COCO: A Platform for Comparing Continuous Optimizers in a Black-Box Setting

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Abstract

COCO is a platform for Comparing Continuous Optimizers in a black-box setting. It aims at automatizing the tedious and repetitive task of benchmarking numerical optimization algorithms to the greatest possible extent. We present the rationals behind the development of the platform as a general proposition for a guideline towards better benchmarking. We detail underlying fundamental concepts of COCO such as the definition of a problem, the idea of instances, the relevance of target values, and runtime as central performance measure. Finally, we give a quick overview of the basic code structure and the currently available test suites.

Contents

1 Introduction

We consider the continuous black-box optimization or search problem to minimize

$$f : X \subset \mathbb{R}^n \to \mathbb{R}^m \qquad n, m \geq 1$$

such that for the l constraints

$$g : X \subset \mathbb{R}^n \to \mathbb{R}^l \qquad l \geq 0$$

we have $g_i(\boldsymbol{x}) \leq 0$ for all $i = 1 \ldots l$. More specifically, we aim to find, as quickly as possible, one or several solutions $\boldsymbol{x}$ in the search space X with *small* value(s) of $f(\boldsymbol{x}) \in \mathbb{R}^m$ that satisfy all above constraints g. We generally consider *time* to be the number of calls to the function f.

A continuous optimization algorithm, also known as *solver*, addresses the above problem. Here, we assume that X is known, but no prior knowledge about f or g is available to the algorithm. That is, f and g are considered as a black-box which the algorithm can query with solutions $\boldsymbol{x} \in \mathbb{R}^n$ to get the respective values $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$.

From these prerequisits, benchmarking optimization algorithms seems to be a rather simple and straightforward task. We run an algorithm on a collection of problems and display the results. However, under closer inspection, benchmarking turns out to be surprisingly tedious, and it appears to be difficult to get results that can be meaningfully interpreted beyond the standard claim that one algorithm is better than another on some problems.[1] Here, we offer a conceptual guideline for benchmarking continuous optimization algorithms which tries to address this challenge and has been implemented within the COCO framework.[2]

The COCO framework provides the practical means for an automatized benchmarking procedure. Installing COCO (in a shell) and benchmarking an optimization algorithm, say, the function `fmin` from `scipy.optimize` in Python, becomes as simple[3] as shown in the figure. The COCO framework provides

- an interface to several languages in which the benchmarked optimizer can be written, currently C/C++, Java, Matlab/Octave, Python

- several benchmark suites or testbeds, currently all written in C

- data logging facilities via the `Observer`

- data post-processing in Python and data browsing through `html`

- article LaTeX templates.

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[1] One common major flaw is to get no indication of *how much* better an algorithm is. That is, the results of benchmarking often provide no indication of *relevance*; the main output is often hundreds of tabulated numbers interpretable on an ordinal (ranking) scale only. Addressing a point of a common confusion, *statistical* significance is only a secondary and by no means sufficient condition for *relevance*.

[2] Confer to the code basis on Github and the C API documentation for implementation details.

[3] See also `example_experiment.py` which runs out-of-the-box as a benchmarking Python script.

```
$ ### get and install the code
$ git clone https://github.com/numbbo/coco.git  # get coco using git
$ cd coco
$ python do.py run-python  # install Python experimental module cocoex
$ python do.py install-postprocessing  # install post-processing :-)
```

```
$ ### (optional) run an example from the shell
$ cp code-experiments/build/python/example_experiment.py .
$ python example_experiment.py      # run the current "default" experiment
$ python -m bbob_pproc exdata/...  # run the post-processing
$ open ppdata/index.html           # browse results
```

```python
#!/usr/bin/env python
"""Python script to benchmark fmin of scipy.optimize"""
from numpy.random import rand
import cocoex
try: import cocopp  # new (future) name
except ImportError: import bbob_pproc as cocopp  # old name
from scipy.optimize import fmin

suite = cocoex.Suite("bbob", "year: 2016", "")
budget_multiply = 1e4  # use 1e1 or even 2 for a quick first test run
observer = cocoex.Observer("bbob", "result_folder: myoptimizer-on-bbob")

for p in suite:  # loop over all problems
    observer.observe(p)  # prepare logging of necessary data
    fmin(p, p.initial_solution)  # disp=False would silence fmin output
    while (not p.final_target_hit and  # apply restarts, if so desired
            p.evaluations < p.dimension * budget_multiplier):
        fmin(p, p.lower_bounds + (rand(p.dimension) + rand(p.dimension)) *
                    (p.upper_bounds - p.lower_bounds) / 2)

cocopp.main('exdata/myoptimizer-on-bbob')  # invoke data post-processing
```

