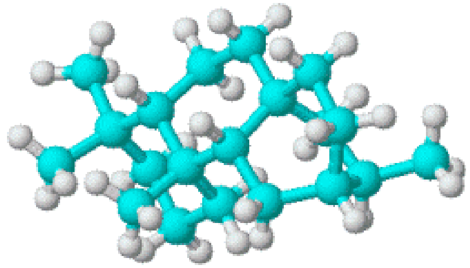
# 6th GECCO Workshop on Blackbox Optimization Benchmarking (BBOB): Welcome and Introduction to COCO/BBOB

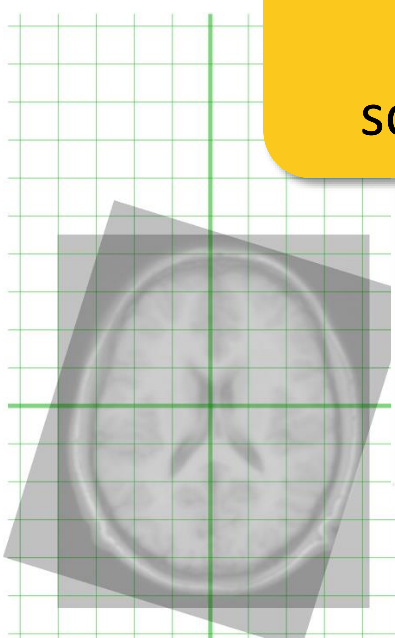
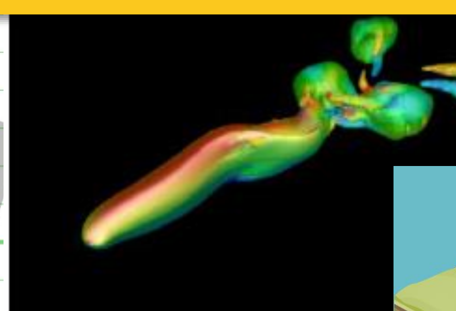
**The BBOBies**
https://github.com/numbbo/coco

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]
- Genetic Algorithms [Holland 1975, Goldberg 1989]

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

# Numerical Blackbox Optimizers

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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**

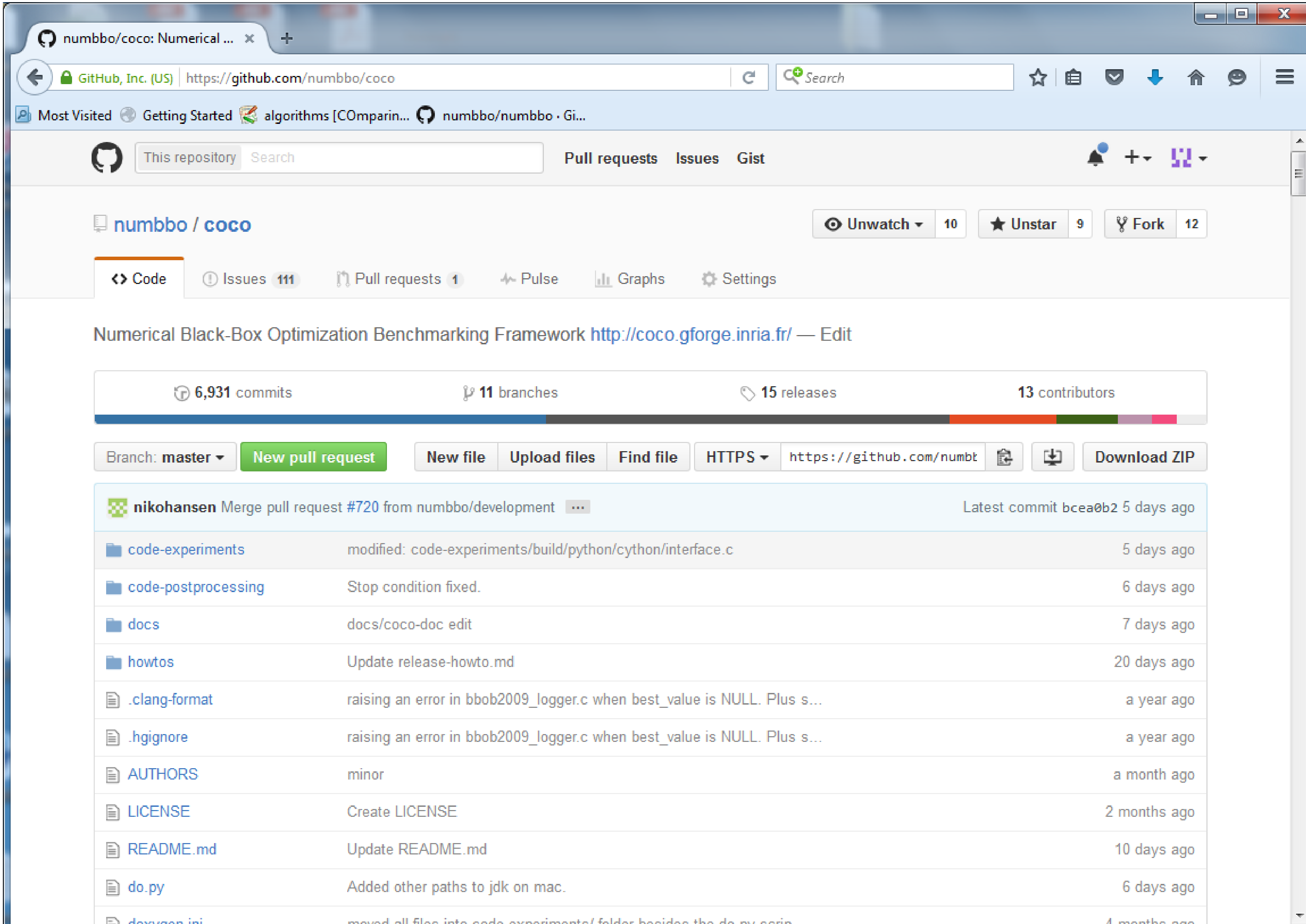
**Comparing Continuous Optimizers Platform**

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

# automatized benchmarking

# How to benchmark algorithms with COCO?

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



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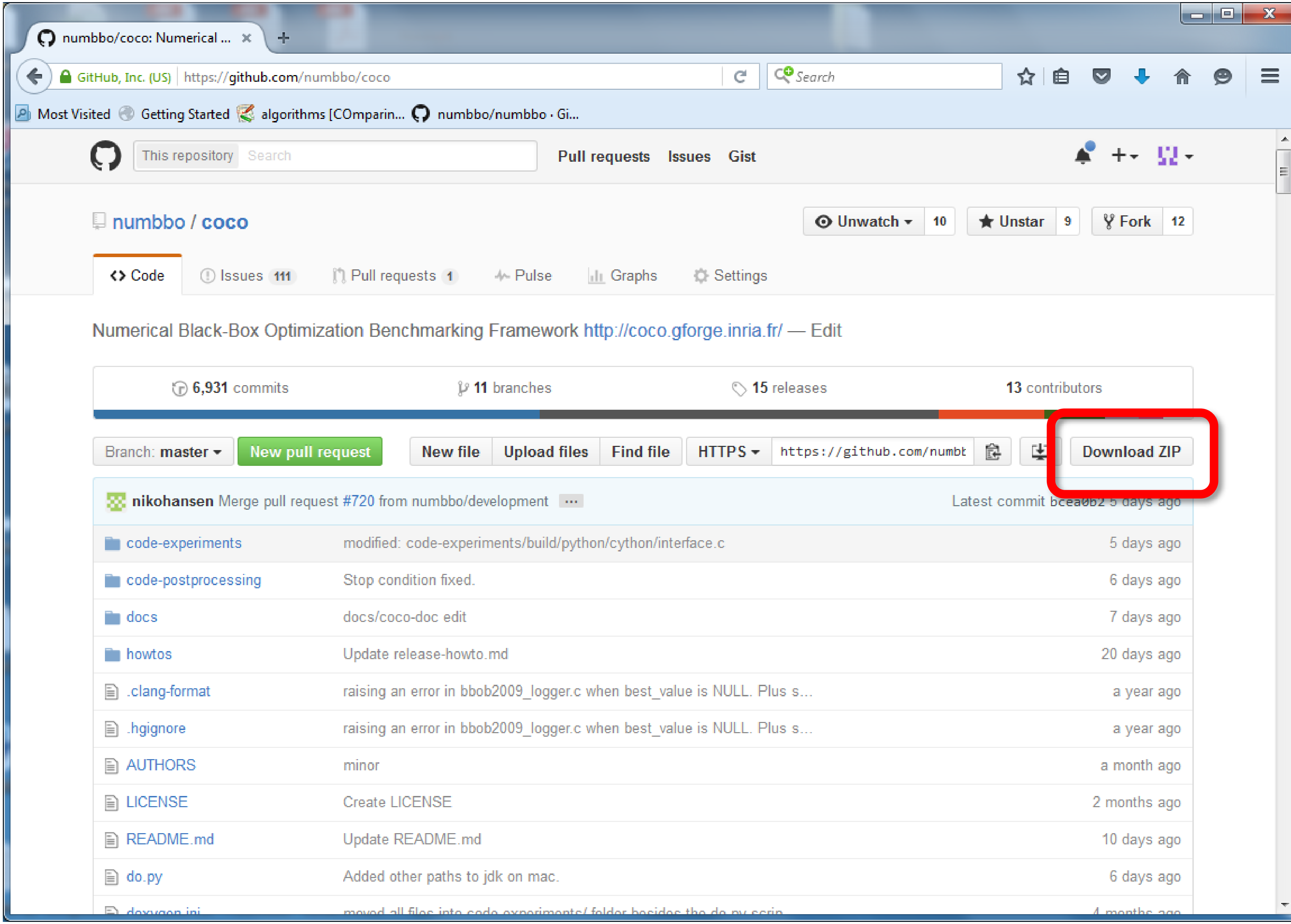

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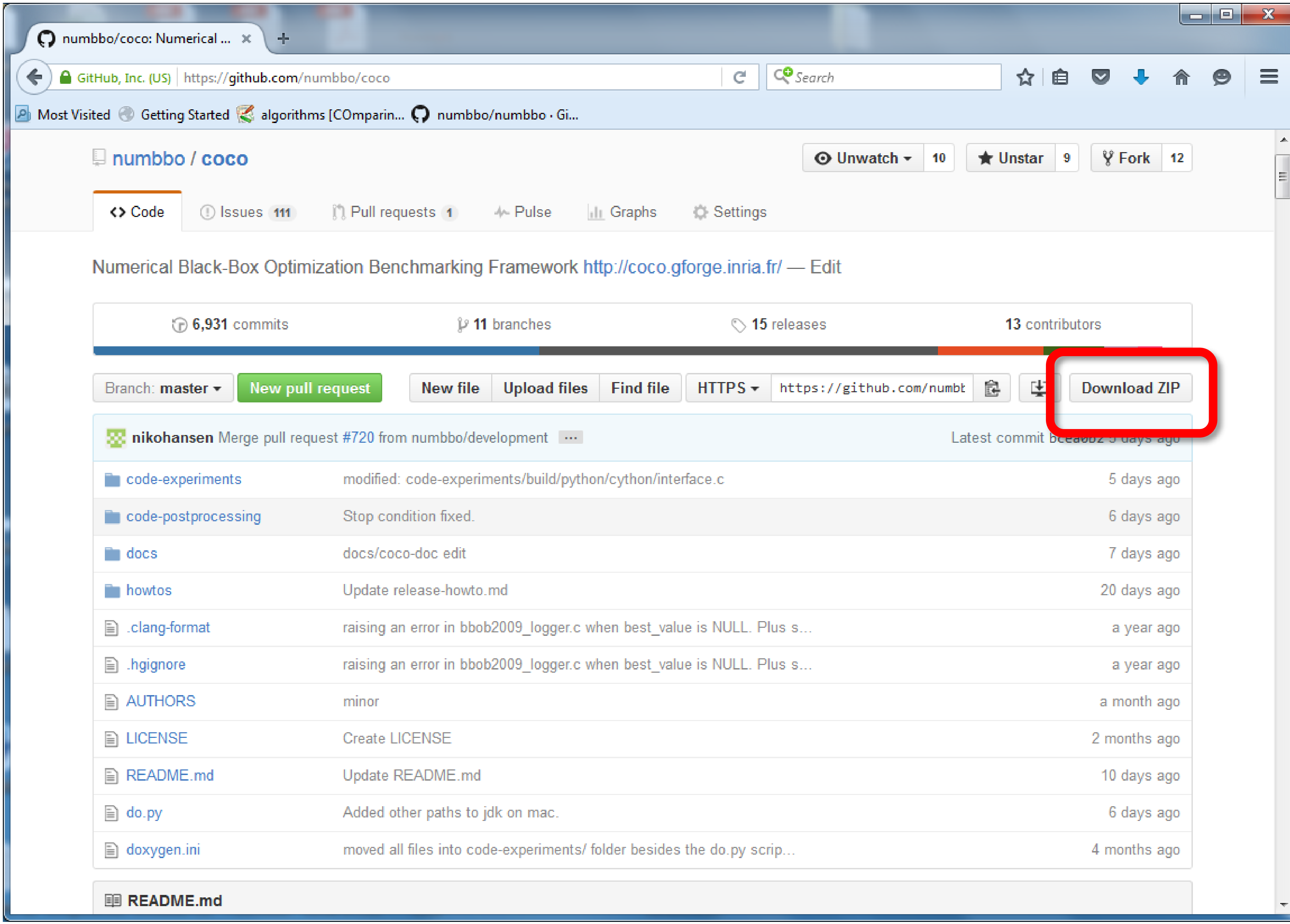

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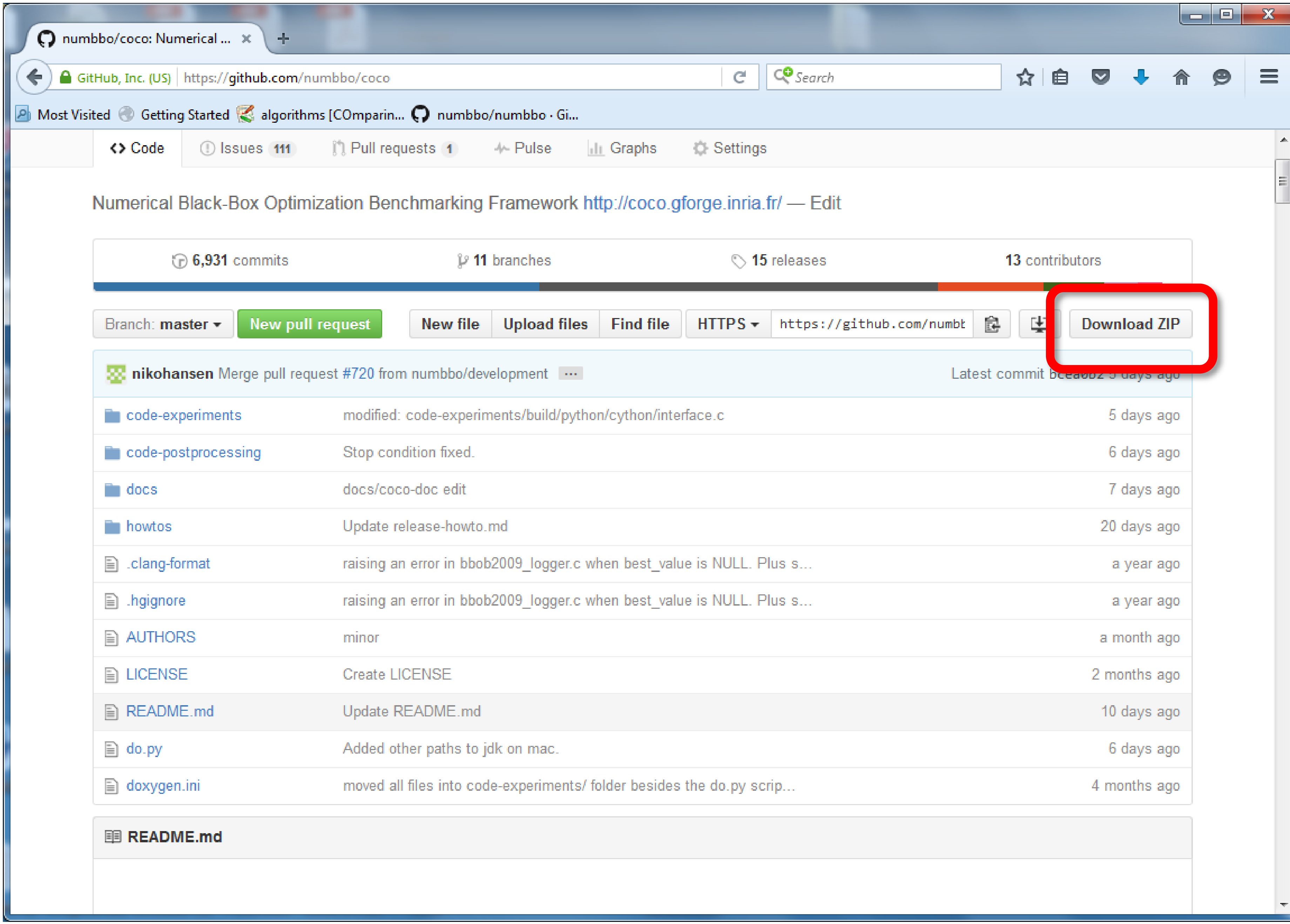

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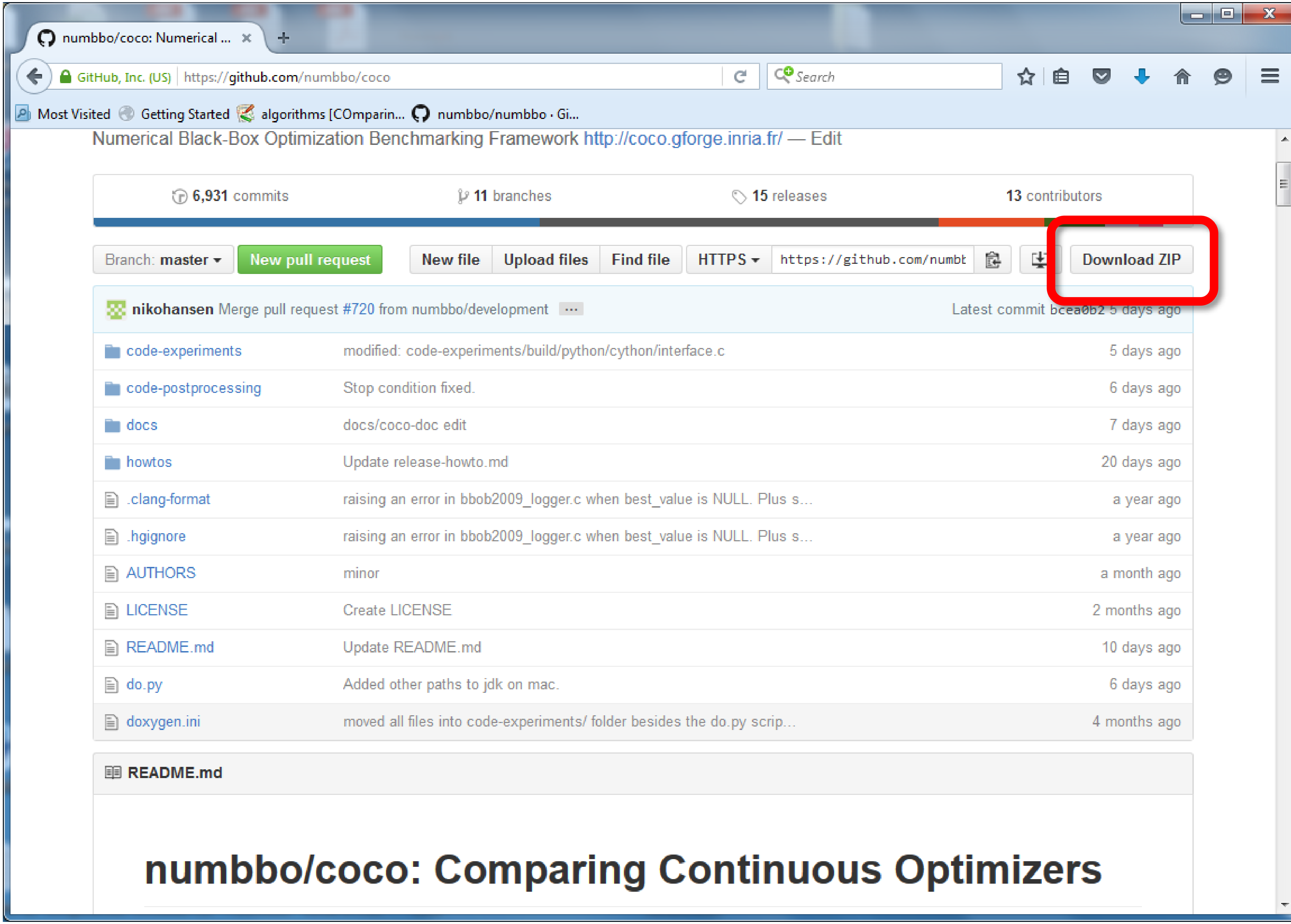

