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

The optimizationBenchmarking.org Experiment Evaluator

Thomas Weise
tweise@ustc.edu.cn · tweise@gmx.de · http://www.it-weise.de

USTC-Birmingham Joint Res. Inst. in Intelligent Computation and Its Applications (UBRI)
University of Science and Technology of China (USTC), Hefei 230027, Anhui, China

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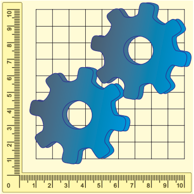
Outline

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 0.8.4) 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)

Highlights

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

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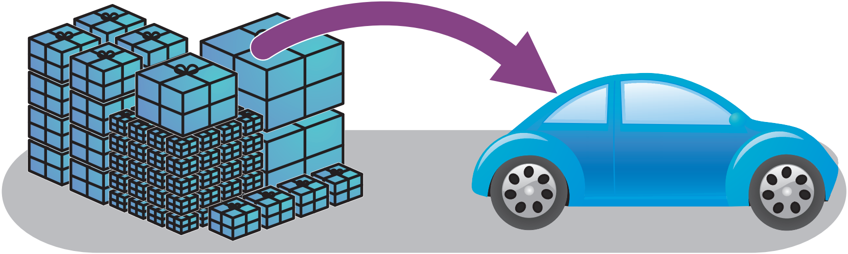
  - Find the *shortest* tour for a salesman to visit certain set of cities
  - I need to transport n items from here to Feixi but they are too big to transport them all at once. How can I load them best into my car so that I have to travel back and forth the least times?



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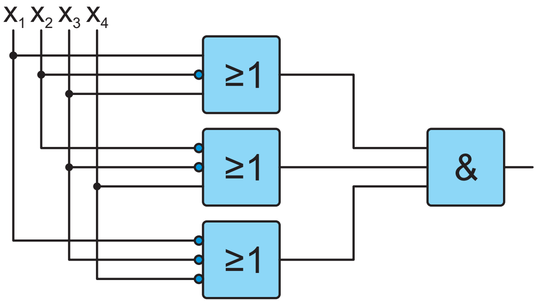

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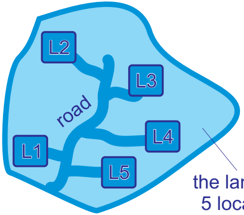
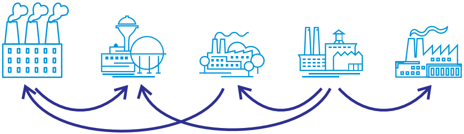
  - I want to build a large factory with n workshops. I know the flow of material between each two workshops and now need to choose the locations of the workshops such that the overall running cost incurred by material transportation is *minimized*.



the land with
5 locations



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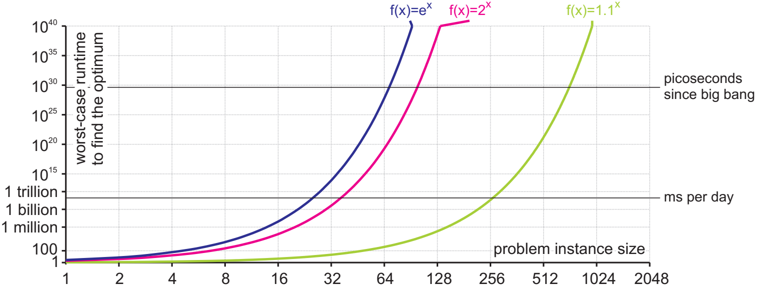

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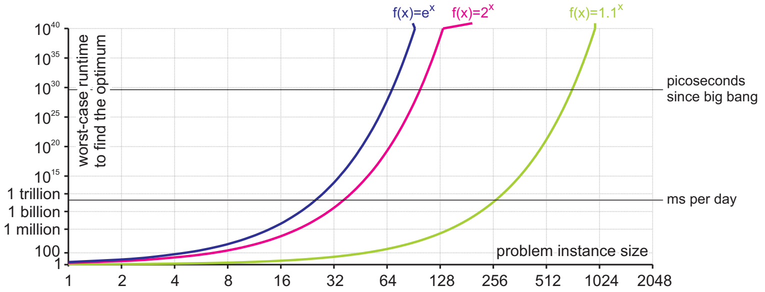

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- Experimental analysis and comparison only practical alternative.

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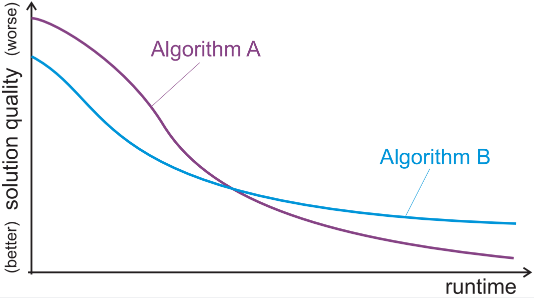

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- Consequence: Most optimization algorithms produce approximate solutions of different qualities at different points during their process.
- Experiments must capture solution quality and runtime data.

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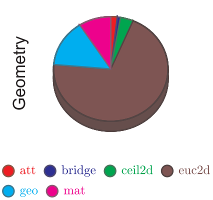
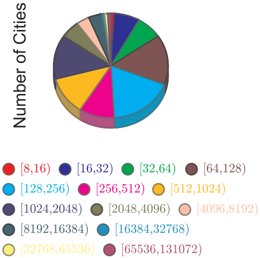
     - e.g., *TSPLib*[77–79] for the TSP has instances with different numbers of cities and geometries





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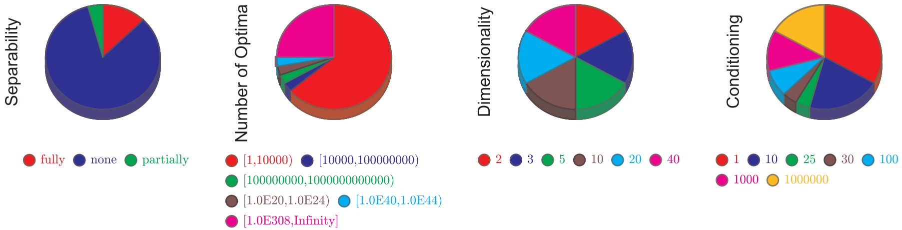
     - e.g., *BBOB*[71, 80–82] offers different benchmark functions for numerical optimization problems



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
     - 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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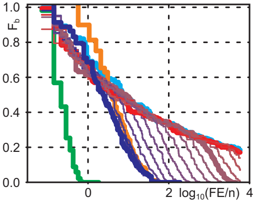

Examples for progress diagrams for different algorithms (signified by different colors) over different sub-sets of the *TSPLib* data.

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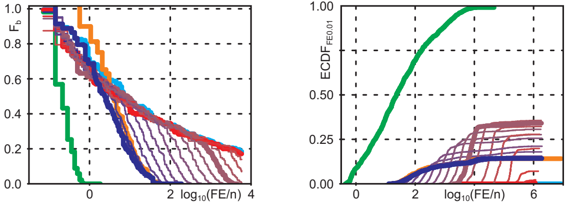

Examples for progress and ERT diagrams for different algorithms (signified by different colors) over different sub-sets of the *TSPLib* data.

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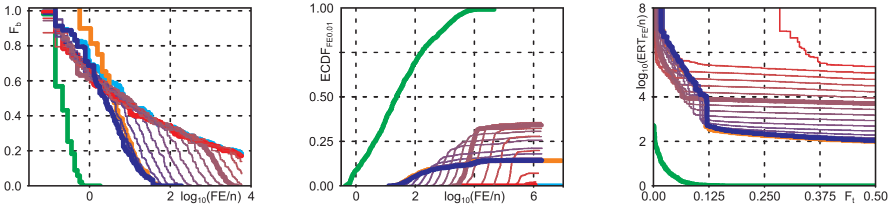

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- The `optimizationBenchmarking` Evaluator can automatize much of this work

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

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

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- 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
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runtime [ns]

F: best $f(\vec{x})$

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Obtained Data

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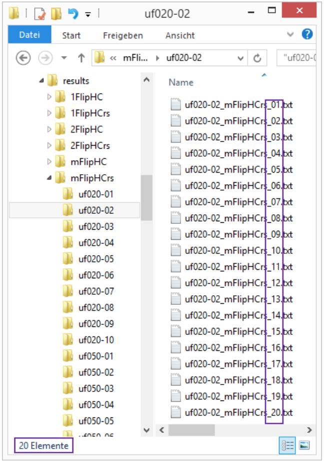

