中国科学技术大学
University of Science and Technology of China

The optimizationBenchmarking.org Experiment Evaluator

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Outline

1. Introduction
2. Example 1: MAX-SAT
3. Example 2: BBOB
4. Conclusions

Visit our website

http://www.optimizationBenchmarking.org

or

http://optimizationbenchmarking.github.io/optimizationBenchmarking

for downloading the software (version 0.8.3) and obtaining more information.

System Requirements:

- Java 1.7 (Ideally a JDK, under JRE slower with more memory requirements)
- optional: a LaTeX installation, such as TeXLive or MiKTeX (needed for generating pdf reports)

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7. Easily extensible: Add your own evaluation modules for your own, maybe problem-specific statistics

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Optimization Algorithms

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  - Find the *shortest* tour for a salesman to visit certain set of cities in China and return to Hefei!

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- Many questions in the real world are actually optimization problems, e.g.,
  - Find the *shortest* tour for a salesman to visit certain set of cities
  - I need to transport n items from here to Feixi but they are too big to transport them all at once. How can I load them best into my car so that I have to travel back and forth the least times?

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  - Find the *shortest* tour for a salesman to visit certain set of cities
  - I need to transport n items from here to Feixi
  - Which setting of x_1, x_2, x_3, and x_4 can make $(x_1 \vee \neg x_2 \vee x_3) \wedge (\neg x_2 \vee \neg x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee \neg x_4)$ become true (or, at least, as *many* of its terms as possible)?

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  - I want to build a large factory with n workshops. I know the flow of material between each two workshops and now need to choose the locations of the workshops such that the overall running cost incurred by material transportation is *minimized*.

the land with
5 locations

5 workshops and goods flows betwee them
which need to be assigned to locations

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  - Traveling Salesman Problem [60–63]
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- How can I make a good algorithm better (for my problem)?

Algorithm Analysis and Comparison

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  - Currently, not mature enough to be an easy-to-use tool for practitioners
- Experimental analysis and comparison only practical alternative.

Performance and Anytime Algorithms

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- Several exact methods like Branch-and-Bound [74–76] are Anytime Algorithms.
- Consequence: Most optimization algorithms produce approximate solutions of different qualities at different points during their process.
- Experiments must capture solution quality and runtime data.

Experimental Procedure

- In optimization or Machine Learning, the following experimental procedure is often used

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  1. Select a benchmark instance

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- In optimization or Machine Learning, the following experimental procedure is often used
  1. Select a set of benchmark instances:
     - multiple instances

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  1. Select a set of benchmark instances:
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     - e.g., *TSPLib*[77–79] for the TSP has instances with different numbers of cities and geometries

The relative amounts of the instances of the 110 symmetric instances of *TSPLib* according to their features (the 10 asymmetric instances are not plotted).

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     - e.g., *BBOB* [71, 80–82] offers different benchmark functions for numerical optimization problems

The relative amounts of *BBOB* benchmark functions according to their features.

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     - conduct several independent runs of algorithm for each benchmark instance

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  1. Select a set of benchmark instances
  2. Do experiment:
     - conduct several independent runs of algorithm for each benchmark instance
     - collect algorithm progress informatio, e.g., as *"runtime bestObjectiveValue"* tuples

1	39334	3	42.19354838709677	4075
2	311078	5	70.32258064516128	3976
3	311078	5	70.32258064516128	3894
4	311078	5	70.32258064516128	3824
5	311078	5	70.32258064516128	3761
6	311078	5	70.32258064516128	3705
...				
24099	1111598495	11393	160237.03225806452	2579

- FEs: function evaluations
- DEs: accesses to distance matrix
- AT: absolute runtime in ms
- NT: absolute runtime divided by machine-specific performance factor
- best objective value: best result so far

Example for data collected in a log file by *TSP Suite* [72, 83].

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     - repeat with other algorithms for comparison purposes

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  3. Evaluate the gathered data:
     - draw diagrams of progress of solution quality over time

Examples for progress diagrams for different algorithms (signified by different colors) over different sub-sets of the *TSPLib* data.

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  3. Evaluate the gathered data:
     - draw diagrams of progress of solution quality over time
     - draw diagrams of advanced statistical parameters such as ECDF [66, 72, 80, 84] (over time)

Examples for progress and ERT diagrams for different algorithms (signified by different colors) over different sub-sets of the *TSPLib* data.

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     - draw diagrams of advanced statistical parameters such as ECDF [66, 72, 80, 84] and ERT [72, 80] (over time)

Examples for progress, ERT, and ECDF diagrams for different algorithms (signified by different colors) over different sub-sets of the *TSPLib* data.

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- The `optimizationBenchmarking` Evaluator can automatize much of this work

Section Outline

1 Introduction

2 Example 1: MAX-SAT

3 Example 2: BBOB

4 Conclusions

Example 1: MAX-SAT

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- Assume that we are a researcher working on the MAX-3SAT problem, with new and fresh ideas...

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  - Goal: find a setting for these variables so that B becomes `true`

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  - $k+1$ different objective values possible

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- Which of these algorithms performs best? When? Why?

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Example of Log File

- Example log file obtained from applying the 2-flip Hill Climber with Restarts to the 2nd benchmark instance of set uf075.

Listing: Log File uf075-02_2FlipHCrs_01.txt.

```
1          9806          46
3          24643         28
17         106040        25
19         115529        23
20         120373        21
25         144087        18
31         172967        16
290        1550118       15
296        1576034       14
297        1579525       13
300        1592492       12
323        1692189       10
332        1732127       9
1082       5436999       8
1558       7670059       7
2008       9765759       6
2024       9830168       5
2809       13302012      4
5246       24105640      3
6330       28508740      2
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1558       7670059       7
2008       9765759       6
2024       9830168       5
2809       13302012      4
5246       24105640      3
6330       28508740      2
17284      73166926      1
60865      238968738     0
```

Example of Log File

- Example log file obtained from applying the 2-flip Hill Climber with Restarts to the 2nd benchmark instance of set uf075.

log point

ellapsed *FEs*

Listing: Log File uf075-02_2FlipHCrs_01.txt.

1	9806	46
3	24643	28
17	106040	25
19	115529	23
20	120373	21
25	144087	18
31	172967	16
290	1550118	15
296	1576034	14
297	1579525	13
300	1592492	12
323	1692189	10
332	1732127	9
1082	5436999	8
1558	7670059	7
2008	9765759	6
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  - of each of the 10 instance sets.
  - We have $6 * 20 * 10 * 10 = 12\,000$ log files!

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- How can we extract useful information from them in order to answer the questions which algorithm performs best, when, and why?
- What you most likely do: Write your own small program.
- What you now can do: Use our `optimizationBenchmarking` Evaluator!

Example Results from optimizationBenchmarking

- In the following, I provide some examples for what our evaluator can do.

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- First, a quick guide to download and run the example on your computer is given
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- Finally, I will show *how* that gets done in detail.

Quick Guide

- You can quickly download all example data and the Evaluator and run the example on your PC by executing the following code snippet.

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- System Requirements:
  - Linux (for `make.sh`), Windows (for `make.bat`, tested: Win 8, should work also under Win 7)
  - Java 1.7 (ideally a `JDK` under a `JRE` slower and higher memory consumption)
  - `svn`
  - optional: a LaTeX installation, such as TeXLive (needed for generating pdf reports)

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Listing: Linux: script `make.sh` for downloading & running the MAX-SAT example.

```
#!/bin/bash

jarName="optimizationBenchmarking-full.jar"

outputDir=`pwd`
echo "Writing output to folder '${outputDir}'"

echo "Downloading experimental results via 'svn export' from GitHub."
svn export https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/branches/master/examples/maxSat/results
echo "Downloading evaluation/configuration via 'svn export' from GitHub."
svn export https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/branches/master/examples/maxSat/evaluation

jarDownloadURL=$(wget "http://optimizationbenchmarking.github.io/optimizationBenchmarking/currentVersion.url" -q -O -)
echo "Downloading evaluator from '${jarDownloadURL}'."
wget -O "${outputDir}/${jarName}" "${jarDownloadURL}"

echo "Applying evaluator and obtaining reports in different formats."
cd "${outputDir}/evaluation"
java -jar "${outputDir}/${jarName}" -configXML=configForIEEEtran.xml
java -jar "${outputDir}/${jarName}" -configXML=configForLNCS.xml
java -jar "${outputDir}/${jarName}" -configXML=configForSigAlternate.xml
java -jar "${outputDir}/${jarName}" -configXML=configForXHTML.xml
java -jar "${outputDir}/${jarName}" -configXML=configForExport.xml

cd "${outputDir}"
echo "Done."
```

