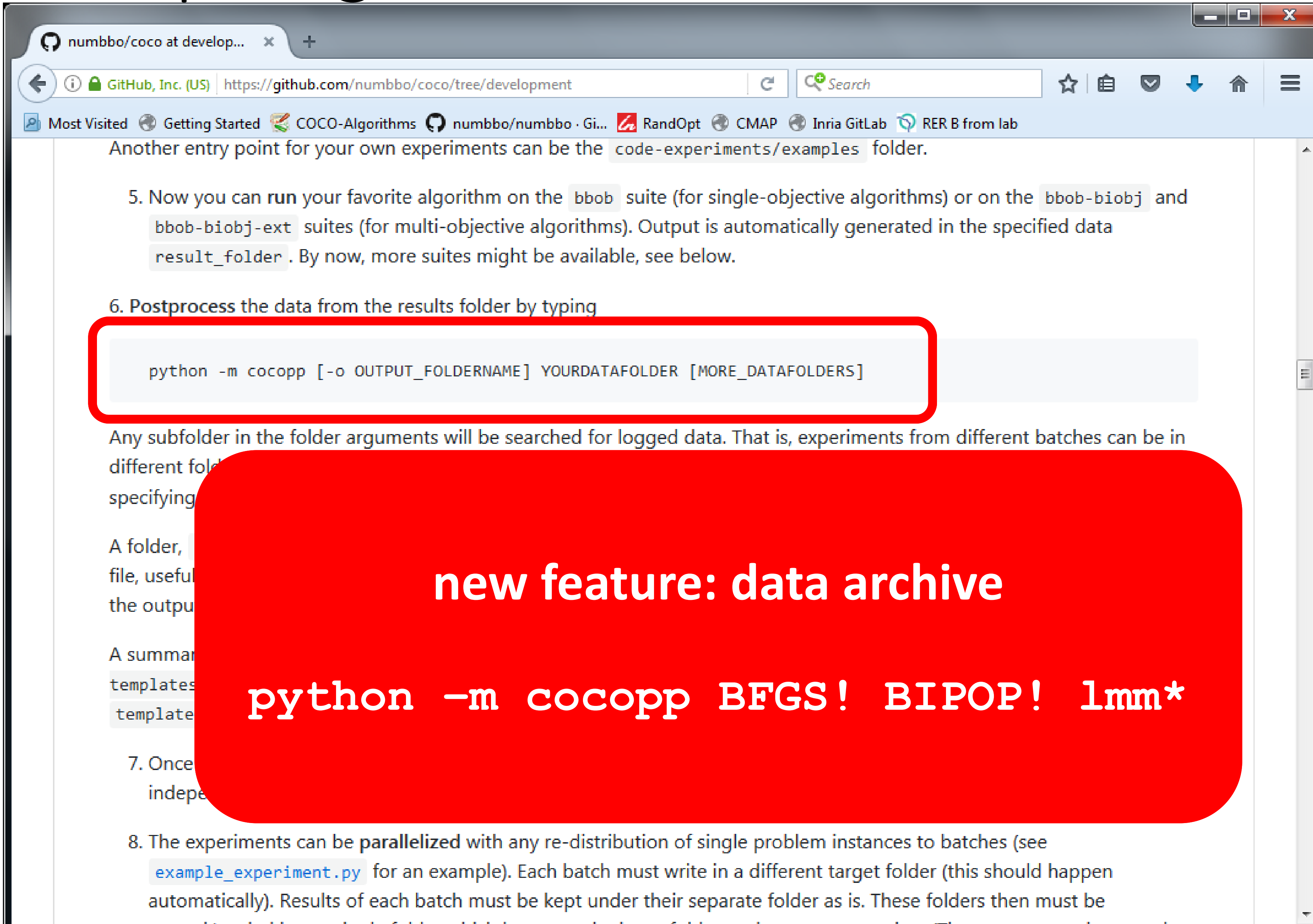
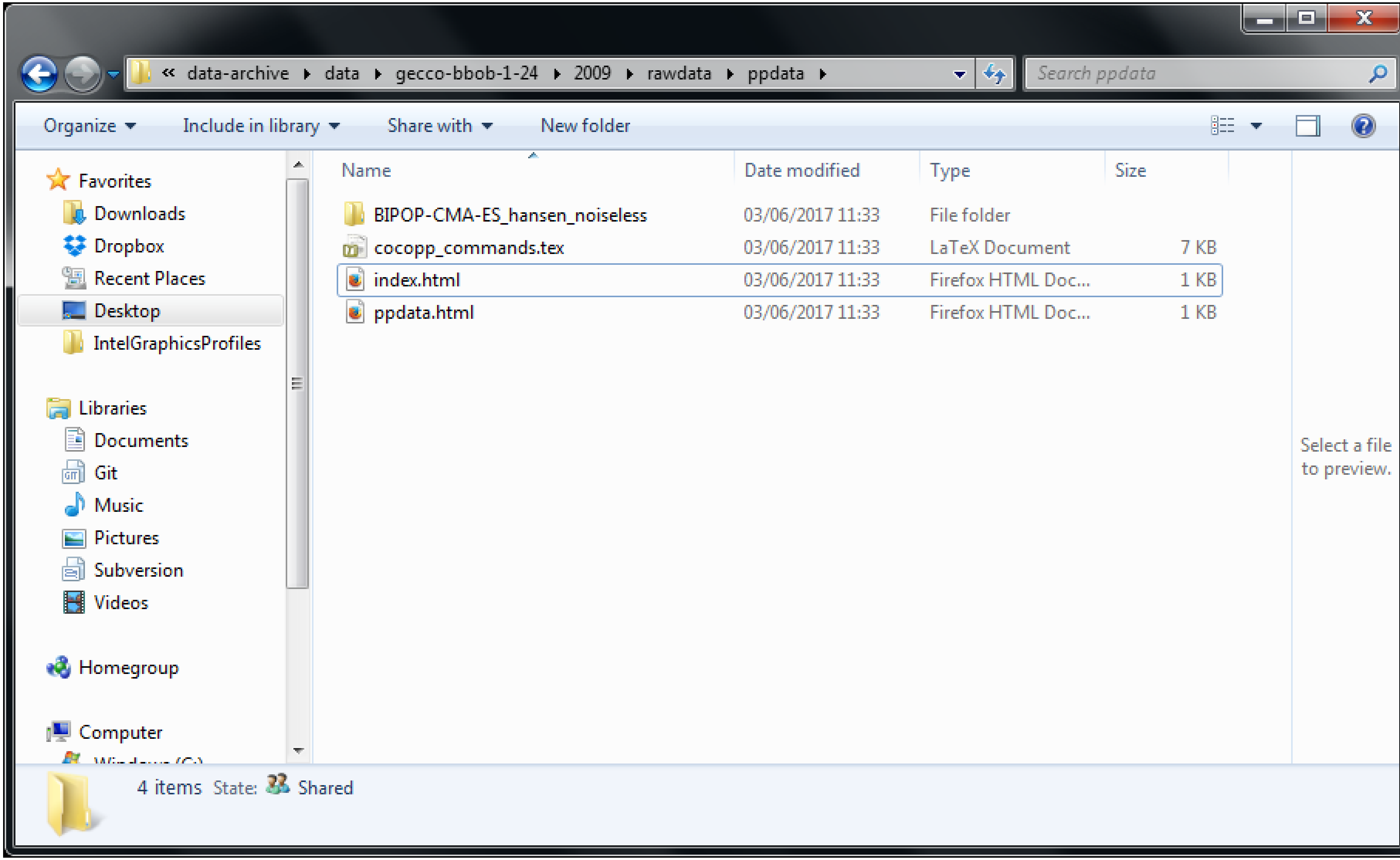
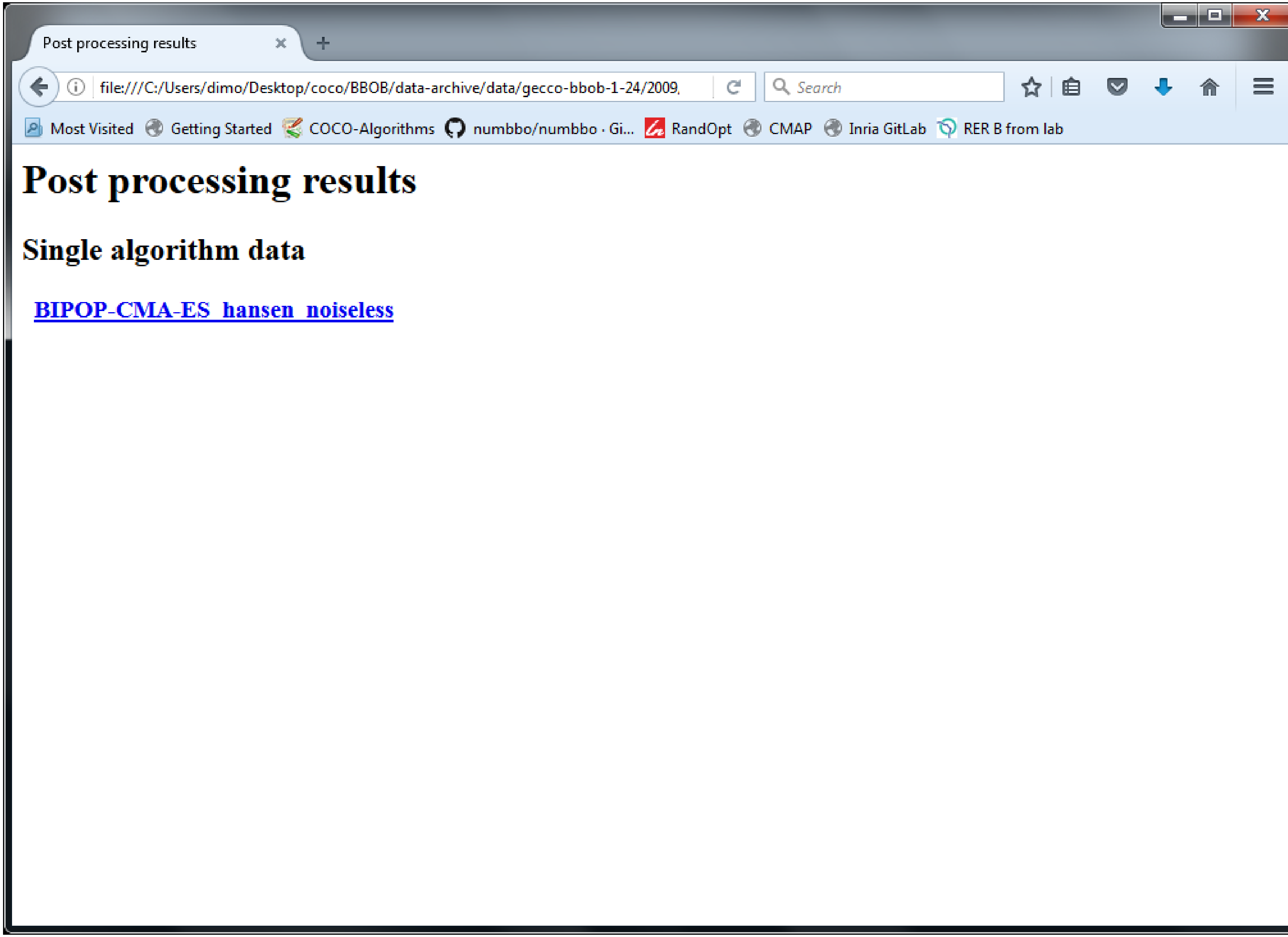


Result Folder



Automatically Generated Results



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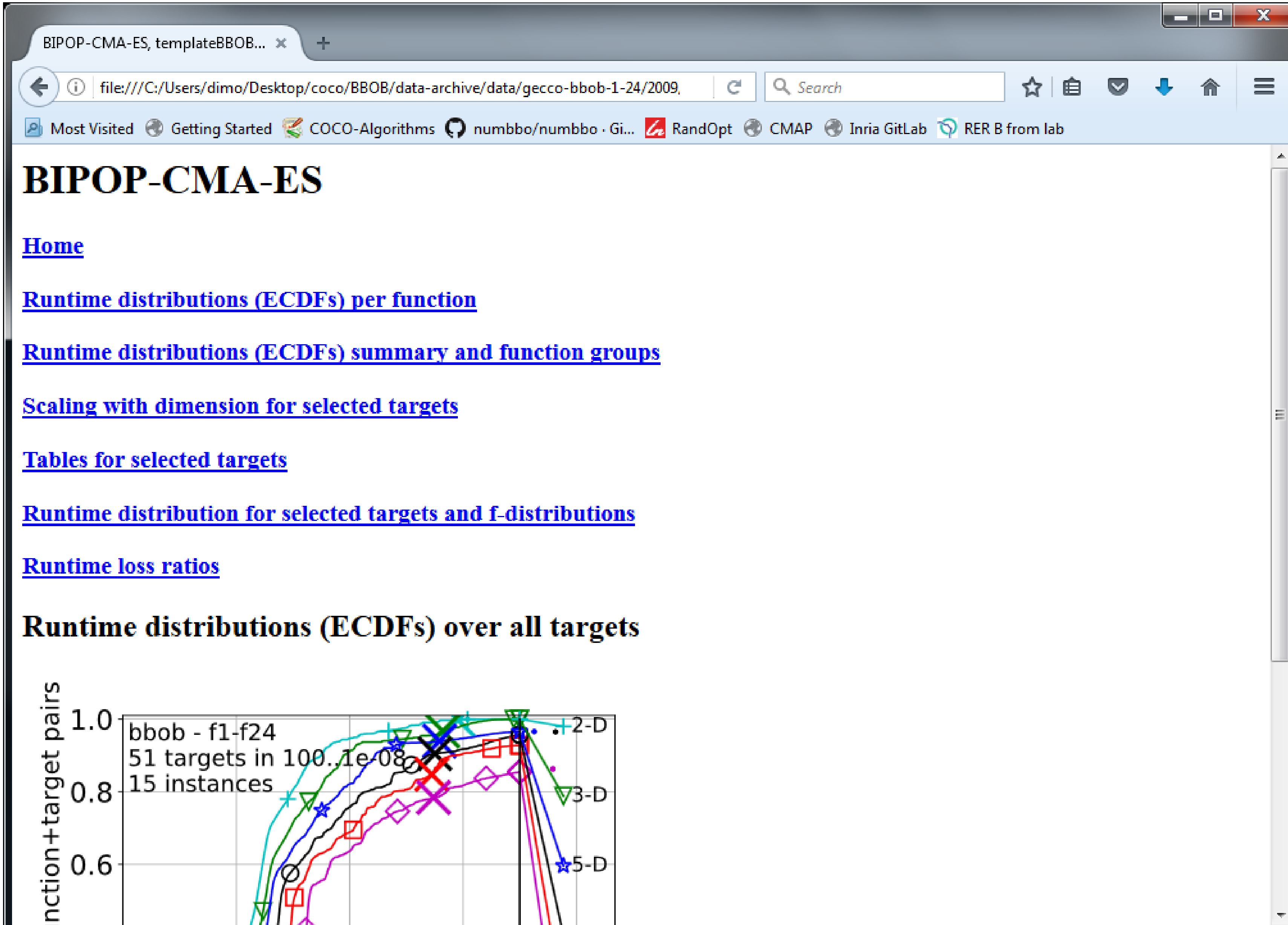