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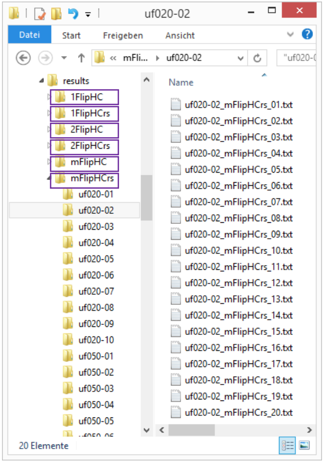

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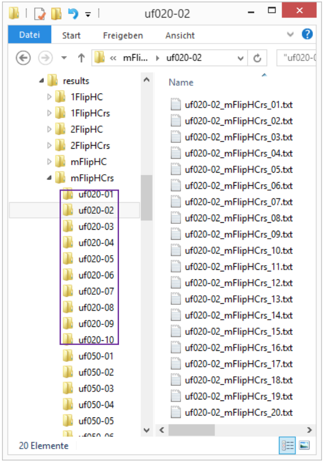

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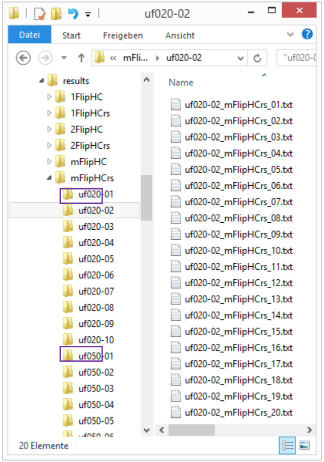

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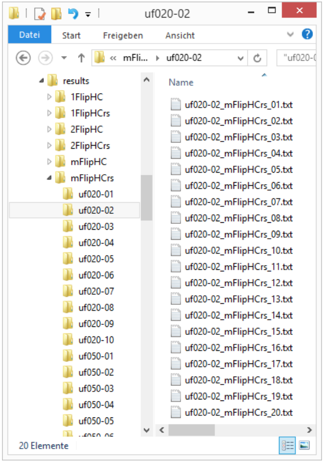

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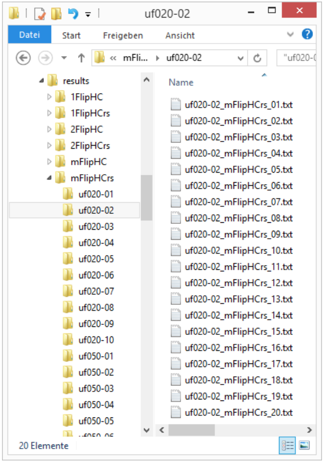

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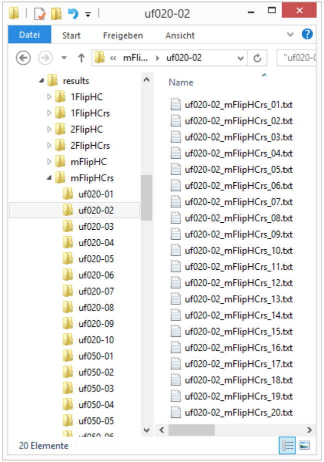

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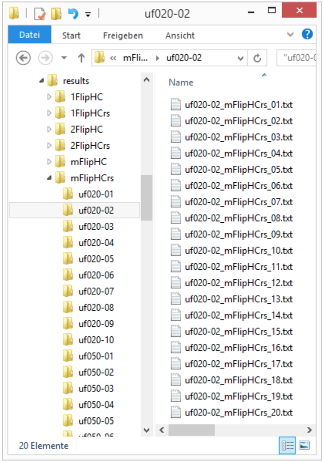
- How can we extract useful information from them



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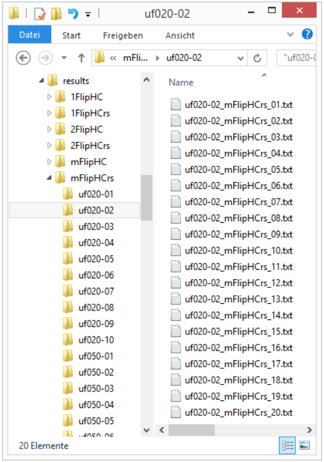

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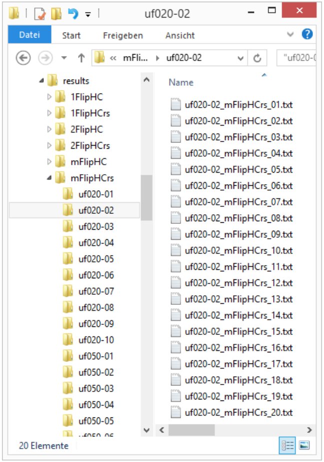

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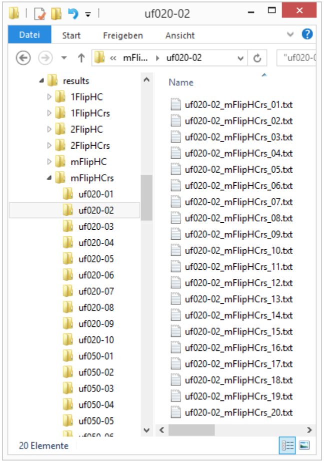
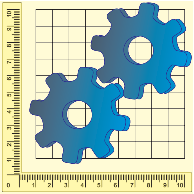
- What you now can do: Use our `optimizationBenchmarking` Evaluator!



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



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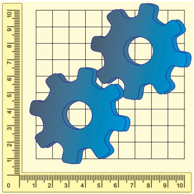

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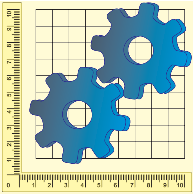

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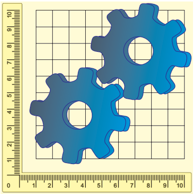
- Finally, I will show *how* that gets done in detail.



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

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.
- 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)

- 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 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
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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
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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)
- After the script, you will have
  - a folder `results` with the log files which have been evaluated
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- But now, let's continue with the example…

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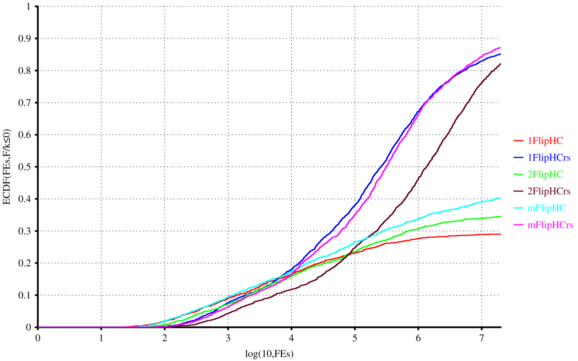

The ECDF in over all 100 benchmark instances for time measure *FEs* (log-scaled).

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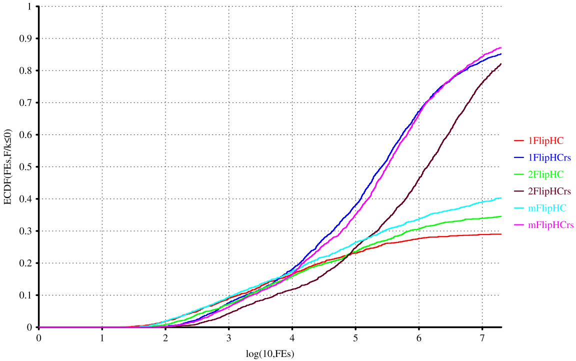

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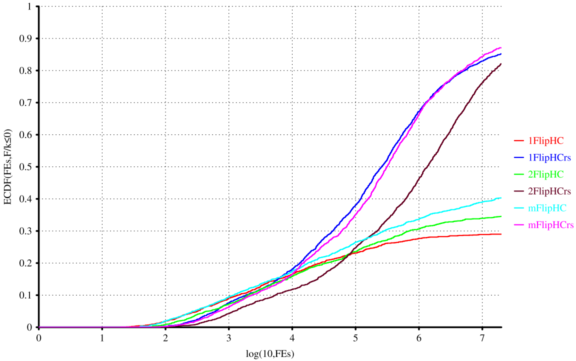

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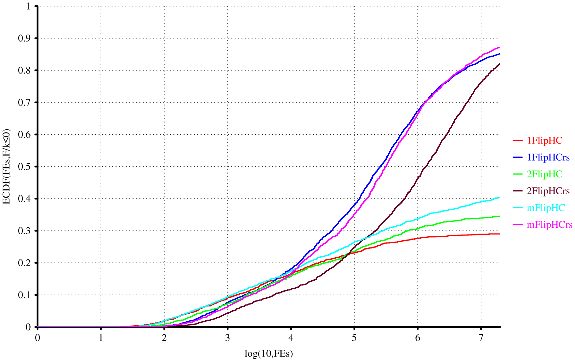

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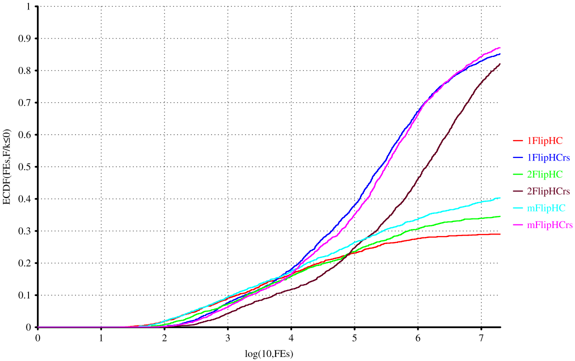

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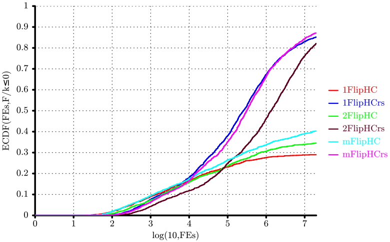

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The ECDF in over all 100 benchmark instances (log-scaled, optimized for LNCS and two figures per row).