- Enter (or create) a folder where you want to have everything, then execute this script via copy-paste to the terminal (it may need quite a while to run due to the downloads)

Listing: Windows: script `make.bat` for downloading & running the MAX-SAT example.

```
echo "Downloading evaluator."
powershell -command "& {iwr http://optimizationbenchmarking.github.io/optimizationBenchmarking/currentVersion.url -OutFile version.txt}"
for /F "delims=" %i in (version.txt) do set downloadURL=%i
powershell -command "& {iwr %downloadURL% -OutFile optimizationBenchmarking.jar}"
del version.txt

echo "Downloading (but not installing!) required 3rd-party software: downloading SVN client and 7-Zip to extract it."
md svn
cd svn
powershell -command "& {iwr https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/raw/master/tools/windows/7zip/7za.exe -OutFile 7za.exe}"
powershell -command "& {iwr https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/raw/master/tools/windows/svn/svn.tar.lzma -OutFile svn.tar.lzma}"
7za x svn.tar.lzma
7za x svn.tar
cd..

echo "Downloading experimental results via 'svn-export' from GitHub."
svn\svn export https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/branches/master/examples/maxSat/results

echo "Downloading evaluation/configuration via 'svn export' from GitHub."
svn\svn export https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/branches/master/examples/maxSat/evaluation

rd /s /q svn

echo "Applying evaluator and obtaining reports in different formats."
cd evaluation
java -jar "..\optimizationBenchmarking.jar" -configXML=configForIEEEtran.xml
java -jar "..\optimizationBenchmarking.jar" -configXML=configForLNCS.xml
java -jar "..\optimizationBenchmarking.jar" -configXML=configForSigAlternate.xml
java -jar "..\optimizationBenchmarking.jar" -configXML=configForXHTML.xml
java -jar "..\optimizationBenchmarking.jar" -configXML=configForExport.xml

cd..
echo "Done."
```

Quick Guide

- Enter (or create) a folder where you want to have everything, then execute this script via copy-paste to the terminal (it may need quite a while to run due to the downloads)
- After the script, you will have
  - a folder `results` with the log files which have been evaluated
  - a folder `evaluation` with the configuration files and the `evaluation.xml` file defining what to do
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  - a filder `reports` with the generated reports
- But now, let's continue with the example...

ECDF

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The ECDF in over all 100 benchmark instances (log-scaled, optimized for XHTML and two figures per row).

ECDF for Different Values of n

We now look at the ECDF for different values of n and a goal of 1% unsatisfied clauses over RT (log-scaled).

legend

ECDF for Different Values of n

For $n = 20$, the methods with restarts are better.

legend

$n = 20$

ECDF for Different Values of n

But for $n \geq 50$, those without reach the goal faster.

legend

$n = 20$

$n = 50$

ECDF for Different Values of n

It seems that 1% unsatisfied clauses can be reached with 1-flips and without restarts.

legend

$n = 20$

$n = 50$

$n = 75$

ECDF for Different Values of n

The 2-flip operator again performs worst.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

ECDF for Different Values of n

It looks as if it gets easier to attain a 1% error margin if n increases (all ECDFs reach 1).

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

ECDF for Different Values of n

For small problems, 1-flip is slightly faster than m-flip.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

$n = 150$

ECDF for Different Values of n

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legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

$n = 150$

$n = 175$

ECDF for Different Values of n

For larger problems, m-flip becomes slightly faster.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

$n = 150$

$n = 175$

$n = 200$

ECDF for Different Values of n

All in all, similar behavior over all scales (reaching 1% error seems to be easy).

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

$n = 150$

$n = 175$

$n = 200$

$n = 225$

ECDF for Different Values of n

Only required runtime increases by up to 100 times.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

$n = 150$

$n = 175$

$n = 200$

$n = 225$

$n = 250$

Progress for Different Values of k

We now look at the progress curves (F over *FEs* divided by[1] n, log-scaled) for different values of k.

legend

[1] We normalize *FEs* with n in the hope to make the time measure comparable over different n.

Progress for Different Values of k

For very small-scale problems, all algorithms behave similar.

legend

$k = 91$

Progress for Different Values of k

But soon, two groups form: with and without restarts.

legend

$k = 91$

$k = 218$

Progress for Different Values of k

Algorithms using *my example restart policy* seem to be slower.

legend

$k = 91$

$k = 218$

$k = 325$

Progress for Different Values of k

The gap increases with rising k

legend

$k = 91$

$k = 218$

$k = 325$

$k = 430$

Progress for Different Values of k

Thus, we find: algorithms with my restart policy are slower than those without...

legend

$k = 91$

$k = 218$

$k = 325$

$k = 430$

$k = 538$

Progress for Different Values of k

. . . but from the ECDF we know they can solve more problems eventually.

legend

$k = 91$

$k = 218$

$k = 325$

$k = 430$

$k = 538$

$k = 645$

Progress for Different Values of k

For all scales, the initial random solutions, seem to have about 12% of unsatisfied clauses (in median).

legend

$k = 91$

$k = 218$

$k = 325$

$k = 430$

$k = 538$

$k = 645$

$k = 753$

Progress for Different Values of k

Convergence seems to happen between $100n$ and $1000n$

legend

$k = 91$

$k = 218$

$k = 325$

$k = 430$

$k = 538$

$k = 645$

$k = 753$

$k = 860$

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$k = 91$

$k = 218$

$k = 325$

$k = 430$

$k = 538$

$k = 645$

$k = 753$

$k = 860$

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$k = 91$

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$k = 430$

$k = 538$

$k = 645$

$k = 753$

$k = 860$

$k = 960$

$k = 1065$

StdDev of F for Different Values of n

Let's look at the standard deviation of the best objective value F (divided by[1] k) found over RT (log-scaled) for different values of n.

legend

[1] Since F is always in $1 \ldots k$, dividing it by k normalizes it into $[0, 1]$ and makes the values comparable for different k or n.

StdDev of F for Different Values of n

For small-scale problems, the standard deviation seems to decrease steadily.

legend

$n = 20$

StdDev of F for Different Values of n

The reason is probably that the algorithms converge nicely.

legend

$n = 20$

$n = 50$

StdDev of F for Different Values of n

For the methods with restarts, it reaches very close to 0.

legend

$n = 20$

$n = 50$

$n = 75$

StdDev of F for Different Values of n

For those without, it remains constant above 0 after some time.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

StdDev of F for Different Values of n

These algorithms probably get stuck at different local optima in different runs.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

StdDev of F for Different Values of n

For increasing scales, the standard deviation goes first down, then up, then farther down.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

$n = 150$

StdDev of F for Different Values of n

Maybe there is some kind of hard-to-attain improvement that some runs find earlier than others.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

$n = 150$

$n = 175$

StdDev of F for Different Values of n

The time of convergence seems to increase for the methods with restarts with n.

legend

$n = 20$

$n = 50$

$n = 75$

$n = 100$

$n = 125$

$n = 150$

$n = 175$

$n = 200$

StdDev of F for Different Values of n

The early standard deviations are usually below 0.03 and highest for small n.

legend

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- So these are *some* of the things `optimizationBenchmarking` can *currently* do.

So... how to get there?

- So these are *some* of the things `optimizationBenchmarking` can *currently* do.
- But how to do them?