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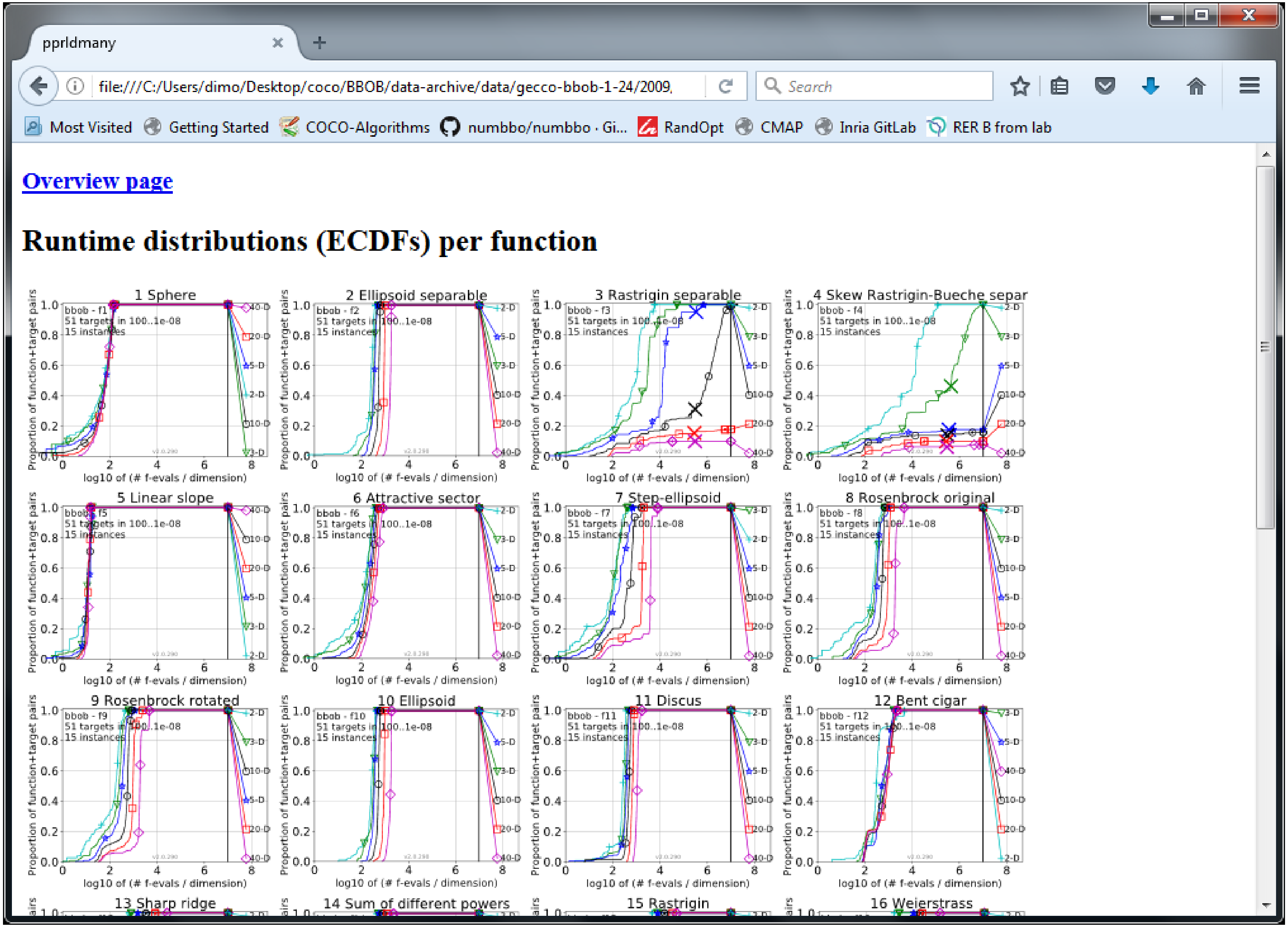

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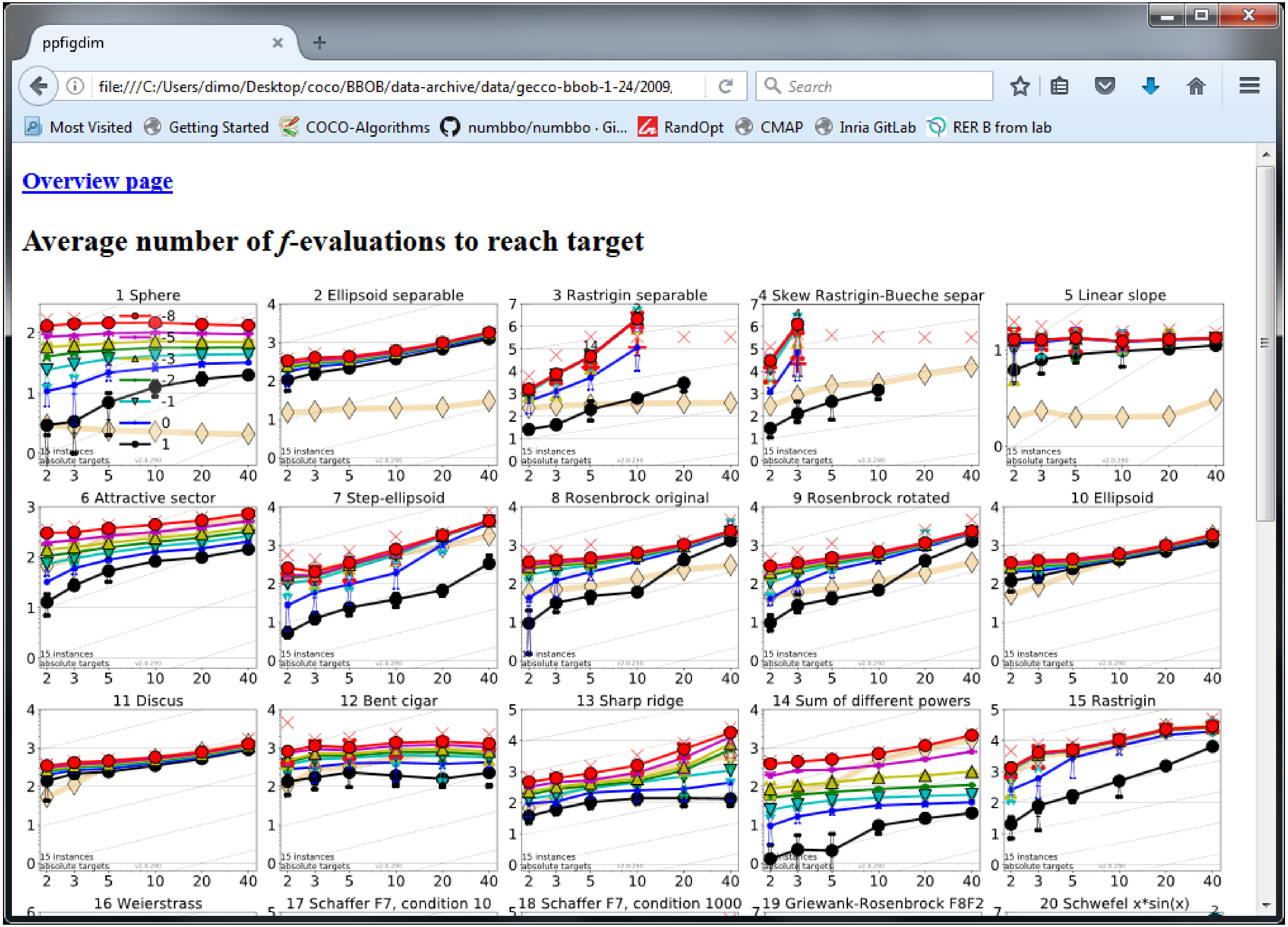


doesn't look too complicated, does it?

[the devil is in the details ☺]

so far (i.e. incl. BBOB-2018):

data for 200+ algorithm variants

(some of which on noisy or multiobjective test functions)

136 workshop papers

by 101 authors from 28 countries

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

Available Test Suites in COCO

• bbob	24 noiseless fcts	180+ algo data sets
• bbob-noisy	30 noisy fcts	40+ algo data sets
• bbob-biobj	55 bi-objective fcts	16 algo data sets

Almost finished:

- extended bi-objective suite (bbob-biobj-ext)
- large-scale version of bbob (bbob-largescale)

Under development/in planning phase:

- constrained test suite (bbob-constrained)
- mixed-integer suite
- real-world problems
  (see also the game benchmarking workshop)

How Do We Measure Performance?

Meaningful quantitative measure

- quantitative on the ratio scale (highest possible)

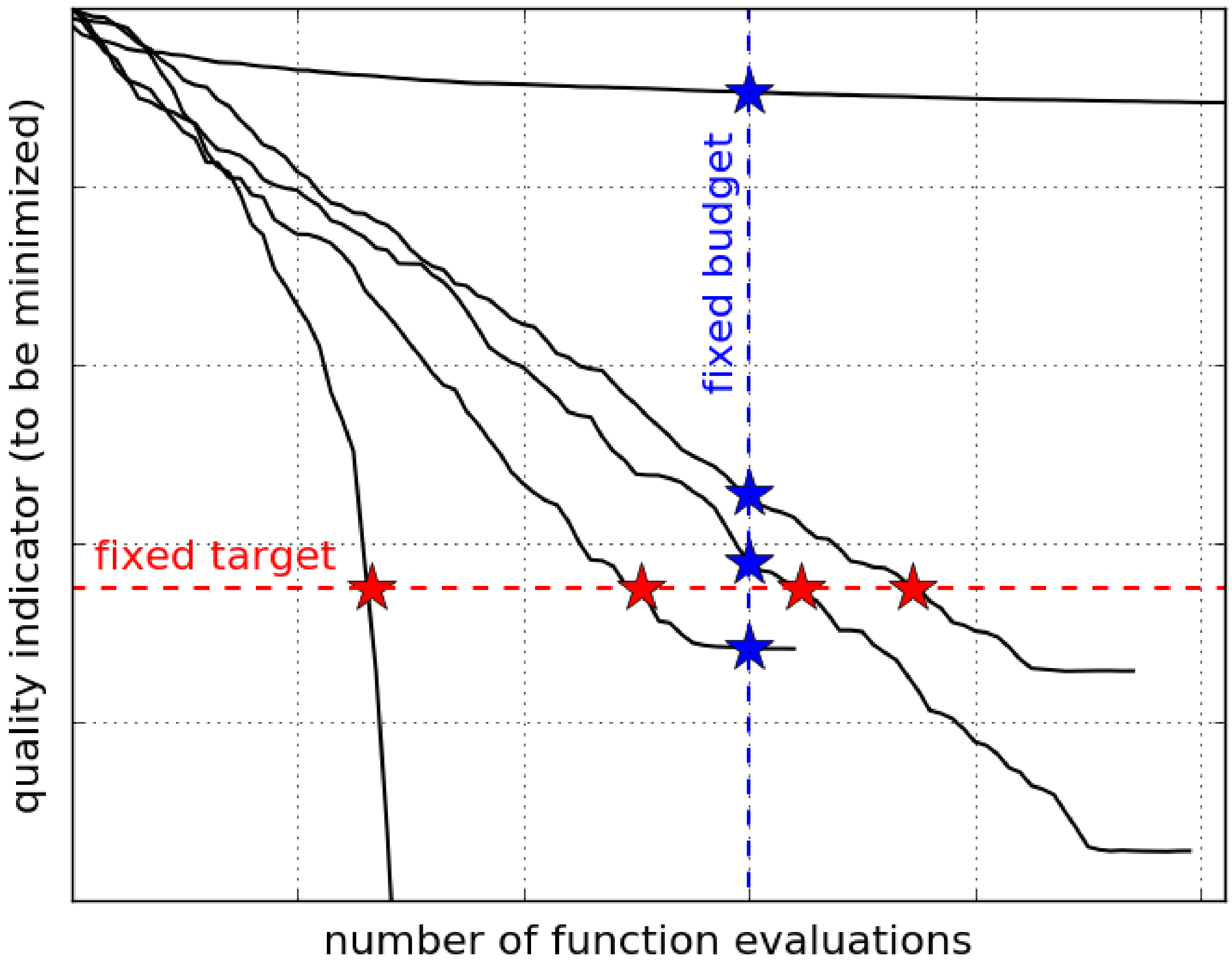
  "algo A is two *times* better than algo B" is a meaningful statement
- assume a wide range of values
- meaningful (interpretable) with regard to the real world

  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...