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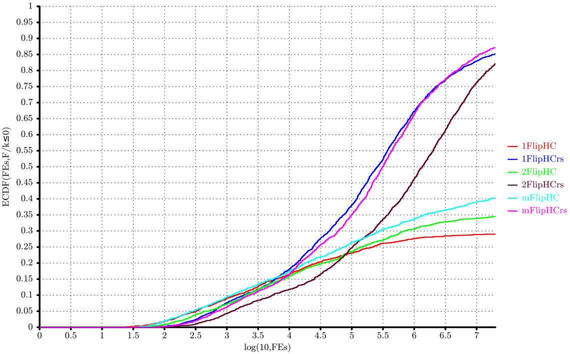

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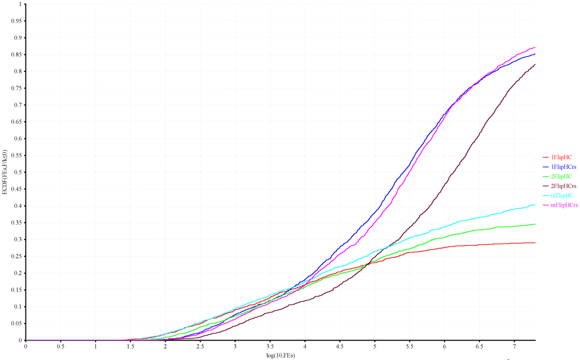

The ECDF in over all 100 benchmark instances (log-scaled, optimized for XHTML and two figures per row).

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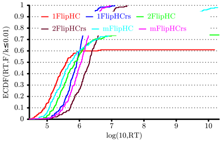
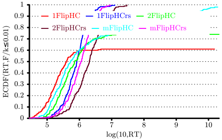
We now look at the ECDF for different values of n and a goal of 1% unsatisfied clauses over RT (log-scaled).



legend

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



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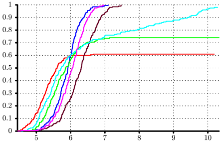

$n = 20$

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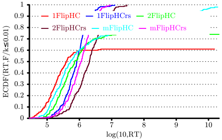
But for $n \geq 50$, those without reach the goal faster.



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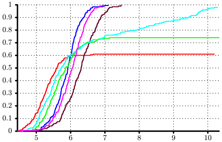
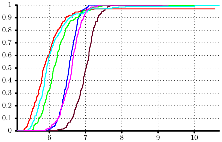


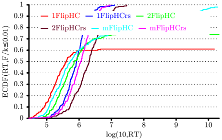
$n = 20$



$n = 50$

ECDF for Different Values of n

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



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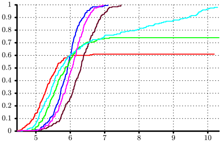
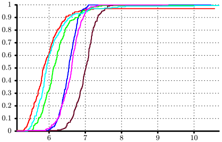
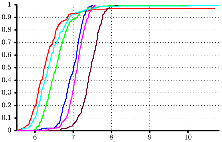


$n = 20$



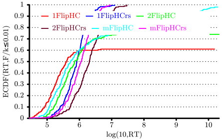
$n = 50$



$n = 75$

ECDF for Different Values of n

The 2-flip operator again performs worst.



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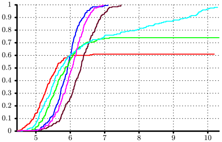
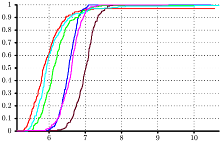
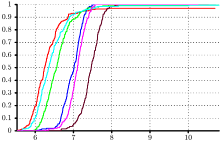


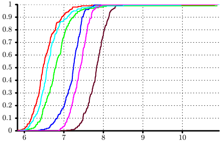
$n = 20$



$n = 50$



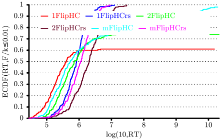
$n = 75$



$n = 100$

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).



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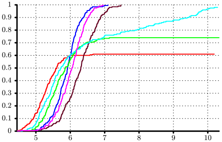
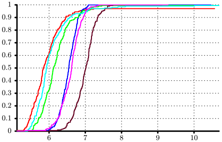
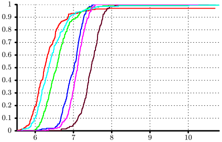


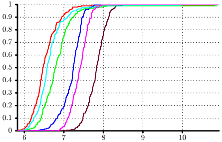
$n = 20$



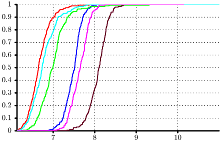
$n = 50$



$n = 75$



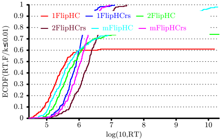
$n = 100$



$n = 125$

ECDF for Different Values of n

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



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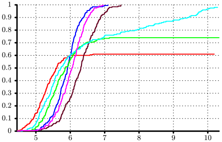
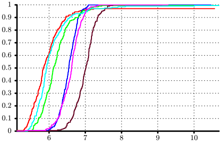
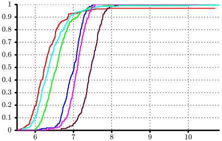


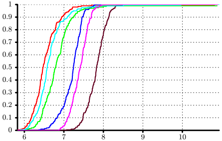
$n = 20$



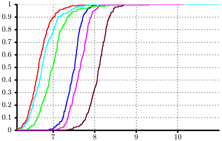
$n = 50$



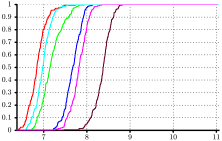
$n = 75$



$n = 100$



$n = 125$



$n = 150$

ECDF for Different Values of n

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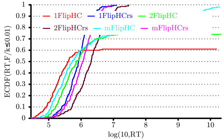
For small problems, 1-flip is slightly faster than m-flip.



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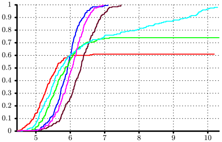
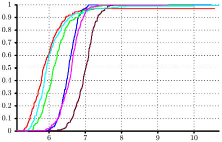
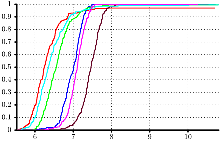


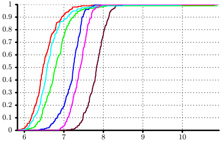
$n = 20$



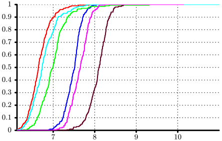
$n = 50$



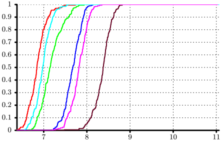
$n = 75$



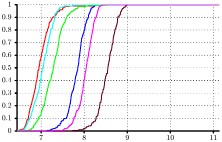
$n = 100$



$n = 125$



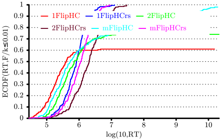
$n = 150$



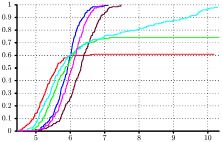
$n = 175$

ECDF for Different Values of n

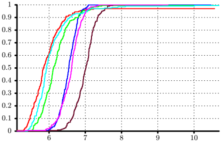
For larger problems, m-flip becomes slightly faster.



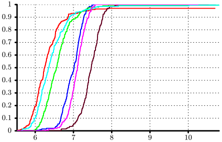
legend



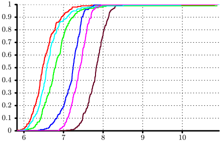
$n = 20$



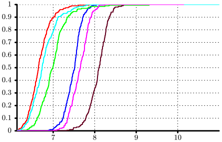
$n = 50$



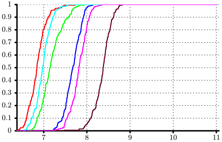
$n = 75$



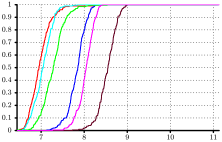
$n = 100$



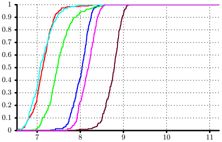
$n = 125$



$n = 150$



$n = 175$



$n = 200$

ECDF for Different Values of n

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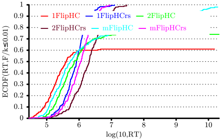
All in all, similar behavior over all scales (reaching 1% error seems to be easy).