The Flow

- Let us now take a closer look on how the `optimizationBenchmarking` evaluator is used (and works)

The Flow

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- We specify which benchmark instances we have and what their features are: 10×10 instances in our example, with features n and k
- For each experiment, we specify the parameters: in our example, these are `algorithm`, `operator`, `restart`

The Flow

- An "input driver" loads the data

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- Via a configuration file, we choose which input and output formats to use, as well as which file specifies the evaluation process
- The `evaluation.xml` specifies *how* to evaluate the data, i.e., which evaluation modules to apply

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- Evaluation modules can be applied multiple times, with different configurations (e.g., we can plot ECDFs for different target solution qualities)

The Flow

- We can choose among several different formats to be used for graphics, including EPS [85], PDF [86], PGF (LaTeX), SVG(Z), EMF, PNG [87], GIF [88], BMP, and JPG

The Flow

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The Flow

- We can also choose among different formats for the report documents, including LaTeX [89–92]:
  - can automatically be compiled to PDF [86], if a LaTeX compiler (such as TeXLive [93] or MiKTeX [94]) is auto-detected

The Flow

- We can also choose among different formats for the report documents, including LaTeX [89–92]:
  - can automatically be compiled to PDF [86], if a LaTeX compiler (such as TeXLive [93] or MiKTeX [94]) is auto-detected
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The Flow

- We can also choose among different formats for the report documents, including LaTeX and XHTML [98] for quick viewing in a browser

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Measured Dimensions

- For each research subject, we may collect different "kinds" of measurements

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    - `runtimeNormalized`, a machine-independent time measure, maybe `runtimeCPU` divide by a performance factor

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    - `runtimeCPU`, i.e., processor time (machine dependent)
    - `runtimeNormalized`, a machine-independent time measure, maybe `runtimeCPU` divide by a performance factor
    - `qualityProblemDependent` a problem-instance specific objective value (e.g., *number* of unsatisfied clauses in SAT)
    - `qualityProblemIndependent` an objective value which can compared over different instances (e.g., the *fraction* of unsatisfied clauses in SAT)

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    - `decreasing`, i.e., values get smaller, but consecutive log points may have same value
    - `decreasingStrictly`, such as the objective value in the log points of our MAX-SAT example

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    - `decreasing`, i.e., values get smaller, but consecutive log points may have same value
    - `decreasingStrictly`, such as the objective value in the log points of our MAX-SAT example
    - `increasing`, like the absolute runtime: due to clock resolution, some log points may be taken at the same clock time

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    - `decreasing`, i.e., values get smaller, but consecutive log points may have same value
    - `decreasingStrictly`, such as the objective value in the log points of our MAX-SAT example
    - `increasing`, like the absolute runtime: due to clock resolution, some log points may be taken at the same clock time
    - `increasingStrictly`, like the *FEs* in our example – no two log points can have the same value in this dimension

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  - a data type, which is either
    - `byte`

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    - `short`

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    - `short`,
    - `int`

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  - a data type, which is either
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    - `short`,
    - `int`,
    - `long`

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  - a data type, which is either
    - `byte`,
    - `short`,
    - `int`,
    - `long`,
    - `float`

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  - a data type, which is either
    - `byte`,
    - `short`,
    - `int`,
    - `long`,
    - `float`, or
    - `double`

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    - `iLowerBound`, a integer lower bound, such as 1 for *FEs*

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    - `iUpperBound`, a integer upper bound

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    - `iUpperBound`, a integer upper bound *or*
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- With this information, the nature of measurements is defined and data can be validated

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  - bounds which can be used in computations and for sanity checks,
  - an optional description
- With this information, the nature of measurements is defined and data can be validated
- Multiple time and quality dimensions can be specified
- Diagrams can be plotted and values can be analyzed according to different dimensions

Measured Dimensions: dimensions.xml

- To specify all this, we can make an XML file called `dimensions.xml` and put it into the `results` folder with our log files.

Listing: File `dimensions.xml` for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<dimensions
  xmlns="http://www.optimizationBenchmarking.org/formats/
      experimentDataInterchange/experimentDataInterchange.1.0.xsd">

  <dimension name="FEs"
    description="The number of function evaluations, i.e., the amount of
        generated candidate solutions."
    dimensionType="iterationFE" direction="increasingStrictly" dataType="long"
    iLowerBound="1" />

  <dimension name="RT" description="The elapsed runtime in nanoseconds."
    dimensionType="runtimeCPU" direction="increasing" dataType="long"
    iLowerBound="0" />

  <dimension name="F" description="The fraction of unsatisfied clauses."
    dimensionType="qualityProblemDependent" direction="decreasing"
    dataType="int" iLowerBound="0" iUpperBound="2000" />

</dimensions>
```

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    - a value (such as 250),
    - an optional description, and
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    - makes particular sense for `qualityProblemDependent`
    - specified as element `bounds` with attribute `dimension` and either `iLowerBound` or `fLowerBound` and/or either `iUpperBound` or `fUpperBound`

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- Numerical features can be used in formulas and computations, e.g., to normalize values
- Bounds allow us to validate measured data and can be used in computations

Benchmark Instances: instances.xml

- To specify all this, we can make an XML file called `instances.xml` and put it into the `results` folder with our log files.

Listing: Excerpt from file `instances.xml` for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<instances
  xmlns="http://www.optimizationBenchmarking.org/formats/experimentDataInterchange/experimentDataInterchange
      .1.0.xsd">
  <instance name="uf020-01"
    description="A uniformly randomly generated satisfiable 3-SAT instance with 20 variables and 91 clauses.
    <feature name="n" value="20" />
    <feature name="k" value="91" />
  </instance>
  <instance name="uf020-02"
    description="A uniformly randomly generated satisfiable 3-SAT instance with 20 variables and 91 clauses.
    <feature name="n" value="20" />
    <feature name="k" value="91" />
  </instance>
  <instance name="uf075-01"
    description="A uniformly randomly generated satisfiable 3-SAT instance with 75 variables and 325 clauses
    <feature name="n" value="75" />
    <feature name="k" value="325" />
  </instance>
  <instance name="uf075-02"
    description="A uniformly randomly generated satisfiable 3-SAT instance with 75 variables and 325 clauses
    <feature name="n" value="75" />
    <feature name="k" value="325" />
  </instance>
```

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    - an optional description

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    - a value (such as "2-flip"),
    - an optional description, and
    - an optional value description

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Experiments

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- Each experiment has a name, parameters, and an optional description
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- The algorithm itself is treated as parameter as well
- Any number of parameters can be defined, different experiments may specify different parameters (e.g., an EA has a population size, HC has not)
- Any parameter value type is possible, numerical features are automatically detected
- Numerical parameter values can be used in computations (e.g., to multiply a "generations" dimension of experiments with an EA with the population size

Experiments: experiment.xml

- To specify all this, we can make a separate XML file called experiment.xml for each experiment and put it into root folder of the experiment, e.g., results/1FlipHC.

Listing: Excerpt from file experiment.xml for the 1-flip Hill Climber without restarts.

```
<?xml version="1.0" encoding="UTF-8"?>
<experiment
  xmlns="http://www.optimizationBenchmarking.org/formats/
      experimentDataInterchange/experimentDataInterchange.1.0.xsd"
  name="1FlipHC" description="An experiment with a 1-flip Hill
      Climber without restarts.">
  <parameter name="algorithm" value="HC" />
  <parameter name="operator" value="1-flip" />
  <parameter name="restart" value="false" />
</experiment>
```

Experiments: experiment.xml

- To specify all this, we can make a separate XML file called experiment.xml for each experiment and put it into root folder of the experiment, e.g., results/1FlipHCrs.

Listing: Excerpt from file experiment.xml for the 1-flip Hill Climber with restarts.

```
<?xml version="1.0" encoding="UTF-8"?>
<experiment
  xmlns="http://www.optimizationBenchmarking.org/formats/
      experimentDataInterchange/experimentDataInterchange.1.0.xsd"
  name="1FlipHCrs" description="An experiment with a 1-flip Hill
      Climber with restarts.">
  <parameter name="algorithm" value="HC" />
  <parameter name="operator" value="1-flip" />
  <parameter name="restart" value="true" />
</experiment>
```

Experiments: experiment.xml

- To specify all this, we can make a separate XML file called experiment.xml for each experiment and put it into root folder of the experiment, e.g., results/mFlipHCrs.

Listing: Excerpt from file experiment.xml for the m-flip Hill Climber with restarts.

```
<?xml version="1.0" encoding="UTF-8"?>
<experiment
  xmlns="http://www.optimizationBenchmarking.org/formats/
      experimentDataInterchange/experimentDataInterchange.1.0.xsd"
  name="mFlipHCrs" description="An experiment with a m-flip Hill
      Climber with restarts.">
  <parameter name="algorithm" value="HC" />
  <parameter name="operator" value="m-flip" />
  <parameter name="restart" value="true" />
</experiment>
```

Specifying Evaluation Process

- Now that we have specified what kind of data we have, we need to tell *what to do with them*.