Fig. 1: Shell code for installation of COCO (above), and Python code to benchmark `fmin` on the
`bbob` suite (below). After the Python script has been executed, the file `ppdata/index.html`
can be used to browse the resulting data.

The underlying philosophy of COCO is to provide everything that experimenters need to setup
and implement if they want to benchmark a given algorithm implementation *properly*. A desired
side effect of reusing the same framework is that data collected over years or even decades can be
effortlessly compared.[4] So far, the framework has been successfully used to benchmark far over a
hundred different algorithms by dozens of researchers.

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[4] For example, see here, here or here to access all data submitted to the BBOB 2009 GECCO workshop.

1.1 Why COCO?

Appart from diminishing the time burden and the pitfalls, bugs or omissions of the repetitive coding task for experimenters, our aim is to provide a *conceptual guideline for better benchmarking*. Our setup and guideline has the following defining features.

1. Benchmark functions are

    (a) used as black boxes for the algorithm, however they are explicitly known to the scientific community.

    (b) designed to be comprehensible, to allow a meaningful interpretation of performance results.

    (c) difficult to "defeat", that is, they do not have artificial regularities that can easily be (intentionally or unintentionally) exploited by an algorithm.[5]

    (d) scalable with the input dimension *[WHI1996]*.

2. There is no predefined budget (number of f-evaluations) for running an experiment, the experimental procedure is *budget-free [HAN2016ex]*.

3. A single performance measure is used — and thereafter aggregated and displayed in several ways —, namely **runtime**, *measured in number of f-evaluations [HAN2016perf]*. This runtime measure has the advantages to

    - be independent of the computational platform, language, compiler, coding styles, and other specific experimental conditions[6]

    - be independent, as a measurement, of the specific function on which it has been obtained

    - be relevant, meaningful and easily interpretable without expert domain knowledge

    - be quantitative on the ratio scale[7] *[STE1946]*

    - assume a wide range of values

    - aggregate over a collection of values in a meaningful way[8].

    A *missing* runtime value is considered as possible outcome (see below).

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[5] For example, the optimum is not in all-zeros, optima are not placed on a regular grid, most functions are not separable *[WHI1996]*. The objective to remain comprehensible makes it more challenging to design non-regular functions. Which regularities are common place in real-world optimization problems remains an open question.

[6] Runtimes measured in f-evaluations are widely comparable and designed to stay. The experimental procedure *[HAN2016ex]* includes however a timing experiment which records the internal computational effort of the algorithm in CPU or wall clock time.

[7] As opposed to a ranking of algorithms based on their solution quality achieved after a given budget.

[8] With the caveat that the *arithmetic average* is dominated by large values which can compromise its informative value.

4. The display is as comprehensible, intuitive and informative as possible. We believe that the details matter. Aggregation over dimension is avoided, because dimension is a parameter known in advance that can and should be used for algorithm design decisions. This is possible without significant drawbacks, because all functions are scalable in the dimension.

We believe however that in the *process* of algorithm *design*, a benchmarking framework like COCO has its limitations. During the design phase, usually fewer benchmark functions should be used, the functions and measuring tools should be tailored to the given algorithm and design question, and the overall procedure should usually be rather informal and interactive with rapid iterations. A benchmarking framework then serves to conduct the formalized validation experiment of the design *outcome* and can be used for regression testing.