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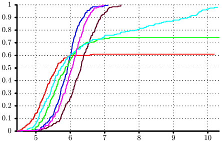
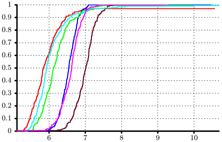
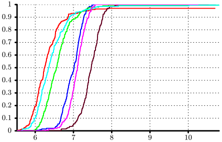


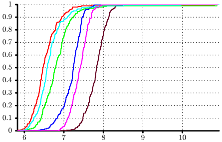
$n = 20$



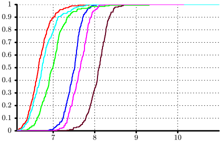
$n = 50$



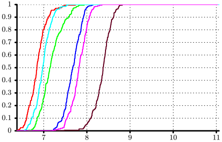
$n = 75$



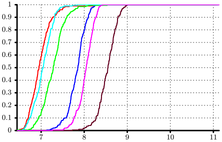
$n = 100$



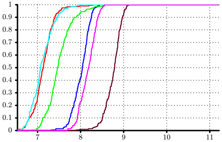
$n = 125$



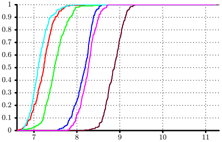
$n = 150$



$n = 175$



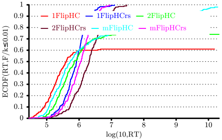
$n = 200$



$n = 225$

ECDF for Different Values of n

Only required runtime increases by up to 100 times.



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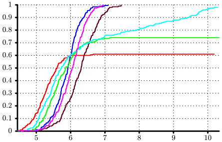
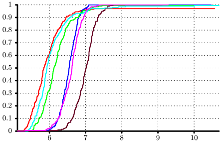
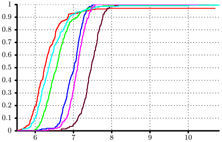


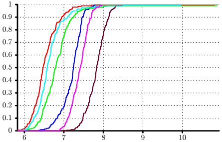
$n = 20$



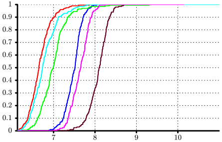
$n = 50$



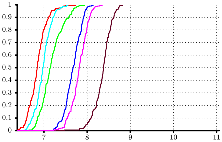
$n = 75$



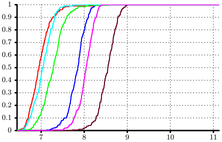
$n = 100$



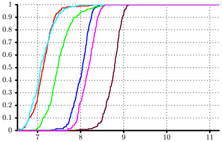
$n = 125$



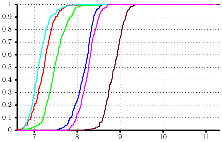
$n = 150$



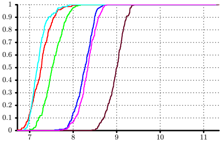
$n = 175$



$n = 200$

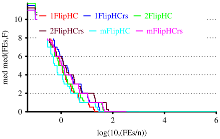


$n = 225$



$n = 250$

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 $\mathbf{k}$

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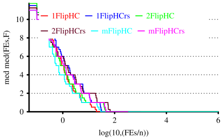
For very small-scale problems, all algorithms behave similar.



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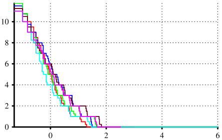
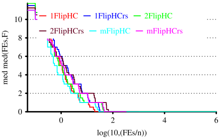


$k = 91$

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



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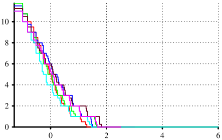
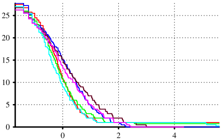
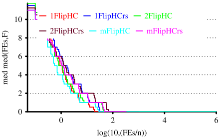


$k = 91$



$k = 218$

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



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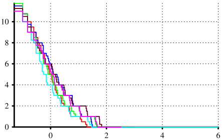
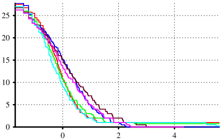


$k = 91$



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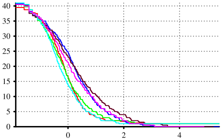
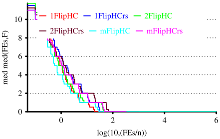


$k = 325$

Progress for Different Values of k

The gap increases with rising k



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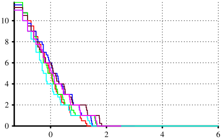

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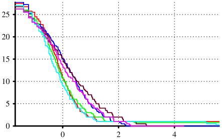

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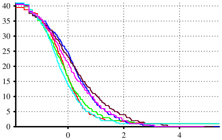

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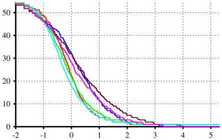
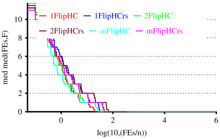


$k = 430$

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



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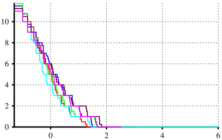

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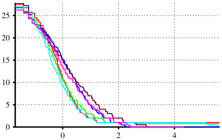

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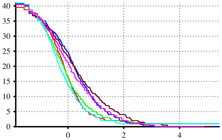

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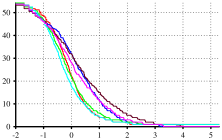

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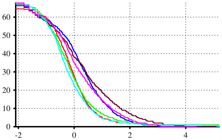
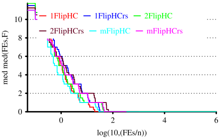


$k = 538$

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



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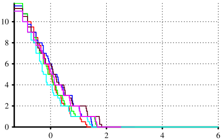

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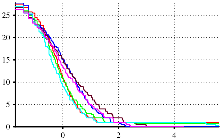

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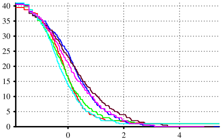

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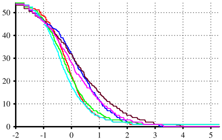

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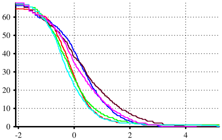

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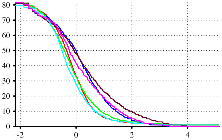
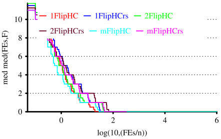


$k = 645$

Progress for Different Values of $\mathbf{k}$

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



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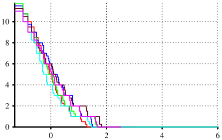

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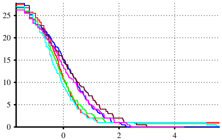

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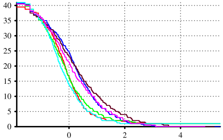

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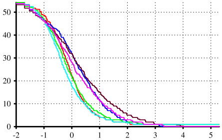
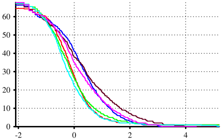


$k = 430$



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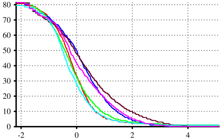

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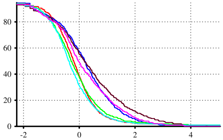
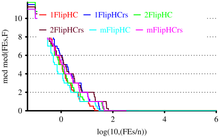


$k = 753$

Progress for Different Values of k

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



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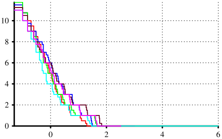
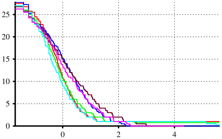
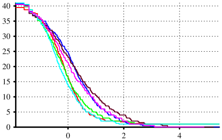


$k = 91$



$k = 218$



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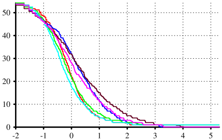

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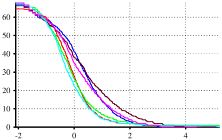

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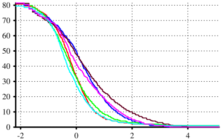

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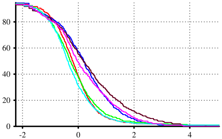

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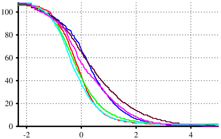
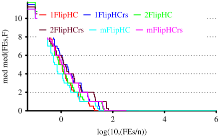