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- The evaluation process of `optimizationBenchmarking` is based on *modules*
- Each module contributes performs one specific computation and adds text and/or figures to the report
- Modules can be configured, e.g., we can tell the "ECDF" module which dimension we want as x-axis
- A module can be applied multiple times with different configurations
- A global basic configuration can be provided
- To specify all this, we supply an XML file called `evaluation.xml`
- In `evaluation.xml`, we can use the names and values of dimensions, features, and parameters

Specifying Evaluation Process: evaluation.xml

- Global base configuration

Listing: Part 1 from file evaluation.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<e:evaluation
  xmlns:e="http://www.optimizationBenchmarking.org/formats/
      evaluationConfiguration/evaluationConfiguration.1.0.xsd"
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/configuration/
      configuration.1.0.xsd">

  <cfg:configuration>
    <cfg:parameter name="figureSize" value="2 per row" />
    <cfg:parameter name="makeLegendFigure" value="true" />
    <cfg:parameter name="nGrouping" value="distinct" />
    <cfg:parameter name="kGrouping" value="distinct" />
  </cfg:configuration>

  <e:module class="description.instances.InstanceInformation" />
```

Specifying Evaluation Process: evaluation.xml

- Global base configuration: 2 figures per row

Listing: Part 1 from file evaluation.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<e:evaluation
  xmlns:e="http://www.optimizationBenchmarking.org/formats/
      evaluationConfiguration/evaluationConfiguration.1.0.xsd"
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/configuration/
      configuration.1.0.xsd">

  <cfg:configuration>
    <cfg:parameter name="figureSize" value="2 per row" />
    <cfg:parameter name="makeLegendFigure" value="true" />
    <cfg:parameter name="nGrouping" value="distinct" />
    <cfg:parameter name="kGrouping" value="distinct" />
  </cfg:configuration>

  <e:module class="description.instances.InstanceInformation" />
```

Specifying Evaluation Process: evaluation.xml

- Global base configuration: 2 figures per row, figure series should have dedicated sub-figure for legend

Listing: Part 1 from file `evaluation.xml` for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<e:evaluation
  xmlns:e="http://www.optimizationBenchmarking.org/formats/
      evaluationConfiguration/evaluationConfiguration.1.0.xsd"
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/configuration/
      configuration.1.0.xsd">

  <cfg:configuration>
    <cfg:parameter name="figureSize" value="2 per row" />
    <cfg:parameter name="makeLegendFigure" value="true" />
    <cfg:parameter name="nGrouping" value="distinct" />
    <cfg:parameter name="kGrouping" value="distinct" />
  </cfg:configuration>

  <e:module class="description.instances.InstanceInformation" />
```

Specifying Evaluation Process: evaluation.xml

- Global base configuration: 2 figures per row, figure series should have dedicated sub-figure for legend, when benchmarks are grouped either by n or by k, put those with same values of these features together

Listing: Part 1 from file `evaluation.xml` for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<e:evaluation
  xmlns:e="http://www.optimizationBenchmarking.org/formats/
      evaluationConfiguration/evaluationConfiguration.1.0.xsd"
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/configuration/
      configuration.1.0.xsd">

  <cfg:configuration>
    <cfg:parameter name="figureSize" value="2 per row" />
    <cfg:parameter name="makeLegendFigure" value="true" />
    <cfg:parameter name="nGrouping" value="distinct" />
    <cfg:parameter name="kGrouping" value="distinct" />
  </cfg:configuration>

  <e:module class="description.instances.InstanceInformation" />
```

Specifying Evaluation Process: evaluation.xml

- Execute one module: print pie charts showing how many benchmark instances have which feature values

Listing: Part 1 from file `evaluation.xml` for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<e:evaluation
  xmlns:e="http://www.optimizationBenchmarking.org/formats/
      evaluationConfiguration/evaluationConfiguration.1.0.xsd"
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/configuration/
      configuration.1.0.xsd">

  <cfg:configuration>
    <cfg:parameter name="figureSize" value="2 per row" />
    <cfg:parameter name="makeLegendFigure" value="true" />
    <cfg:parameter name="nGrouping" value="distinct" />
    <cfg:parameter name="kGrouping" value="distinct" />
  </cfg:configuration>

  <e:module class="description.instances.InstanceInformation" />
```

Specifying Evaluation Process: evaluation.xml

- The ECDF module is applied two times

Listing: Part 2 from file `evaluation.xml` for our MAX-SAT example.

```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="goal" value="0" />
    <cfg:parameter name="figureSize" value="page wide" />
    <cfg:parameter name="makeLegendFigure" value="false" />
  </cfg:configuration>
</e:module>

<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg RT" />
    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="goal" value="0.01" />
    <cfg:parameter name="groupBy" value="n" />
  </cfg:configuration>
</e:module>
```

Specifying Evaluation Process: evaluation.xml

- The ECDF module is applied two times: in order to aggregate the ECDF over all problem instances, F is scaled by k and the ECDF is computed for a goal value of $\frac{F}{k} = 0$. The x-axis in *FEs* is log-scaled and figures are rendered page-wide

Listing: Part 2 from file `evaluation.xml` for our MAX-SAT example.

```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="goal" value="0" />
    <cfg:parameter name="figureSize" value="page wide" />
    <cfg:parameter name="makeLegendFigure" value="false" />
  </cfg:configuration>
</e:module>

<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg RT" />
    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="goal" value="0.01" />
    <cfg:parameter name="groupBy" value="n" />
  </cfg:configuration>
</e:module>
```

Specifying Evaluation Process: evaluation.xml

- The ECDF module is applied two times: then one ECDF diagram is drawn for each distinct value of n, the log-scaled time measure RT, and a goal 0.01 for $\frac{F}{k}$, i.e., for reaching no more than 1% of unsatisfied clauses (and the globally configured figure size)

Listing: Part 2 from file `evaluation.xml` for our MAX-SAT example.

```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="goal" value="0" />
    <cfg:parameter name="figureSize" value="page wide" />
    <cfg:parameter name="makeLegendFigure" value="false" />
  </cfg:configuration>
</e:module>

<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg RT" />
    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="goal" value="0.01" />
    <cfg:parameter name="groupBy" value="n" />
  </cfg:configuration>
</e:module>
```

Specifying Evaluation Process: evaluation.xml

- The "Aggregation" module is applied twice as well

Listing: Part 3 from file `evaluation.xml` for our MAX-SAT example.

```
<e:module class="all.aggregation2D.AllAggregation2D">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg(FEs/n)" />
    <cfg:parameter name="yAxis" value="F" />
    <cfg:parameter name="aggregate" value="median" />
    <cfg:parameter name="groupBy" value="k" />
  </cfg:configuration>
</e:module>

<e:module class="all.aggregation2D.AllAggregation2D">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg RT" />
    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="aggregate" value="stddev" />
    <cfg:parameter name="groupBy" value="n" />
  </cfg:configuration>
```

Specifying Evaluation Process: evaluation.xml

- The "Aggregation" module is applied twice as well: once we plot the median F over runtime measured in *FEs* and divided by n (log-scaled) aggregated over benchmark instances with the same k feature

Listing: Part 3 from file `evaluation.xml` for our MAX-SAT example.

```
<e:module class="all.aggregation2D.AllAggregation2D">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg(FEs/n)" />
    <cfg:parameter name="yAxis" value="F" />
    <cfg:parameter name="aggregate" value="median" />
    <cfg:parameter name="groupBy" value="k" />
  </cfg:configuration>
</e:module>

<e:module class="all.aggregation2D.AllAggregation2D">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg RT" />
    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="aggregate" value="stddev" />
    <cfg:parameter name="groupBy" value="n" />
  </cfg:configuration>
```

Specifying Evaluation Process: evaluation.xml

- The "Aggregation" module is applied twice as well: then the "standard deviation" is computed, for $\frac{F}{k}$ but this time over the absolute CPU time RT (log-scaled), with one diagram for each distinct value of n

Listing: Part 3 from file `evaluation.xml` for our MAX-SAT example.

```
<e:module class="all.aggregation2D.AllAggregation2D">
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    <cfg:parameter name="groupBy" value="k" />
  </cfg:configuration>
</e:module>

<e:module class="all.aggregation2D.AllAggregation2D">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg RT" />
    <cfg:parameter name="yAxis" value="F/k" />
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```

Gluing everything together

- We now have all the information ready to start an evaluation process

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  - In case of LaTeX, what document class to use (IEEEtran? sig-alternate? ...)