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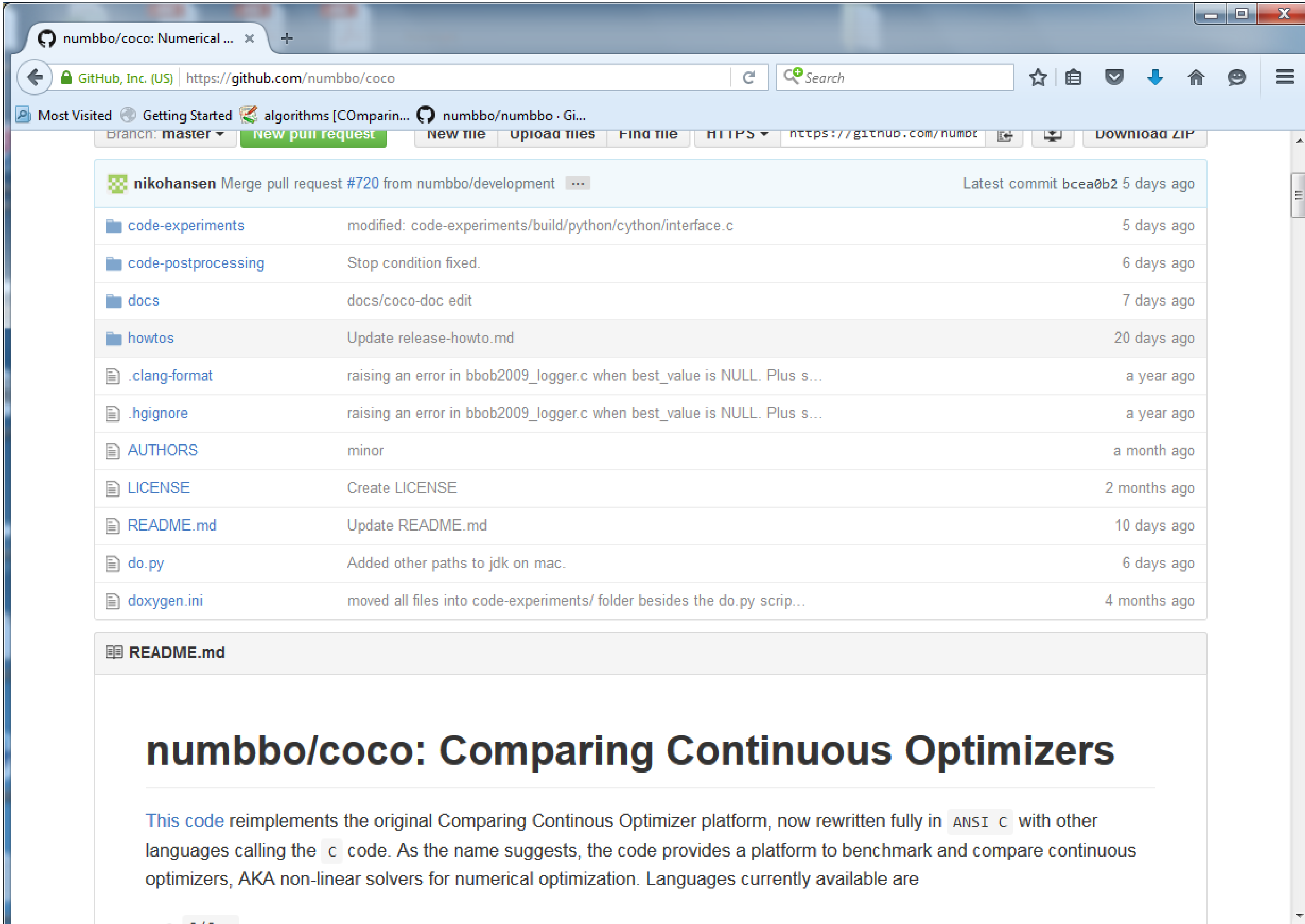

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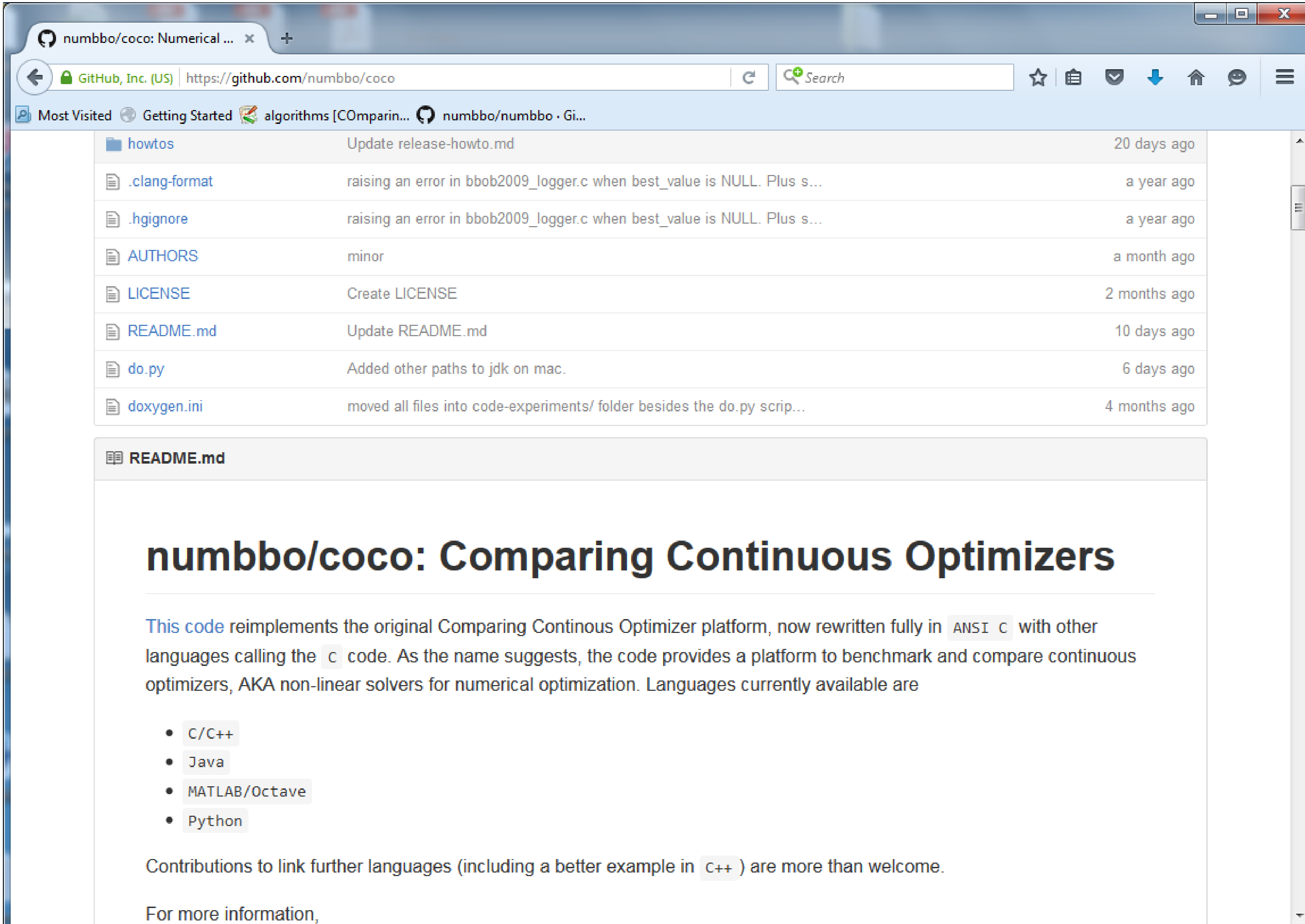

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| | | |
|---|---|---|
| howtos | Update release-howto.md | 20 days ago |
| .clang-format | raising an error in bbob2009_logger.c when best_value is NULL. Plus s... | a year ago |
| .hgignore | raising an error in bbob2009_logger.c when best_value is 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 |

**README.md**

## numbbo/coco: Comparing Continuous Optimizers

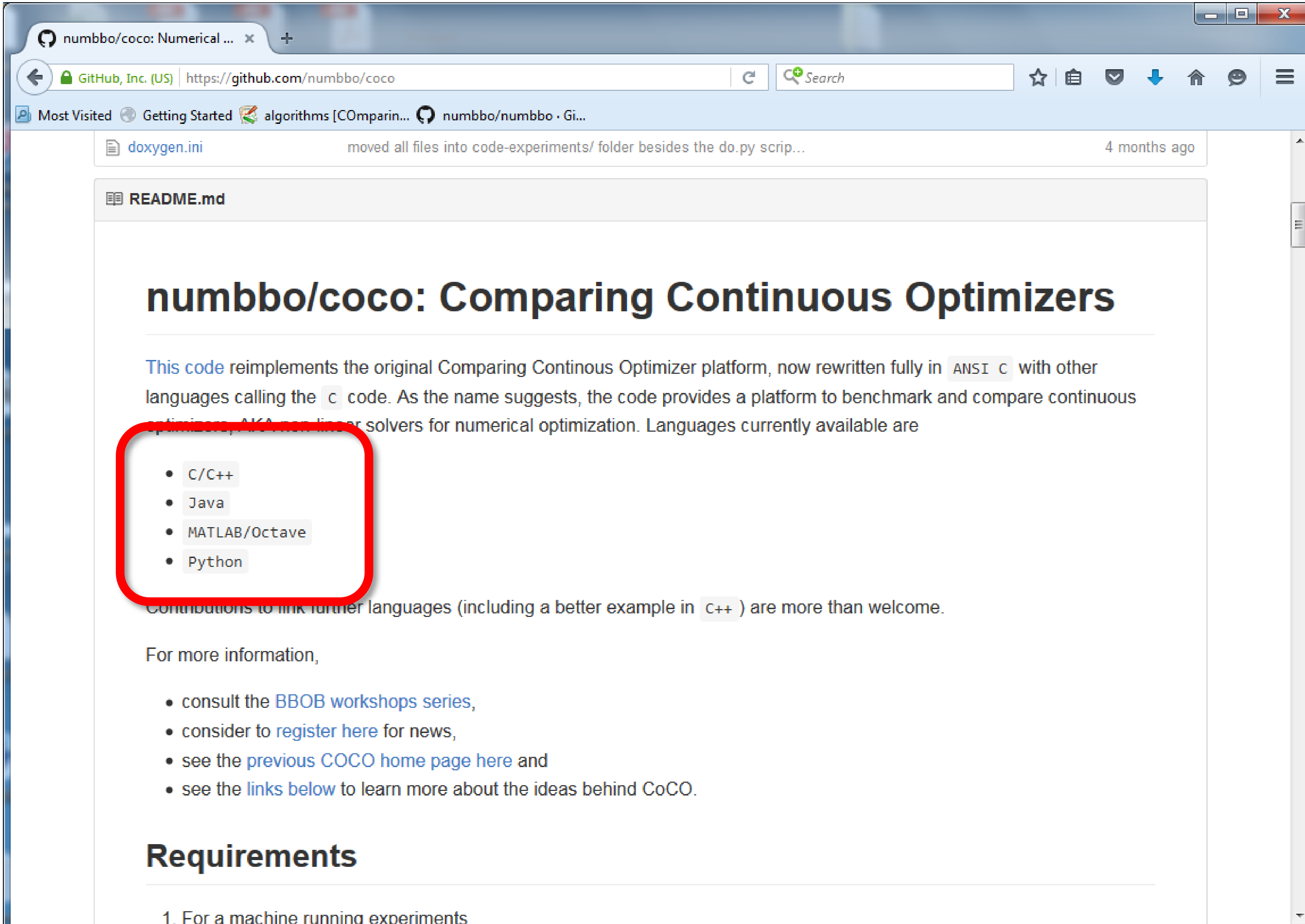
This code reimplements the original Comparing Continous Optimizer platform, now rewritten fully in `ANSI C` with other languages calling the `C` code. As the name suggests, the code provides a platform to benchmark and compare continuous optimizers, AKA non-linear solvers for numerical optimization.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

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



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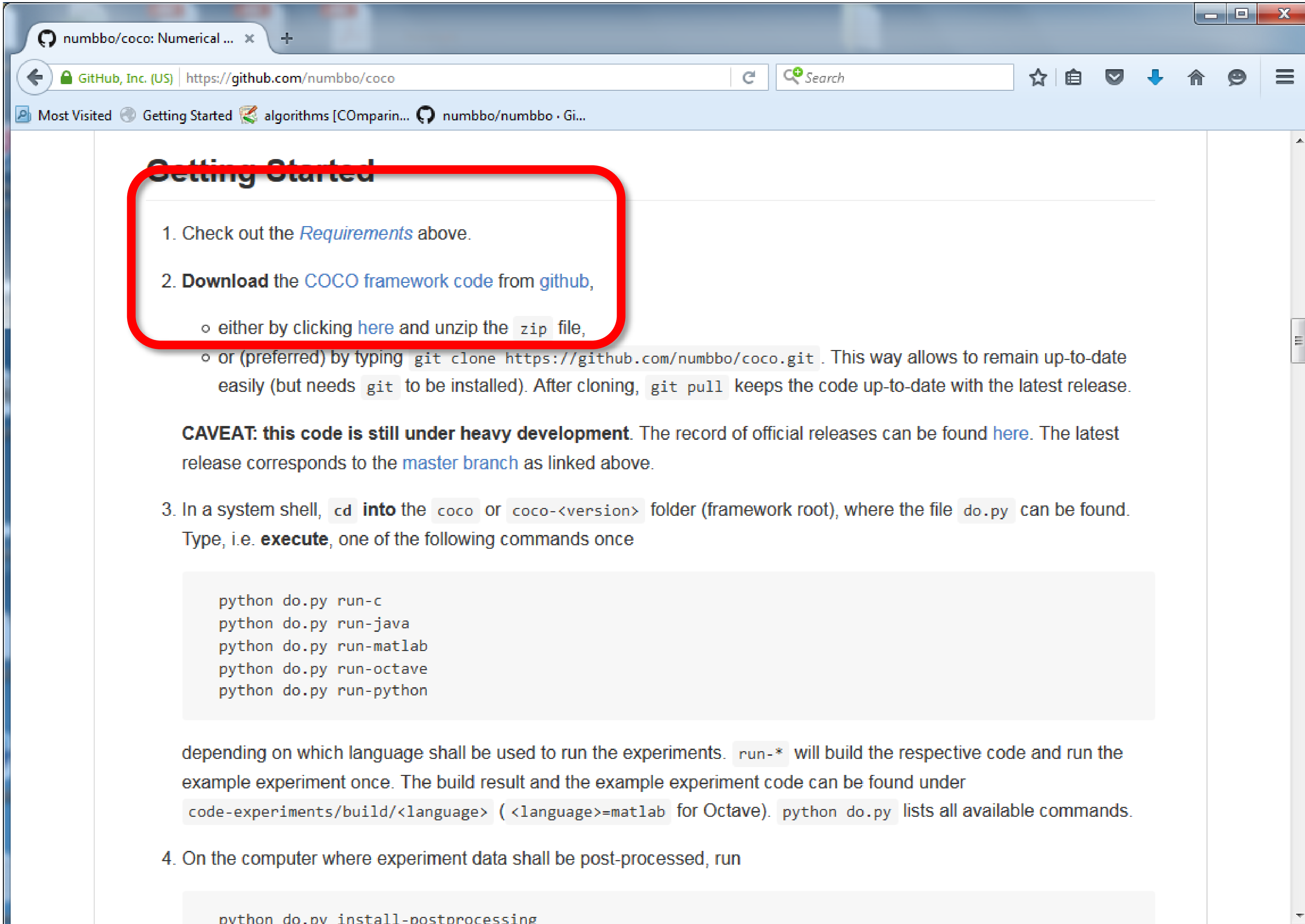

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## Getting Started

1. Check out the *Requirements* above.
2. **Download** the COCO framework code from github,
   - either by clicking here and unzip the `zip` file,
   - or (preferred) 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.

   **CAVEAT: this code is still under heavy development**. The record of official releases can be found here. The latest release corresponds to the master branch as linked above.
3. 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.
4. On the computer where experiment data shall be post-processed, run