1.2 Terminology

We specify a few terms which are used later.

function We talk about an objective *function* as a parametrized mapping $\mathbb{R}^n \rightarrow \mathbb{R}^m$ with scalable input space, $n \geq 2$, and usually $m \in \{1, 2\}$. Functions are parametrized such that different *instances* of the "same" function are available, e.g. translated or shifted versions.

problem We talk about a *problem*, `coco_problem_t`, as a specific *function instance* on which an optimization algorithm is run. A problem can be evaluated and returns an f-value or -vector and, in case, a g-vector. In the context of performance assessment, a target f- or indicator-value is added to define a problem. A problem is considered as solved when the given or the most difficult available target is obtained.

runtime We define *runtime*, or *run-length [HOO1998]* as the *number of evaluations* conducted on a given problem until a prescribed target value is hit, also referred to as number of *function* evaluations or f-evaluations. Runtime is our central performance measure.

suite A test- or benchmark-suite is a collection of problems, typically between twenty and a hundred, where the number of objectives m is fixed.

2 Functions, Instances, and Problems

In the COCO framework we consider **functions**, f_i, for each suite distinguished by their identifier $i = 1, 2, \ldots$. Functions are further *parametrized* by the (input) dimension, n, and the instance number, j. We can think of j as an index to a continuous parameter vector setting, as it parametrizes, among others things, translations and rotations. In practice, j is the discrete identifier for single instantiations of these parameters. For a given m, we then have

$$f_i^j \equiv f(n, i, j) : \mathbb{R}^n \rightarrow \mathbb{R}^m \quad \boldsymbol{x} \mapsto f_i^j(\boldsymbol{x}) = f(n, i, j)(\boldsymbol{x}) \ .$$

Varying n or j leads to a variation of the same function i of a given suite. Fixing n and j of function f_i defines an optimization **problem** $(n, i, j) \equiv (f_i, n, j)$ that can be presented to the optimization

algorithm. Each problem receives again an index in the suite, mapping the triple (n, i, j) to a single number.

As the formalization above suggests, the differentiation between function (index) and instance index is of purely semantic nature. This semantics however is important in how we display and interpret the results. We interpret **varying the instance** parameter as a natural randomization for experiments[9] in order to

- generate repetitions on a function and

- average away irrelevant aspects of the function definition, thereby providing

    - generality which alleviates the problem of overfitting, and

    - a fair setup which prevents intentional or unintentional exploitation of irrelevant or artificial function properties.

For example, we consider the absolute location of the optimum not a defining function feature. Consequently, in a typical COCO benchmark suite, instances with randomized search space translations are presented to the optimizer.[10]

3 Runtime and Target Values

In order to measure the runtime of an algorithm on a problem, we establish a hitting time condition. We prescribe a **target value**, t, which is an f-value or more generally a quality indicator-value *[HAN2016perf] [BRO2016]*. For a single run, when an algorithm reaches or surpasses the target value t on problem (f_i, n, j), we say it has *solved the problem* (f_i, n, j, t) — it was successful.[11]

Now, the **runtime** is the evaluation count when the target value t was reached or surpassed for the first time. That is, runtime is the number of f-evaluations needed to solve the problem (f_i, n, j, t).[12] *Measured runtimes are the only way how we assess the performance of an algorithm.* Observed success rates are generally translated into runtimes on a subset of problems.

If an algorithm does not hit the target in a single run, this runtime remains undefined — while it has been bounded from below by the number of evaluations in this unsuccessful run. The number

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[9] Changing or sweeping through a relevant feature of the problem class, systematically or randomized, is another possible usage of instance parametrization.

[10] Conducting either several trials on instances with randomized search space translations or with a randomized initial solution is equivalent, given that the optimizer behaves translation invariant (disregarding domain boundaries).

[11] Reflecting the *anytime* aspect of the experimental setup, we use the term *problem* in two meanings: as the problem the algorithm is benchmarked on, (f_i, n, j), and as the problem, (f_i, n, j, t), an algorithm may solve by hitting the target t with the runtime, $\text{RT}(f_i, n, j, t)$, or may fail to solve. Each problem (f_i, n, j) gives raise to a collection of dependent problems (f_i, n, j, t). Viewed as random variables, the events $\text{RT}(f_i, n, j, t)$ given (f_i, n, j) are not independent events for different values of t.

[12] Target values are directly linked to a problem, leaving the burden to define the targets with the designer of the benchmark suite. The alternative, namely to present the obtained f- or indicator-values as results, leaves the (rather unsurmountable) burden to interpret the meaning of these indicator values to the experimenter or the final audience. Fortunately, there is an automatized generic way to generate target values from observed runtimes, the so-called run-length based target values *[HAN2016perf]*.

of available runtime values depends on the budget the algorithm has explored. Therefore, larger budgets are preferable — however they should not come at the expense of abandoning reasonable termination conditions. Instead, restarts should be done *[HAN2016ex]*.