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  - What format to use for the report document (LaTeX/PDF? XHTML? Export?)
  - What kind of figures to generate in the report (PDF? EPS? ...)
  - In case of LaTeX, what document class to use (IEEEtran? sig-alternate? ...)
- So let's glue everything together

Gluing everything together: config.xml

- Use csv+edi as input format (as in our example)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Use csv+edi as input format (as in our example, but we could also use tspSuite or bbob as input format)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Specify path to input folder, relative to current path

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Specify path to input folder, relative to current path (but we could also specify a URL or the path to a ZIP file)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Specify path to input folder, relative to current path (but we could also specify a URL or the path to a ZIP file, actually, we can specify multiple paths, URLs, and ZIP files)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Choose LaTeX as output format

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Choose LaTeX as output format (but we could also choose XHTML or export)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Choose LaTeX as output format (but we could also choose XHTML or export, LaTeX documents will automatically be compiled to PDF if LaTeX installation is auto-detected)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Choose PDF as graphics format

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Choose PDF as graphics format (but we could also choose EPS, PNG, TEX, ...)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Specify output path relative to current directory

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Specify base name of output document

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- If LaTeX is the output format, specify document class (here IEEEtran)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- If LaTeX is the output format, specify document class (here IEEEtran, but we could also choose LNCS, sig-alternate, ...)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Specify path to evaluation.xml, relative to current directory

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Specify path to evaluation.xml, relative to current directory (but we could also specify a URL or the path to a ZIP file)

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Optional: Tell the system to produce lots of log output to the console and detailed error messages, if any

Listing: Example file configForIEEEtran.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/IEEEtran/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="IEEEtran" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

- Now let's use the LaTeX document class for Springer's LNCS instead...

Listing: Example file configForLNCS.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="LaTeX" />
  <cfg:parameter name="graphicDriver" value="pdf" />

  <cfg:parameter name="output" value="../reports/LaTeX/LNCS/" />
  <cfg:parameter name="docName" value="report" />
  <cfg:parameter name="documentClass" value="LNCS" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Now let's create an XHTML web page with PNG figures instead...

Listing: Example file configForXHTML.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="XHTML" />
  <cfg:parameter name="graphicDriver" value="png" />

  <cfg:parameter name="output" value="../reports/XHTML/" />
  <cfg:parameter name="docName" value="report" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Gluing everything together: config.xml

- Now let's export all figures to CSV text files instead, so that we can load them into GnuPlot, MatLab, or whatever for post-processing

Listing: Example file configForExport.xml for our MAX-SAT example.

```
<?xml version="1.0" encoding="UTF-8"?>
<cfg:configuration
  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/
      configuration/configuration.1.0.xsd">

  <cfg:parameter name="inputDriver" value="csv+edi" />
  <cfg:parameter name="inputSource" value="path(../results/)" />

  <cfg:parameter name="documentDriver" value="export" />

  <cfg:parameter name="output" value="../reports/export/" />
  <cfg:parameter name="docName" value="report" />

  <cfg:parameter name="evaluationSetup" value="path(evaluation.xml)" />

  <cfg:parameter name="logger" value="global;ALL" />
</cfg:configuration>
```

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)
3. cd into the directory with the configuration file

Execute `optimizationBenchmarking`

1. Now we can finally execute the `optimizationBenchmarking` Evaluator
2. Open a new terminal (command line)
3. `cd` into the directory with the configuration file
4. Then execute

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)
3. cd into the directory with the configuration file
4. Then execute:
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForIEEEtran.xml`

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)
3. cd into the directory with the configuration file
4. Then execute:
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForLNCS.xml`

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)
3. cd into the directory with the configuration file
4. Then execute:
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForXHTML.xml`

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)
3. cd into the directory with the configuration file
4. Then execute:
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForXHTML.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForExport.xml`

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)
3. cd into the directory with the configuration file
4. Then execute:
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForXHTML.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForExport.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=whatever.xml`

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)
3. cd into the directory with the configuration file
4. Then execute:
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForXHTML.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForExport.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=whatever.xml`
5. ...and that's it.

Execute optimizationBenchmarking

1. Now we can finally execute the optimizationBenchmarking Evaluator
2. Open a new terminal (command line)
3. cd into the directory with the configuration file
4. Then execute:
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForXHTML.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=configForExport.xml` or
   - `java -jar optimizationBenchmarking-0.8.3-full.jar -configXML=whatever.xml`
5. ... and that's it.
6. Requirement: Java 1.7

Result

- The Evaluator will now produce report documents containing the requested information (and figures)

Result

- The Evaluator will now produce report documents containing the requested information (and figures)

Evaluation Report on Six Experiments

Anne Anonymous

***Abstract*—This is the evaluation report on six experiments, namely 1FlipBC, 1FlipBCvs, 2FlipBC, 2FlipBCvs, mFlipBC, and mFlipBCvs on 100 benchmark instances. This report has been generated with the version 0.8.3 of the Evaluator Component of the Optimization Benchmarking Tool Suite.**

I. Instance Information

In Figure 2 we illustrate the relative amount of benchmark runs per instance feature. In total, we have 100 benchmark instances and each of them is characterized by two features, namely k and n. The slices in the pie charts are the bigger, the more benchmark instances have the associated feature value, in comparison to the other values. If a slice is bigger than other slices, this therefore means that the used benchmark instances focus on investigating that feature while less runs are applied to the other features.

II. Performance Comparisons

A. Estimated Cumulative Distribution Function

We analyze the estimated cumulative distribution function (*ECDF*) [1], [2], [3] computed based on $\frac{F}{k}$ over $\log_{10} FEs$. The $\text{ECDF}\left(FEs, \frac{F}{k} \leq 0\right)$ represents the fraction of runs which reach a value of $\frac{F}{k}$ less than or equal to 0 for a given ellapsed runtime measured in FEs. The *ECDF* is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate the results by computing their arithmetic mean. The x-axis does not represent the values of FEs directly, but instead $\log_{10} FEs$. The *ECDF* is always between 0 and 1 — and the higher it is, the better.

B. Estimated Cumulative Distribution Function

We analyze the estimated cumulative distribution function (*ECDF*) [1], [2], [3] computed based on $\frac{F}{k}$ over $\log_{10} RT$. The $\text{ECDF}\left(RT, \frac{F}{k} \leq 0.01\right)$ represents the fraction of runs which reach a value of $\frac{F}{k}$ less than or equal to 0.01 for a given ellapsed runtime measured in RT. The *ECDF* is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate the results by computing their arithmetic mean. The x-axis does not represent the values of RT directly, but instead $\log_{10} RT$. The *ECDF* is always between 0 and 1 — and the higher it is, the better. The instance run sets belonging to instances with the same value of the feature n grouped together.

C. Median of Medians

We analyze the median of medians (*med med*) of F over $\log_{10}\left(\frac{FEs}{n}\right)$. The $\text{med med}(FEs, F)$ represents the median of the F for a given ellapsed runtime measured in FEs. The median is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate these medians by computing their median. The x-axis does not represent the values of FEs directly, but instead $\log_{10}\left(\frac{FEs}{n}\right)$. The instance run sets belonging to instances with the same value of the feature k grouped together.

D. Median of Standard Deviations

We analyze the median of standard deviations (*med stddev*) computed based on $\frac{F}{k}$ over $\log_{10} RT$. The $\text{med stddev}\left(RT, \frac{F}{k}\right)$ represents the standard deviation of the $\frac{F}{k}$ for a given ellapsed runtime measured in RT. The standard deviation is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate these standard deviations by computing their median. The x-axis does not represent the values of RT directly, but instead $\log_{10} RT$. The instance run sets belonging to instances with the same value of the feature n grouped together.

References

[1] H. H. Hoos and T. Stützle, "Evaluating las vegas algorithms — pitfalls and remedies," in *Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence (UAI'98)*, G. F. Cooper and S. Moral, Eds., Madison, WI, USA: San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., Jul. 24–26, 1998, pp. 238–245. [Online]. Available: http://www.cs.ubc.ca/spider/hoos/Publications/uai98-lv.pdf.

[2] D. A. D. Tompkins and H. H. Hoos, "Ubcsat: An implementation and experimentation environment for sls algorithms for sat and max-sat," in *Revised Selected Papers from the Seventh International Conference on Theory and Applications of Satisfiability Testing (SAT'04)*, ser. Lecture Notes in Computer Science (LNCS), H. H. Hoos and D. G. Mitchell, Eds., vol. 3542, Vancouver, BC, Canada: Berlin, Germany: Springer-Verlag GmbH, May 10–13, 2004, pp. 306–320. [Online]. Available: http://www.cs.ubc.ca/spider/hoos/Publications/sat04-ubcsat.pdf.