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

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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]
```

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# 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),
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```

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.

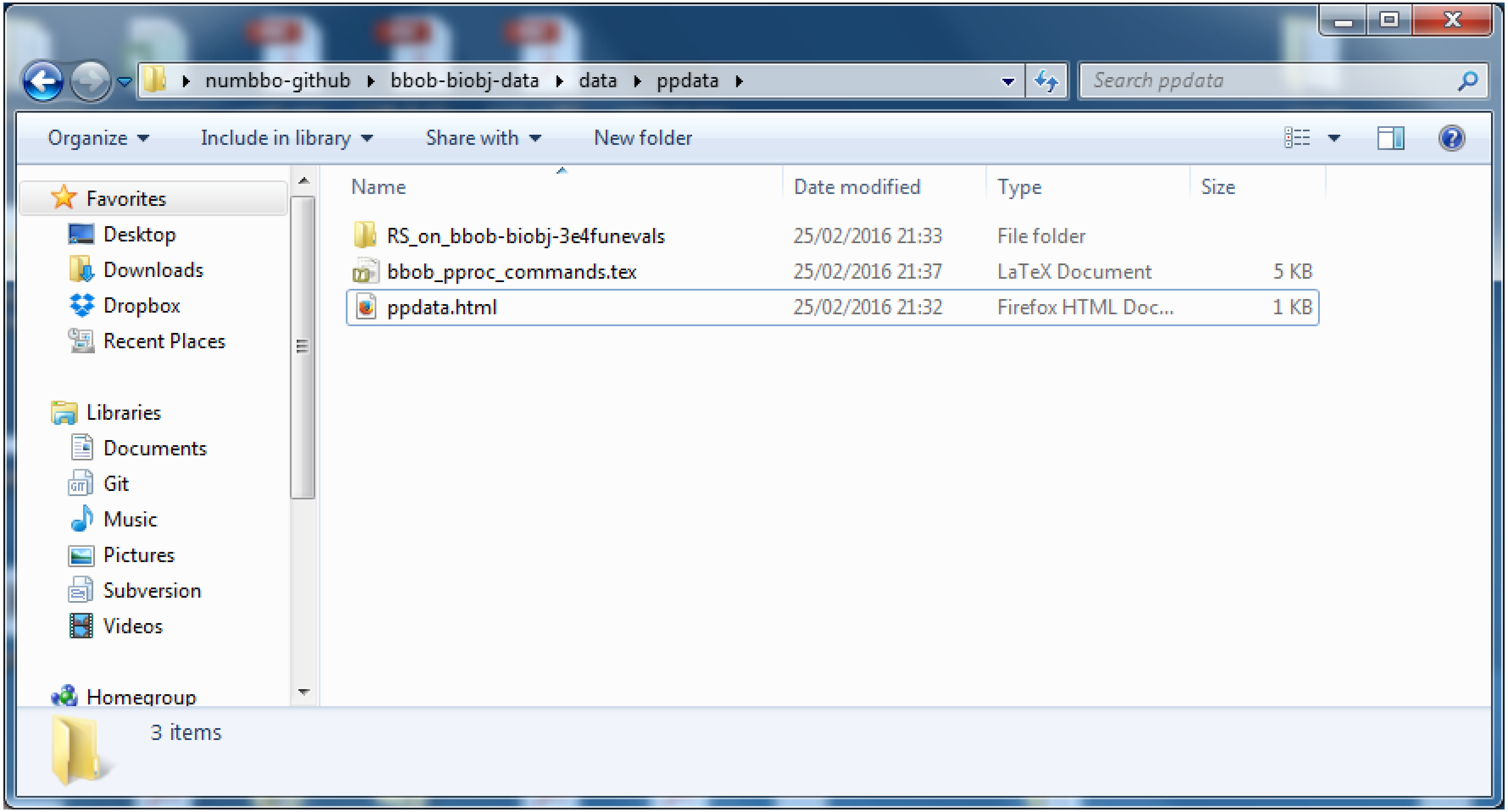
A folder, `ppdata` by default, will be generated, which contains all output from the post-processing, including a `ppdata.html` file, useful as main entry point to explore the result with a browser. Data might be overwritten, it is therefore useful to change the output folder name with the `-o OUTPUT_FOLDERNAME`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

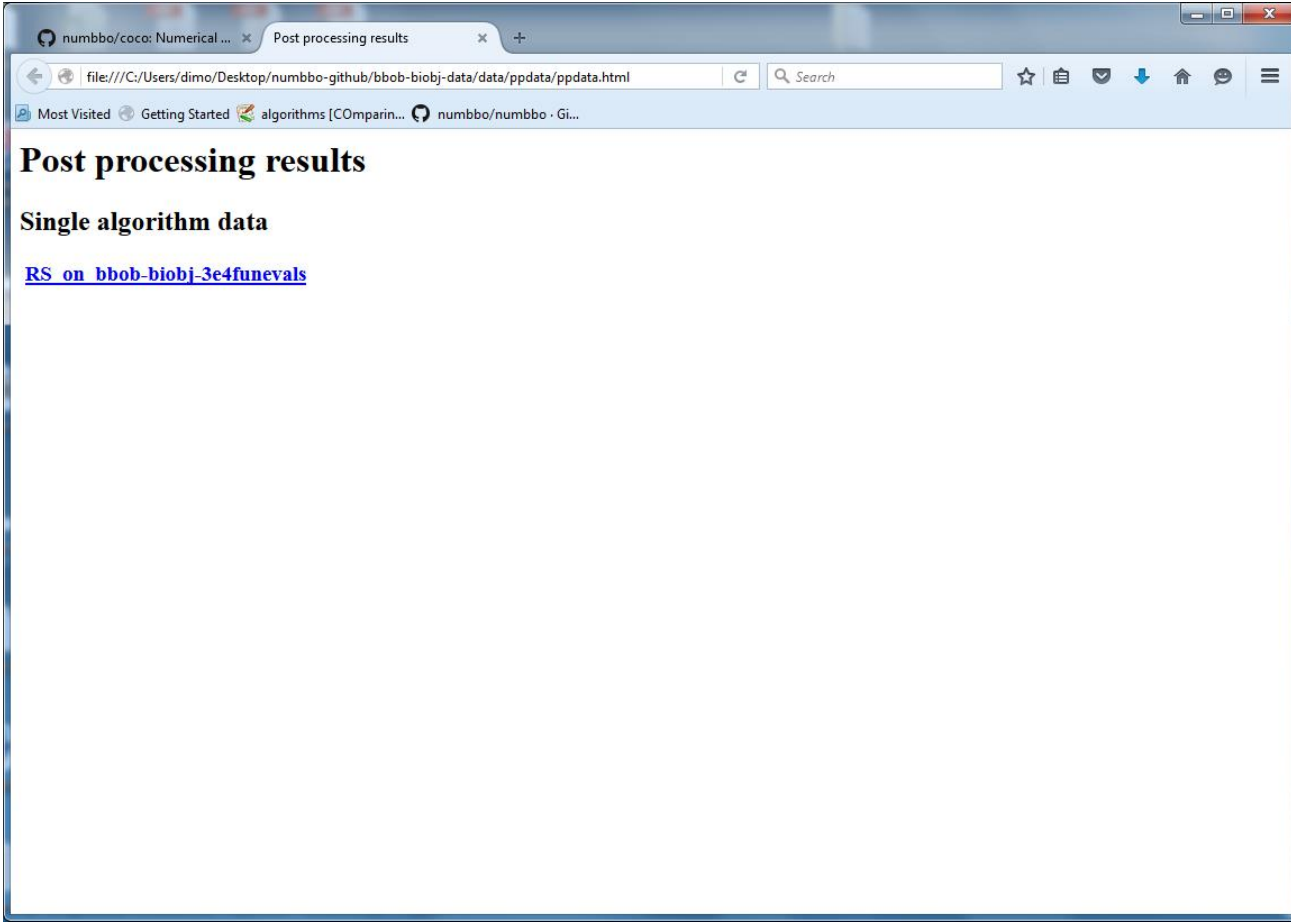
8. Once your algorithm runs well, **increase the budget** in your experiment script, if necessary implement randomized independent restarts, and follow the above steps successively until you are happy.

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



# automatically generated results



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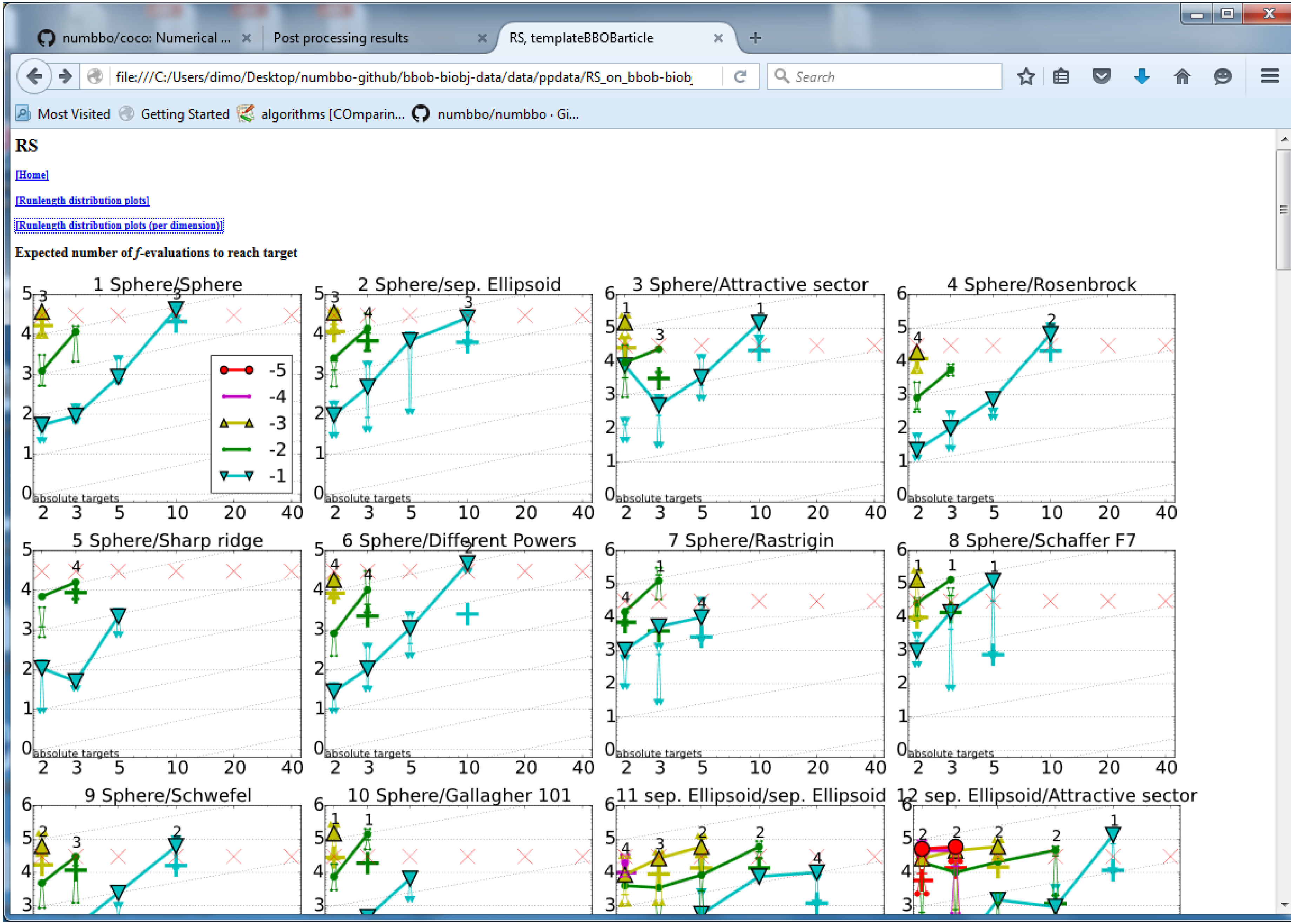

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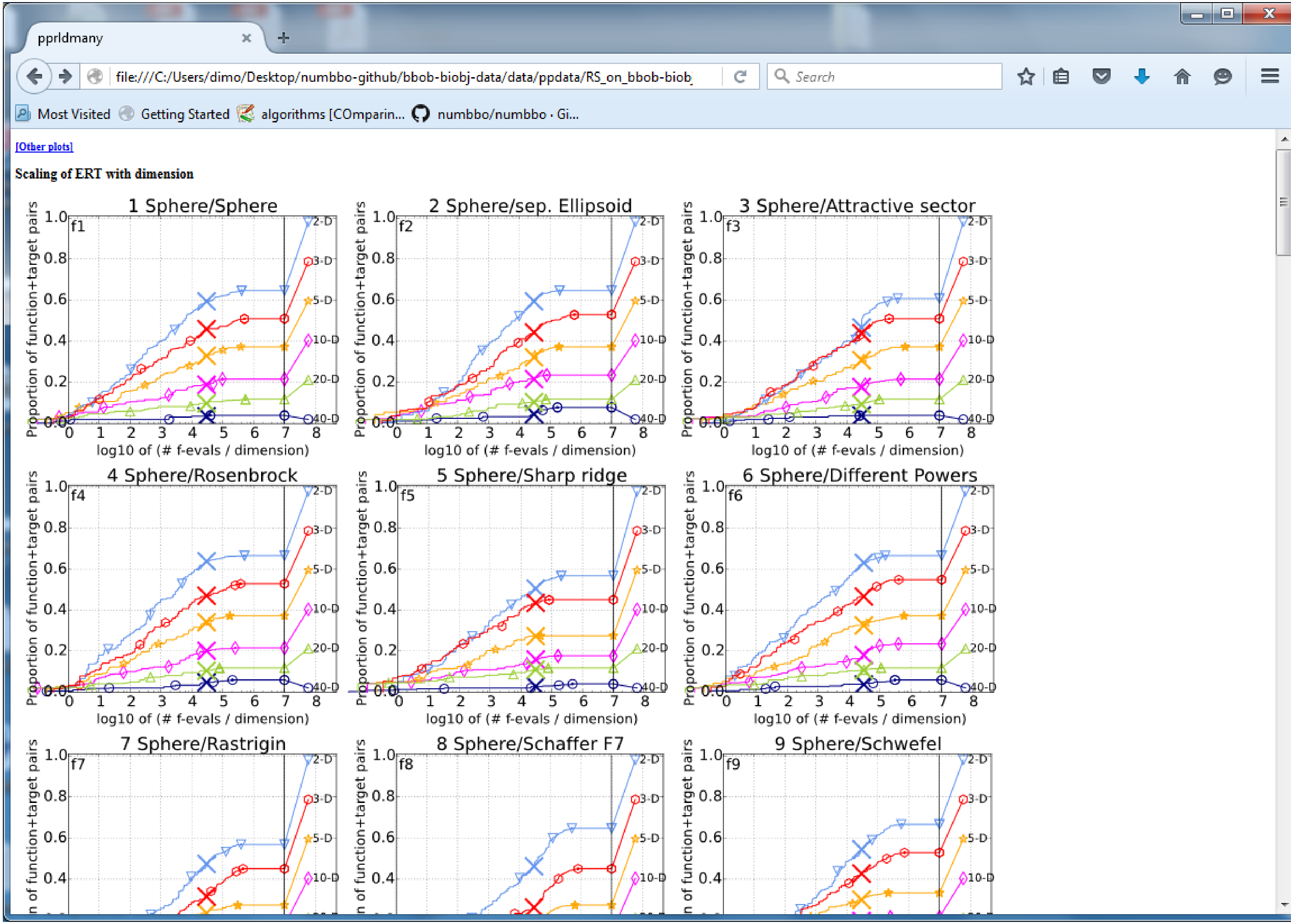


**doesn't look too complicated, does it?**

[the devil is in the details ☺]

**so far (i.e. before 2016):**

data for about 150 algorithm variants

118 workshop papers