$k = 860$

Progress for Different Values of k

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



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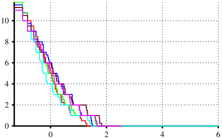
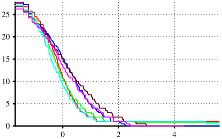
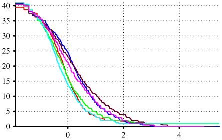


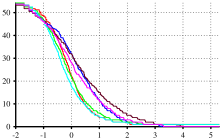
$k = 91$



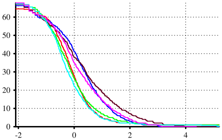
$k = 218$



$k = 325$



$k = 430$



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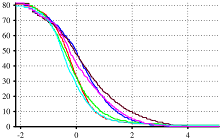

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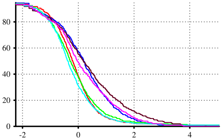
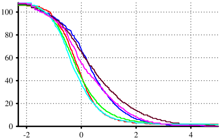
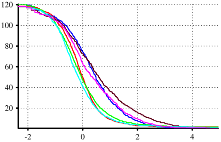


$k = 753$



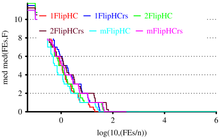
$k = 860$



$k = 960$

Progress for Different Values of k

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



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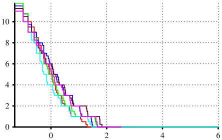

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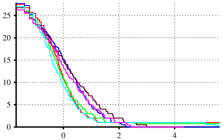

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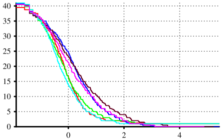

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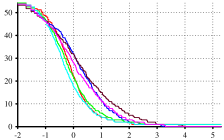

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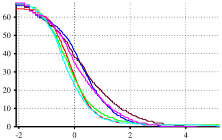
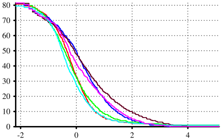


$k = 538$



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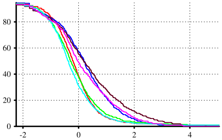
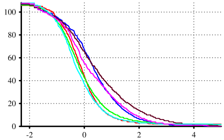


$k = 753$



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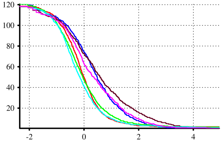

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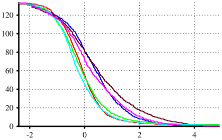
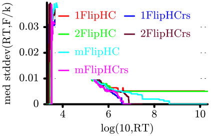


$k = 1065$

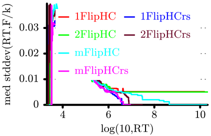
Let's look at the standard deviation of the best objective value F (divided by[1] k) found over RT (log-scaled) for different values of n.



legend

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

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



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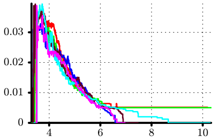
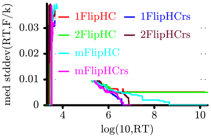


$n = 20$

The reason is probably that the algorithms converge nicely.



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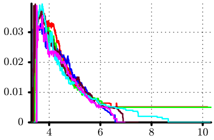
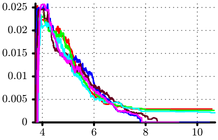
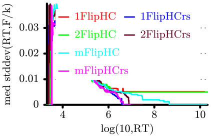


$n = 20$



$n = 50$

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



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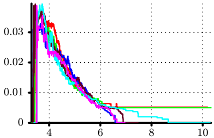
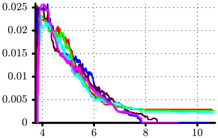
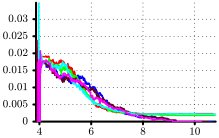


$n = 20$

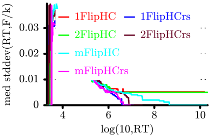


$n = 50$



$n = 75$

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



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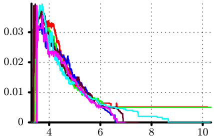
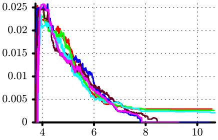
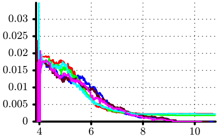


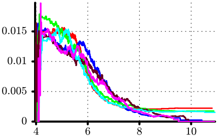
$n = 20$



$n = 50$



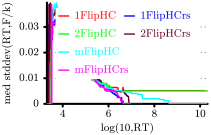
$n = 75$



$n = 100$

StdDev of F for Different Values of n

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



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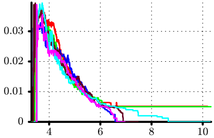
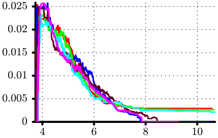
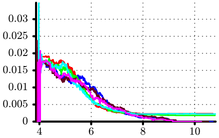


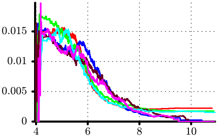
$n = 20$



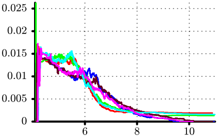
$n = 50$



$n = 75$

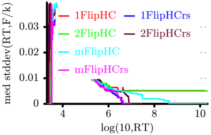


$n = 100$



$n = 125$

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



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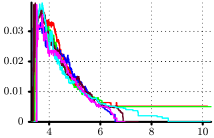
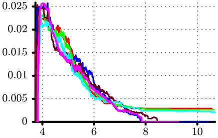
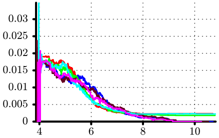


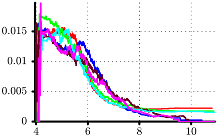
$n = 20$



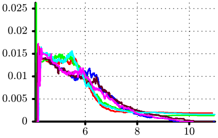
$n = 50$



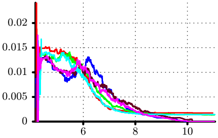
$n = 75$



$n = 100$



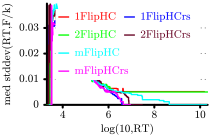
$n = 125$



$n = 150$

StdDev of F for Different Values of $\mathbf{n}$

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



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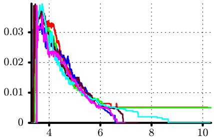
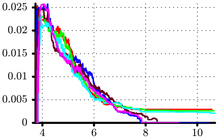
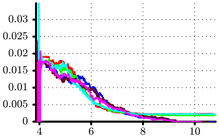


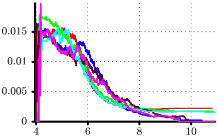
$n = 20$



$n = 50$



$n = 75$



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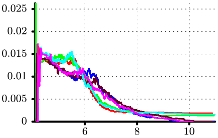

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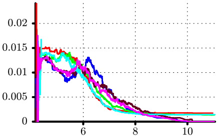
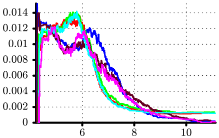


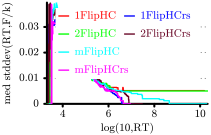
$n = 150$



$n = 175$

StdDev of F for Different Values of n

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



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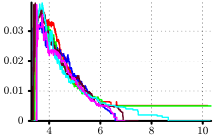
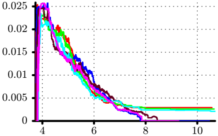
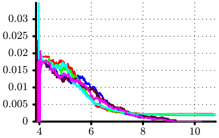


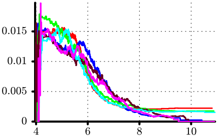
$n = 20$



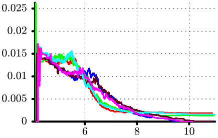
$n = 50$



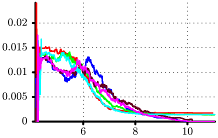
$n = 75$



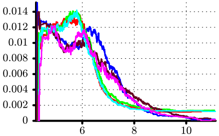
$n = 100$



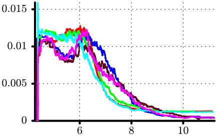
$n = 125$



$n = 150$



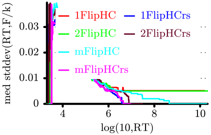
$n = 175$



$n = 200$

StdDev of F for Different Values of $\mathbf{n}$

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



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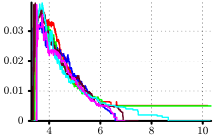
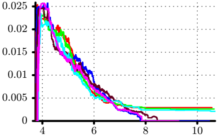
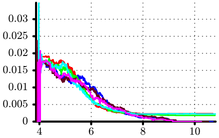