3.1 Restarts and Simulated Restarts

An optimization algorithm is bound to terminate and, in the single-objective case, return a recommended solution, $\boldsymbol{x}$, for the problem, (f_i, n, j).[13] The algorithm solves thereby all problems (f_i, n, j, t) for which $f(\boldsymbol{x}) \leq t$. Independent restarts from different, randomized initial solutions are a simple but powerful tool to increase the number of solved problems *[HAR1999]* — namely by increasing the number of t-values, for which the problem (f_i, n, j) was solved.[14] Independent restarts tend to increase the success rate, but they generally do not *change* the performance *assessment*, because the successes materialize at greater runtimes *[HAN2016perf]*. Therefore, we call our approach *budget-free*. Restarts however "*improve the reliability, comparability, precision, and "visibility" of the measured results*" *[HAN2016ex]*.

Simulated restarts [HAN2010] [HAN2016perf] are used to determine a runtime for unsuccessful runs. Semantically, *this is only valid if we can interpret different instances as random repetitions*. Resembling the bootstrapping method *[EFR1994]*, when we face an unsolved problem, we draw uniformly at random a new j until we find an instance such that (f_i, n, j, t) was solved.[15] The evaluations done on the first unsolved problem and on all subsequently drawn unsolved problems are added to the runtime on the last problem and are considered as runtime on the originally unsolved problem. This method is applied if a problem instance was not solved and is (only) available if at least one problem instance was solved. It allows to directly compare algorithms with different success probabilities.

3.2 Aggregation

A typical benchmark suite consists of about 20–100 functions with 5–15 instances for each function. For each instance, up to about 100 targets are considered for the performance assessment. This means we consider at least $20 \times 5 = 100$, and up to $100 \times 15 \times 100 = 150\,000$ runtimes for the performance assessment. To make them amenable to the experimenter, we need to summarize these data.

Our idea behind an aggregation is to make a statistical summary over a set or subset of *problems of interest over which we assume a uniform distribution*. From a practical perspective this means to have no simple way to distinguish between these problems and to select an optimization algorithm

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[13] More specifically, we use the anytime scenario where we consider at each evaluation the evolving quality indicator value.

[14] The quality indicator is always defined such that for a given problem (f_i, n, j) the number of acquired runtime values $\mathrm{RT}(f_i, n, j, t)$ (hitting a target indicator value t) is monotonously increasing with the used budget. Considered as random variables, these runtimes are not independent.

[15] More specifically, we consider the problems $(f_i, n, j, t(j))$ for all benchmarked instances j. The targets $t(j)$ depend on the instance in a way to make the problems comparable.

accordingly — in which case an aggregation for a single algorithm would not be helpful — and that we face each problem with similar probability. We do not aggregate over dimension, because dimension can and should be used for algorithm selection.

We have several ways to aggregate the resulting runtimes.

- Empirical (cumulative) distribution functions (ECDF). In the domain of optimization, ECDF are also known as *data profiles [MOR2009]*. We prefer the simple ECDF over the more innovative performance profiles *[MOR2002]* for two reasons. ECDF (i) do not depend on other (presented) algorithms, that is, they are unconditionally comparable across different publications, and (ii) let us distinguish, for the considered algorithm, in a natural way easy problems from difficult problems.[16] We usually display ECDF on the log scale, which makes the area above the curve and the *difference area* between two curves a meaningful conception.

- Averaging, as an estimator of the expected runtime. The average runtime is often plotted against dimension to indicate scaling with dimension. The *arithmetic* average is only meaningful if the underlying distribution of the values is similar. Otherwise, the average of log-runtimes, or *geometric* average, is recommended.

- Restarts and simulated restarts, see Section *Restarts and Simulated Restarts*, do not aggregate runtimes in the literal meaning (they are literally defined only when t was hit). They aggregate, however, time data to eventually supplement, if applicable, all missing runtime values.

4 General Code Structure

The code basis of the COCO code consists of two parts.