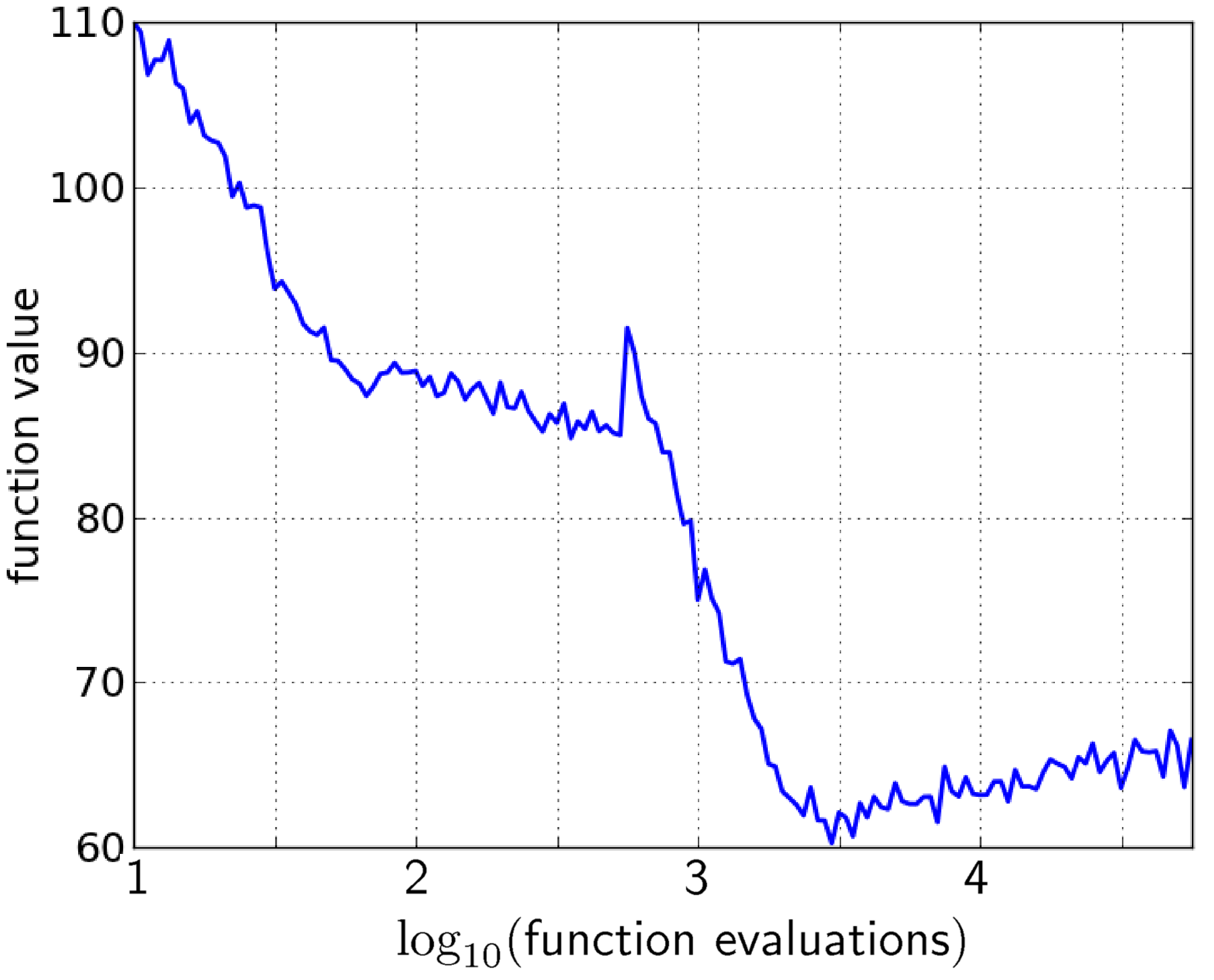


ECDF:

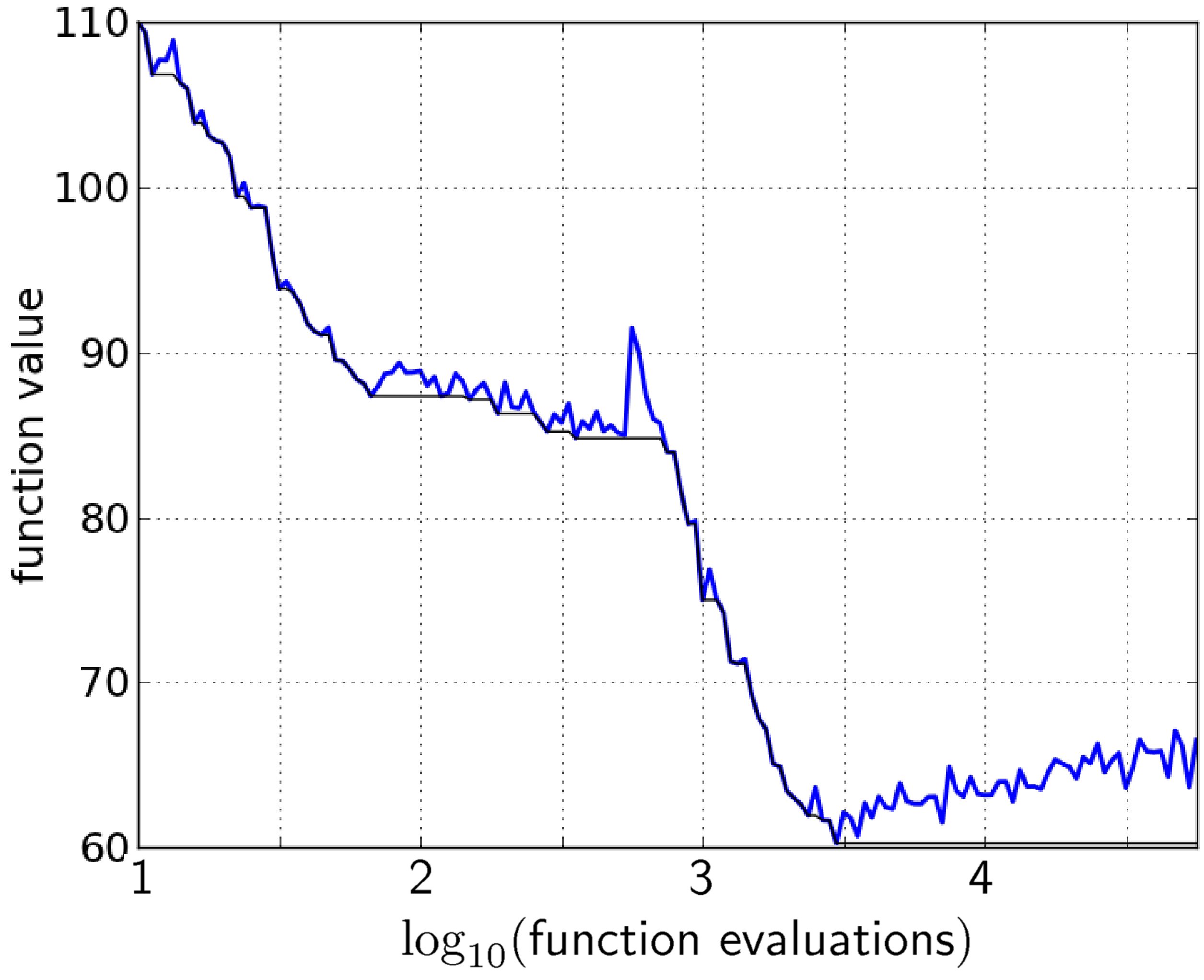
Empirical Cumulative Distribution Function of the Runtime

[aka data profile]