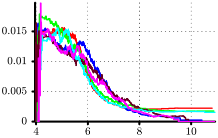
$n = 20$



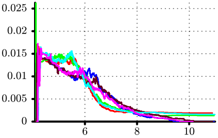
$n = 50$



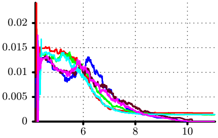
$n = 75$



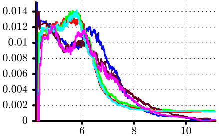
$n = 100$



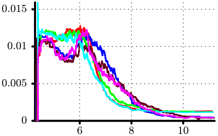
$n = 125$



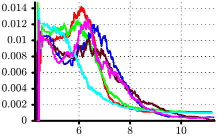
$n = 150$



$n = 175$



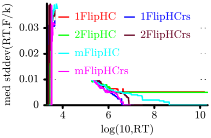
$n = 200$



$n = 225$

StdDev of F for Different Values of n

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



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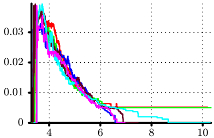
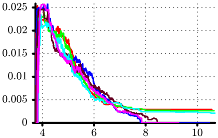
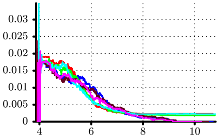


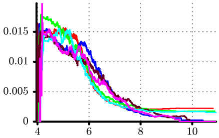
$n = 20$



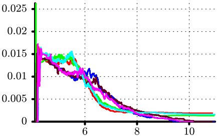
$n = 50$



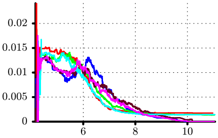
$n = 75$



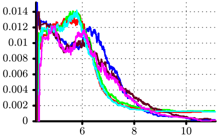
$n = 100$



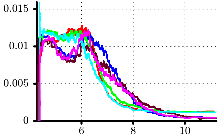
$n = 125$



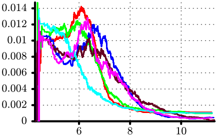
$n = 150$



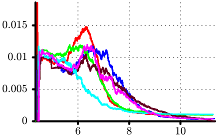
$n = 175$



$n = 200$

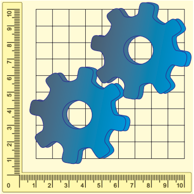


$n = 225$

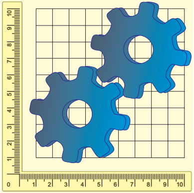


$n = 250$

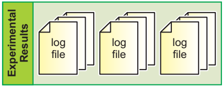
- So these are *some* of the things `optimizationBenchmarking` can *currently* do.

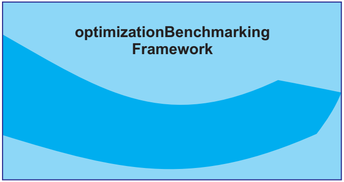


- So these are *some* of the things `optimizationBenchmarking` can *currently* do.
- But how to do them?

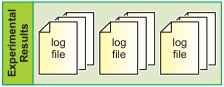


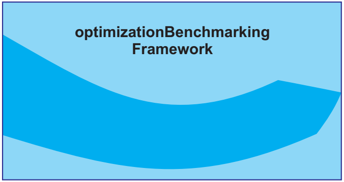
- Let us now take a closer look on how the `optimizationBenchmarking` evaluator is used (and works)



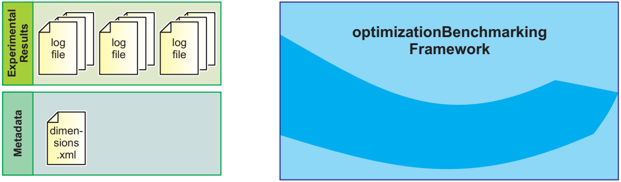


- We got a couple of log files for each experiment

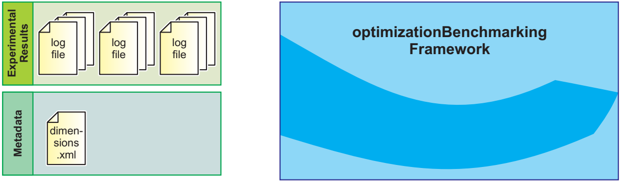




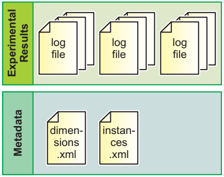
- We got a couple of log files for each experiment: 6 experiments in our example, each with $10 \times 10 \times 20 = 2000$ log files

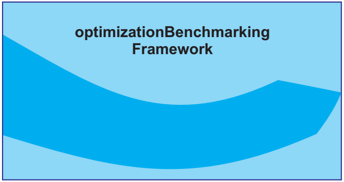


- We got a couple of log files for each experiment: 6 experiments in our example, each with $10 \times 10 \times 20 = 2000$ log files
- We specify which dimensions we have measured

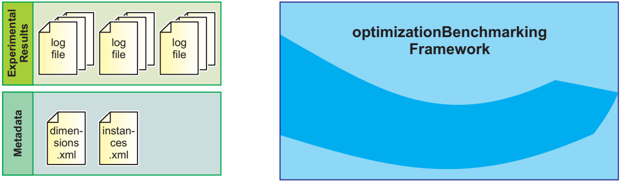


- We got a couple of log files for each experiment: 6 experiments in our example, each with $10 \times 10 \times 20 = 2000$ log files
- We specify which dimensions we have measured: *FEs*, *RT*, and F in our example

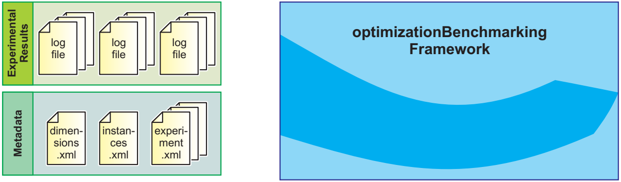




- We got a couple of log files for each experiment: 6 experiments in our example, each with $10 \times 10 \times 20 = 2000$ log files
- We specify which dimensions we have measured: *FEs*, *RT*, and F in our example
- We specify which benchmark instances we have and what their features are



- We got a couple of log files for each experiment: 6 experiments in our example, each with $10 \times 10 \times 20 = 2000$ log files
- We specify which dimensions we have measured: *FEs*, *RT*, and F in our example
- We specify which benchmark instances we have and what their features are: 10×10 instances in our example, with features n and k



- We got a couple of log files for each experiment: 6 experiments in our example, each with $10 \times 10 \times 20 = 2000$ log files
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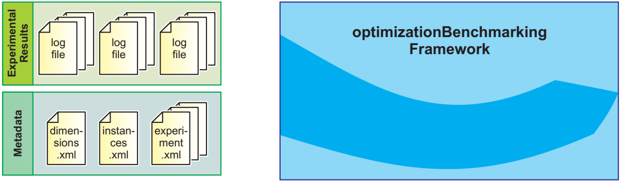

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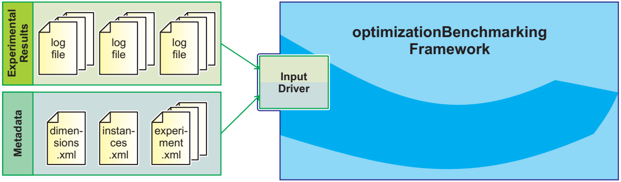
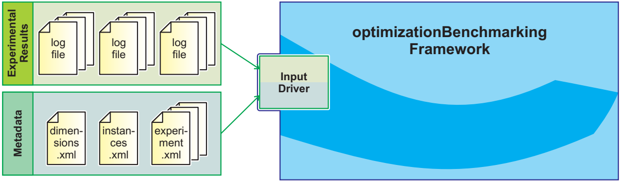
- For each experiment, we specify the parameters: in our example, these are `algorithm`, `operator`, `restart`

The Flow



- An "input driver" loads the data



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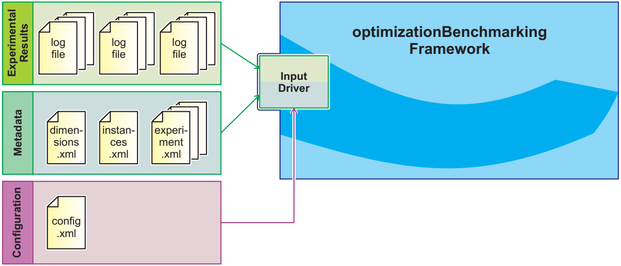

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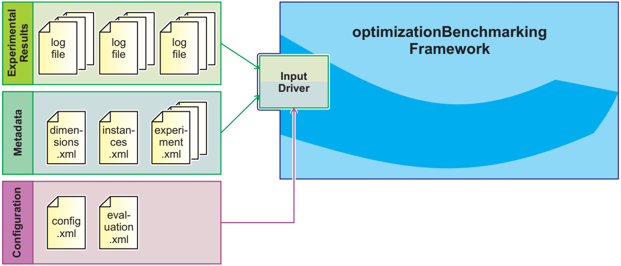