by 79 authors from 25 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

- a number of testbeds are around

- 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

## Under development:

- large-scale versions
- constrained test suite

## Long-term goals:

- combining difficulties
- almost real-world problems
- real-world problems

# 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?

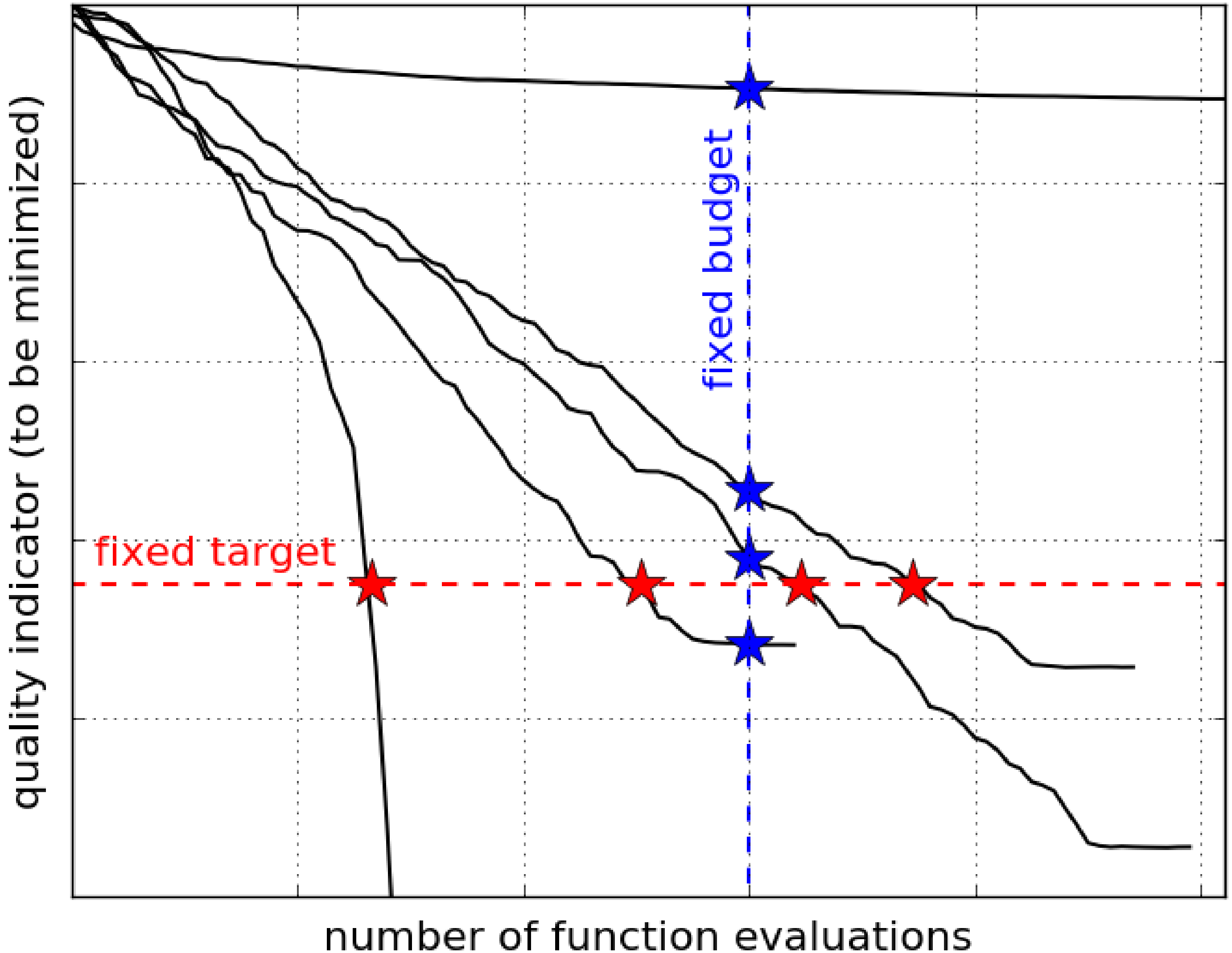
**Two objectives:**

- 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

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

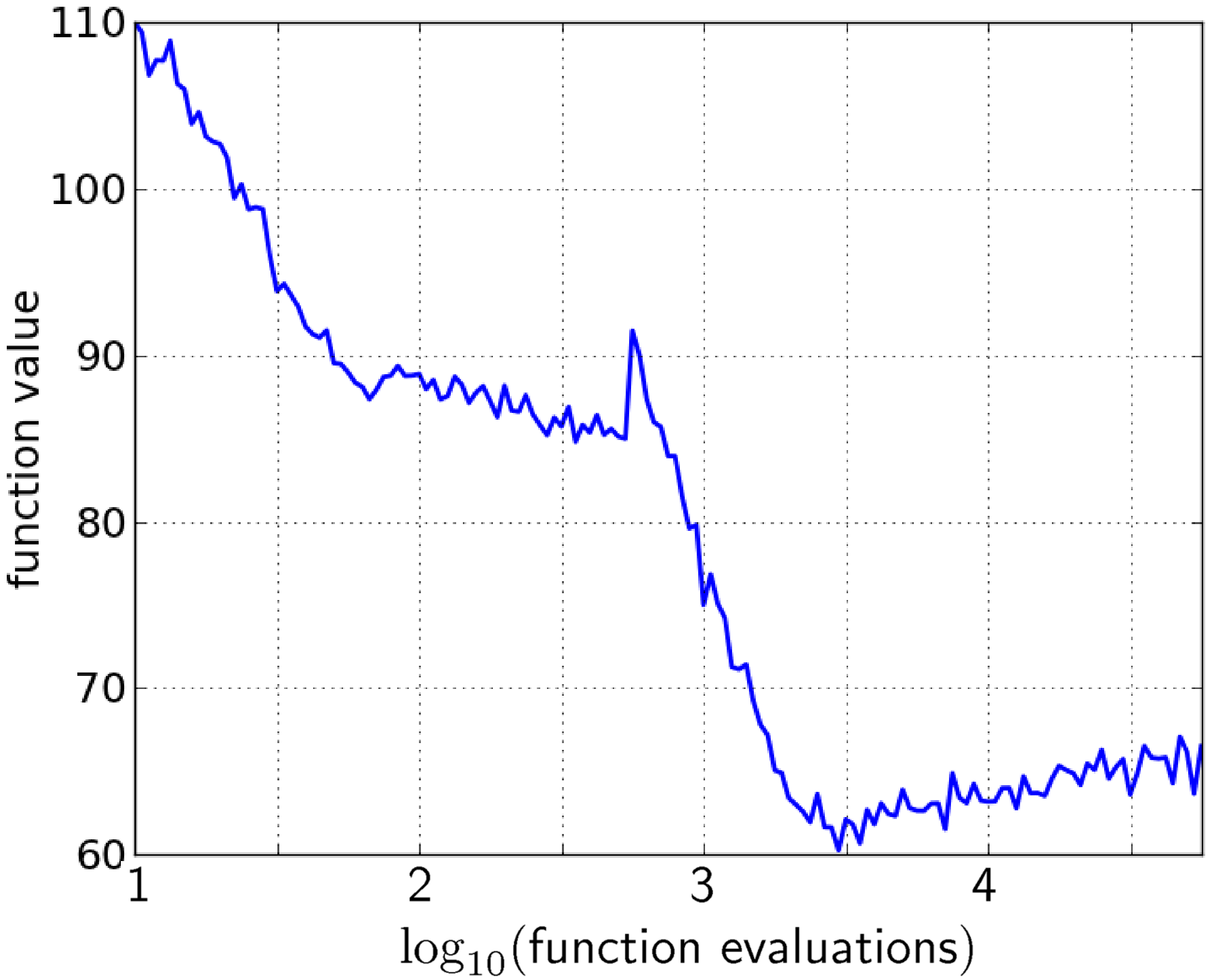


**ECDF:**

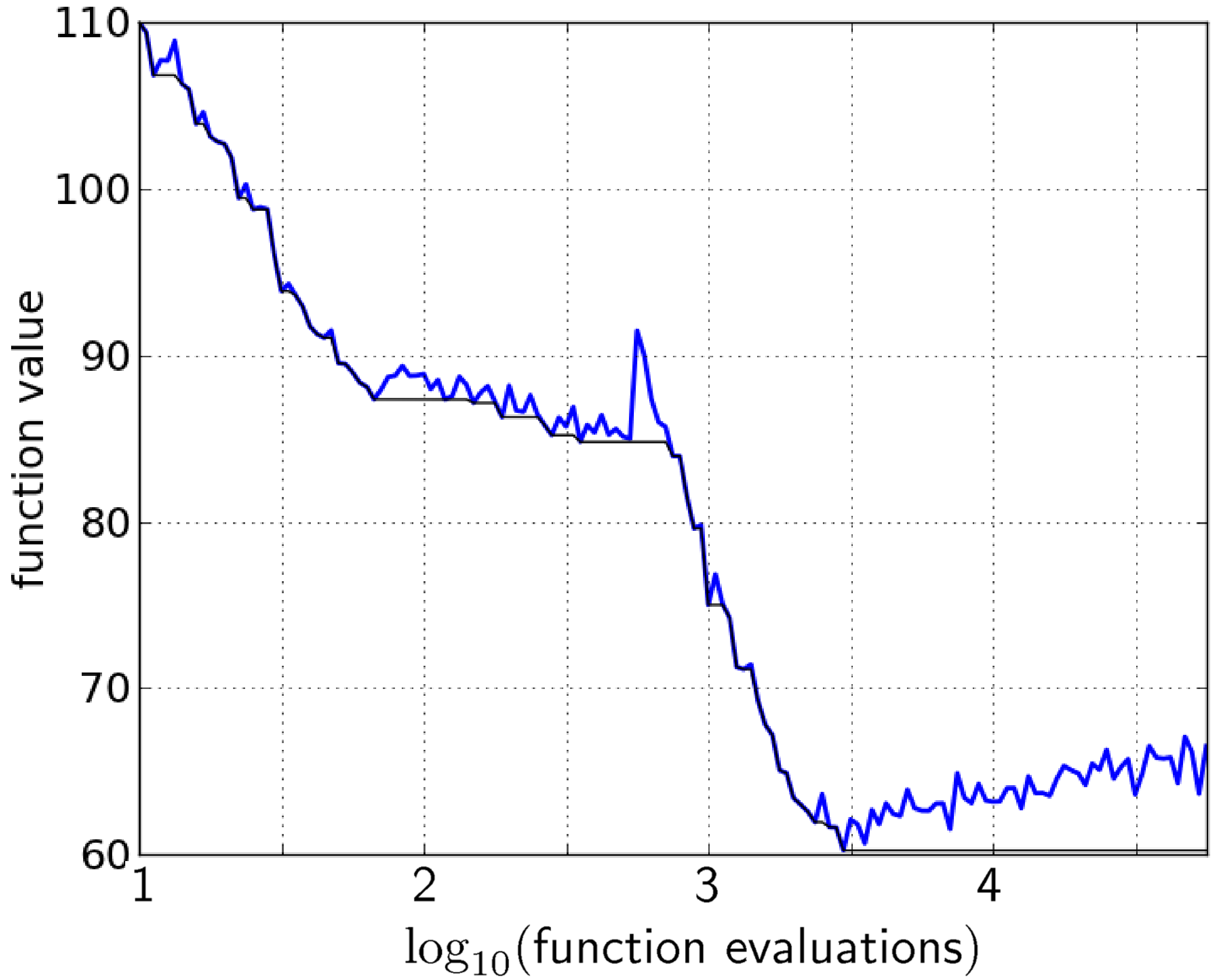
Empirical Cumulative Distribution Function of the Runtime

[aka data profile]

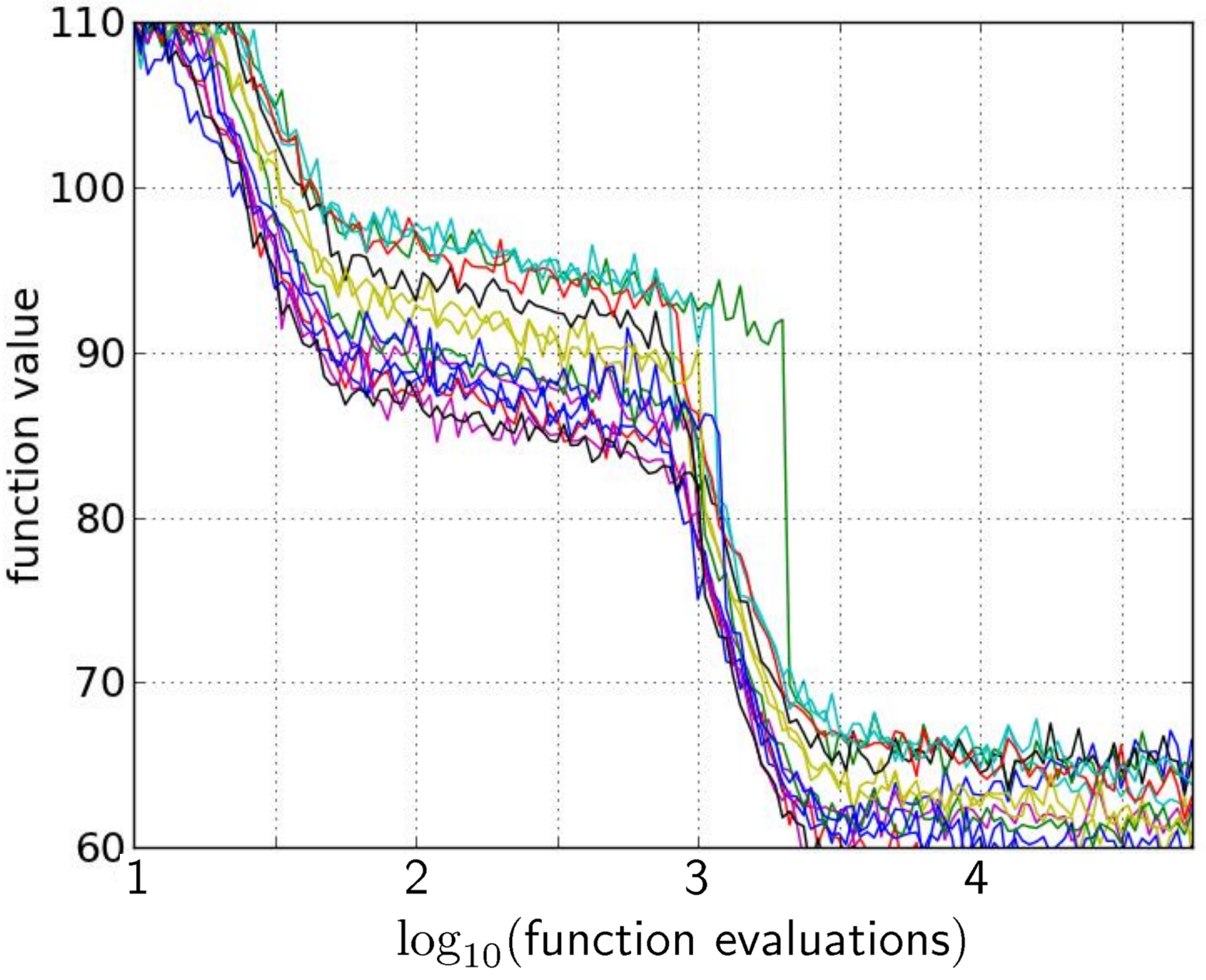
# A Convergence Graph .



# First Hitting Time is Monotonous



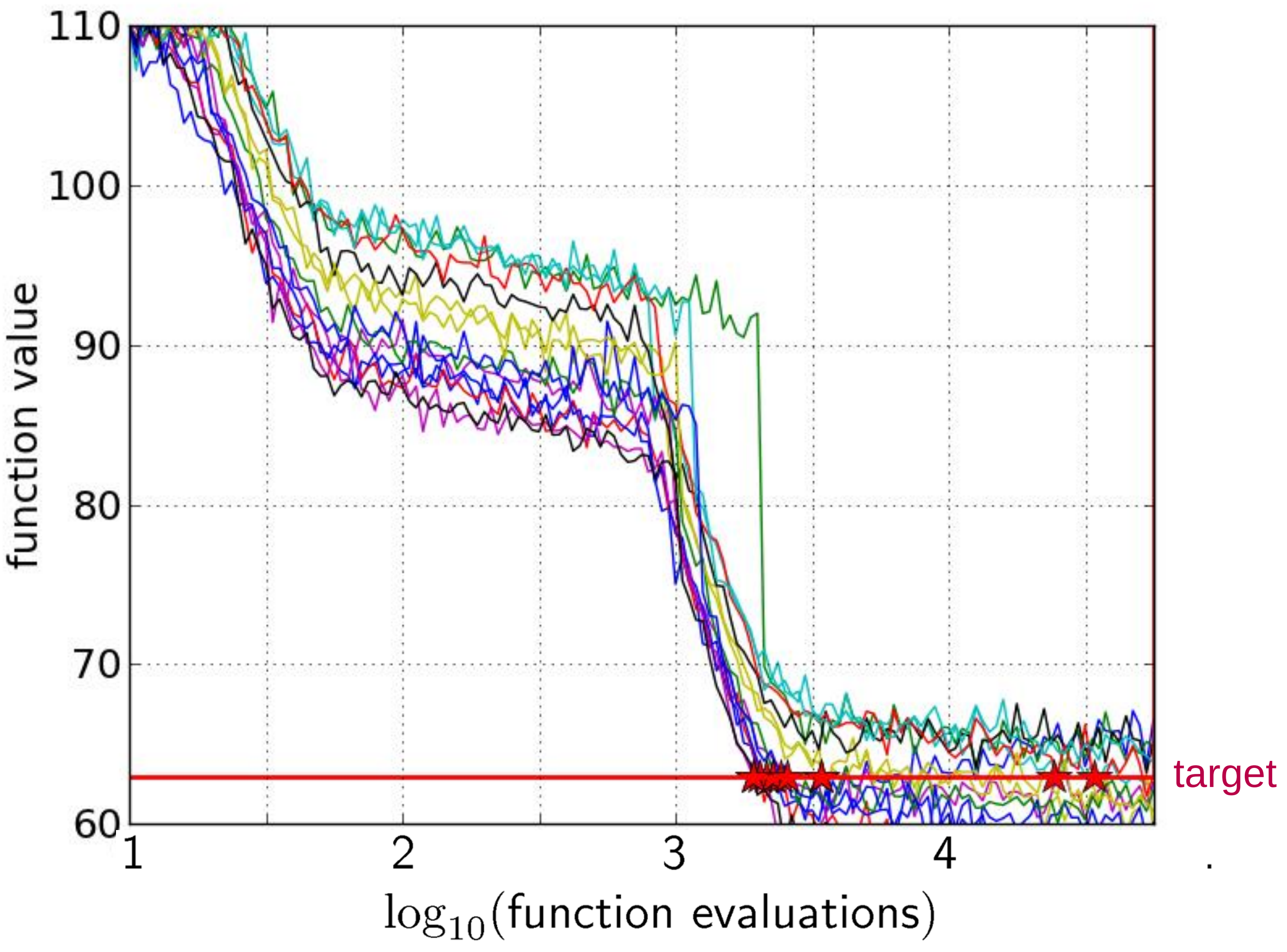
# 15 Runs



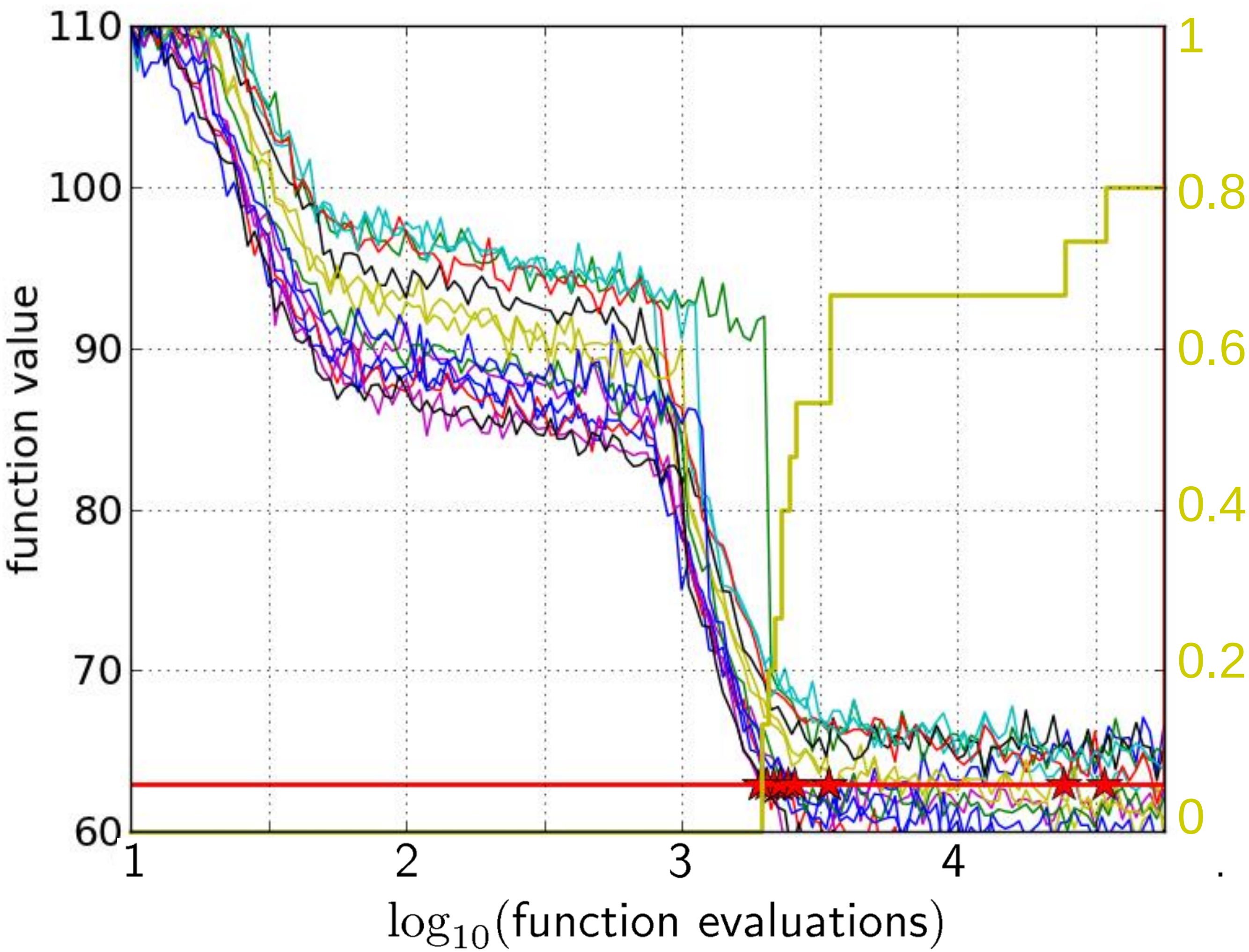
110
100
90
80
70
60
function value
1
2
3
4
$\log_{10}$(function evaluations)


.

# 15 Runs ≤ 15 Runtime Data Points



# Empirical Cumulative Distribution

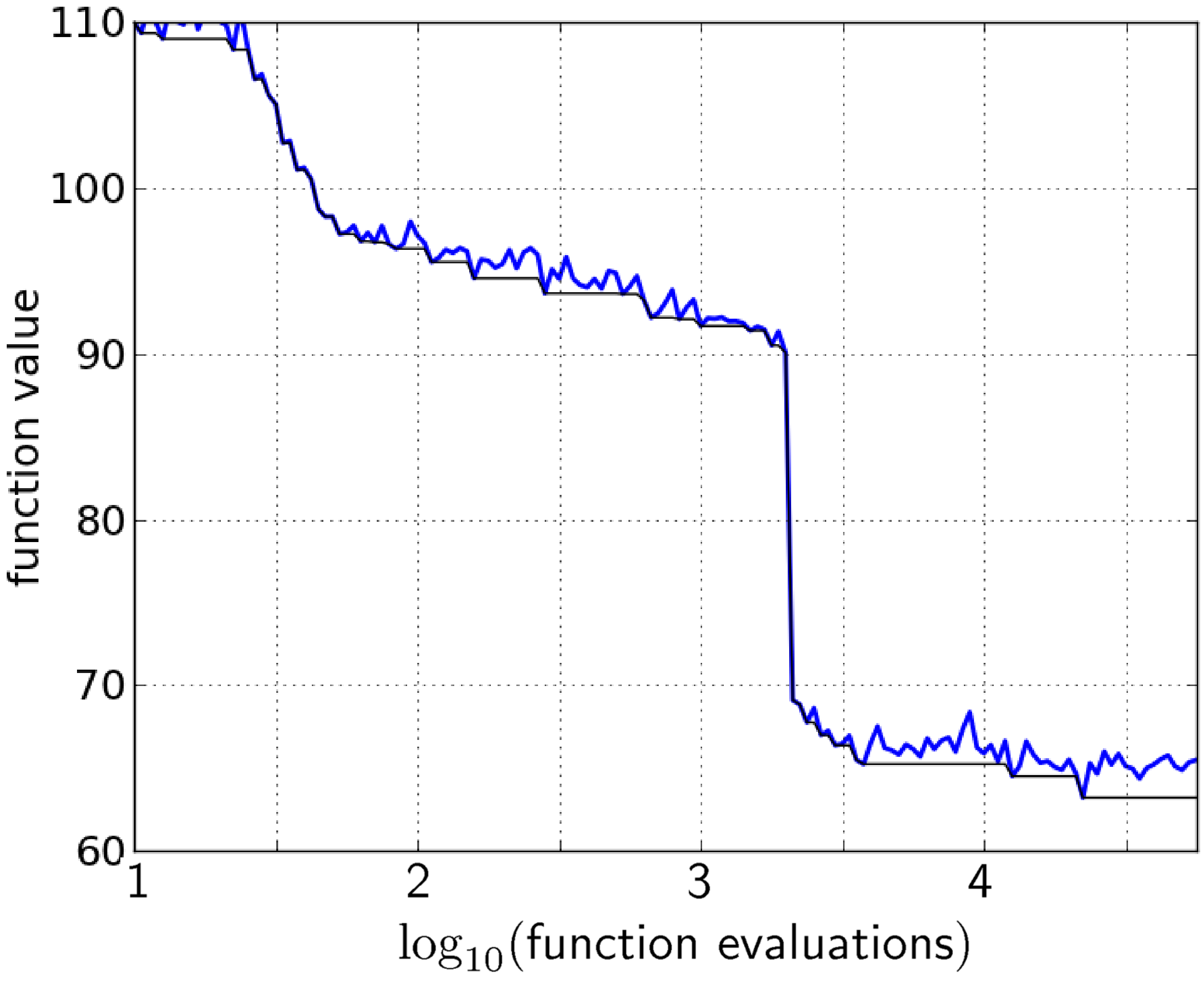



the ECDF of run lengths to reach the target

- 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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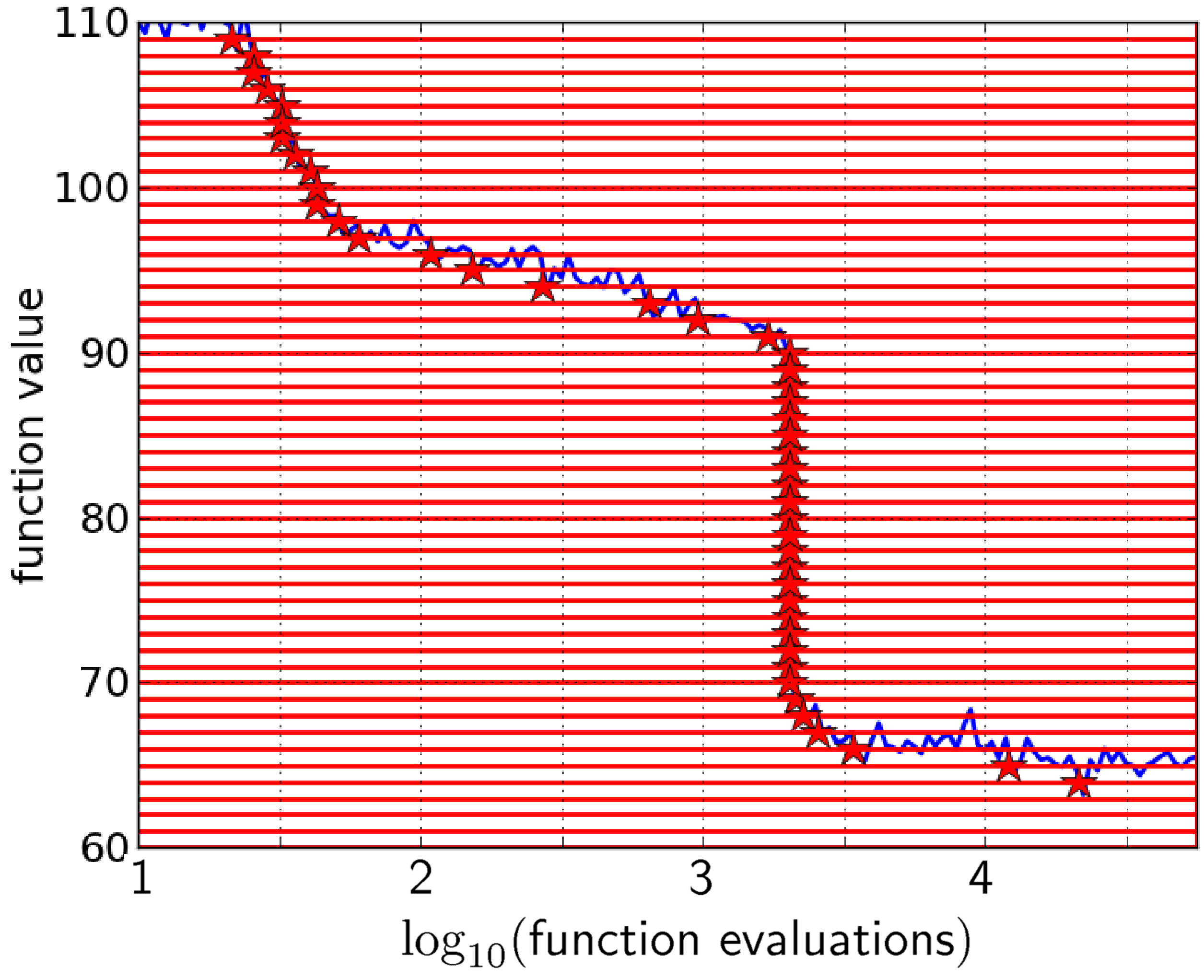
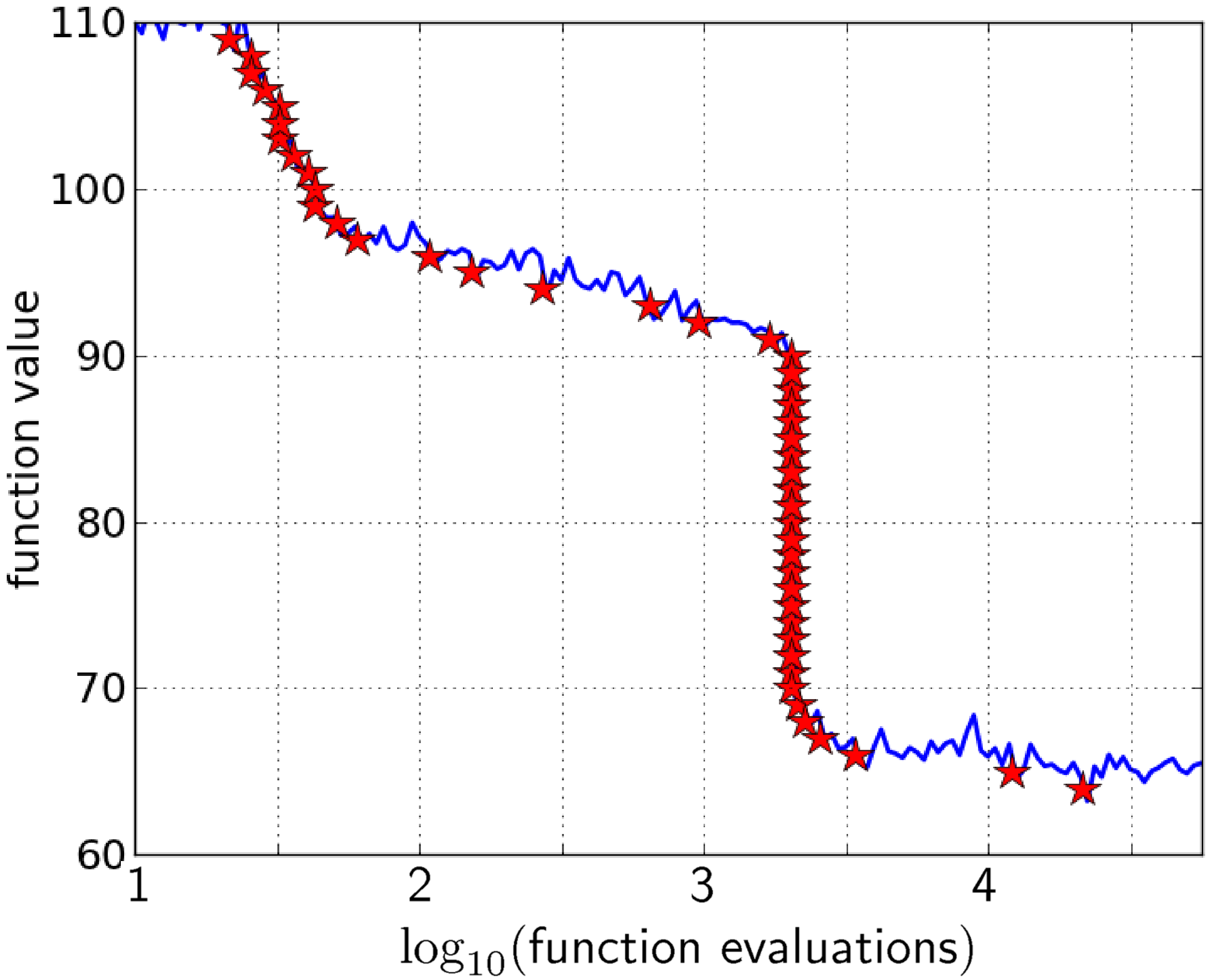



50 equally spaced targets

# Reconstructing A Single Run



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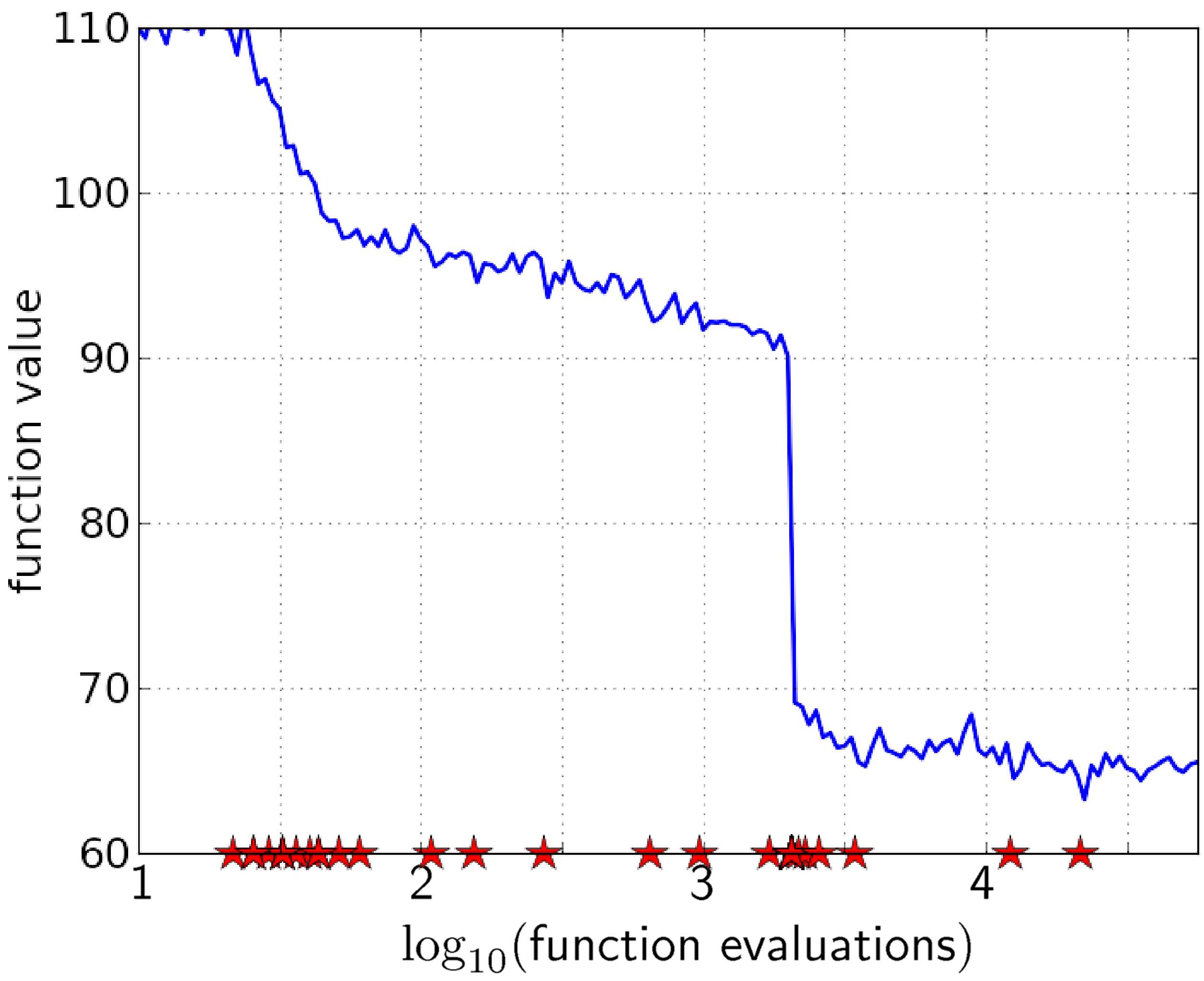