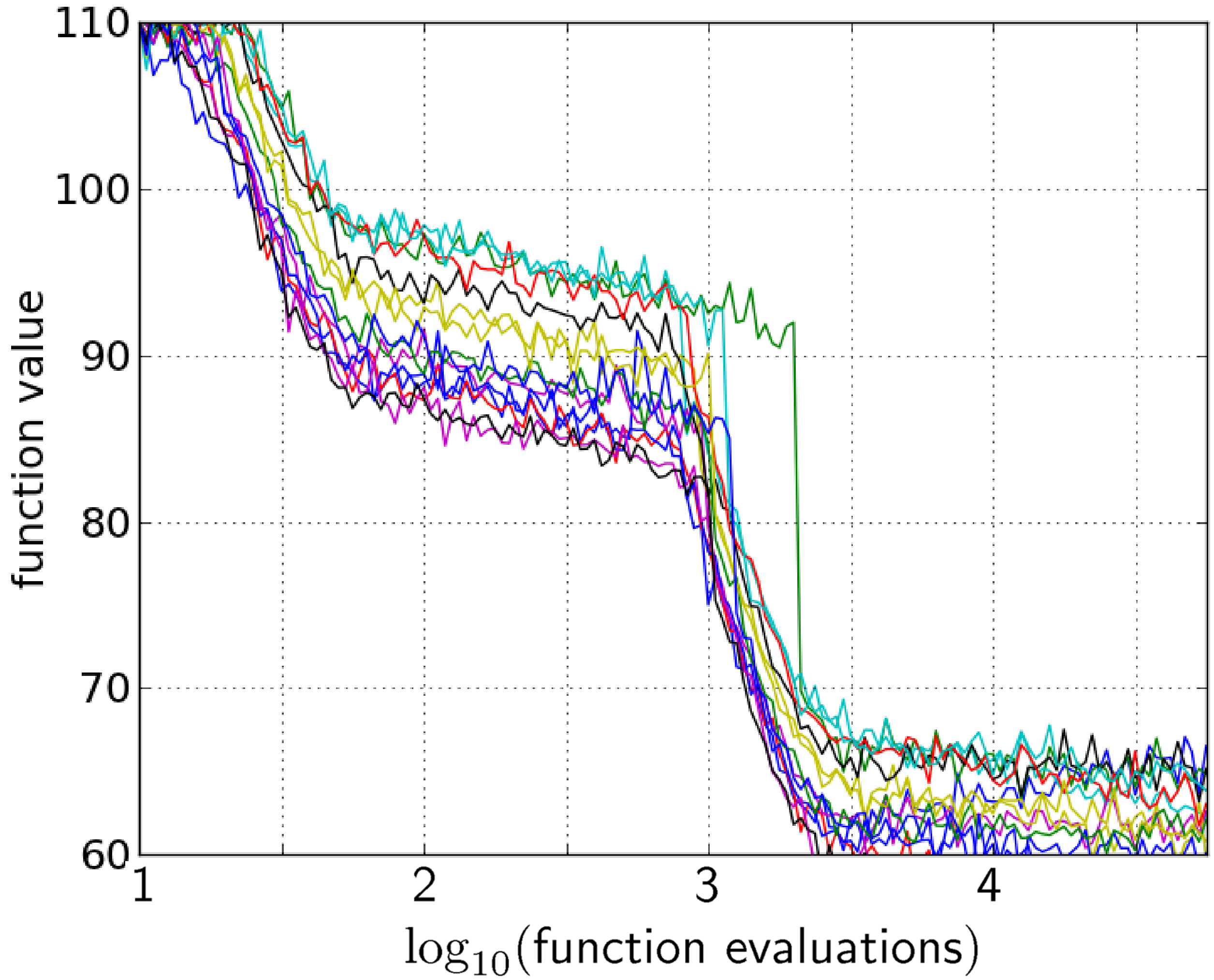
A Convergence Graph



First Hitting Time is Monotonous

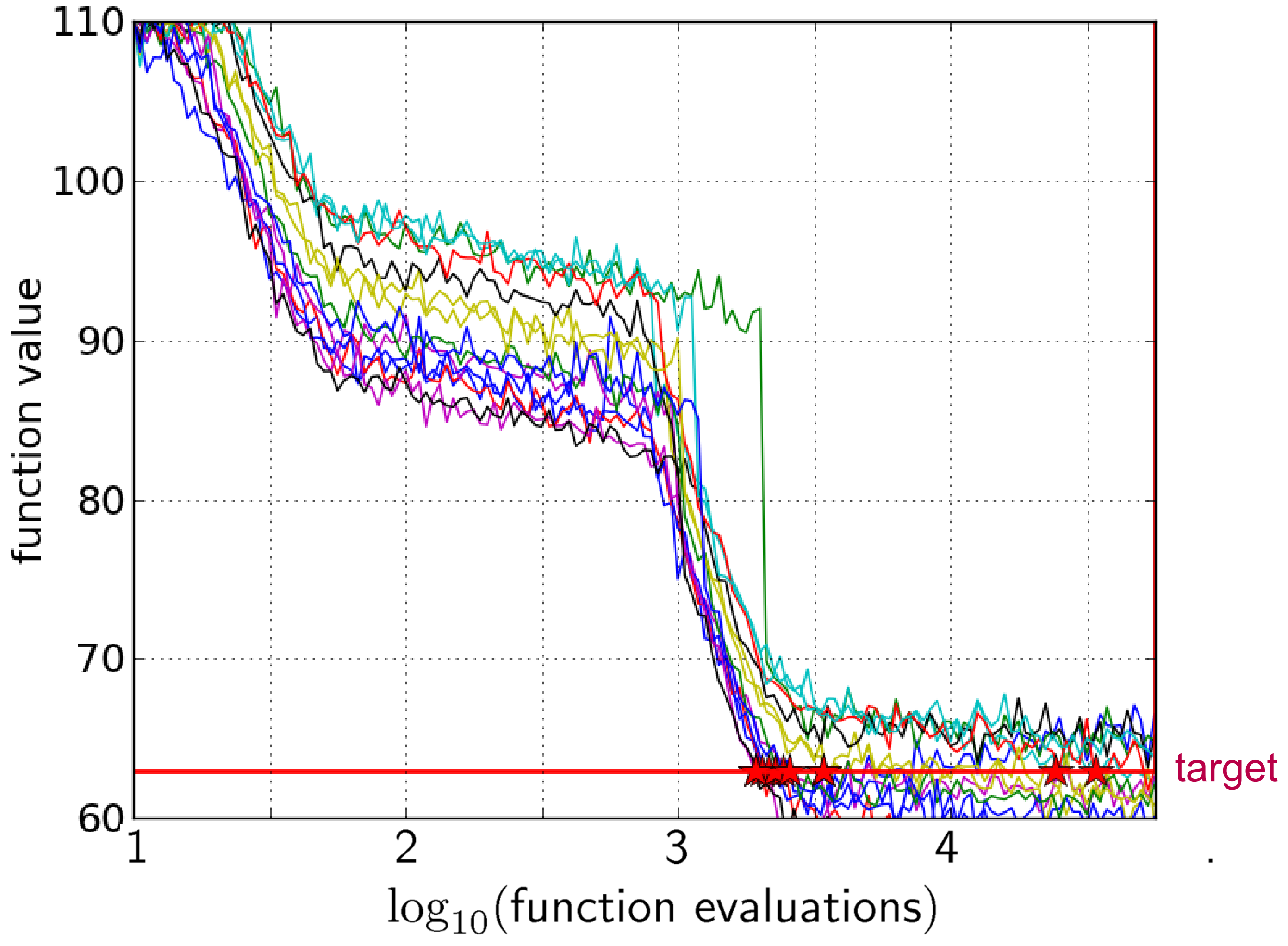


15 Runs

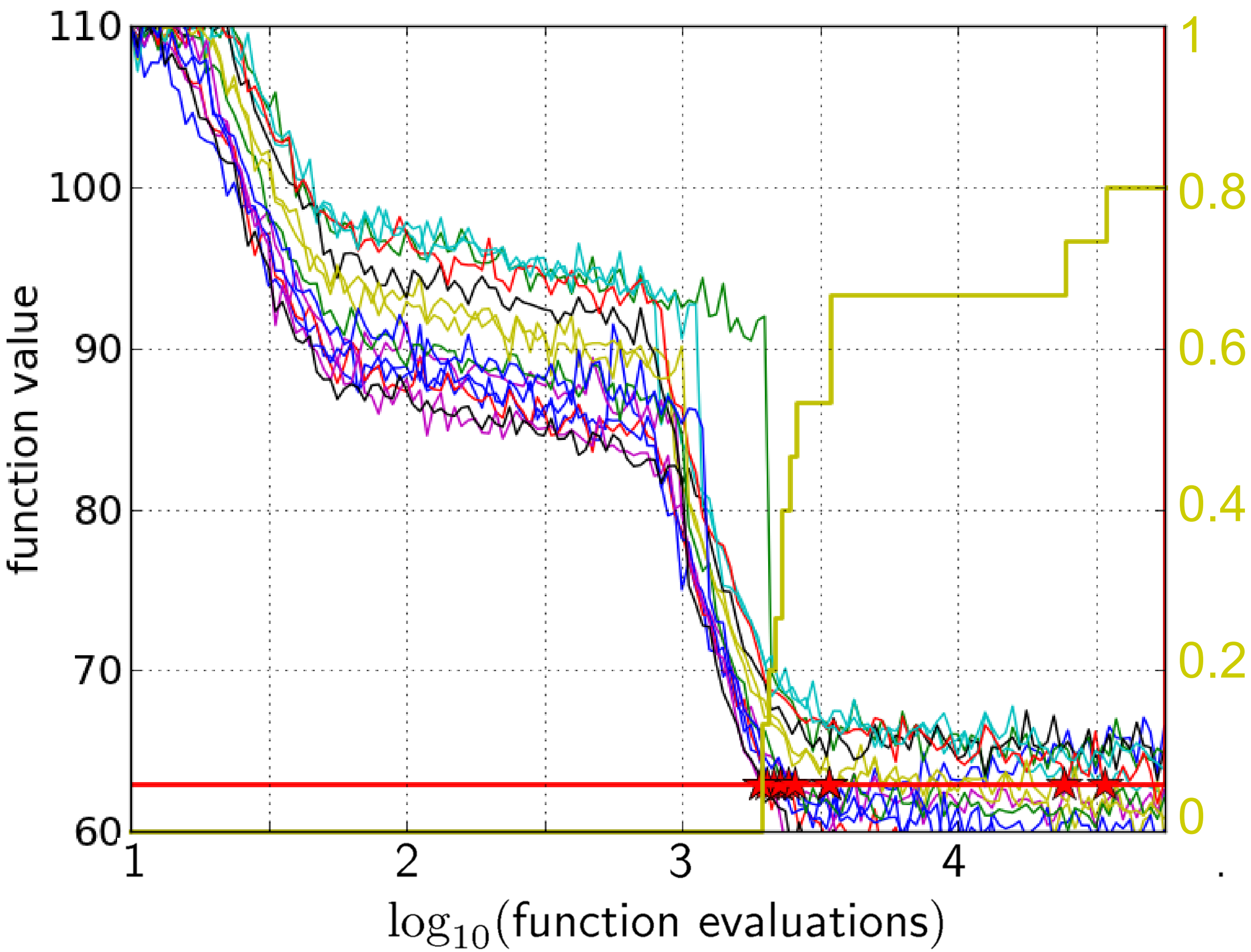


110
100
90
80
70
60
function value
1
2
3
4
$\log_{10}$(function evaluations)

15 Runs ≤ 15 Runtime Data Points



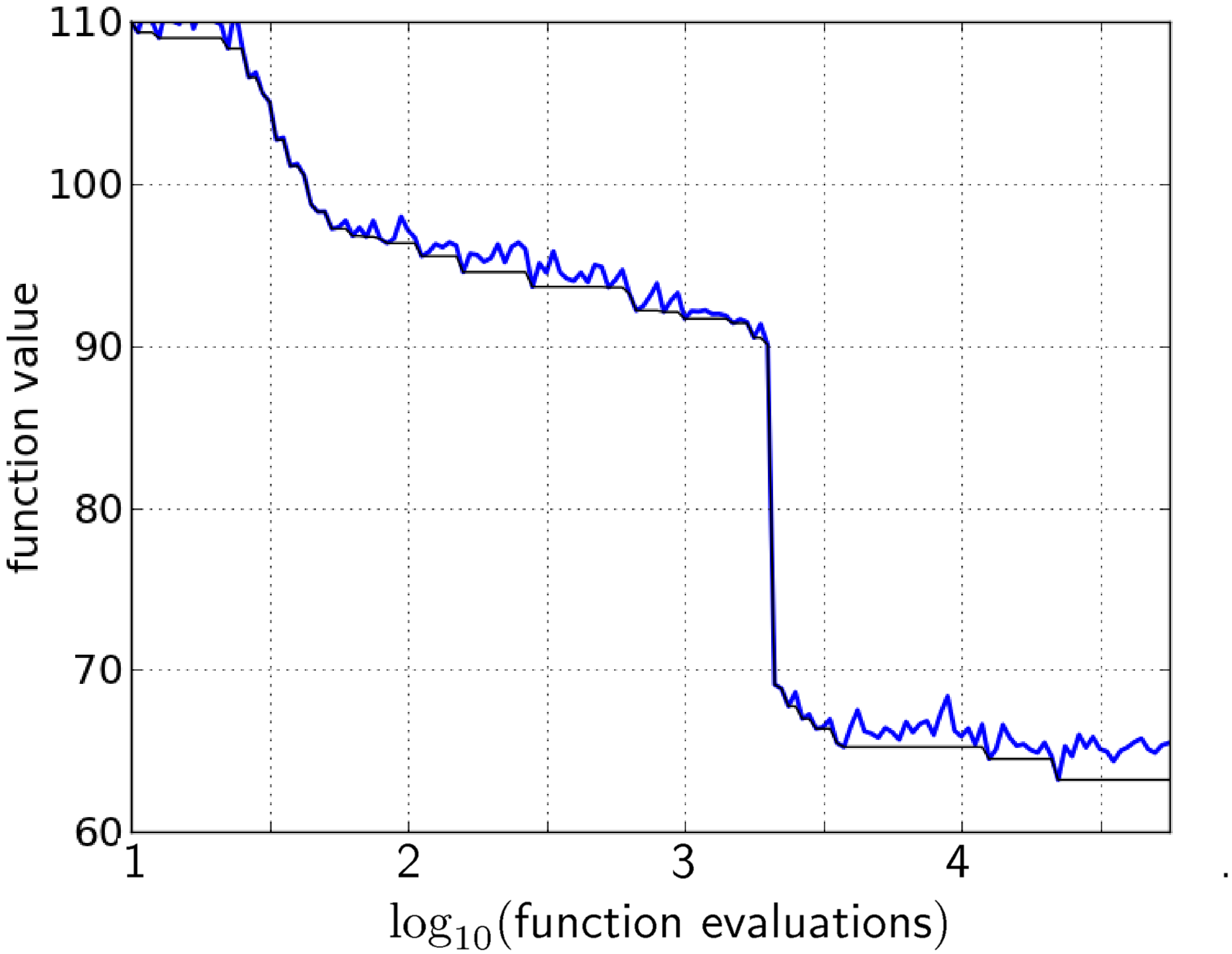
Empirical Cumulative Distribution



- 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

Reconstructing A Single Run



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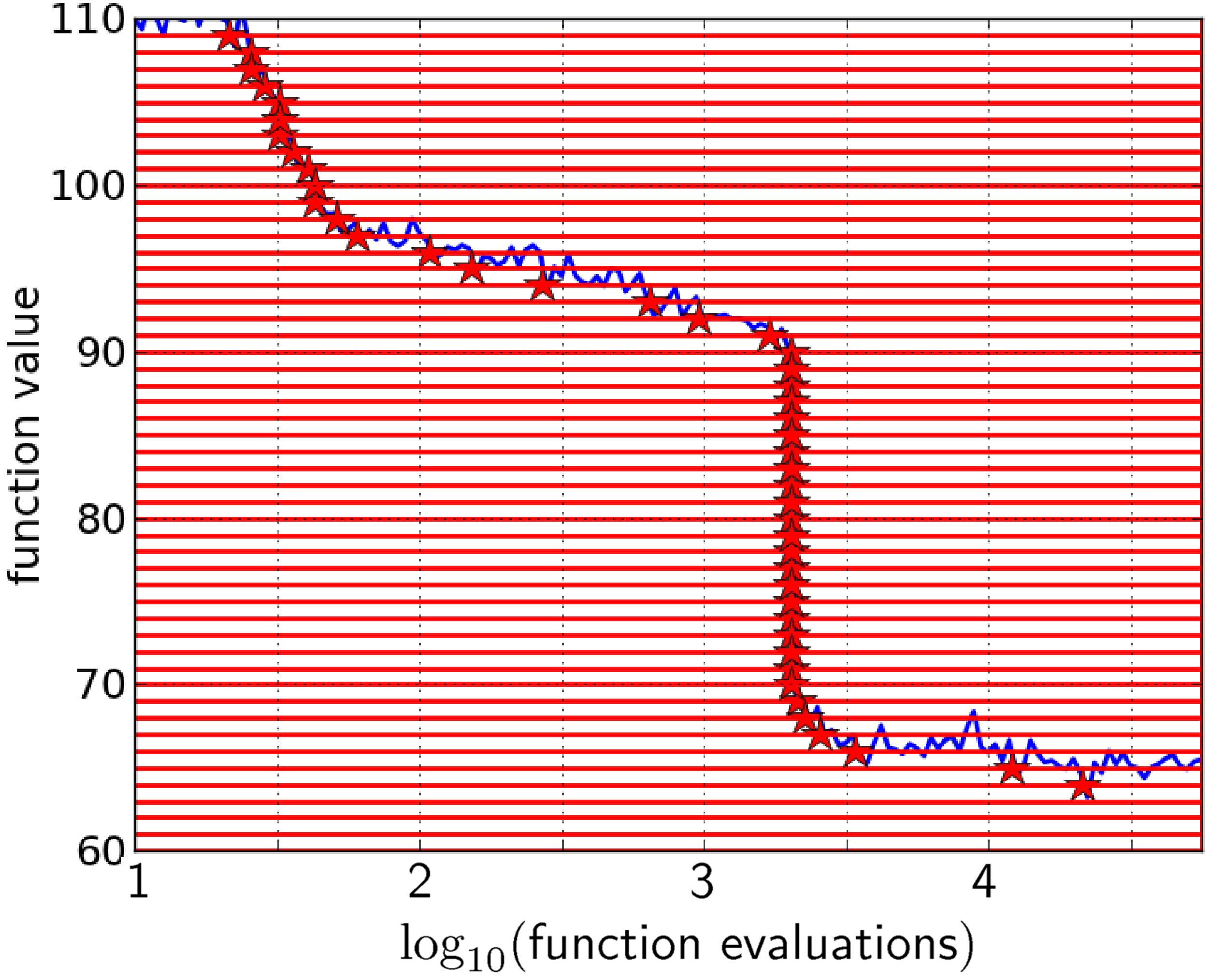
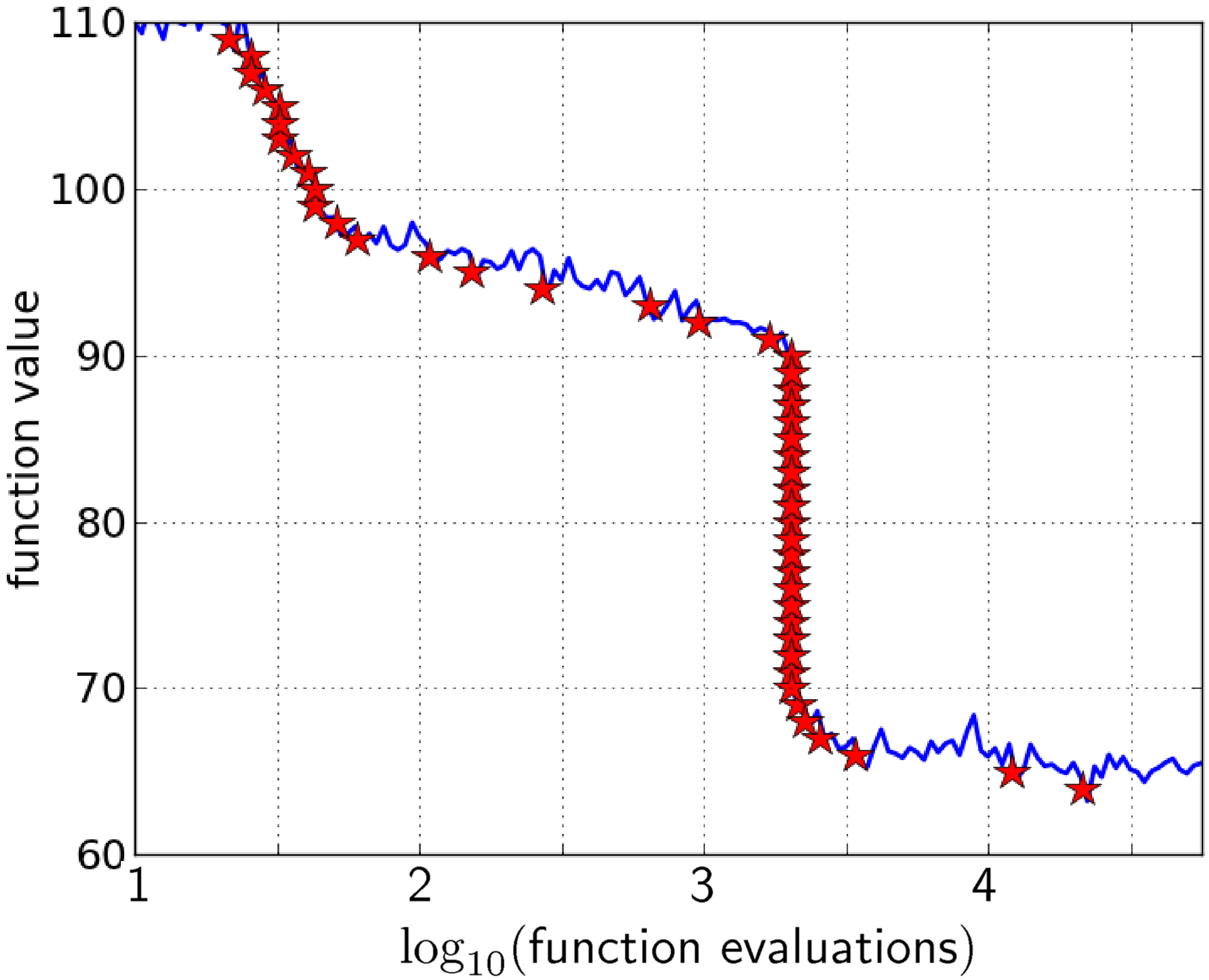