[3] N. Hansen, A. Auger, S. Finck, and R. Ros, "Real-parameter black-box optimization benchmarking: Experimental setup," Orsay, France: Université Paris Sud, Institut National de Recherche en Informatique et en Automatique (INRIA) Futurs, Équipe TAO, Tech. Rep., Mar 24, 2012. [Online]. Available: http://coco.lri.fr/BBOB-downloads/download11.05/bbobdocexperiment.pdf

first page of the report in LaTeX for `IEEEtran`

Result

- The Evaluator will now produce report documents containing the requested information (and figures)

Evaluation Report on Six Experiments

Anne Anonymous

Abstract—This is the evaluation report on six experiments, namely 1Fluf6C, 1Fluf6Cvs, 2Fluf6C, 2Fluf6Cvs, noFluf6C, and noFluf6Cvs on 100 benchmark instances. This report has been generated with the version 0.0.3 of the Evaluator Component of the Optimization Benchmarking Tool Suite.

I. Instance Information

In Figure 2 we illustrate the relative amount of benchmark runs per instance feature. In total, we have 100 benchmark instances and each of them is characterized by two features, namely k and n. The slices in the pie charts are the bigger, the more benchmark instances have the associated feature value, in comparison to the other values. If a slice is bigger than other slices, this therefore means that the used benchmark instances focus on investigating that feature while less runs are applied to the other features.

II. Performance Comparisons

A. Estimated Cumulative Distribution Function

We analyze the estimated cumulative distribution function (*ECDF*) [1], [2], [3] computed based on $\frac{F}{k}$ over $\log_{10} FEs$. The ECDF$\left(FEs, \frac{F}{k} \leq 0\right)$ represents the fraction of runs which reach a value of $\frac{F}{k}$ less than or equal to 0 for a given ellapsed runtime measured in *FEs*. The *ECDF* is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate the results by computing their arithmetic mean. The x-axis does not represent the values of *FEs* directly, but instead $\log_{10} FEs$. The *ECDF* is always between 0 and 1 — and the higher it is, the better.

B. Estimated Cumulative Distribution Function

We analyze the estimated cumulative distribution function (*ECDF*) [1], [2], [3] computed based on $\frac{F}{k}$ over $\log_{10} RT$. The ECDF$\left(RT, \frac{F}{k} \leq 0.01\right)$ represents the fraction of runs which reach a value of $\frac{F}{k}$ less than or equal to 0.01 for a given ellapsed runtime measured in *RT*. The *ECDF* is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate the results by computing their arithmetic mean. The x-axis does not represent the values of *RT* directly, but instead $\log_{10} RT$. The *ECDF* is always between 0 and 1 — and the higher it is, the better. The instance run sets belonging to instances with the same value of the feature n grouped together.

C. Median of Medians

We analyze the median of medians (*med med*) of F over $\log_{10}\left(\frac{FEs}{n}\right)$. The med med$(FEs, F)$ represents the median of the F for a given ellapsed runtime measured in *FEs*. The median is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate these medians by computing their median. The x-axis does not represent the values of *FEs* directly, but instead $\log_{10}\left(\frac{FEs}{n}\right)$. The instance run sets belonging to instances with the same value of the feature k grouped together.

D. Median of Standard Deviations

We analyze the median of standard deviations (*med stddev*) computed based on $\frac{F}{k}$ over $\log_{10} RT$. The med stddev$\left(RT, \frac{F}{k}\right)$ represents the standard deviation of the $\frac{F}{k}$ for a given ellapsed runtime measured in *RT*. The standard deviation is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate these standard deviations by computing their median. The x-axis does not represent the values of *RT* directly, but instead $\log_{10} RT$. The instance run sets belonging to instances with the same value of the feature n grouped together.

References

[1] H. H. Hoos and T. Stützle, "Evaluating las vegas algorithms — pitfalls and remedies," in *Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence (UAI'98)*, G. F. Cooper and S. Moral, Eds., Madison, WI, USA: San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., Jul. 24–26, 1998, pp. 238–245. [Online]. Available: http://www.cs.ubc.ca/spider/hoos/Publications/uai98-lvs.pdf
[2] D. A. D. Tompkins and H. H. Hoos, "Ubcsat: An implementation and experimentation environment for sls algorithms for sat and max-sat," in *Revised Selected Papers from the Seventh International Conference on Theory and Applications of Satisfiability Testing (SAT'04)*, ser. Lecture Notes in Computer Science (LNCS), H. H. Hoos and D. G. Mitchell, Eds., vol. 3542, Vancouver, BC, Canada: Berlin, Germany: Springer-Verlag GmbH, May 10–13, 2004, pp. 306–320. [Online]. Available: http://www.cs.ubc.ca/spider/hoos/Publications/sat04-ubcsat.pdf
[3] N. Hansen, A. Auger, S. Finck, and R. Ros, "Real-parameter black-box optimization benchmarking: Experimental setup," Orsay, France: Université Paris Sud, Institut National de Recherche en Informatique et en Automatique (INRIA) Futurs, Équipe TAO, Tech. Rep., Mar 24, 2012. [Online]. Available: http://coco.lri.fr/BBOB-downloads/download11.05/bbobdocexperiment.pdf

first page of the report in LaTeX for `IEEEtran`

Evaluation Report on Six Experiments

Anne Anonymous

No Institute Given

Abstract. This is the evaluation report on six experiments, namely 1Fluf6C, 1Fluf6Cvs, 2Fluf6C, 2Fluf6Cvs, noFluf6C, and noFluf6Cvs on 100 benchmark instances. This report has been generated with the version 0.0.3 of the Evaluator Component of the Optimization Benchmarking Tool Suite.

1 Instance Information

In Figure 2 we illustrate the relative amount of benchmark runs per instance feature. In total, we have 100 benchmark instances and each of them is characterized by two features, namely k and n. The slices in the pie charts are the bigger, the more benchmark instances have the associated feature value, in comparison to the other values. If a slice is bigger than other slices, this therefore means that the used benchmark instances focus on investigating that feature while less runs are applied to the other features.

2 Performance Comparisons

2.1 Estimated Cumulative Distribution Function

We analyze the estimated cumulative distribution function (*ECDF*) [2,3,1] computed based on $\frac{F}{k}$ over $\log_{10} FEs$. The ECDF$\left(FEs, \frac{F}{k} \leq 0\right)$ represents the fraction of runs which reach a value of $\frac{F}{k}$ less than or equal to 0 for a given ellapsed runtime measured in *FEs*. The *ECDF* is always computed over the runs of an experiment for a given benchmark instance. If runs for multiple instances are available, we aggregate the results by computing their arithmetic mean. The x-axis does not represent the values of *FEs* directly, but instead $\log_{10} FEs$. The *ECDF* is always between 0 and 1 — and the higher it is, the better.

2.2 Estimated Cumulative Distribution Function

We analyze the estimated cumulative distribution function (*ECDF*) [2,3,1] computed based on $\frac{F}{k}$ over $\log_{10} RT$. The ECDF$\left(RT, \frac{F}{k} \leq 0.01\right)$ represents the fraction of runs which reach a value of $\frac{F}{k}$ less than or equal to 0.01 for a given ellapsed runtime measured in *RT*. The *ECDF* is always computed over the runs of an

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Result

- The Evaluator will now produce report documents containing the requested information (and figures)

Evaluation Report on Six Experiments

Anne Anonymous

Evaluation Report on Six Experiments

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Evaluation Report on Six Experiments

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first page of the report in LaTeX for `IEEEtran`

first page of the report in LaTeX for `LNCS`

first page of the report in LaTeX for `sig-alternate`

Result

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Evaluation Report on Six Experiments

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Evaluation Report on Six Experiments

first page of the report in LaTeX for IEEEtran

first page of the report in LaTeX for LNCS

first page of the report in LaTeX for sig-alternate

first page of the report in XHTML

Usage Summary

1. Implement your optimization or Machine Learning or whatever algorithm

Usage Summary

1. Implement your optimization or Machine Learning or whatever algorithm
2. Select a well-known set of benchmark instances

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7. Define your evaluation process in a file `evaluation.xml`
8. Execute `optimizationBenchmarking` evaluator

Section Outline

1. Introduction
2. Example 1: MAX-SAT
3. Example 2: BBOB
4. Conclusions

BBOB

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(figures taken from [82])

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- *COCO* can automatically run experiments, collect log files, and evaluate them
- The framework and the results of past *BBOB*s are available at `http://coco.gforge.inria.fr`
- `optimizationBenchmarking` has an experimental input driver for *COCO* data
- No need to specify `dimensions.xml` and `instances.xml`, as these are fixed and known for *COCO*/*BBOB*.