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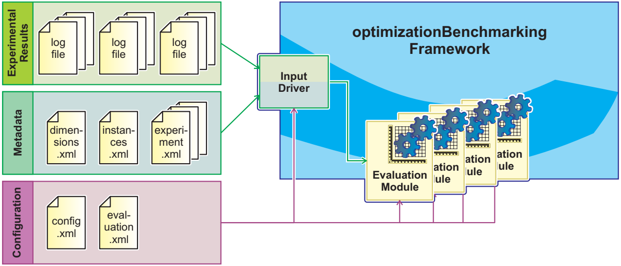
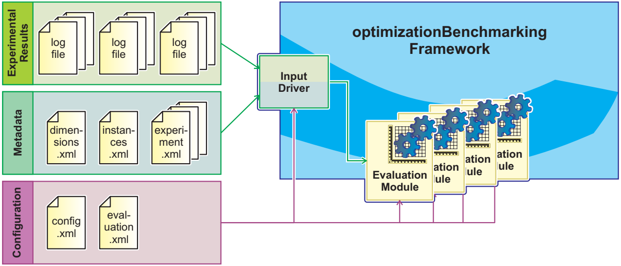
- The `evaluation.xml` specifies *how* to evaluate the data, i.e., which evaluation modules to apply

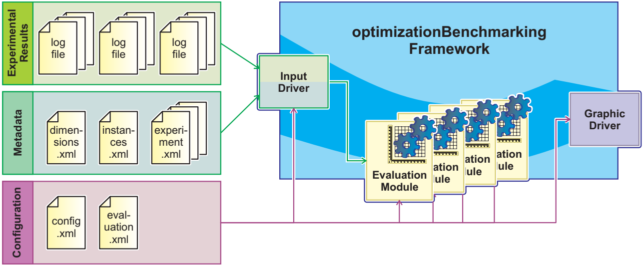
The Flow



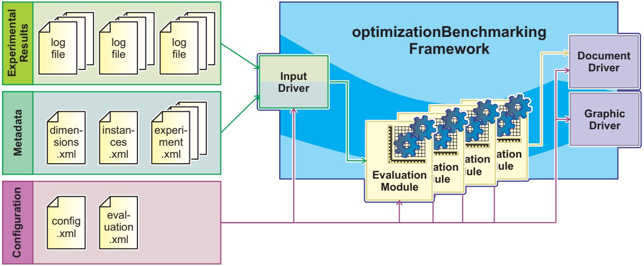
- An evaluation module prints on particular type of information about an experiment or experiment set, such as the ECDF, or a table with final results, etc. . .



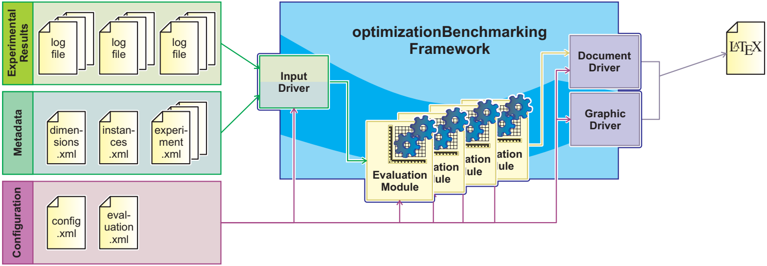
- An evaluation module prints on particular type of information about an experiment or experiment set, such as the ECDF, or a table with final results, etc. . .
- Evaluation modules can be applied multiple times, with different configurations (e.g., we can plot ECDFs for different target solution qualities)



- 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



- We can also choose among different formats for the report documents, including. . .



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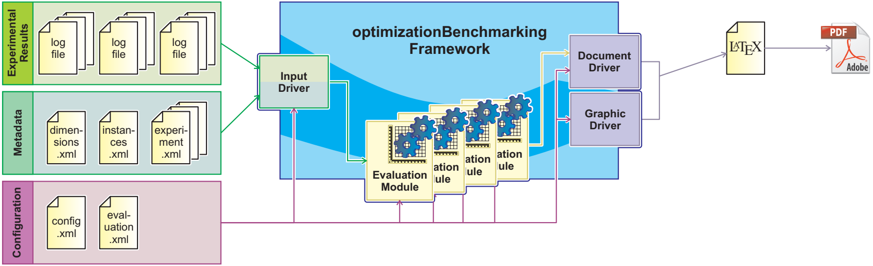

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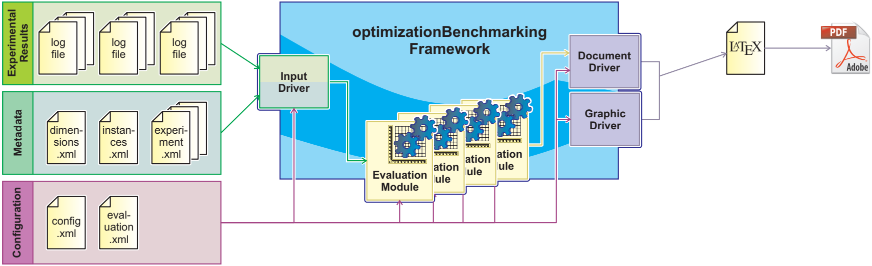

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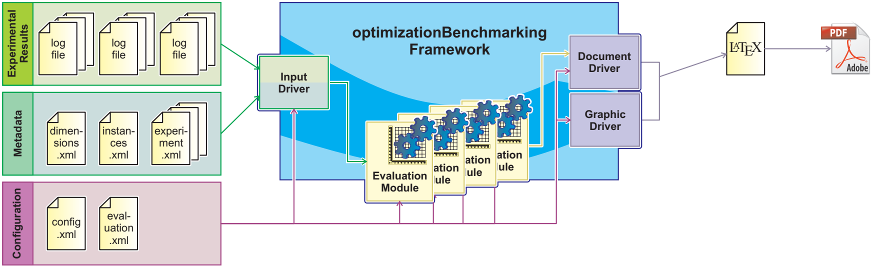

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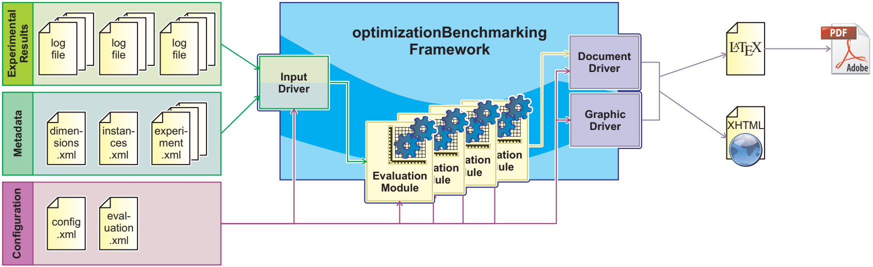
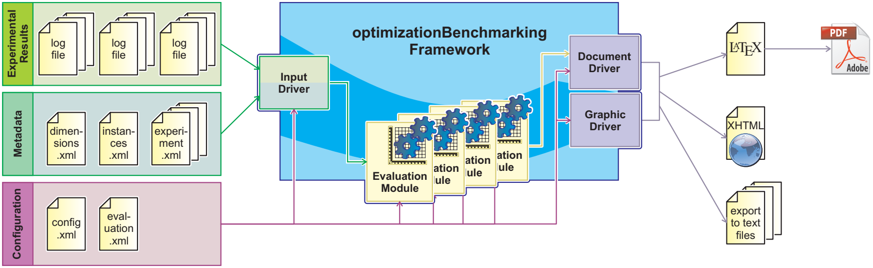
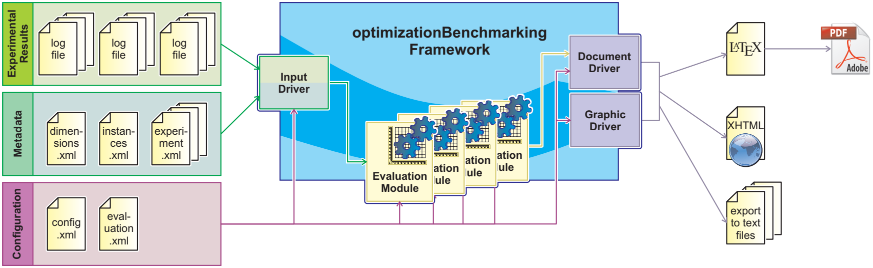
  - graphic sizes and fonts used in graphics are automatically adapted to document class



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



- We can also choose among different formats for the report documents, including LaTeX, XHTML [98], and a plain text format to export results to other applications