50 equally spaced targets

Reconstructing A Single Run



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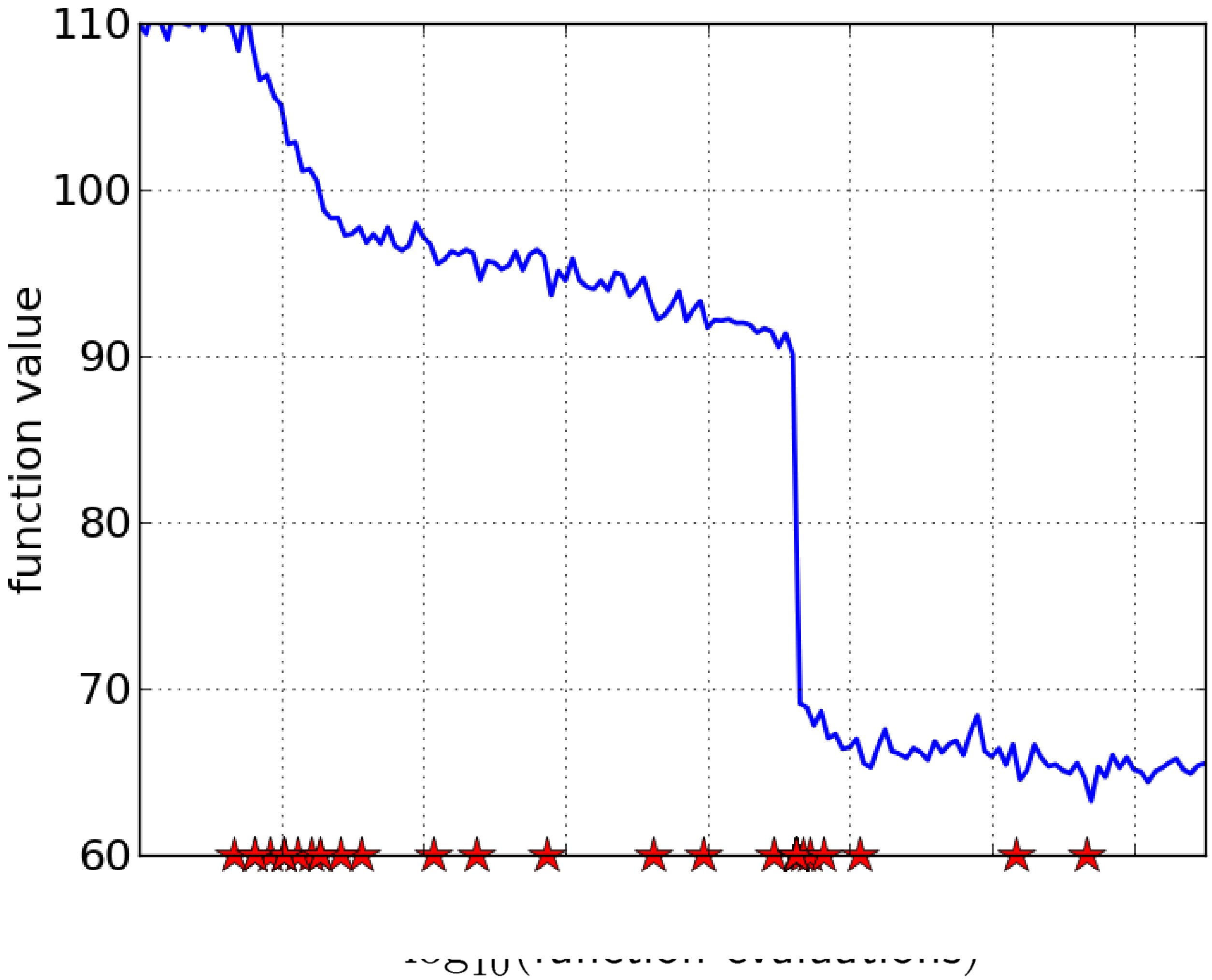
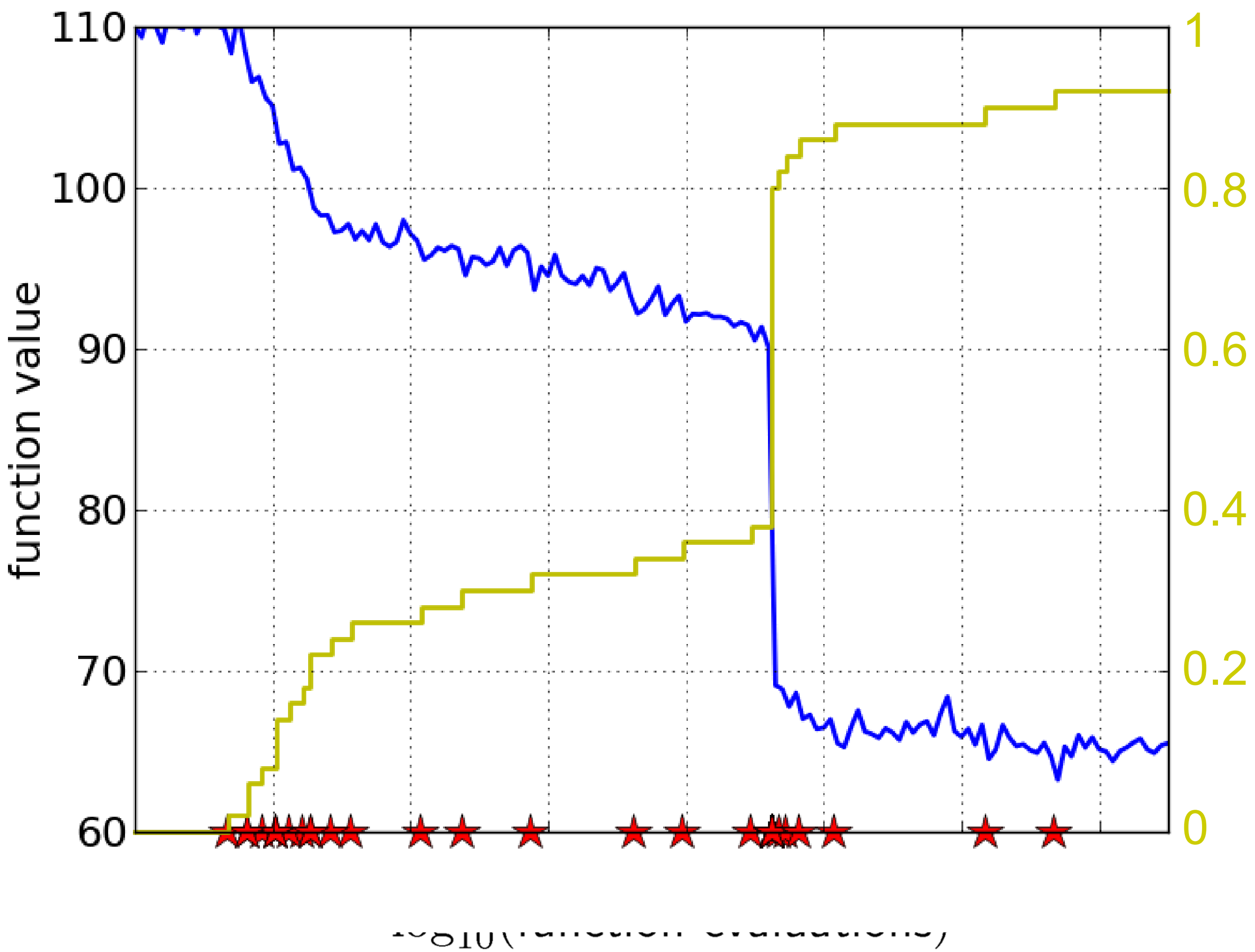
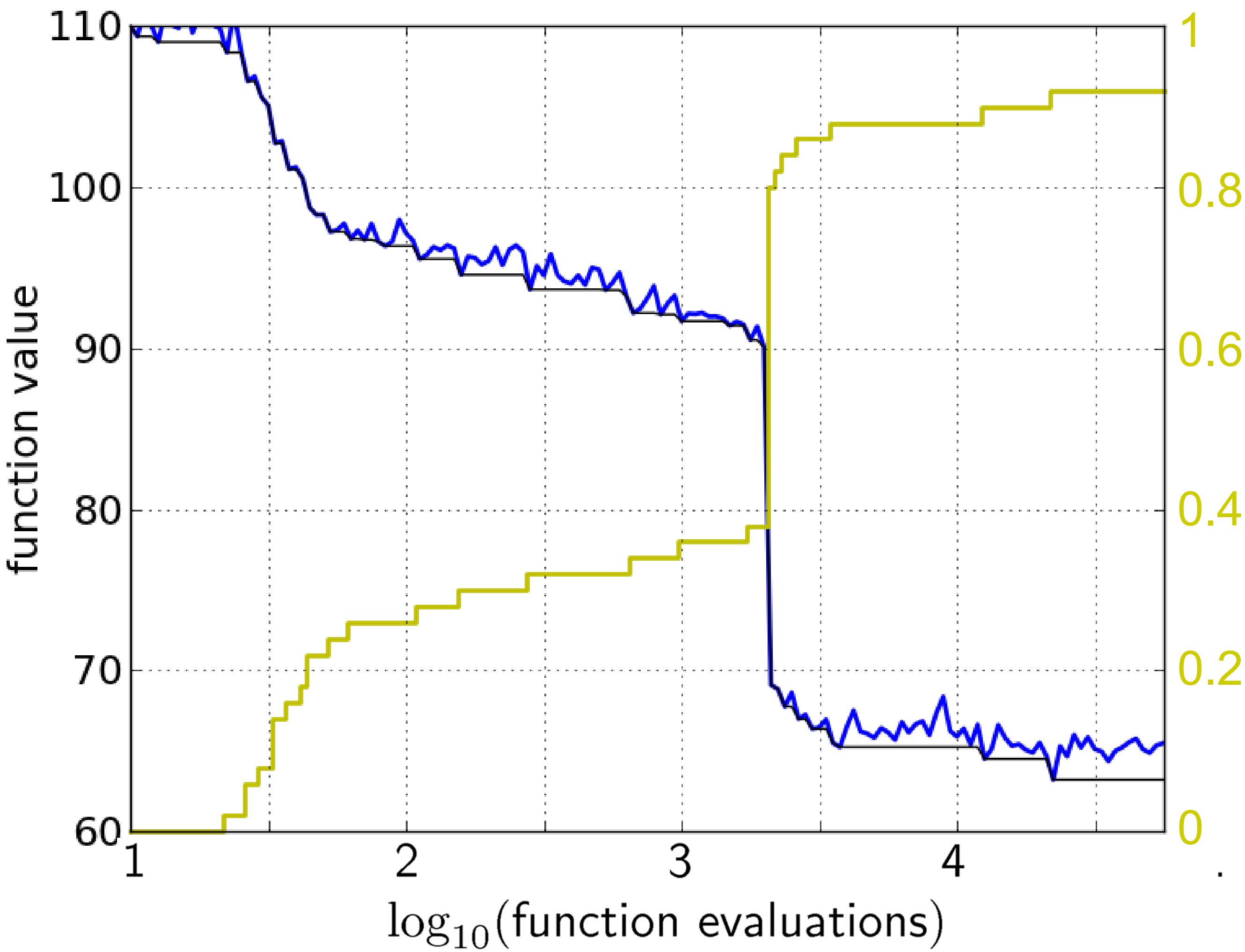


Reconstructing A Single Run



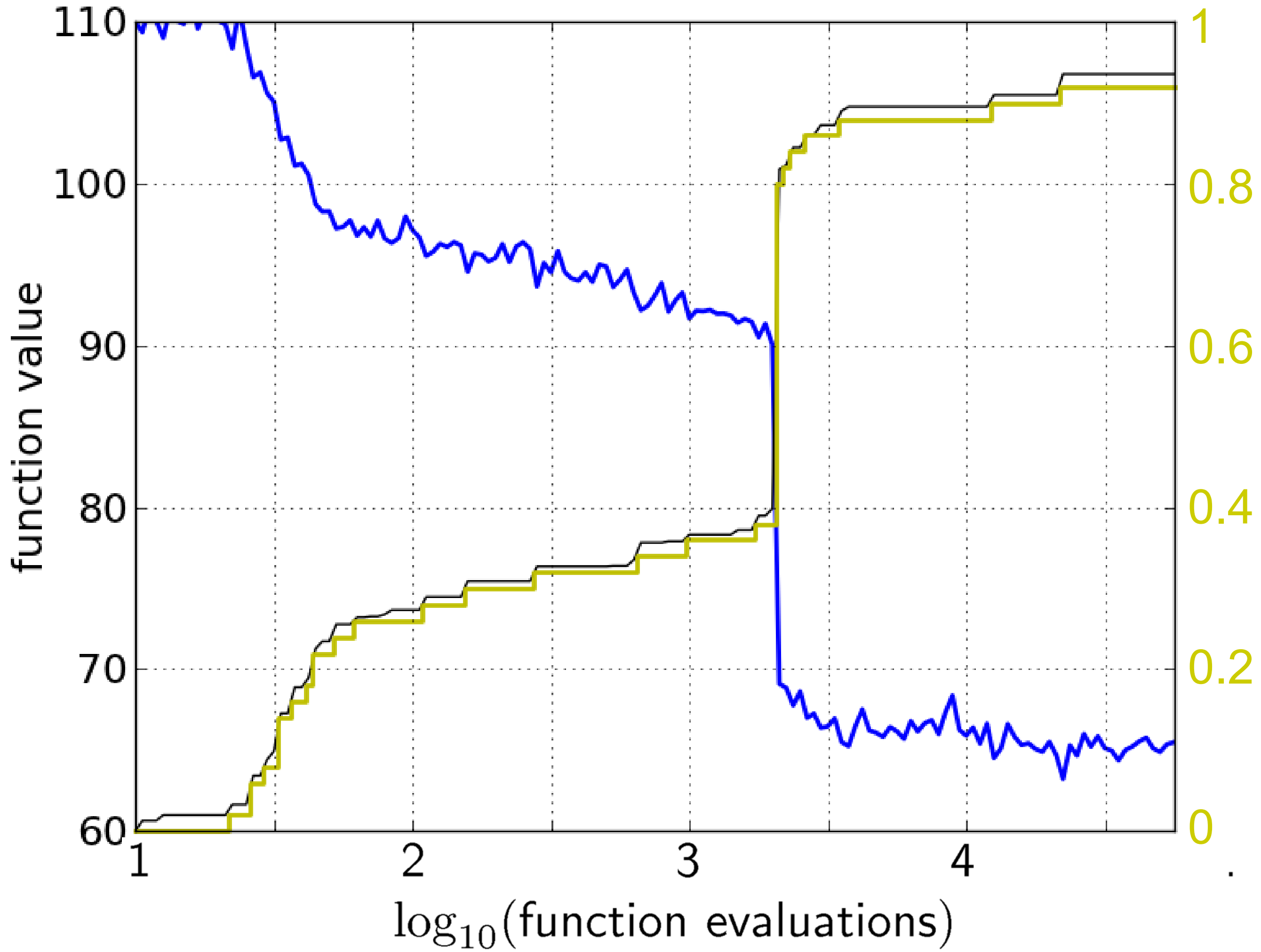
ıe empirical CDF makes a step for each star, is monotonous and displays for each budget the fraction of targets achieved within the budget