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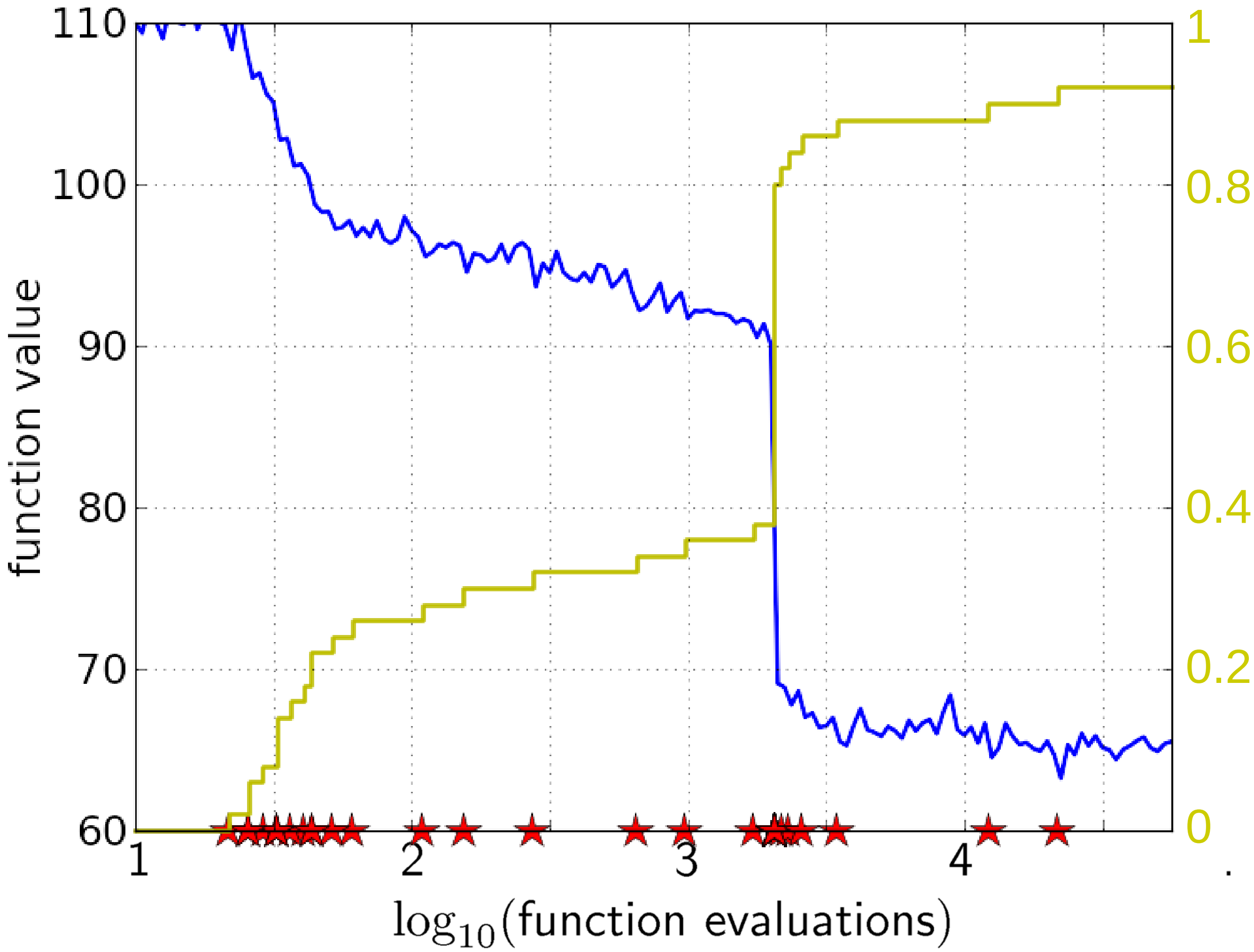
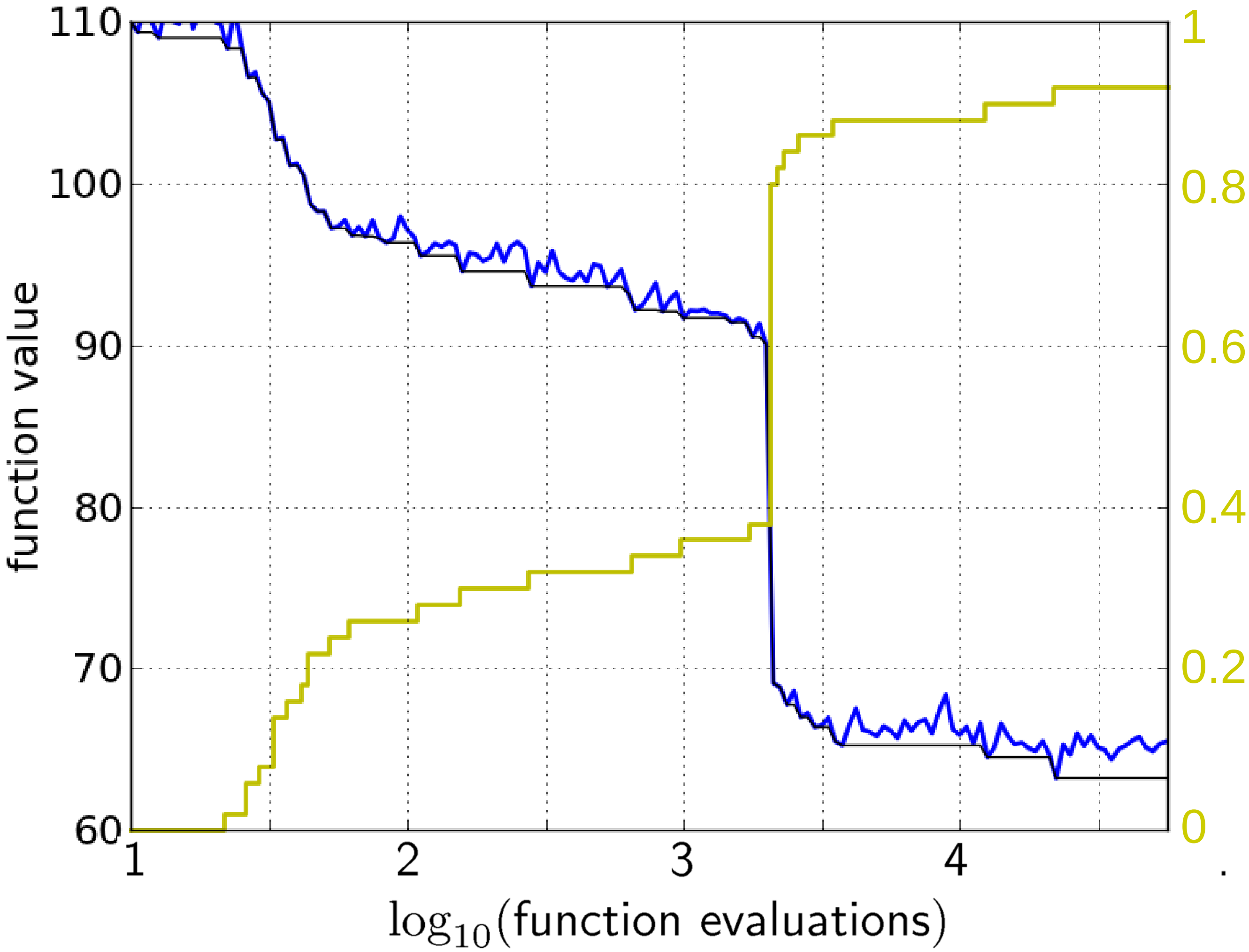


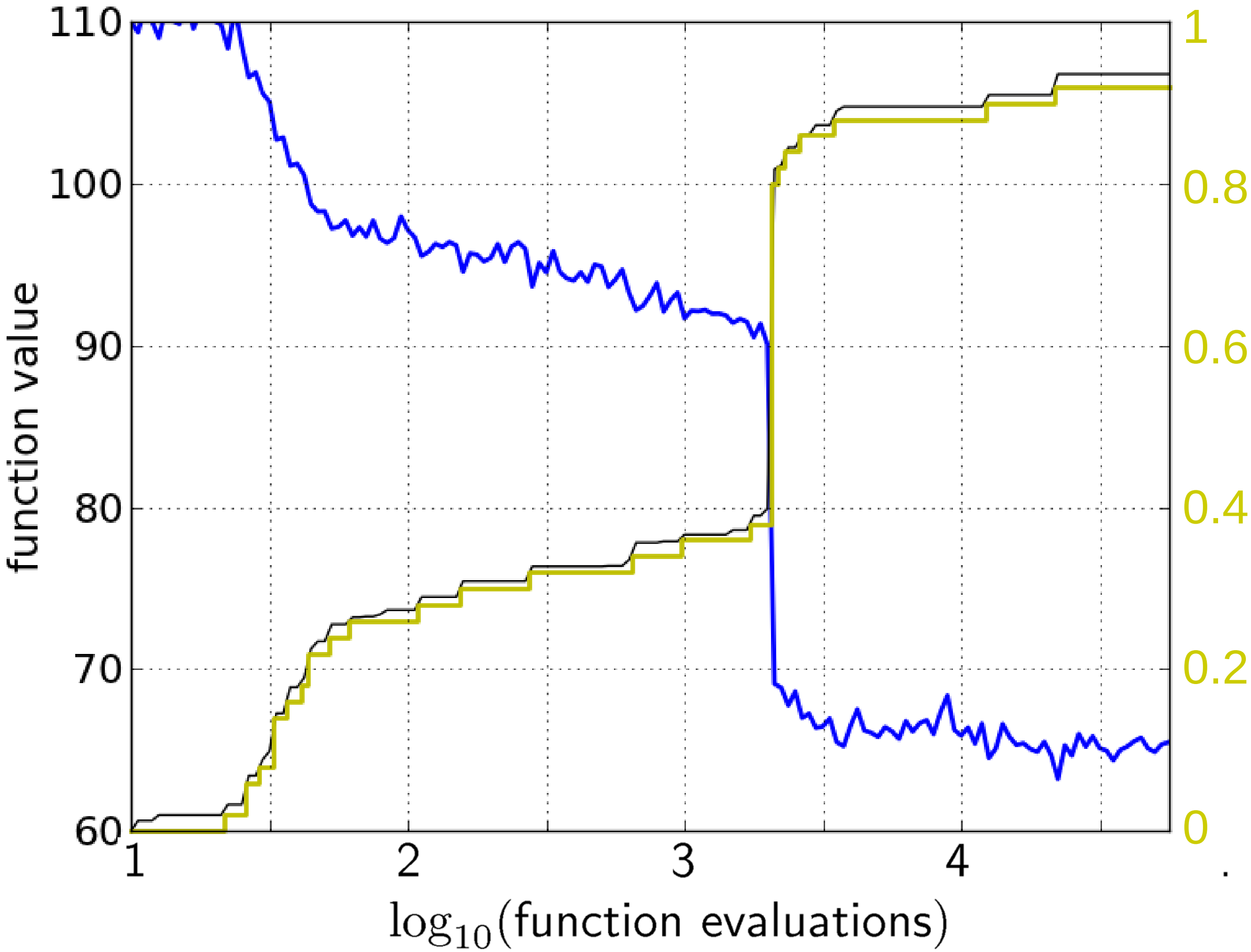

the empirical CDF makes a step for each star, is monotonous and displays for each budget the fraction of targets achieved within the budget

# Reconstructing A Single Run



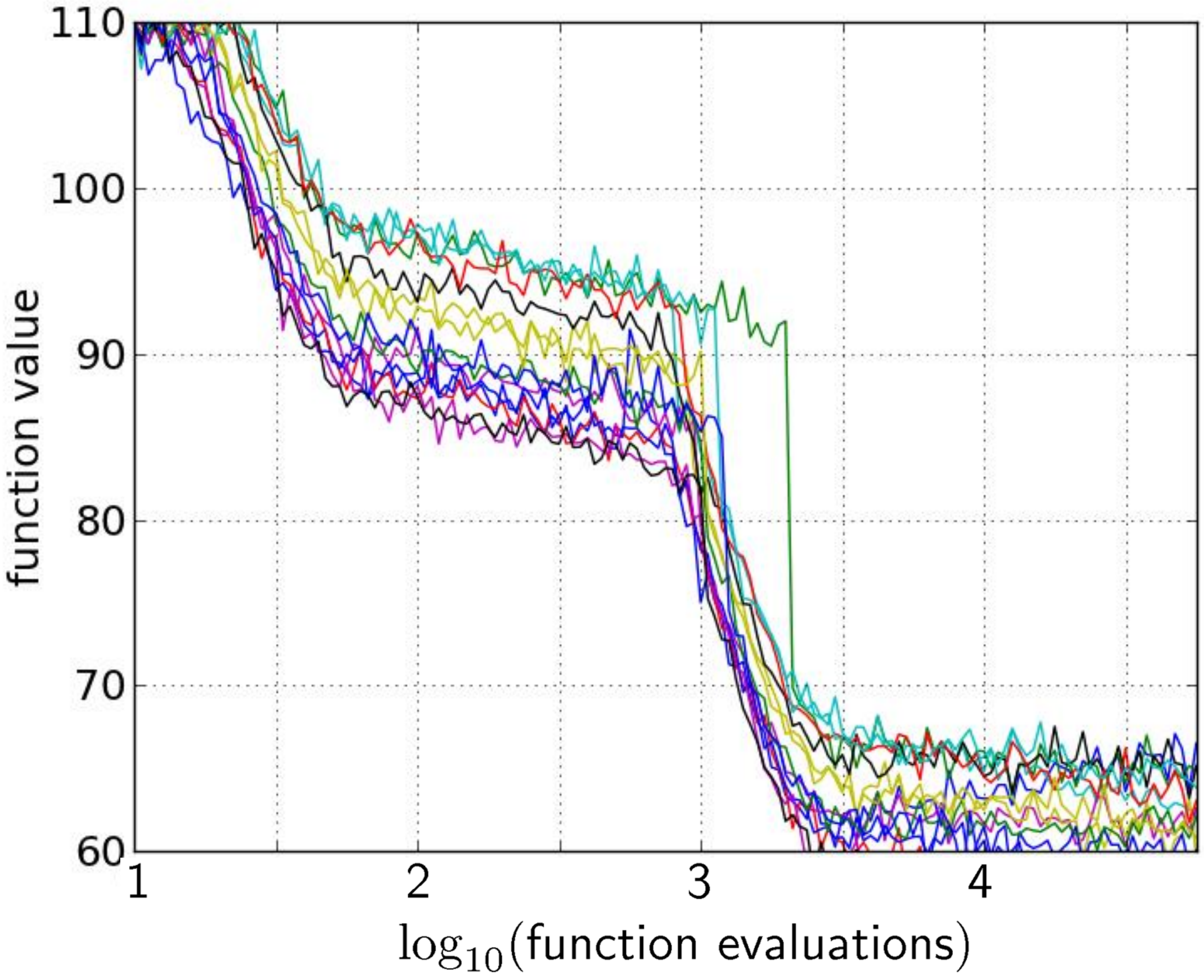

the ECDF recovers the monotonous graph, discretised and flipped

# Reconstructing A Single Run



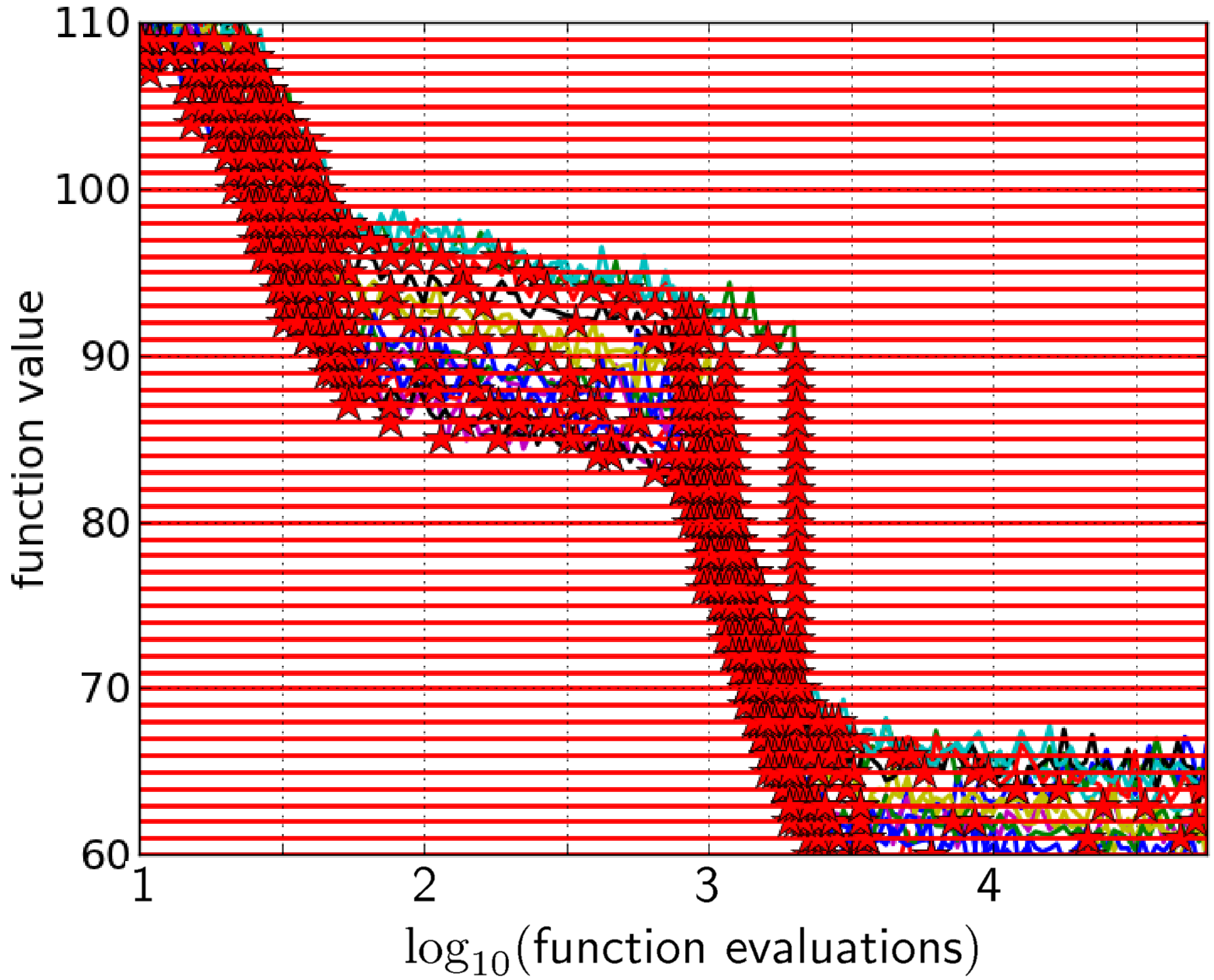

the ECDF recovers the monotonous graph, discretised and flipped

# Aggregation




15 runs

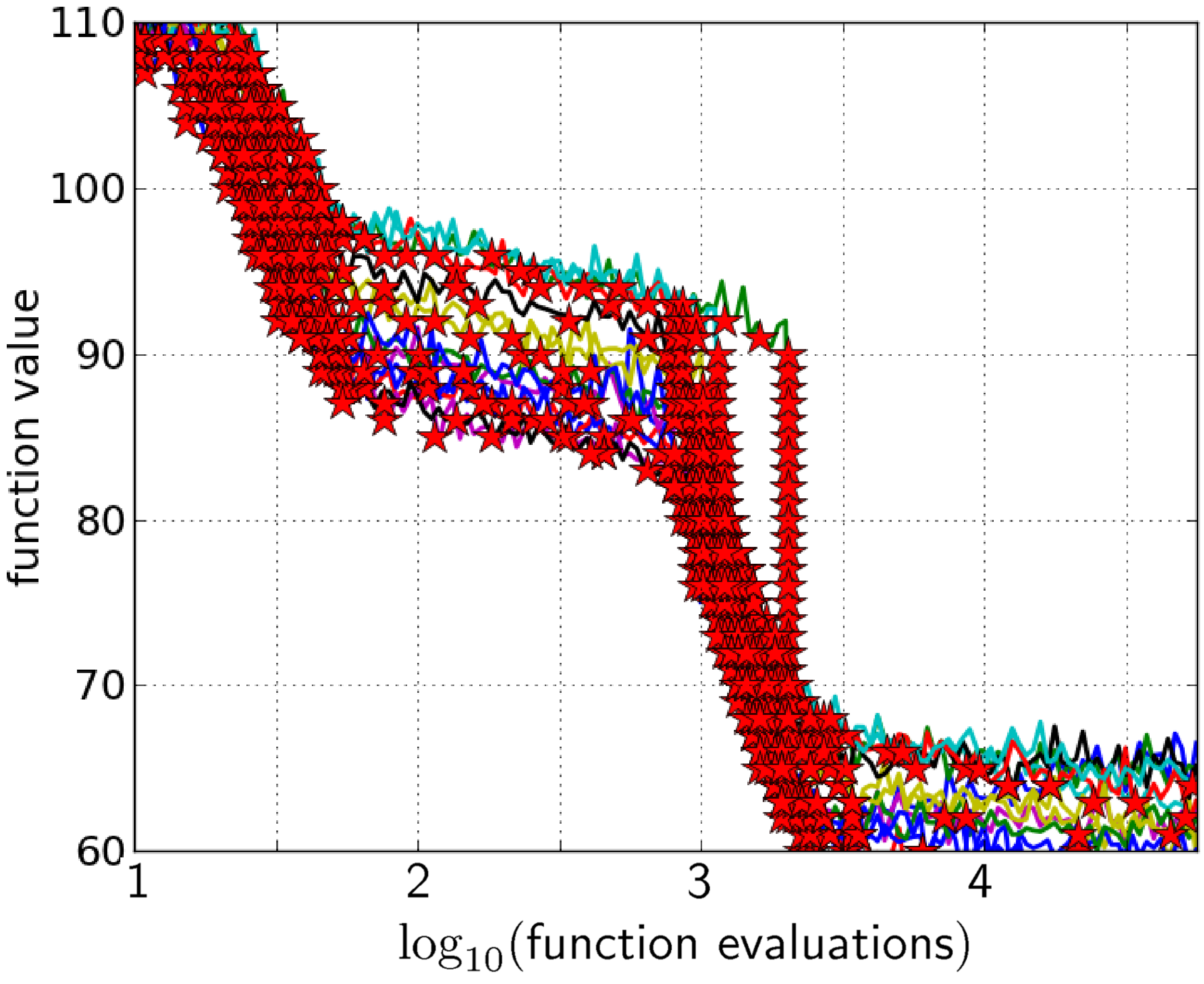
# Aggregation




15 runs

50 targets

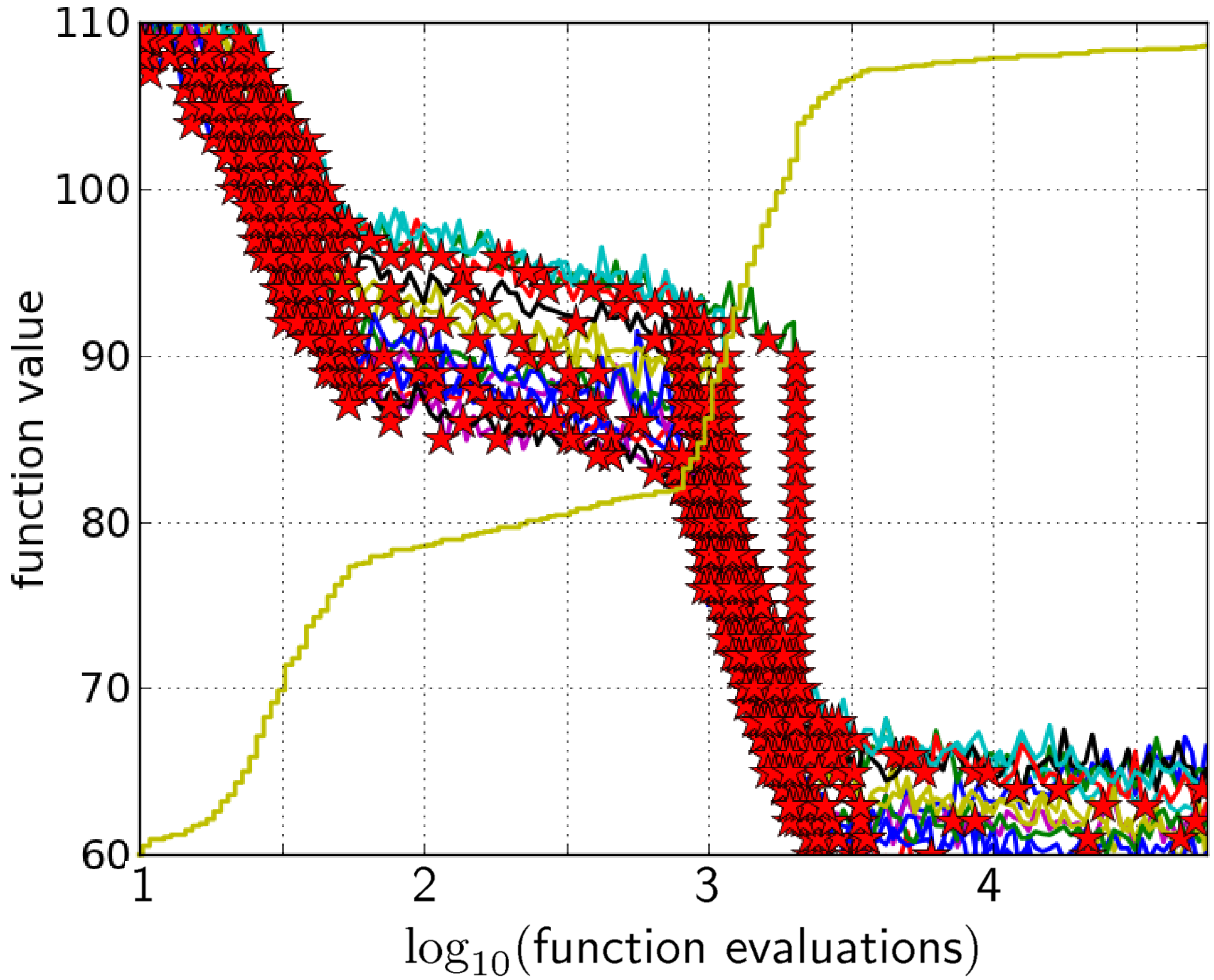
# Aggregation




15 runs

50 targets

# Aggregation

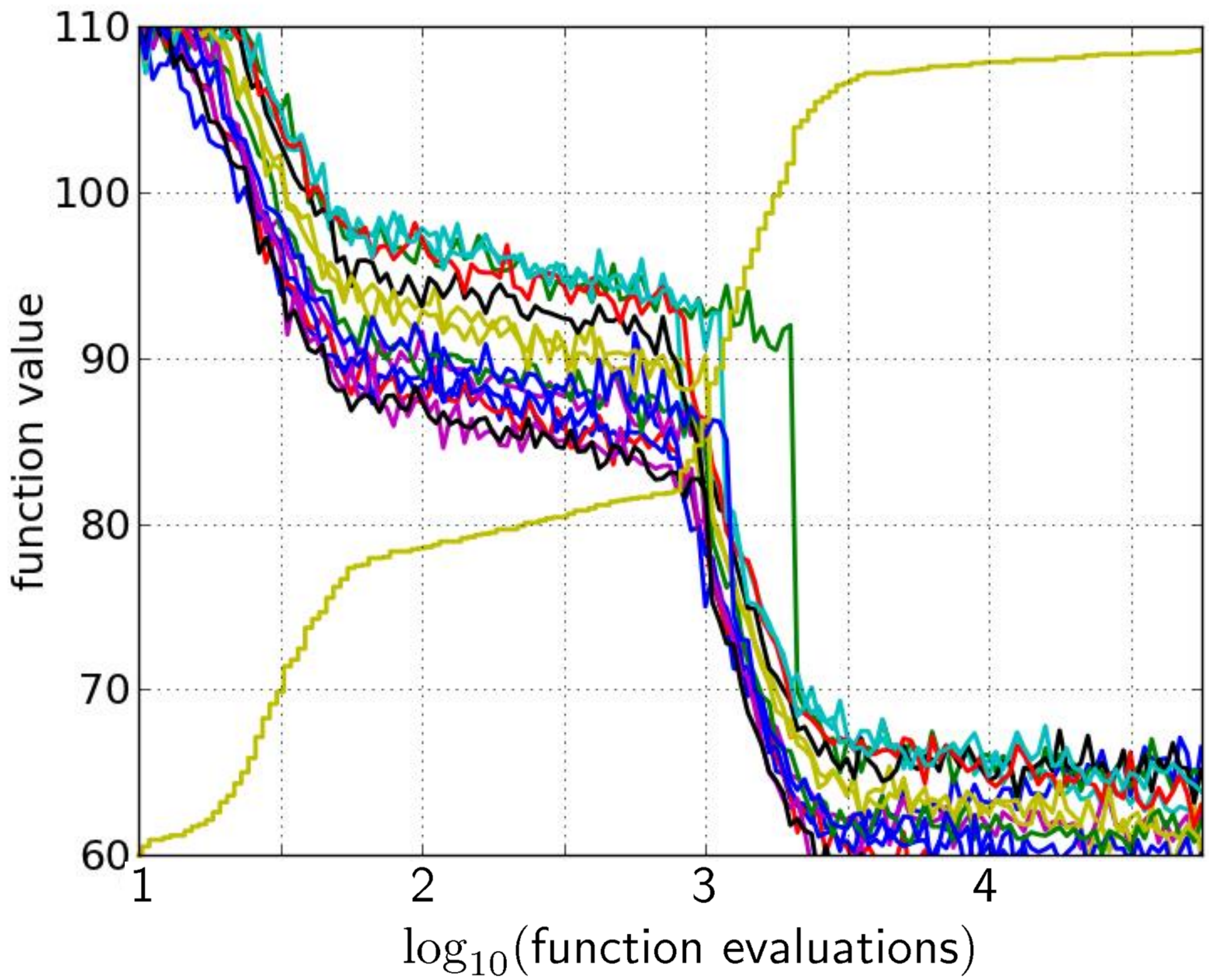



15 runs

50 targets

ECDF with 750 steps

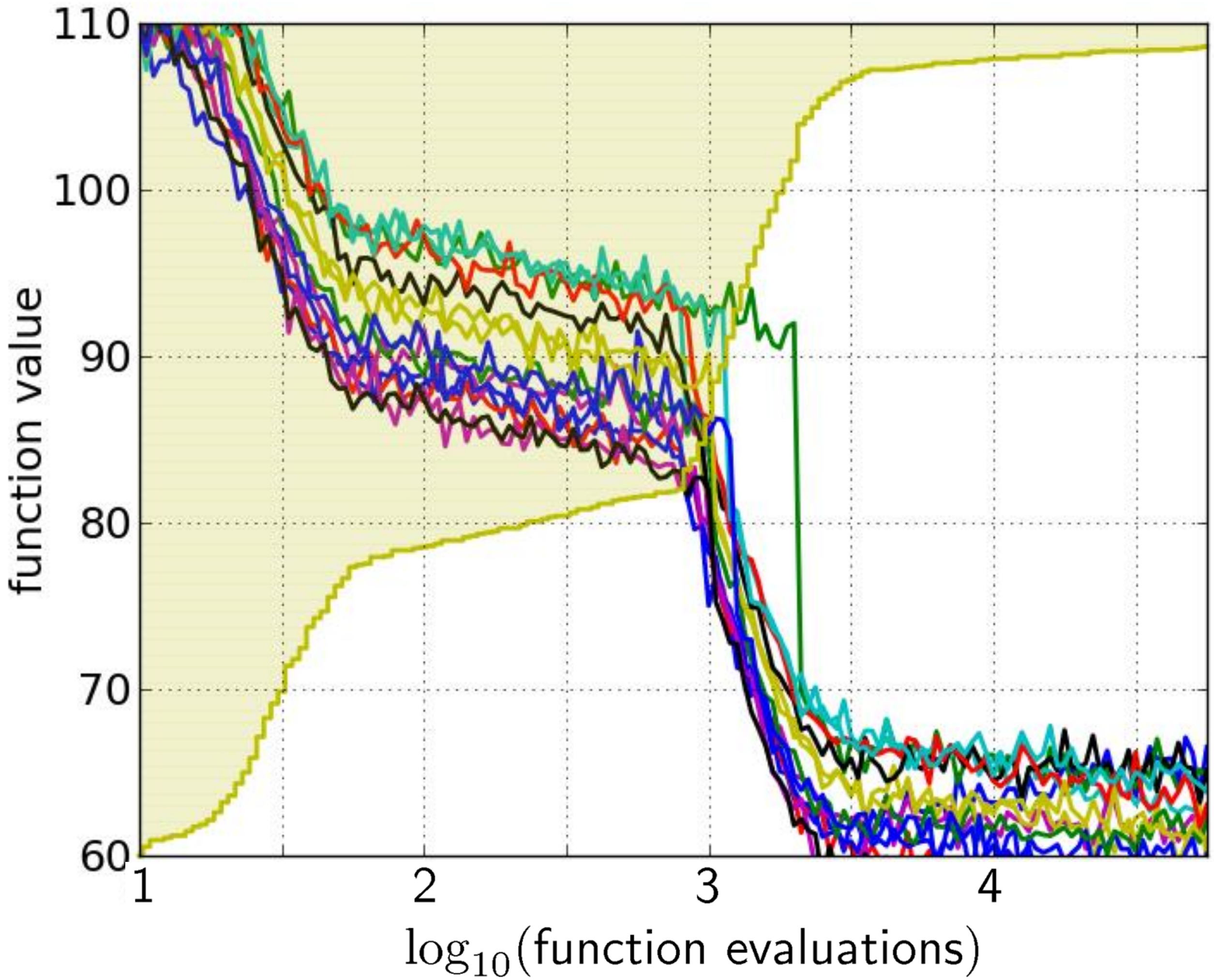
# Aggregation




50 targets from 15 runs

...integrated in a single graph

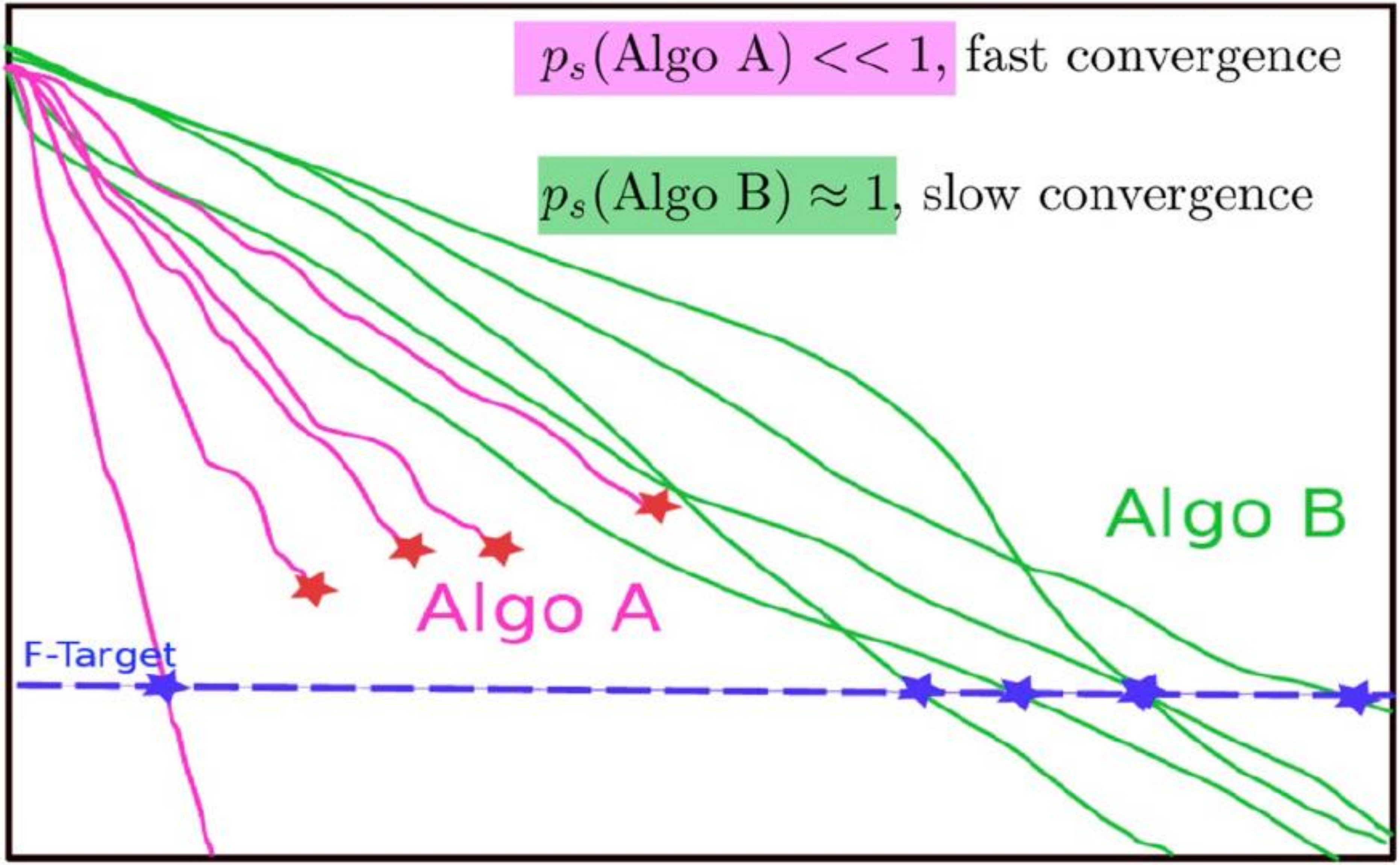
# Interpretation




50 targets from
15 runs
integrated in a
single graph

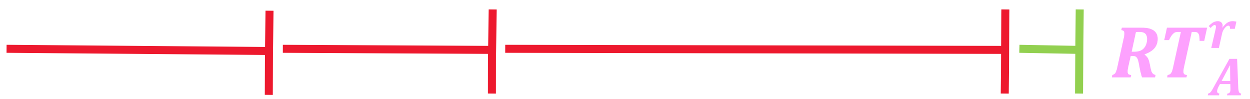
area over the ECDF
curve
=
average log runtime
(or geometric avg.
runtime) over all
targets (difficult and
easy) and all runs

# Fixed-target: Measuring Runtime



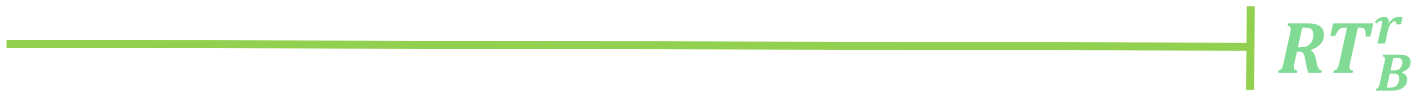
# Fixed-target: Measuring Runtime

- 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):

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

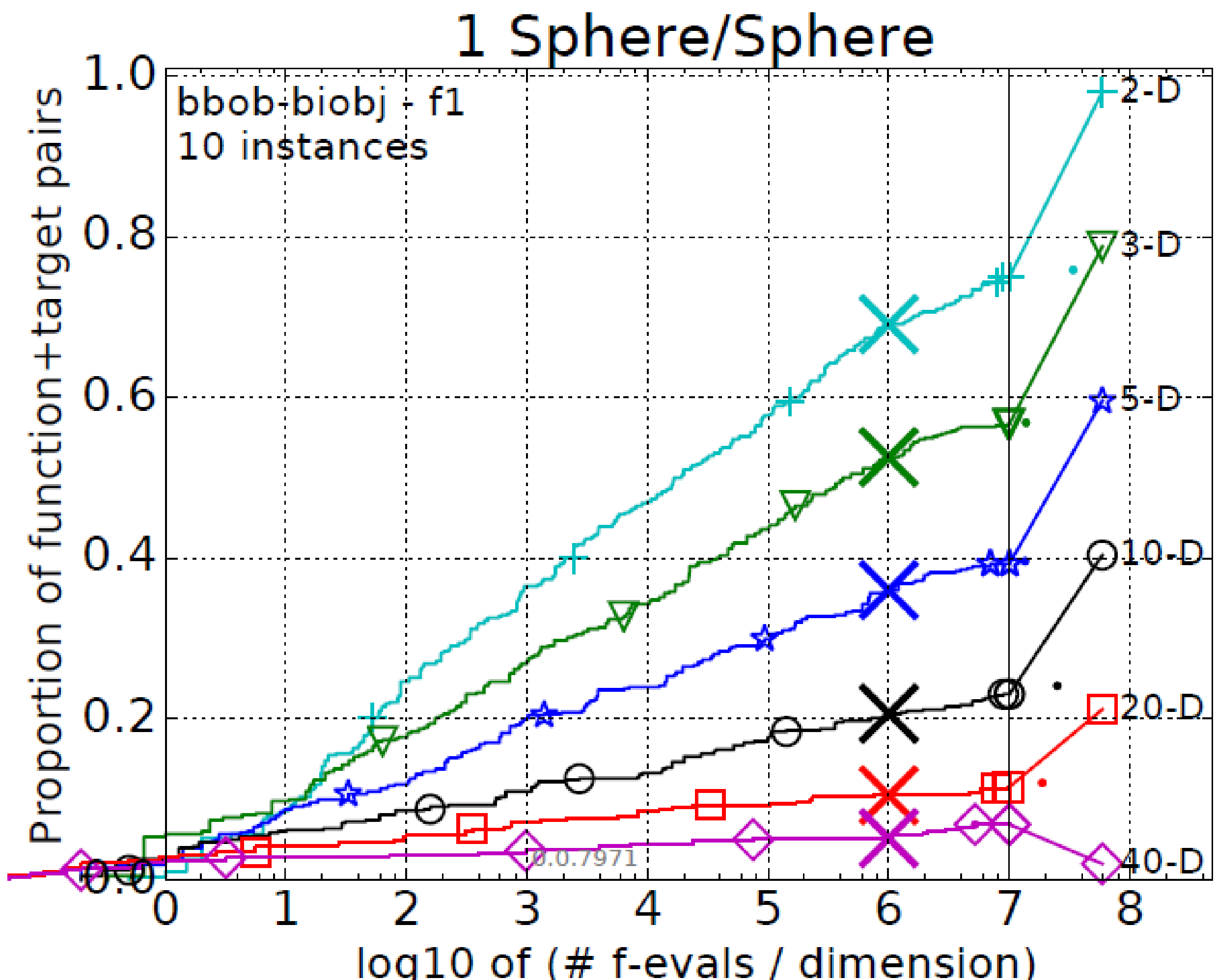