Quick Guide

- You can quickly download all example data and the Evaluator and run the example on your PC by executing the following code snippet.

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- You can quickly download all example data and the Evaluator and run the example on your PC by executing the following code snippet.
- System Requirements:
  - Linux (for `make.sh`), Windows (for `make.bat`, tested: Win 8, should work also under Win 7)
  - Java 1.7 (ideally a `JDK` under a `JRE` slower and higher memory consumption)
  - `svn`
  - optional: a LaTeX installation, such as TeXLive (needed for generating pdf reports)

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- Enter (or create) a folder where you want to have everything, then execute this script via copy-paste to the terminal (it may need quite a while to run due to the downloads)

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Listing: Linux: script `make.sh` for downloading & running the *BBOB* example.

```
#!/bin/bash

jarName="optimizationBenchmarking-full.jar"
bbobDownloadBaseURL="http://coco.lri.fr/BBOB2013/rawdata"

outputDir=`pwd`
echo "Writing output to folder '${outputDir}'"

echo "Downloading selected experimental results from '${bbobDownloadBaseURL}'."
mkdir -p "${outputDir}/results"
cd "${outputDir}/results"
for archive in "hutter2013_CMAES.tar.gz" "liao2013_IPOP.tar.gz" "liao2013_IPOP-500.tar.gz" "liao2013_IPOP-tany.tar.gz" \
              "liao2013_IPOP-texp.tar.gz" "tran2013_P-DCN.tar.gz" "pal2013_DE.tar.gz" "pal2013_fmincon.tar.gz" \
              "pal2013_simplex.tar.gz" "pal2013_HMLSL.tar.gz" "holtschulte2013_hill.tar.gz" "holtschulte2013_ga100.tar.gz"
do
  wget -O "${outputDir}/results/${archive}" "${bbobDownloadBaseURL}/$archive"
  tar -xvf "${outputDir}/results/${archive}"
  rm "${outputDir}/results/${archive}"
done

echo "Downloading evaluation/configuration via 'svn export' from GitHub."
cd "${outputDir}"
svn export https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/branches/master/examples/bbob/evaluation

jarDownloadURL=$(wget "http://optimizationbenchmarking.github.io/optimizationBenchmarking/currentVersion.url" -q -O -)
echo "Downloading evaluator from '${jarDownloadURL}'."
wget -O "${outputDir}/${jarName}" "${jarDownloadURL}"

echo "Applying evaluator and obtaining report in IEEEtran format."
cd "${outputDir}/evaluation"
java -jar "${outputDir}/${jarName}" -configXML=configForIEEEtran.xml

cd "${outputDir}"
echo "Done."
```

- Enter (or create) a folder where you want to have everything, then execute this script via copy-paste to the terminal (it may need quite a while to run due to the downloads)

Listing: Windows: script `make.sh` for downloading & running the *BBOB* example.

```
echo "Downloading evaluator."
powershell -command "& {iwr http://optimizationbenchmarking.github.io/optimizationBenchmarking/currentVersion.url -OutFile version.txt}"
for /F "delims=" %i in (version.txt) do set downloadURL=%i
powershell -command "& {iwr %downloadURL% -OutFile optimizationBenchmarking.jar}"
del version.txt

echo "Downloading (but not installing!) required 3rd-party software: downloading SVN client and 7-Zip to extract it."
md svn
cd svn
powershell -command "& {iwr https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/raw/master/tools/windows/7zip/7za.exe -OutFile 7za.exe}"
powershell -command "& {iwr https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/raw/master/tools/windows/svn/svn.tar.lzma -OutFile svn.tar.lzma}"
7za x svn.tar.lzma
7za x svn.tar
cd..

echo "Downloading experimental results from http://coco.lri.fr/BBOB2013/rawdata/
md results
cd results
for %i in (hutter2013_CMAES.tar liao2013_IPOP.tar liao2013_IPOP-500.tar liao2013_IPOP-tany.tar ^
liao2013_IPOP-texp.tar tran2013_P-DCN.tar pal2013_DE.tar pal2013_fmincon.tar ^
pal2013_simplex.tar pal2013_HMLSL.tar holtschulte2013_hill.tar holtschulte2013_ga100.tar) do ^
powershell -command "& { iwr http://coco.lri.fr/BBOB2013/rawdata/%i.gz -OutFile %i.gz }" && ^
..\svn\7za x %i.gz && ^
..\svn\7za x %i && ^
del %i.gz && ^
del %i

cd ..

echo "Downloading evaluation/configuration via 'svn export' from GitHub."
svn\svn export https://github.com/optimizationBenchmarking/optimizationBenchmarkingDocu/branches/master/examples/bbob/evaluation

rd /s /q svn

echo "Applying evaluator and obtaining report in IEEEtran format."
cd evaluation
java -jar "..\optimizationBenchmarking.jar" -configXML=configForIEEEtran.xml

cd..
echo "Done."
```

Quick Guide

- Enter (or create) a folder where you want to have everything, then execute this script via copy-paste to the terminal (it may need quite a while to run due to the downloads)
- After the script, you will have
  - a folder `results` with the log files which have been evaluated
  - a folder `evaluation` with the configuration files and the `evaluation.xml` file defining what to do
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- But now, let's continue with the example...

Experiment

- We select a set of experiments from the *BBOB* 2013 workshop for evaluation with the `optimizationBenchmarking` Evaluator

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- ...and unpack them into one common folder

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- We now look at the interesting parts of the `evaluation.xml` file (the file in general has been discussed in the previous example)

ECDF over Everything

- Let's first plot the ECDF aggregated over all benchmark instances

Listing: Part 1 from file `evaluation.xml` for our *BBOB* example.

```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
    <cfg:parameter name="yAxis" value="F" />
    <cfg:parameter name="goal" value="1e-8" />
    <cfg:parameter name="figureSize" value="page wide" />
    <cfg:parameter name="makeLegendFigure" value="false" />
  </cfg:configuration>
</e:module>
```

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```

ECDF over Everything

- Let's first plot the ECDF aggregated over all benchmark instances
- We set the goal "error" to $1 \cdot 10^{-8}$
- For the time measured in *FEs* and log-scaled, we plot the fraction of runs achieving this goal

Listing: Part 1 from file `evaluation.xml` for our *BBOB* example.

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- The different `IPOP` variants in general reach this value more often than the other algorithms
- `pal2013_fmincon` and `pal2013_HMLSL` both solve more problems during approximately the first 2500 *FEs*, i.e., are initially faster
- The Hill Climber and GA (`holtshulte`) solve the least problems in the comparison

ECDF by Dimension

- Let's now plot the ECDF aggregated over each distinct value of the benchmark feature *dimension*

Listing: Part 2 from file `evaluation.xml` for our *BBOB* example.

```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
    <cfg:parameter name="yAxis" value="F" />
    <cfg:parameter name="goal" value="1e-8" />
    <cfg:parameter name="groupBy" value="dim" />
  </cfg:configuration>
</e:module>
```

ECDF by Dimension

- Let's now plot the ECDF aggregated over each distinct value of the benchmark feature *dimension*
- The goal "error" to achieve is again $1 \cdot 10^{-8}$

Listing: Part 2 from file `evaluation.xml` for our *BBOB* example.

```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
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  </cfg:configuration>
</e:module>
```

ECDF by Dimension

- Let's now plot the ECDF aggregated over each distinct value of the benchmark feature *dimension*
- The goal "error" to achieve is again $1 \cdot 10^{-8}$ and
- also use the (only) time measured in *FEs*, log-scaled.