The *experiments* part defines test suites, allows to conduct experiments, and provides the output data. The code base is written in C, and wrapped in different languages (currently Java, Python, Matlab/Octave). An amalgamation technique is used that outputs two files `coco.h` and `coco.c` which suffice to run experiments within the COCO framework.

The *post-processing* part processes the data and displays the resulting runtimes. This part is entirely written in Python and heavily depends on `matplotlib` *[HUN2007]*.

5 Test Suites

Currently, the COCO framework provides three different test suites.

bbob contains 24 functions in five subgroups *[HAN2009fun]*.

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[16] When reading a performance profile, a question immediately crossing ones mind is often whether a large runtime difference is observed mainly because one algorithm solves the problem very quickly. This question cannot be answered from the profile. The advantage (i) over data profiles disappears when using run-length based target values *[HAN2016perf]*.

bbob-noisy contains 30 noisy problems in three subgroups *[HAN2009noi]*, currently only implemented in the old code basis.

bbob-biobj contains 55 bi-objective ($m = 2$) functions in 15 subgroups *[TUS2016]*.

Acknowledgments

References

[BRO2016]   D. Brockhoff, T. Tušar, D. Tušar, T. Wagner, N. Hansen, A. Auger, (2016). Biobjective Performance Assessment with the COCO Platform. *ArXiv e-prints*, arXiv:1605.01746.

[HAN2016perf] N. Hansen, A. Auger, D. Brockhoff, D. Tušar, T. Tušar (2016). COCO: Performance Assessment. *ArXiv e-prints*, arXiv:1605.03560.

[HAN2010]   N. Hansen, A. Auger, R. Ros, S. Finck, and P. Posik (2010). Comparing Results of 31 Algorithms from the Black-Box Optimization Benchmarking BBOB-2009. Workshop Proceedings of the GECCO Genetic and Evolutionary Computation Conference 2010, ACM, pp. 1689-1696.

[HAN2009fun] N. Hansen, S. Finck, R. Ros, and A. Auger (2009). Real-parameter black-box optimization benchmarking 2009: Noiseless functions definitions. Research Report RR-6829, Inria, updated February 2010.

[HAN2009noi] N. Hansen, S. Finck, R. Ros, and A. Auger (2009). Real-Parameter Black-Box Optimization Benchmarking 2009: Noisy Functions Definitions. Research Report RR-6869, Inria, updated February 2010.

[HAN2016ex]   N. Hansen, T. Tušar, A. Auger, D. Brockhoff, O. Mersmann (2016). COCO: The Experimental Procedure, *ArXiv e-prints*, arXiv:1603.08776.

[HUN2007]   J. D. Hunter (2007). Matplotlib: A 2D graphics environment, *Computing In Science & Engineering*, 9(3): 90-95.

[EFR1994]   B. Efron and R. Tibshirani (1994). *An introduction to the bootstrap*. CRC Press.

[HAR1999]   G. R. Harik and F. G. Lobo (1999). A parameter-less genetic algorithm. In *Proceedings of the Genetic and Evolutionary Computation Conference (GECCO)*, volume 1, pages 258-265. ACM.

[HOO1998]   H. H. Hoos and T. Stützle (1998). Evaluating Las Vegas algorithms: pitfalls and remedies. In *Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence (UAI-98)*, pages 238-245.

[MOR2009]   J. Moré and S. Wild (2009). Benchmarking Derivative-Free Optimization Algorithms. *SIAM J. Optimization*, 20(1):172-191.

[MOR2002]   D. Dolan and J. J. Moré (2002). Benchmarking Optimization Software with Performance Profiles. *Mathematical Programming*, 91:201-213.

[STE1946]   S.S. Stevens (1946). On the theory of scales of measurement. *Science* 103(2684), pp. 677-680.

[TUS2016]   T. Tušar, D. Brockhoff, N. Hansen, A. Auger (2016). COCO: The Bi-objective Black Box Optimization Benchmarking (bbob-biobj) Test Suite, *ArXiv e-prints*, arXiv:1604.00359.

[WHI1996]   D. Whitley, S. Rana, J. Dzubera, K. E. Mathias (1996). Evaluating evolutionary algorithms. *Artificial intelligence*, 85(1), 245-276.