$$\widehat{RT_{unsucc}} = \text{Average evals of unsuccessful runs}$$

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

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

# ECDFs with Simulated Restarts

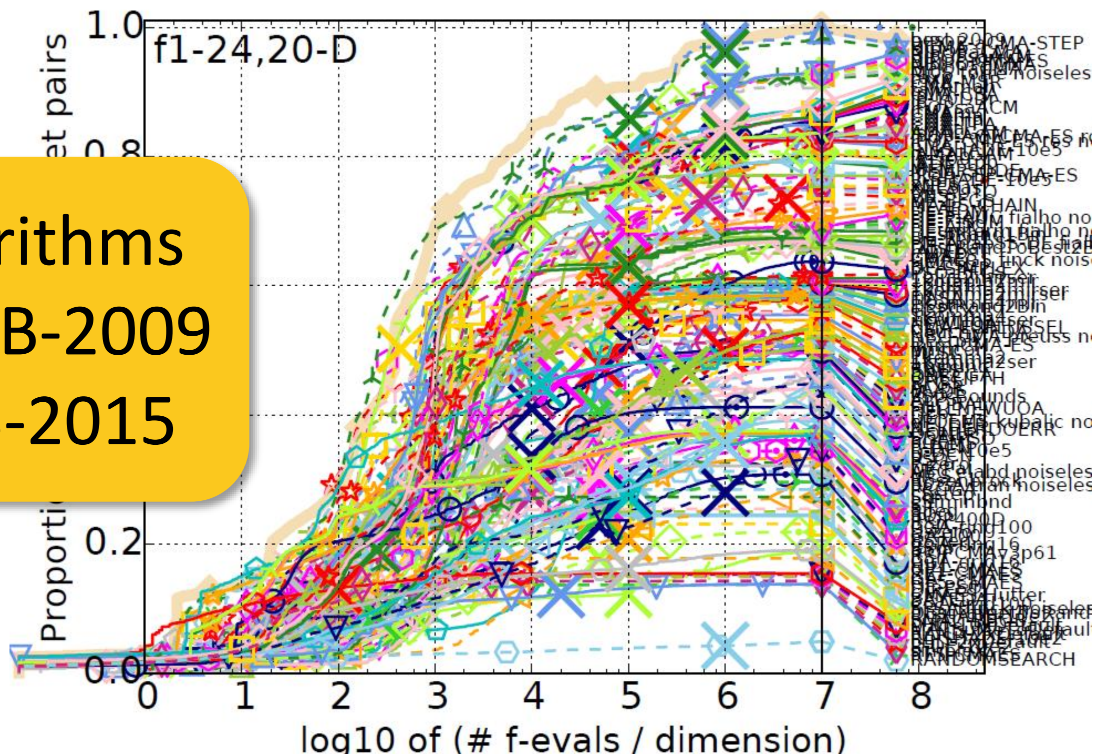
What we typically plot are ECDFs of the simulated restarted algorithms:



# Worth to Note: ECDFs in COCO

In COCO, ECDF graphs

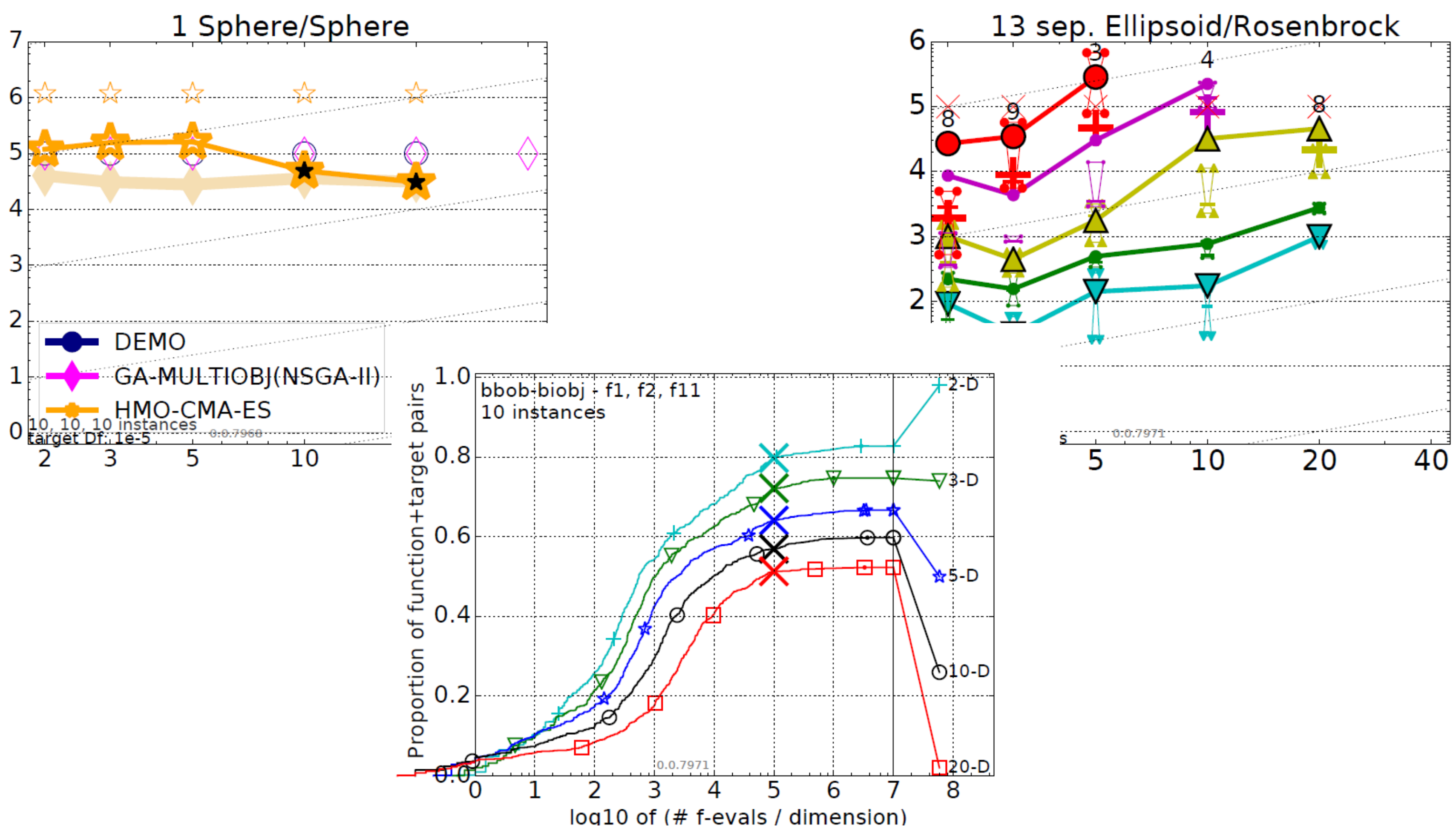
- never aggregate over dimension
    - but often over targets and functions
- can show data of more than 1 algorithm at a time




150 algorithms from BBOB-2009 till BBOB-2015

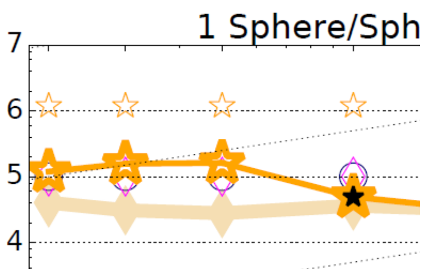
# More Automated Plots...

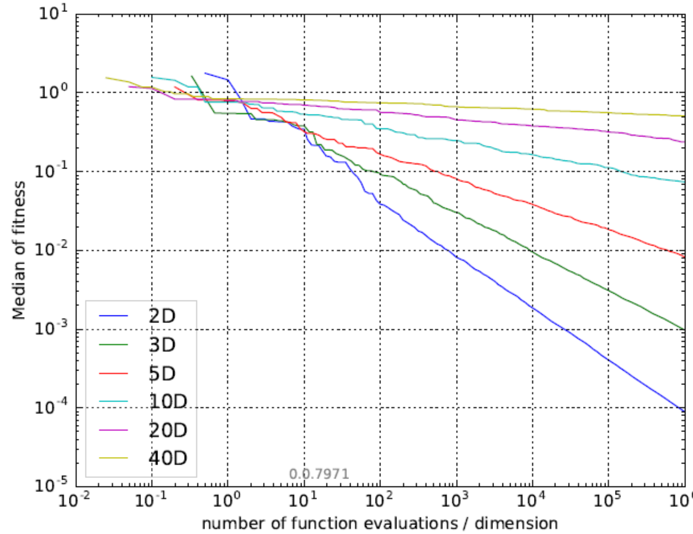
...but no time to explain them here ☹

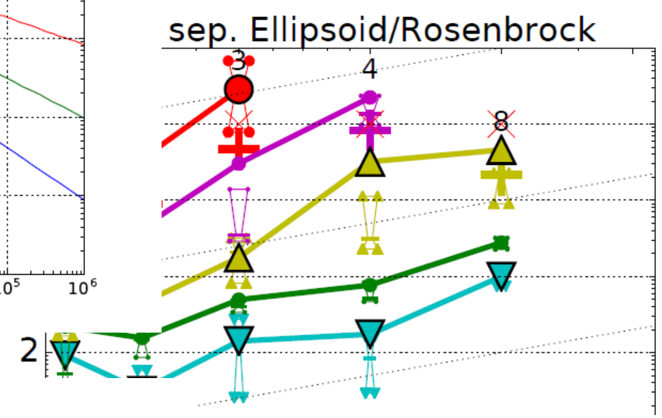


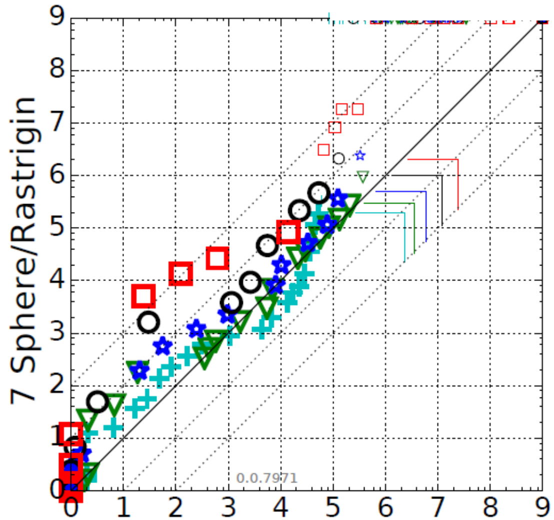
# More Automated Plots...

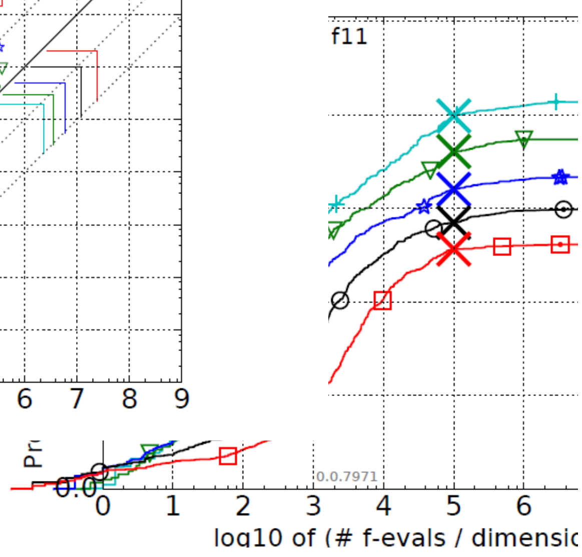
...but no time t

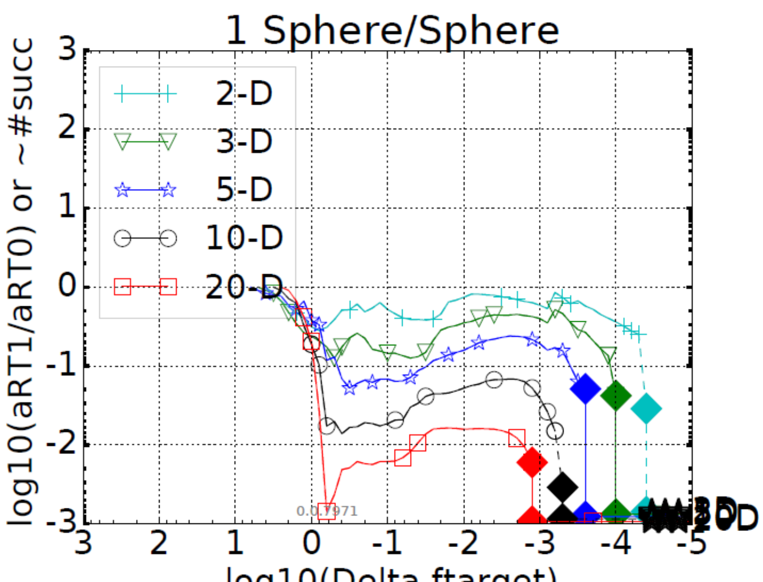


# The single-objective BBOB functions

# 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

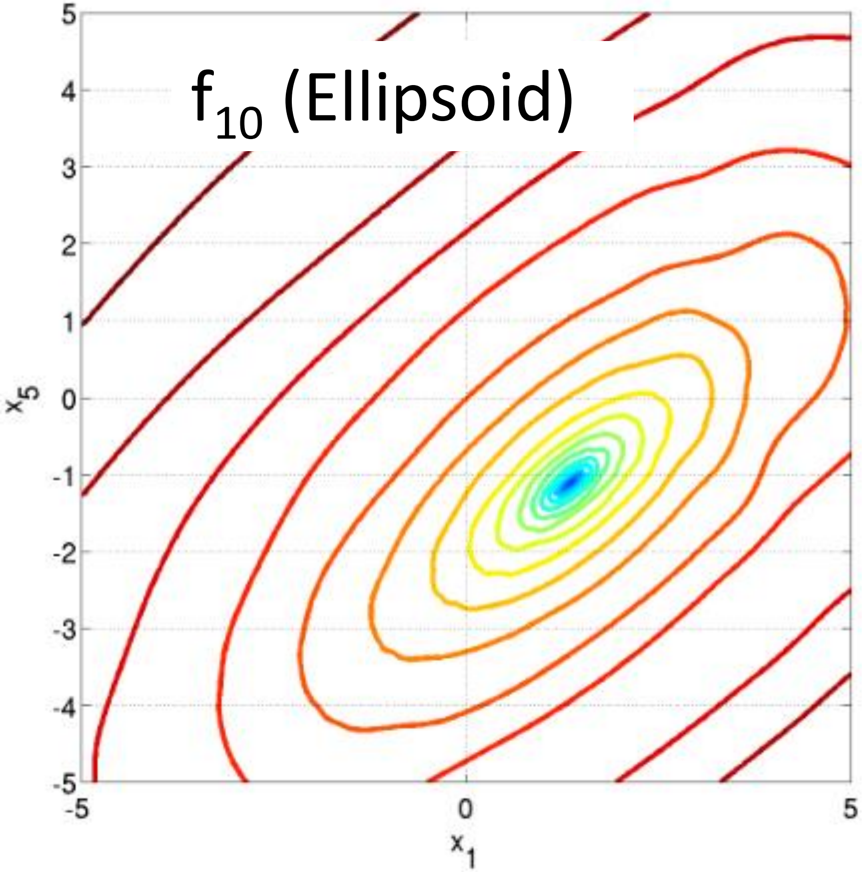
- All COCO problems come in form of instances
  - e.g. as translated/rotated versions of the same function
- Prescribed instances typically change from year to year
  - avoid overfitting
  - 5 instances are always kept the same

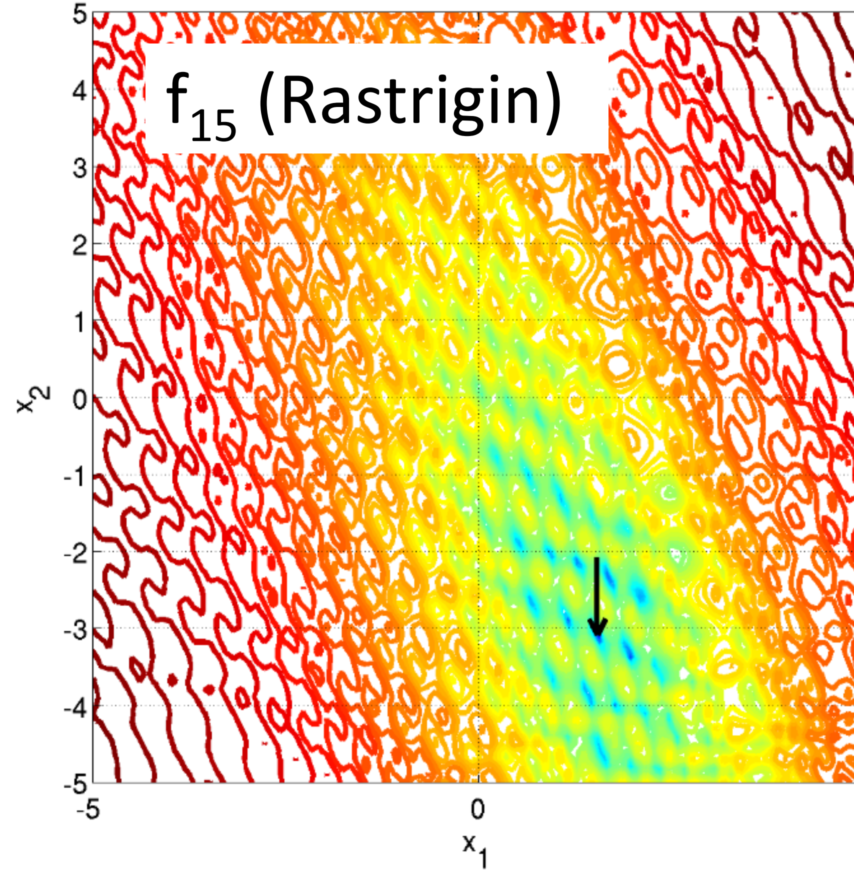
Plus:

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

# Notion of Instances

- All COCO problems come in form of instances




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)