Reconstructing A Single Run



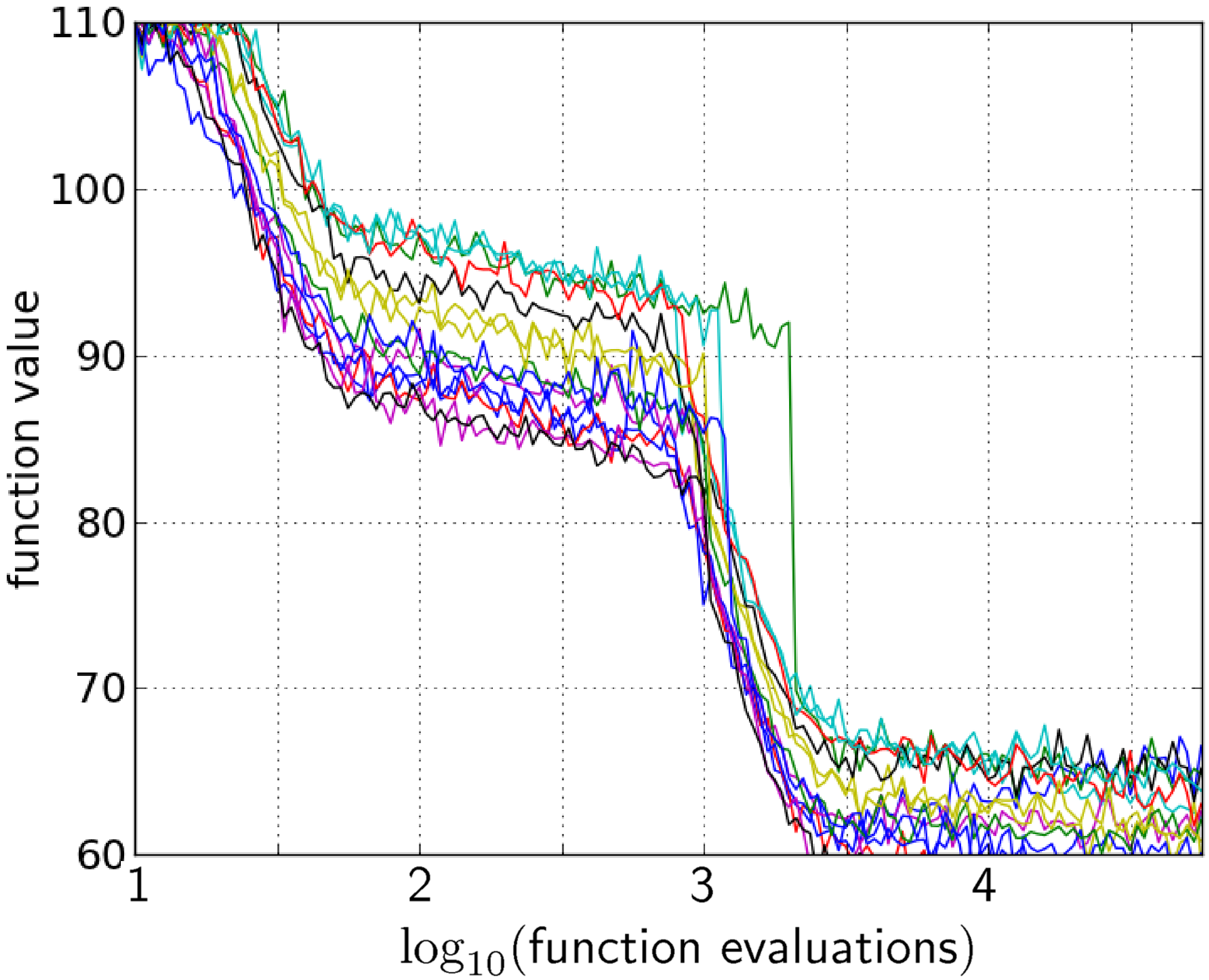
the ECDF recovers the monotonous graph, discretised and flipped

Reconstructing A Single Run



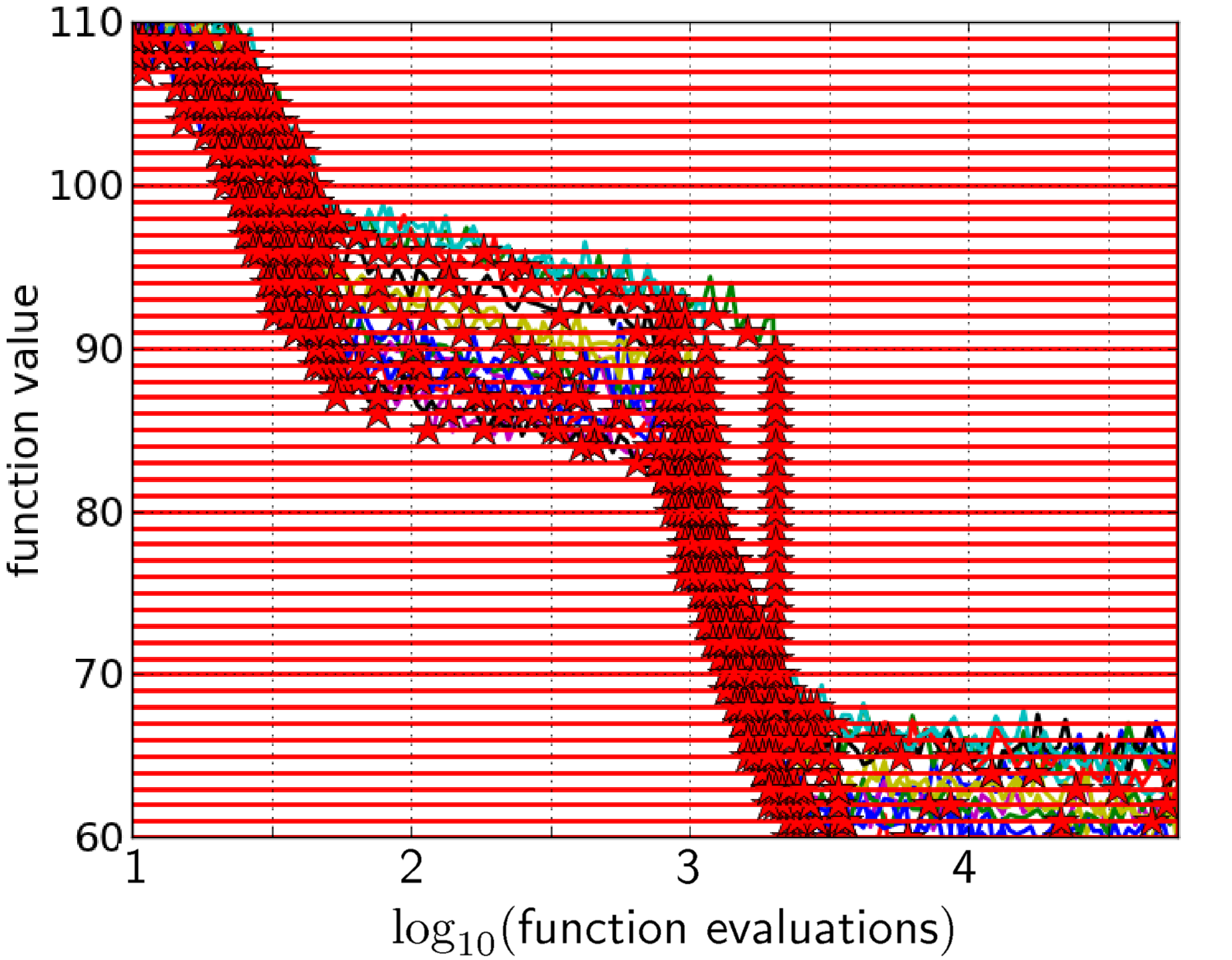
the ECDF recovers the monotonous graph, discretised and flipped