Listing: Part 2 from file `evaluation.xml` for our *BBOB* example.

```
<e:module class="all.ecdf.AllECDF">
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    <cfg:parameter name="groupBy" value="dim" />
  </cfg:configuration>
</e:module>
```

ECDF by Dimension

- Let's now plot the ECDF aggregated over each distinct value of the benchmark feature *dimension*

legend

$\texttt{dim} = 2$

$\texttt{dim} = 4$

$\texttt{dim} = 5$

$\texttt{dim} = 10$

$\texttt{dim} = 20$

ECDF by Dimension

- We find that for larger dimension, fewer problems can be solved

legend

$\texttt{dim} = 2$

$\texttt{dim} = 4$

$\texttt{dim} = 5$

$\texttt{dim} = 10$

$\texttt{dim} = 20$

ECDF by Dimension

- While the overall performance of `pal2013_fmincon` and `pal2013_simplex` look similar when considering *all* problems, we find that the simplex algorithm is very heavily influenced by the dimension

legend

dim = 2

dim = 4

dim = 5

dim = 10

dim = 20

ECDF by Dimension

- Similarly, the performance of DE breaks down when the dimension increases

legend

$\texttt{dim} = 2$

$\texttt{dim} = 4$

$\texttt{dim} = 5$

$\texttt{dim} = 10$

$\texttt{dim} = 20$

ECDF by Dimension

- The performance of the IPOP algorithm family, on the other hand, degenerates gracefully with rising dimension

legend

$\texttt{dim} = 2$

$\texttt{dim} = 4$

$\texttt{dim} = 5$

$\texttt{dim} = 10$

$\texttt{dim} = 20$

ECDF by Condition Number

- Let's now plot the ECDF aggregated over the benchmark instances with the same value of feature *condition number*

Listing: Part 3 from file `evaluation.xml` for our *BBOB* example.

```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
    <cfg:parameter name="yAxis" value="F" />
    <cfg:parameter name="goal" value="1e-5" />
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ECDF by Condition Number

- Let's now plot the ECDF aggregated over the benchmark instances with the same value of feature *condition number*
- *"the condition number corresponds to the square root of the ratio between the largest axis of the ellipsoid and the shortest axis"* [82]

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- *"the condition number corresponds to the square root of the ratio between the largest axis of the ellipsoid and the shortest axis"* [82]
- As goal "error" to achieve, this time we pick $1 \cdot 10^{-5}$

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legend

$\texttt{cond} = 1$

$\texttt{cond} = 10$

$\texttt{cond} = 25$

$\texttt{cond} = 30$

$\texttt{cond} = 100$

$\texttt{cond} = 1000$

$\texttt{cond} = 1\,000\,000$

ECDF by Condition Number

- The influence of the condition number on problem hardness does not seem to obvious at first glance

legend

cond = 1

cond = 10

cond = 25

cond = 30

cond = 100

cond = 1000

cond = 1 000 000

ECDF by Condition Number

- Some algorithms perform bad on some mediocre condition numbers while performing better on smaller and larger ones (e.g., P-DCN on cond $= 1000$)

legend | cond $= 1$ | cond $= 10$ | cond $= 25$

cond $= 30$ | cond $= 100$ | cond $= 1000$ | cond $= 1\,000\,000$

ECDF by Condition Number

- For some problems, there doesn't seem to be a direct relationship between conditioning and performance (e.g., DE)

legend

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ECDF by Condition Number

- Possible reason: The problems in the benchmark belonging to a certain condition number may have various other features making them hard or easy

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ECDF by Condition Number

- Possible reasons: The problems in the benchmark belonging to a certain condition number may have various other features making them hard or easy and the number of problems per condition number differs largely

The relative amounts of *BBOB* benchmark functions according to their features. (This diagram has also been created with `optimizationBenchmarking`.)

ECDF by Condition Number

- Possible reason: The problems in the benchmark belonging to a certain condition number may have various other features making them hard or easy, the number of problems per condition number differs largely, and the goal value $1 \cdot 10^{-5}$ may be too easy to achieve, leading to a large variance in the results

Progress by Separability

- Finally, let's see how the algorithms progress on problems of different degrees of separability

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[1] Yes, the square. Because *why not*. You can do arbitrary mathematical expressions (as long as the preserve the order of the values)

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- The x-axis be again the log-scaled *FEs* divided by the square of the benchmark instance dimension[1] and
- on the y-axis, we plot the median of the log-scaled objective value F

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Progress by Separability

- We find that `pal2013_fmincon` and `pal2013_HMLSL` are quite good in solving fully and partially separable problems but both (and especially `pal2013_fmincon`) perform worse on non-separable problems

Progress by Separability

- Here seems to be the strength of the IPOP family of algorithms

Progress by Separability

- Generally, a decrease in separability, i.e., stronger "variable interactions" [108], makes optimization problems harder for numerical optimization algorithms, which either need longer to or cease to achieve high-quality solutions

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Section Outline

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2 Example 1: MAX-SAT

3 Example 2: BBOB

4 Conclusions

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- Btw, you could even compare general algorithms (like GAs and HC) on entirely different problem types at once (like MAX-SAT and *BBOB*) by making the problem type an instance feature...

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- Btw: This is Big Data, since we can collect *much* information...

Visit our website

http://www.optimizationBenchmarking.org

or

http://optimizationbenchmarking.github.io/optimizationBenchmarking

for downloading the software (version 0.8.3) and obtaining more information.

System Requirements:

- Java 1.7 (Ideally a JDK, under JRE slower with more memory requirements)
- optional: a LaTeX installation, such as TeXLive or MiKTeX (needed for generating pdf reports)

谢谢！

Thank you.

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Caspar David Friedrich, “Der Wanderer über dem Nebelmeer”, 1818
http://en.wikipedia.org/wiki/Wanderer_above_the_Sea_of_Fog

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- We use `git` [109] as versioning system and `gitHub` [109–111] for hosting
- For building and dependency management, we use `Maven`
- As developer environment, we recommend `Eclipse` [112] (version $\geq$ Luna), as it natively supports `git` and `Maven` [113, 114].

1. Prerequisites

Contribution Lifecycle

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   3. Join group `optimizationBenchmarking`

Contribution Lifecycle

1. Prerequisites
2. Fork project
   `optimizationBenchmarking/optimizationBenchmarking`

Contribution Lifecycle

1. Prerequisites
2. Fork project
3. Add your code, e.g., an own evaluation module, in the appropriate location (maybe an own package)

Contribution Lifecycle

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3. Add your code
4. Test your code

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   - add `JUnit` [115–117] tests if possible

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   - add `JUnit` [115–117] tests if possible
   - provide examples, example data, and expected results

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4. Test your code
5. Make sure your code is properly documented and that your commits contain sufficient explanations

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6. Create a `pull request`, i.e., ask me to include your code in the main project

Contribution Lifecycle

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4. Test your code
5. Make sure your code is properly documented
6. Create a `pull request`
7. After a discussion, your code will (very likely) become part of the main project

Import Fork into Eclipse

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- In the following, I provide a step-by-step screenshot series on how to do all of that...

Import Fork into Eclipse

I here use Eclipse Luna to import the `optimizationBenchmarking/optimiztionBenchmarking` repository.

You can import other (your own) repositories in the same way, just use their naemes instead.

Import Fork into Eclipse

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Provide your passphrase for your public/private key pair that you specified to GitHub.

Import Fork into Eclipse

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Choose a directory where to import the project to. All project files will be stored into this directory, including the Java sources and git meta-data.

Import Fork into Eclipse

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Import Fork into Eclipse

Cloning from ssh://git@github.com/optimizationBenchmarking/optimizationBenchmarking.git

Import Projects

Import projects from a Git repository

Projects:

type filter text to filter unselected projects

Select All

Deselect All

optimizationBenchmarking (/tmp/git/optimizationBenchmarking)

The Eclipse project inside the repository will be discovered and you can import it.

Search for nested projects

Working sets

Add project to working sets

Working sets:

Select...

< Back | Next > | Cancel | Finish

Import Fork into Eclipse

Eclipse will now compile the newly imported Project.
If the project is a Maven Project, like optimizationBenchmarking or tspSuite, you will likely see many errors. But that's OK.

Import Fork into Eclipse

Here we can see the errors. Also, the project structure may look odd.

No problem, we will fix this.

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- After the run, all the log points held in memory are written to a file. No file operations during the run to not mess up time measurements!

Visit our website

http://www.optimizationBenchmarking.org

or

http://optimizationbenchmarking.github.io/optimizationBenchmarking

for downloading the software (version 0.8.3) and obtaining more information.

System Requirements:

- Java 1.7 (Ideally a JDK, under JRE slower with more memory requirements)
- optional: a LaTeX installation, such as TeXLive or MiKTeX (needed for generating pdf reports)