# the recent extension to multi-objective optimization

# bbob-biobj Testbed (new in 2016)

- 55 functions by combining 2 **bbob** functions

| | |
|---|---|
| **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 ✓ |
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| **4 Multi-modal functions with adequate global structure** | |
| f15 | Rastrigin Function ✓ |
| f16 | Weierstrass Function |
| f17 | Schaffers F7 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 |

# bbob-biobj Testbed (new in 2016)

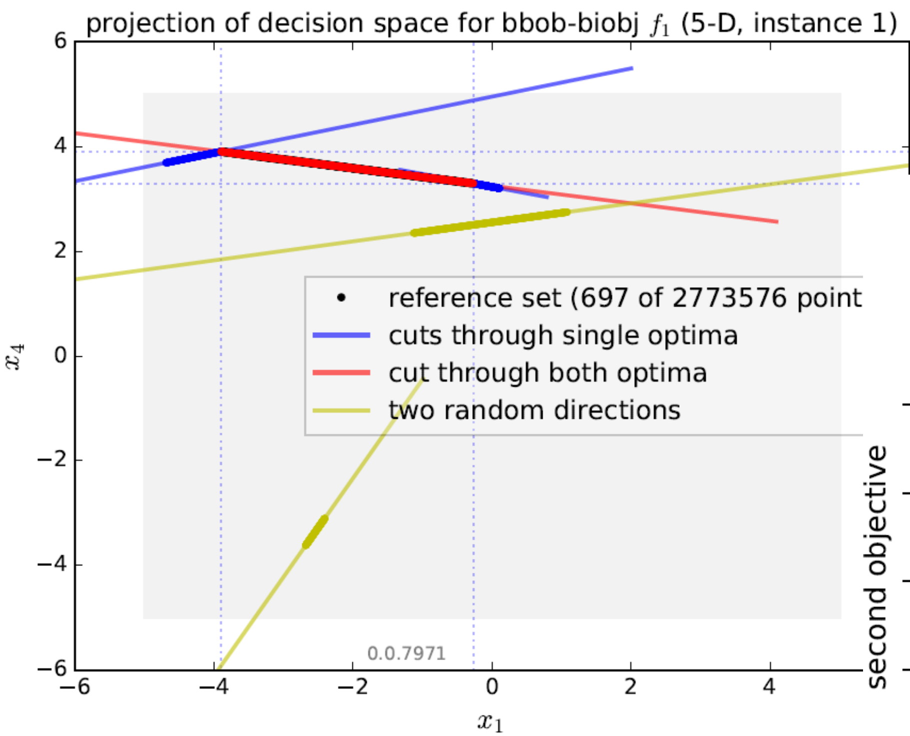
- 55 functions by combining 2 bbob functions
- 15 function groups with 3-4 functions each
  - separable – separable, separable – moderate, separable - ill-conditioned, ...
- 6 dimensions: 2, 3, 5, 10, 20, (40 optional)
- instances derived from bbob instances:
  - more or less 2i+1 for 1st objective and 2i+2 for 2nd objective
  - exceptions: instances 1 and 2 and when optima are too close
- no normalization (algo has to cope with different orders of magnitude)
- for performance assessment: ideal/nadir points known

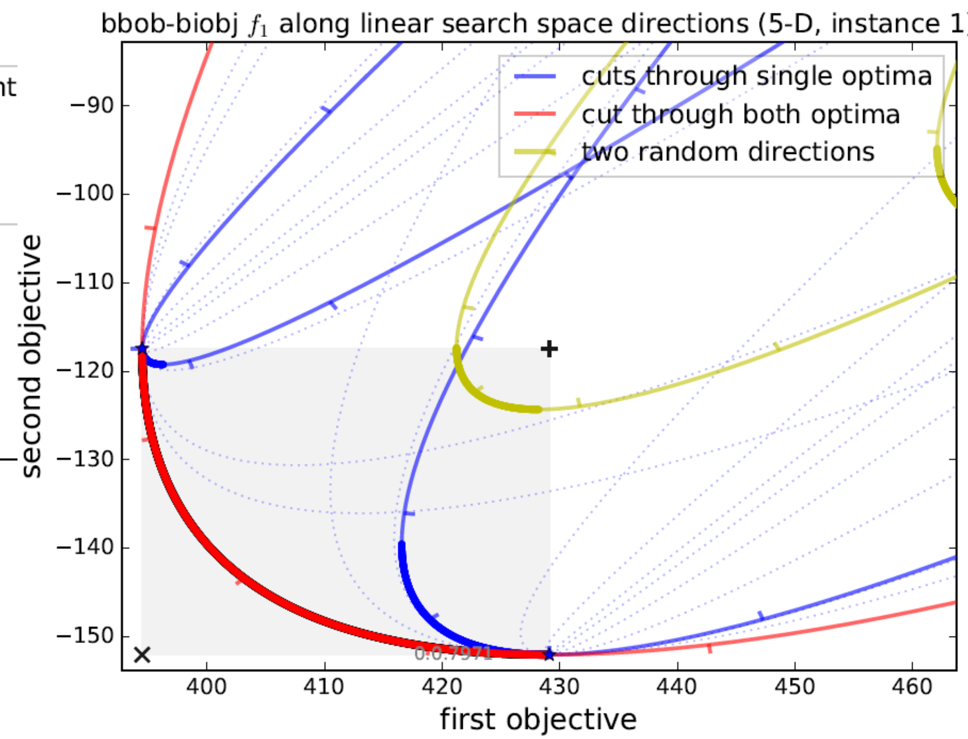
# bbob-biobj Testbed (cont'd)

- Pareto set and Pareto front unknown
  - but we have a good idea of where they are by running quite some algorithms and keeping track of all non-dominated points found so far
- Various types of shapes

# bbob-biobj Testbed (cont'd)

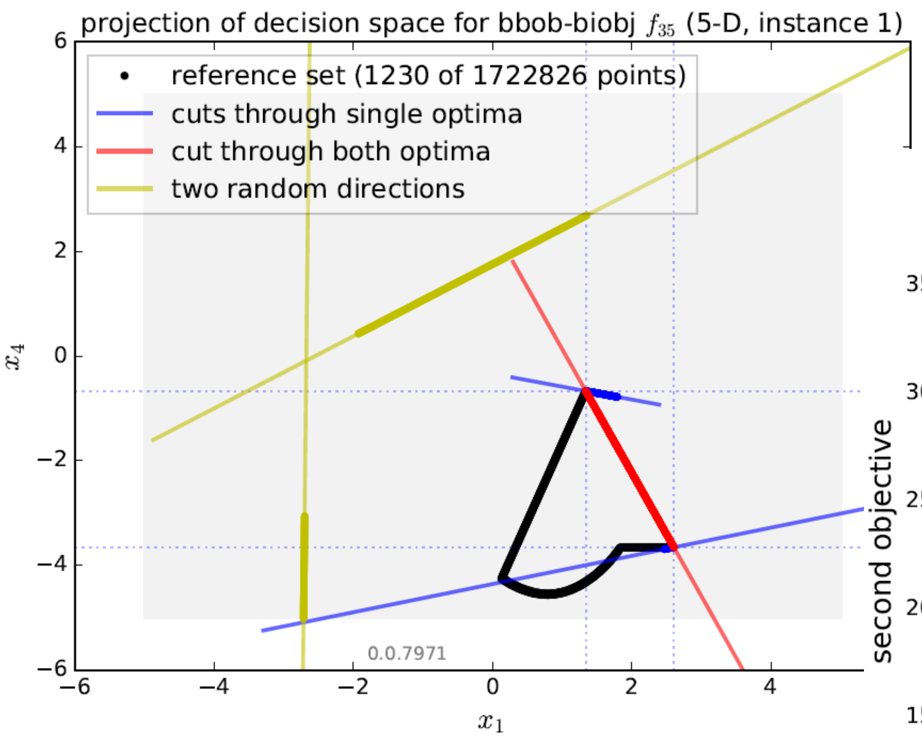
Example: sphere with sphere

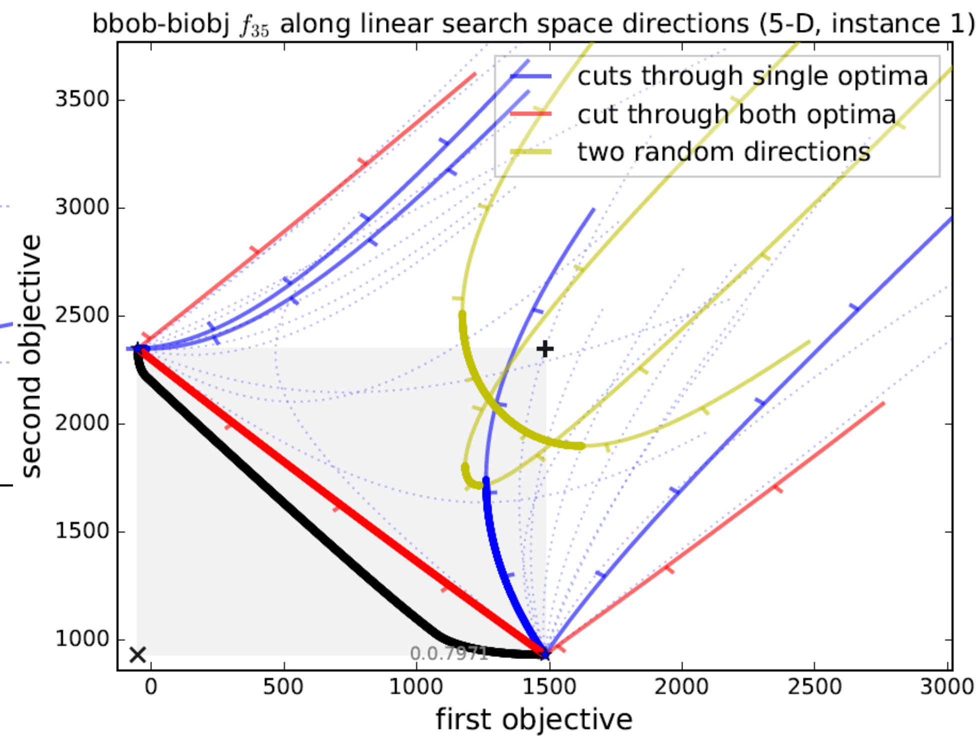