Aggregation



15 runs

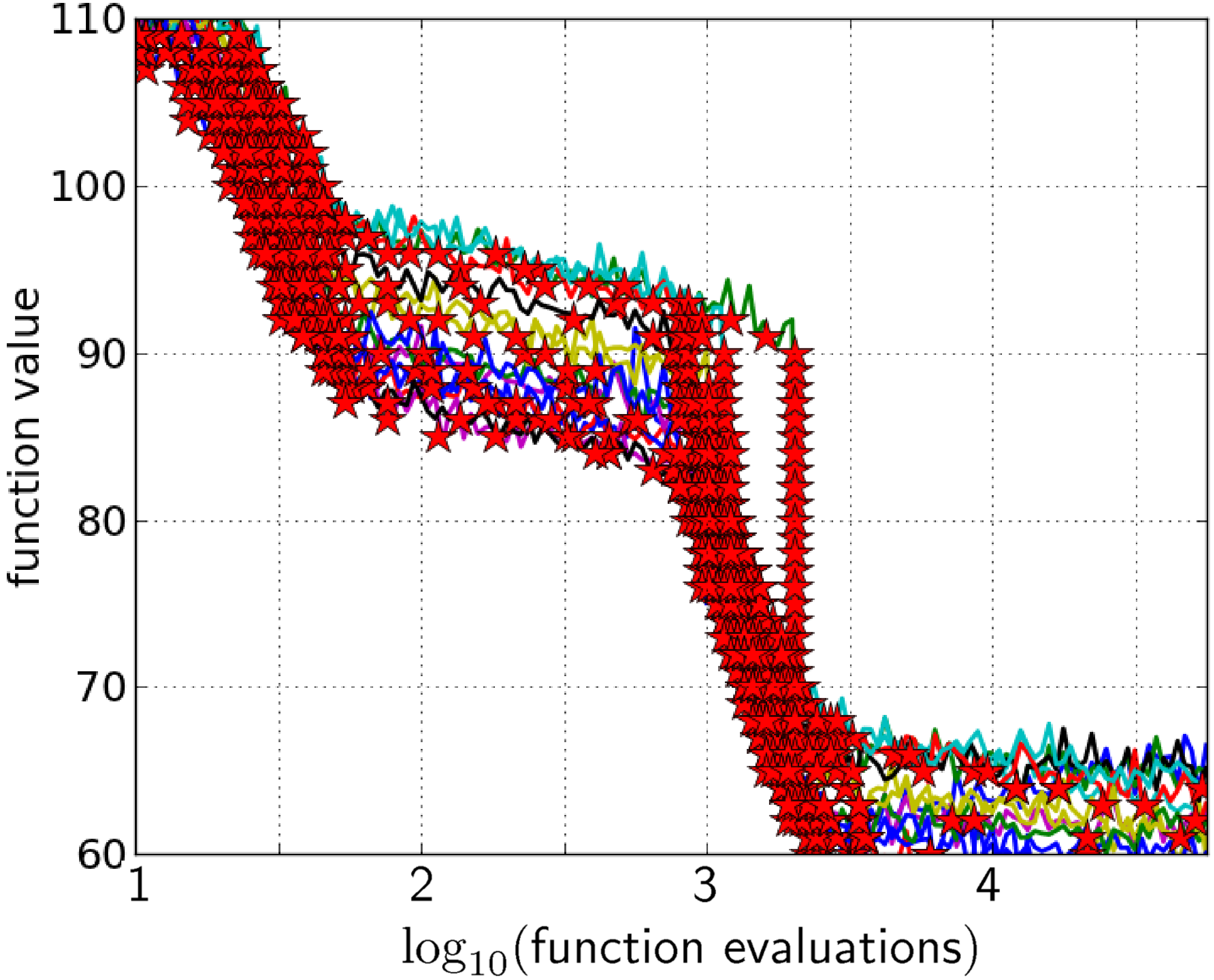
Aggregation



15 runs

50 targets

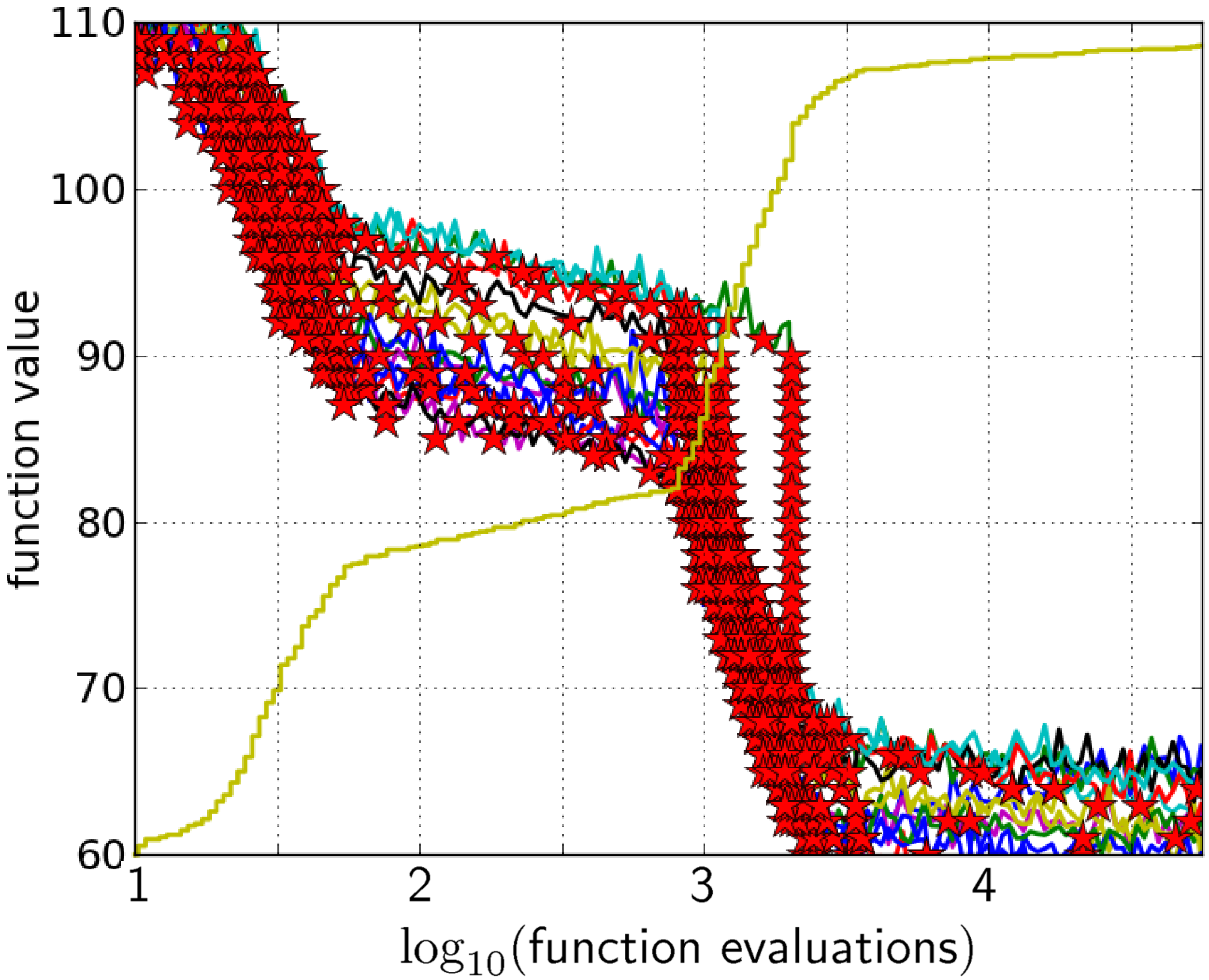
Aggregation



15 runs

50 targets

Aggregation

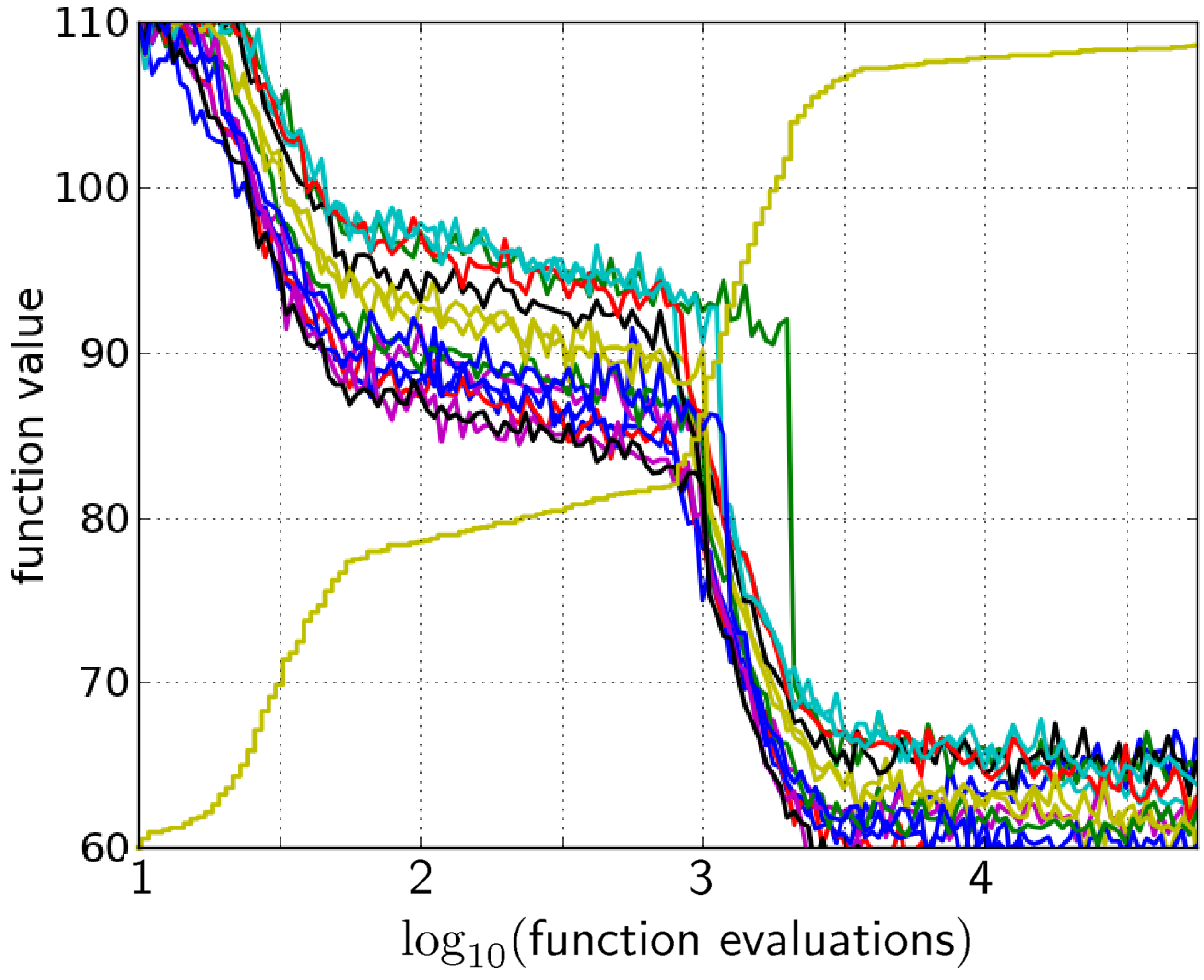


15 runs

50 targets

ECDF with 750 steps

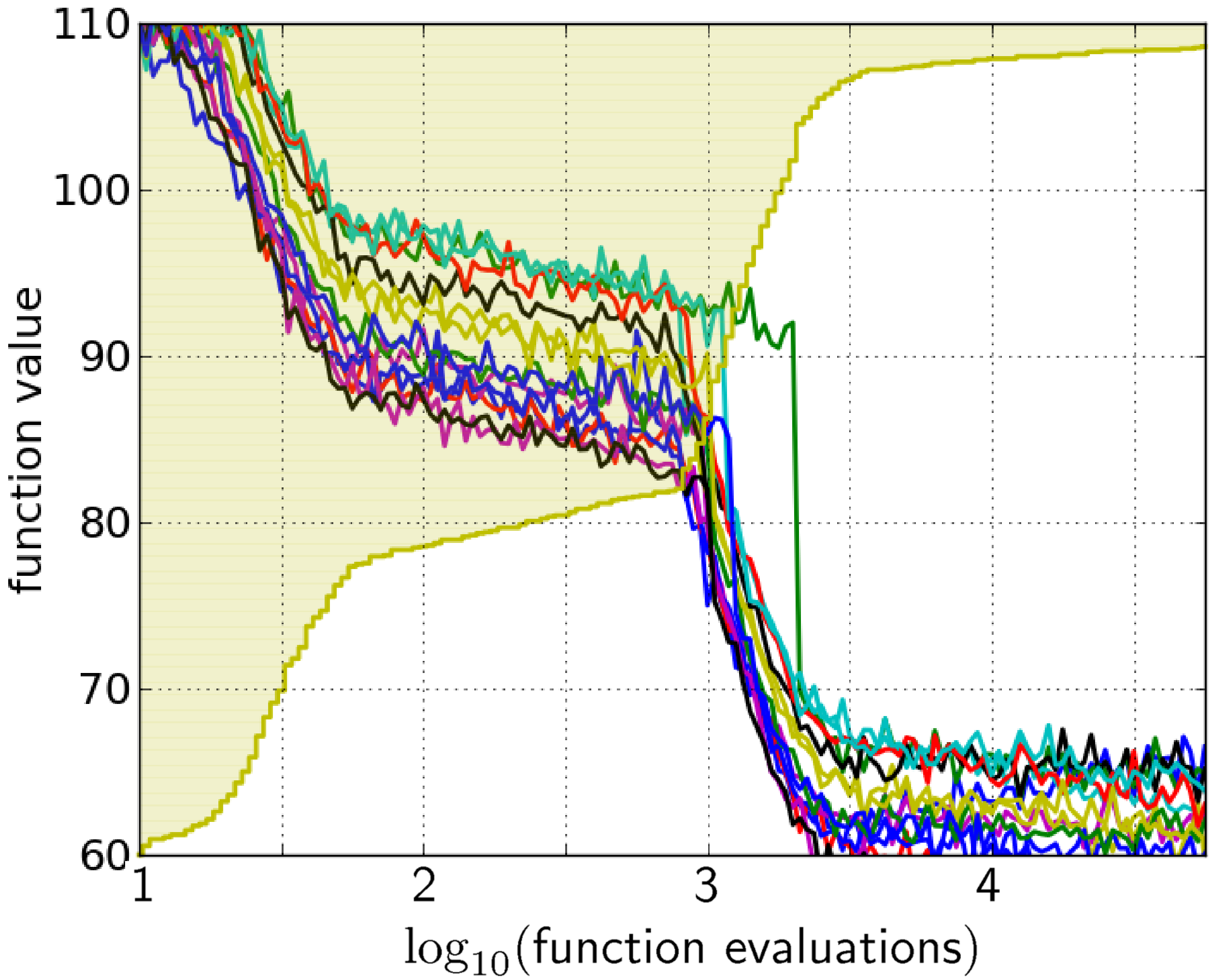
Aggregation



50 targets from 15 runs

...integrated in a single graph

Interpretation



50 targets from 15 runs integrated in a single graph

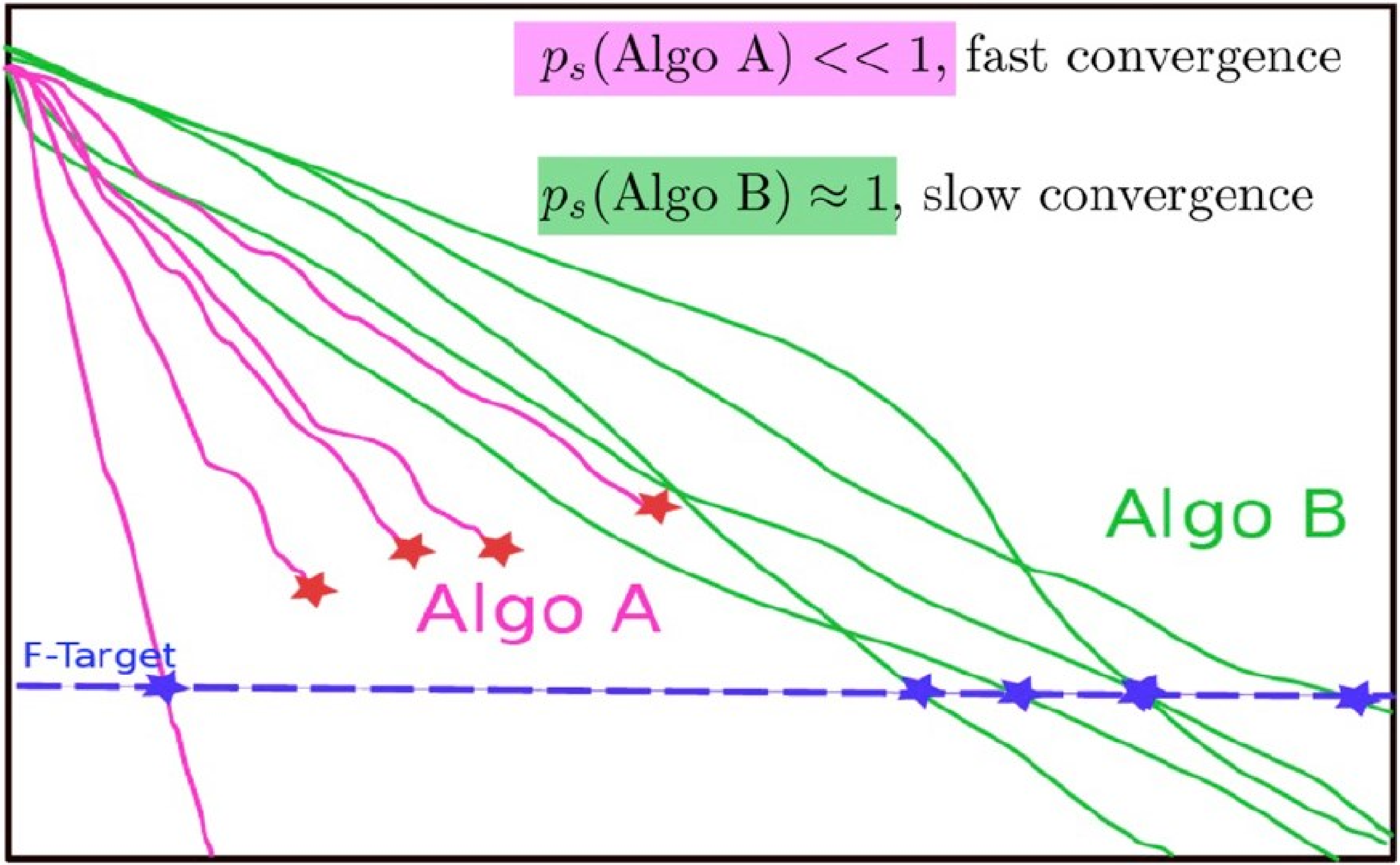
area over the ECDF curve

=

average log runtime

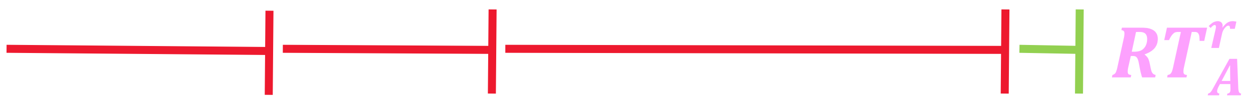
(or geometric avg. runtime) over all targets (difficult and easy) and all runs

Fixed-target: Measuring Runtime



Fixed-target: Measuring Runtime

- Algo Restart A:



p_s(Algo Restart A) = 1

- Algo Restart 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):