# bbob-biobj Testbed (cont'd)

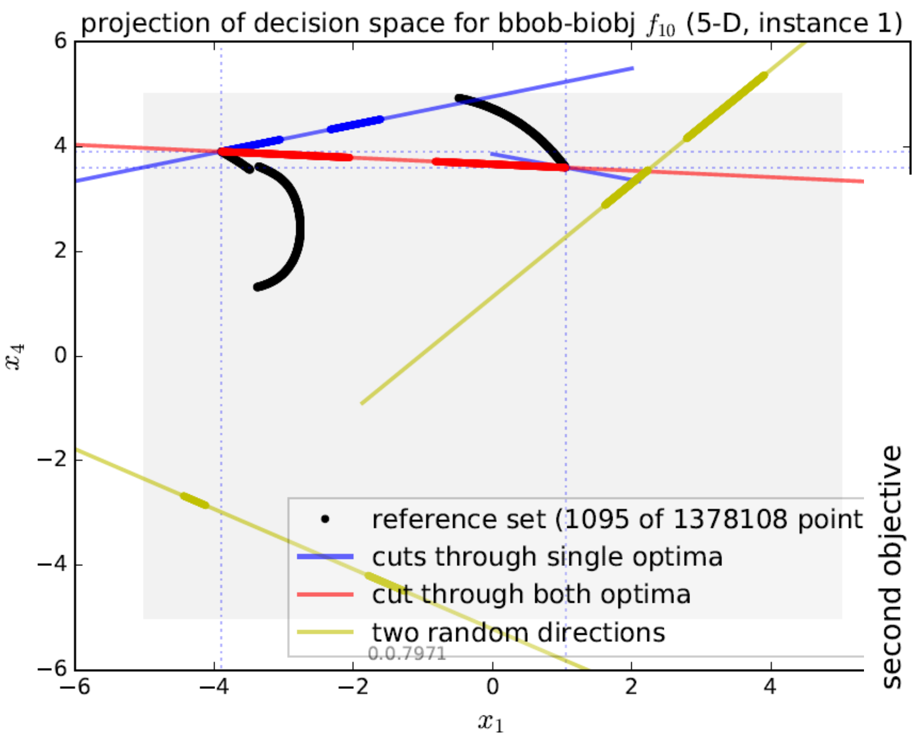
Example: sharp ridge with sharp ridge

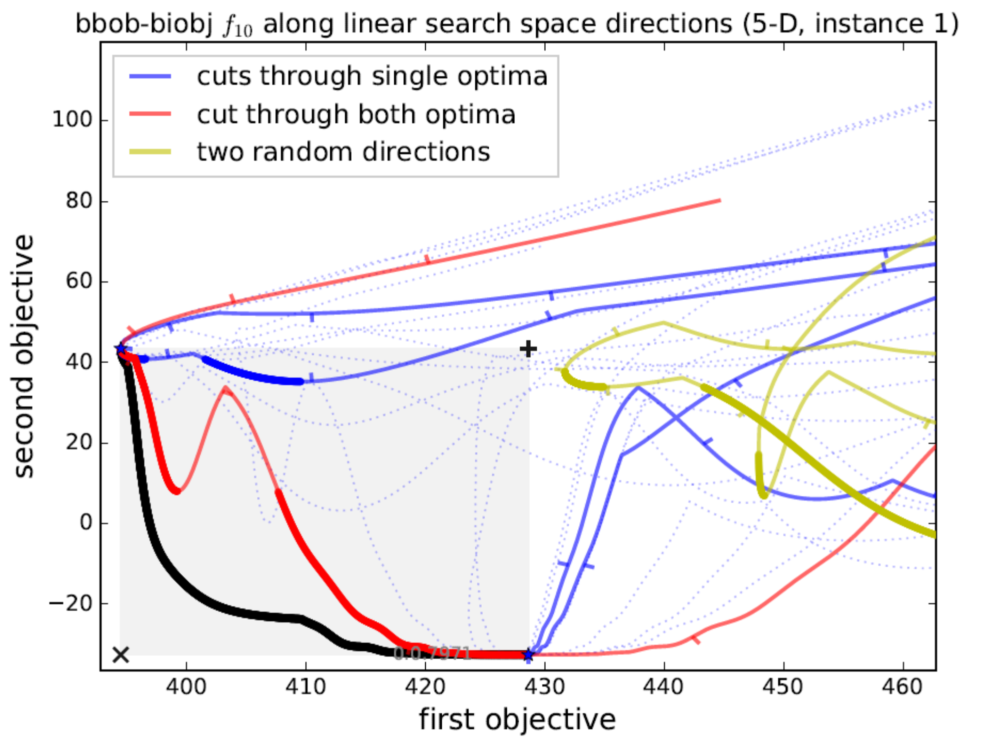


# bbob-biobj Testbed (cont'd)

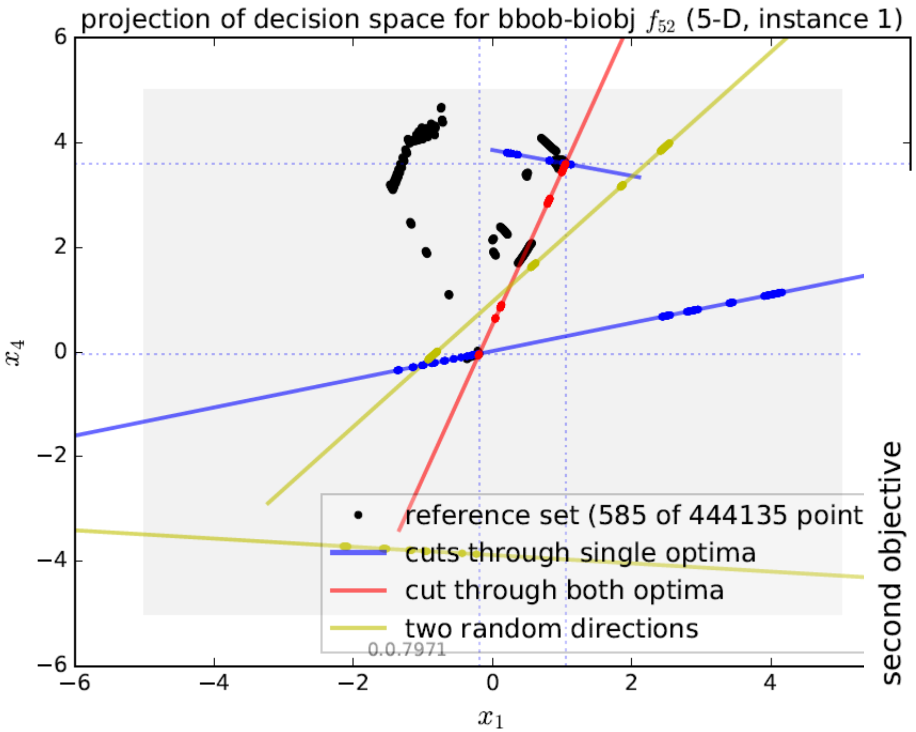
Example: sphere with Gallagher 101 peaks

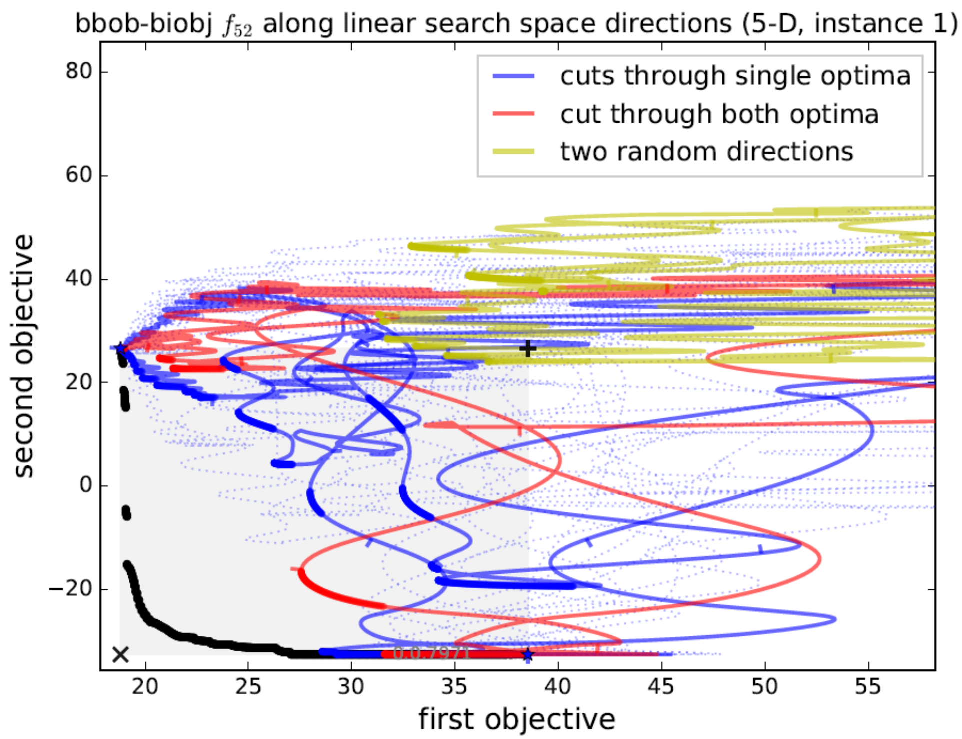


# bbob-biobj Testbed (cont'd)

Example: Schaffer F7, cond. 10 with Gallagher 101 peaks



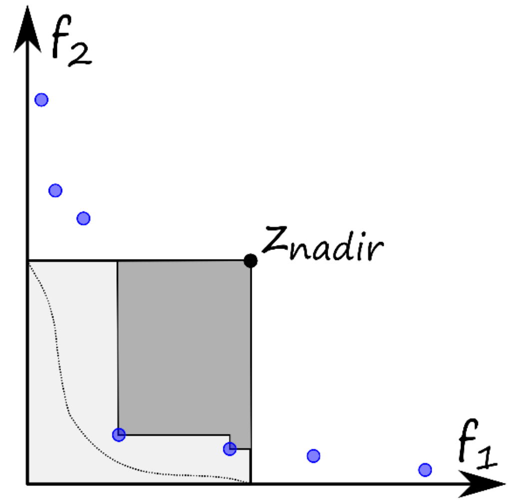



# Bi-objective Performance Assessment

algorithm quality =

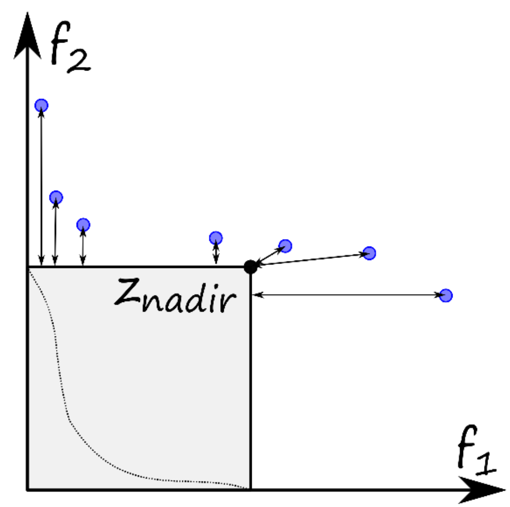
normalized* hypervolume (HV)
of all non-dominated solutions

*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

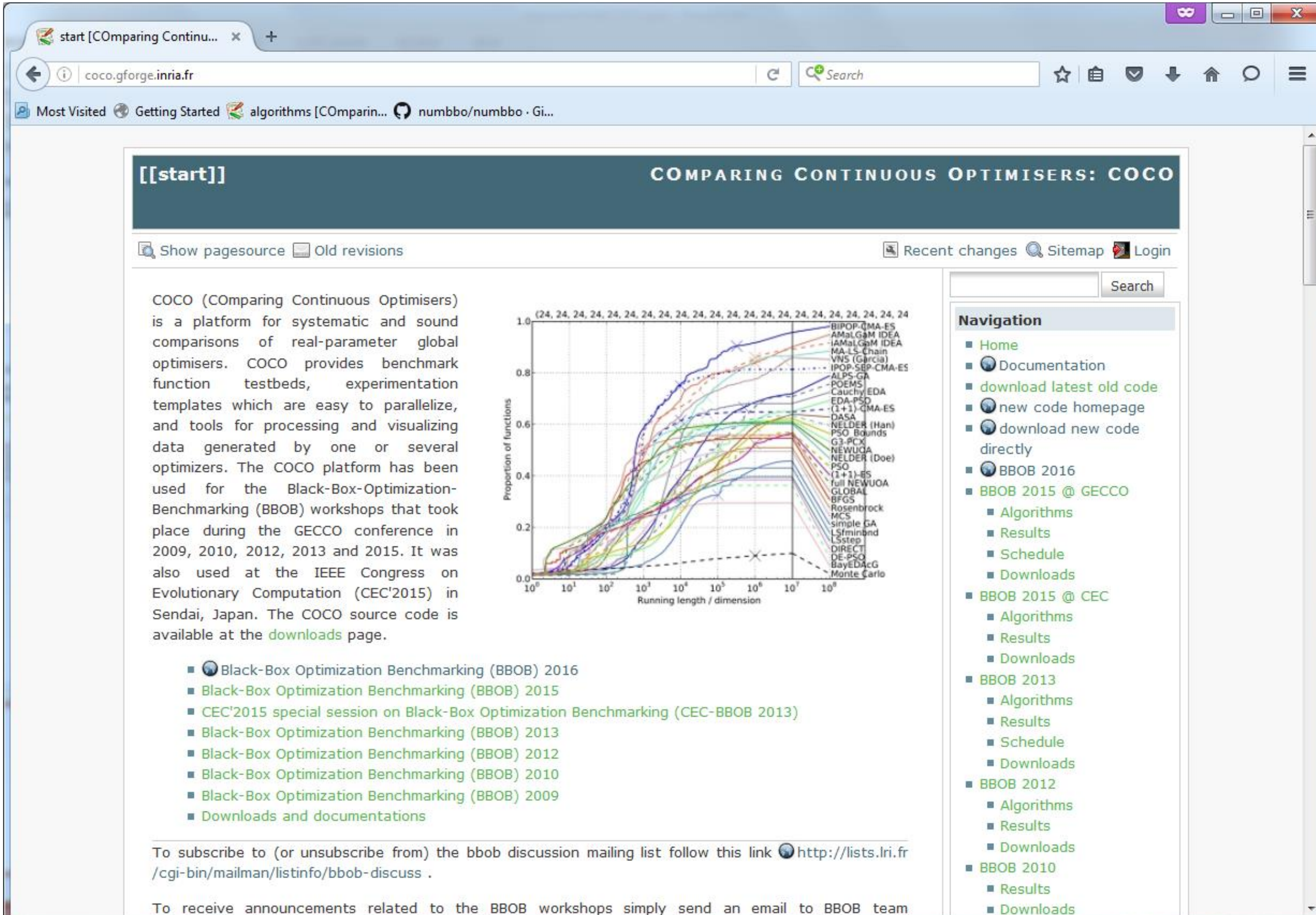
**and now?**

# BBOB-2016

## Enjoy the talks in this and the next two slots:

| | |
|---|---|
| **Session I** | |
| **08:30 - 09:30** | The BBOBies: Introduction to Blackbox Optimization Benchmarking |
| **09:30 - 09:55** | Tea Tušar*, Bogdan Filipič: Performance of the DEMO algorithm on the bi-objective BBOB test suite |
| **09:55 - 10:20** | Ilya Loshchilov, Tobias Glasmachers*: Anytime Bi-Objective Optimization with a Hybrid Multi-Objective CMA-ES (HMO-CMA-ES) |
| **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 |
| **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 |

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



by the way...

**we are hiring!**

at the moment:

**1 engineer position for 1 year in Paris**

**+ potential PhD, postdoc, and internship positions**

if you are interested, please talk to:

Anne Auger or Dimo Brockhoff