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

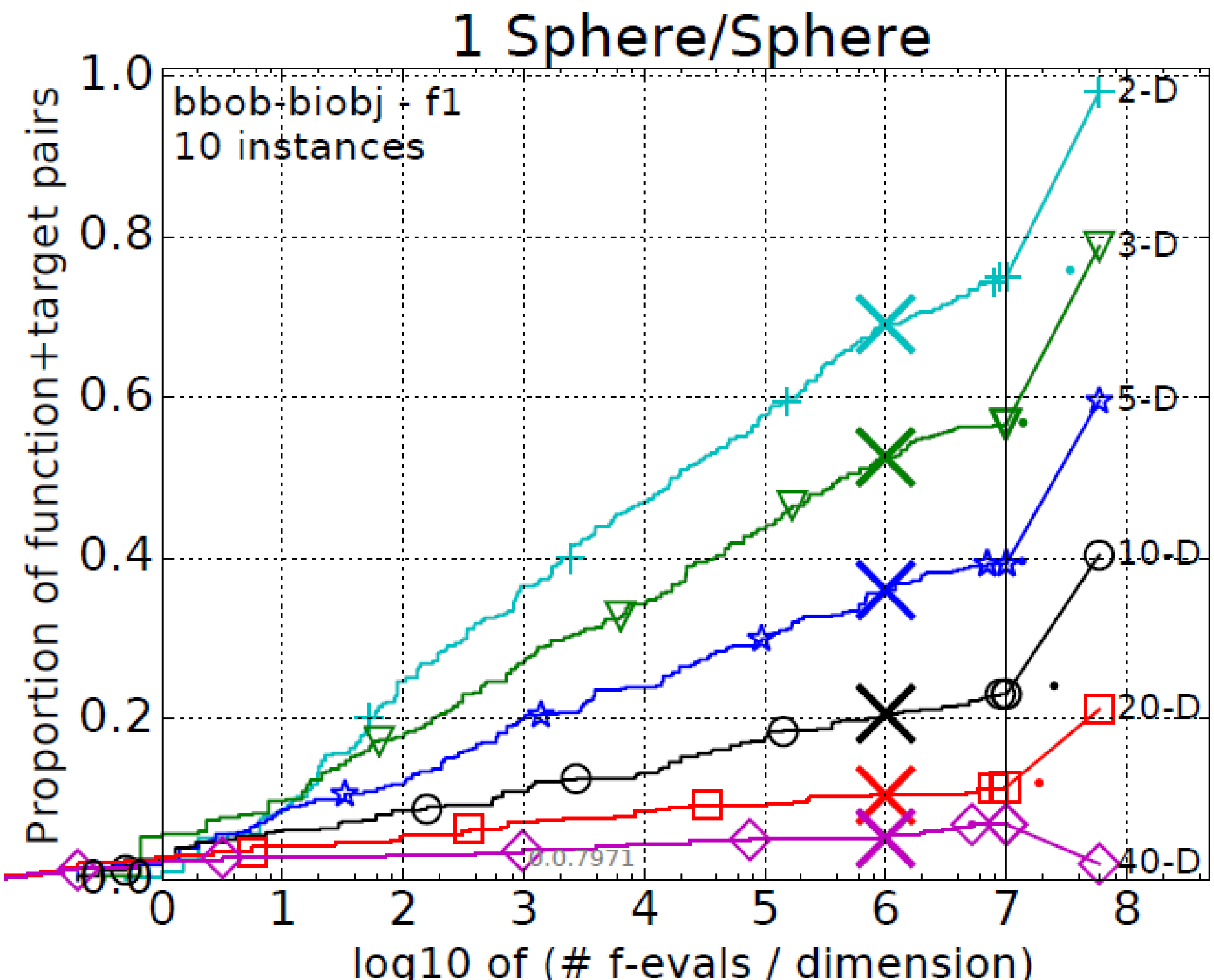
$$\widehat{RT_{unsucc}} = \text{Average evals of unsuccessful runs}$$

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

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

ECDFs with Simulated Restarts

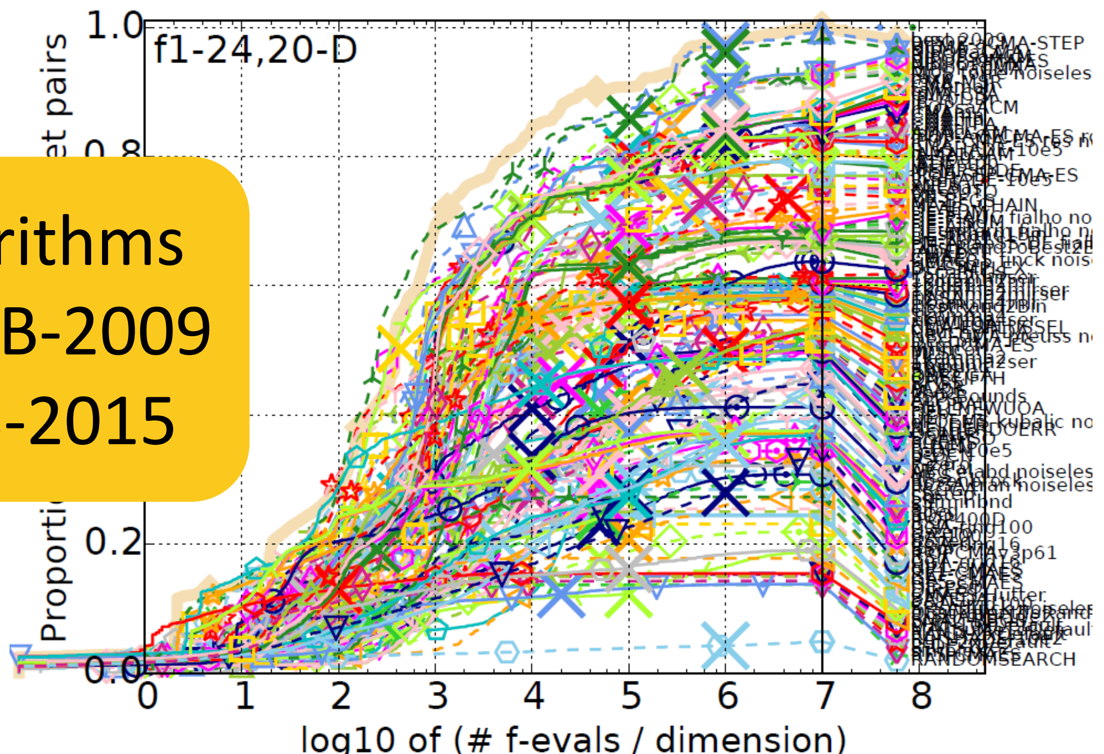
What we typically plot are ECDFs of the simulated restarted algorithms:



Worth to Note: ECDFs in COCO

In COCO, ECDF graphs

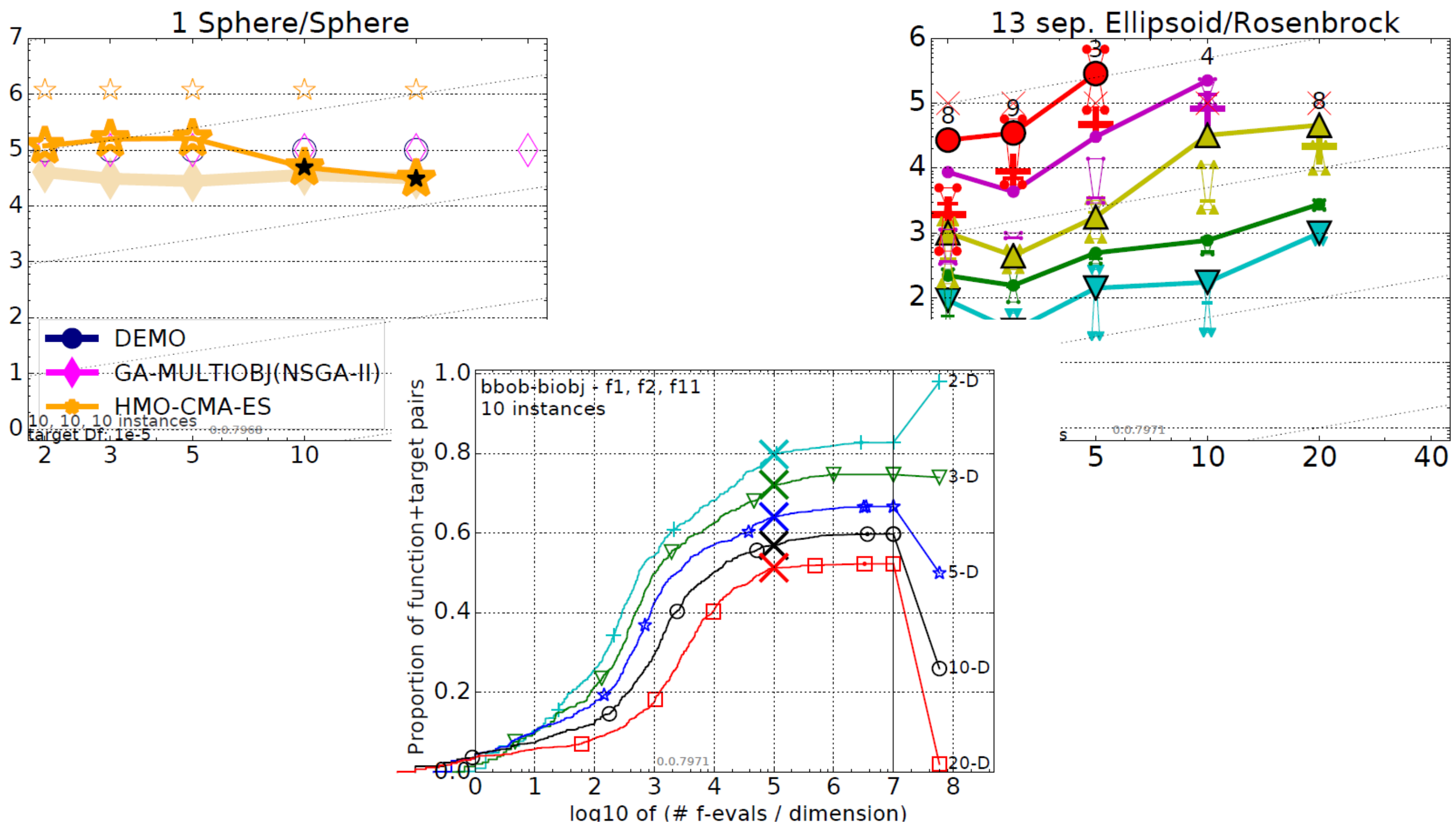
- never aggregate over dimension
    - but often over targets and functions
- can show data of more than 1 algorithm at a time



150 algorithms from BBOB-2009 till BBOB-2015

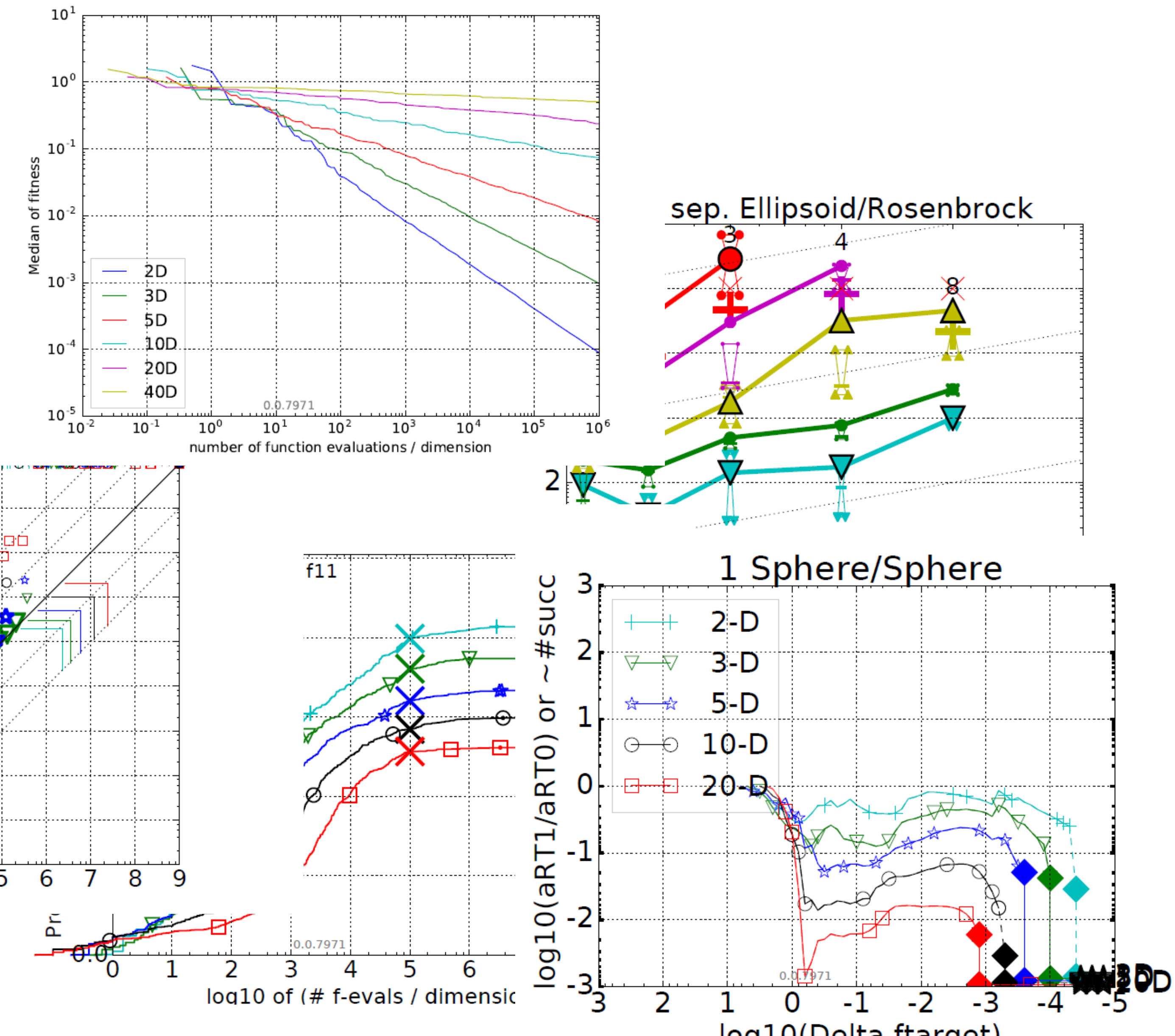
More Automated Plots...

...but no time to explain them here ☹



More Automated Plots...

...but no time t



and now?

BBOB-2018

Session Sunday 15th of July, 2018 - Training Room 1 (2F)	
09:30 - 09:45	The BBOBies: **A Short Introduction to COCO and BBOB**
09:45 - 10:05	Kouhei Nishida* and Youhei Akimoto: **Benchmarking the PSA-CMA-ES on the BBOB Noiseless Testbed**
10:05 - 10:25	Duc Manh Nguyen: **Benchmarking a Variant of the CMAES-APOP on the BBOB Noiseless Testbed**
10:25 – 10:40	Aurore Blelly, Matheus Felipe-Gomes, Anne Auger, and Dimo Brockhoff*: **Stopping Criteria, Initialization, and Implementations of BFGS and their Effect on the BBOB Test Suite**
10:40 - 11:00	Aljoša Vodopija, Tea Tušar*, Bogdan Filipič: **Comparing Black-Box Differential Evolution and Classic Differential Evolution**
11:00 - 11:10	The BBOBies: **Workshop Wrapup and Discussion**

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