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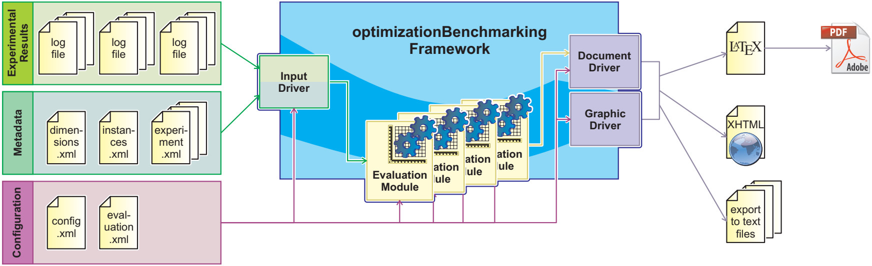

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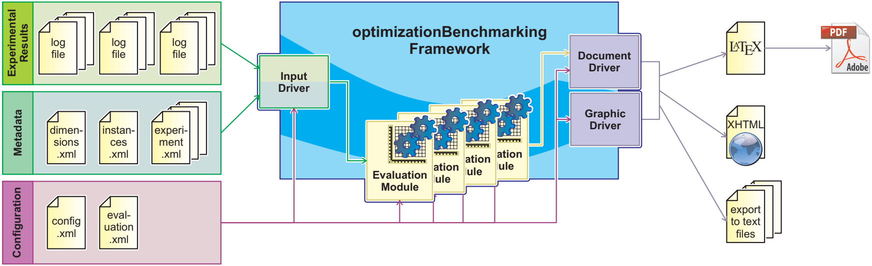

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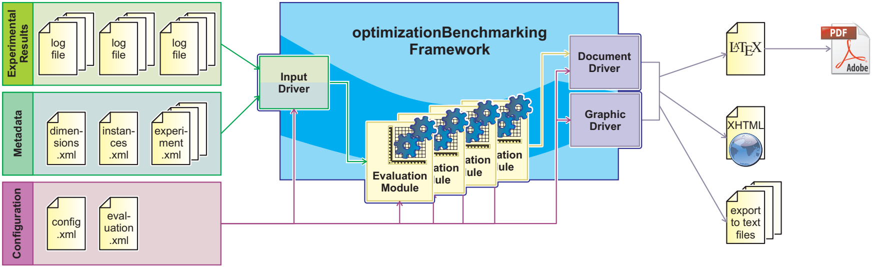

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- Evaluation Modules as well as Input, Document, and Graphic Drivers can easily be added: implement the corresponding interface, throw your class into the classpath, and tell the system to use it in the `config.xml` or `evaluation.xml`...

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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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    - `increasingStrictly`, like the *FEs* in our example – no two log points can have the same value in this dimension

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    - `byte`

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    - `float`, or
    - `double`

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

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- Multiple time and quality dimensions can be specified
- Diagrams can be plotted and values can be analyized according to different dimensions

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- 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 number of unsatisfied clauses."
    dimensionType="qualityProblemDependent" direction="decreasing"
    dataType="int" iLowerBound="0" iUpperBound="2000" />

</dimensions>
```

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  - *features*, such as n or k in our example
  - each feature has
    - a name (such as n)

- In an experiment, an optimization algorithm is applied to different *benchmark instances*
- Each instance has
  - a name,
  - *features*, such as n or k in our example
  - each feature has
    - a name (such as n),
    - a value (such as 250)

- In an experiment, an optimization algorithm is applied to different *benchmark instances*
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  - a name,
  - *features*, such as n or k in our example
  - each feature has
    - a name (such as n),
    - a value (such as 250),
    - an optional description

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  - *features*, such as n or k in our example
  - each feature has
    - a name (such as n),
    - a value (such as 250),
    - an optional description, and
    - an optional value description

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  - optional bounds for each dimension
    - makes particular sense for `qualityProblemDependent`
    - specified as element `bounds` with attribute `dimension` and either `iLowerBound` or `fLowerBound` and/or either `iUpperBound` or `fUpperBound`

Benchmark Instances

- In an experiment, an optimization algorithm is applied to different *benchmark instances*
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- Feature specifications allow us to explore relationship between instance features and algorithm behavior

Benchmark Instances

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  - optional bounds for each dimension, and
  - an optional description
- Feature specifications allow us to explore relationship between instance features and algorithm behavior
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Benchmark Instances

- In an experiment, an optimization algorithm is applied to different *benchmark instances*
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- Any number of features can be defined, but all instances much specify the same features (may with different values)
- Any feature value type is possible, numerical features are automatically detected
- 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

- 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 value description

Experiments

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- 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

- 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>
```

- 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>
```

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- 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>
```

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- 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

- 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

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- Global base configuration: 2 figures per row

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

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- 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

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```

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

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```xml
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  xmlns:cfg="http://www.optimizationBenchmarking.org/formats/configuration/
      configuration.1.0.xsd">

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

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

- 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>
```

- 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>
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    <cfg:parameter name="yAxis" value="F/k" />
    <cfg:parameter name="goal" value="0" />
    <cfg:parameter name="figureSize" value="page wide" />
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    <cfg:parameter name="goal" value="0.01" />
    <cfg:parameter name="groupBy" value="n" />
  </cfg:configuration>
</e:module>
```

- 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)

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<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
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    <cfg:parameter name="goal" value="0.01" />
    <cfg:parameter name="groupBy" value="n" />
  </cfg:configuration>
</e:module>
```

- 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>
```

- 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

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

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  <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>
```

- 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

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<e:module class="all.aggregation2D.AllAggregation2D">
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  </cfg:configuration>
```

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    - Where all of this is

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- So let's glue everything together

- 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>
```

- 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
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  <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>
```

- 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

University of Science and Technology of China

- 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>
```

- 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>
```

- 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>
```

- 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>
```

- 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>
```

- 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>
```

- 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>
```

- 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>
```

- 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>
```

- 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`

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- 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>
```

- 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>
```

- 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>
```

- 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>
```

- 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>
```

- 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>
```

1. Now we can finally execute the `optimizationBenchmarking` Evaluator

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

1. Now we can finally execute the `optimizationBenchmarking` Evaluator
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3. `cd` into the directory with the configuration file

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

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-0.8.4-full.jar -configXML=configForIEEEtran.xml`

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-0.8.4-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForLNCS.xml`

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-0.8.4-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-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-0.8.4-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForXHTML.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-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-0.8.4-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForXHTML.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForExport.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=whatever.xml`

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-0.8.4-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForXHTML.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForExport.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=whatever.xml`
5. . . . and that's it.

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-0.8.4-full.jar -configXML=configForIEEEtran.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForLNCS.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForXHTML.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=configForExport.xml` or
   - `java -jar optimizationBenchmarking-0.8.4-full.jar -configXML=whatever.xml`
5. . . . and that's it.
6. Requirement: Java 1.7

- 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)

1

Evaluation Report on Six Experiments

Anne Anonymous

***Abstract*—This is the evaluation report on six experiments, namely 1FlipHC, 1FlipHCrs, 2FlipHC, 2FlipHCrs, mFlipHC, and mFlipHCrs on 100 benchmark instances. This report has been generated with the version 0.8.4 of the Evaluator Component of the Optimization Benchmarking Tool Suite.**

I. Instance Information

Experiments were conducted on 100 benchmark instances, which can be distinguished by two features.

The benchmark instances are characterized by two features:

- n (ten values, ranging from 20 to 250)
- k (ten values, ranging from 91 to 1065)

In Figure 2 we illustrate the relative amount of benchmark instances per feature value over all 100 benchmark instances. The slices in the pie charts are the bigger, the more benchmark instances have the associated feature value in comparison to the other values. The more similar the pie sizes are, the more evenly are the benchmark instances distributed over the benchmark feature values, which may be a good idea for fair experimentation.

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 $\mathrm{ECDF}\left(FEs, \frac{F}{k} \leq 0\right)$ 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.

The corresponding plot is illustrated in Figure 1.

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 $\mathrm{ECDF}\left(RT, \frac{F}{k} \leq 0.01\right)$ 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.

The corresponding plots are illustrated in Figure 3.

C. Median of Medians

We analyze the median of medians (*med med*) of F over $\log_{10}\left(\frac{FEs}{n}\right)$. The $\mathrm{med\ med}(FEs, F)$ 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.

The corresponding plots are illustrated in Figure 4.

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 $\mathrm{med\ stddev}\left(RT, \frac{F}{k}\right)$ 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.

The corresponding plots are illustrated in Figure 5.

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.intellektik.informatik.tu-darmstadt.de/TR/1998/98-02.ps.Z

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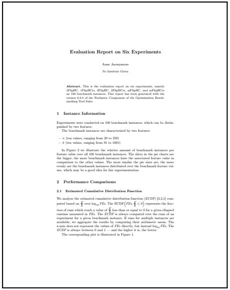
[3] N. Hansen, A. Auger, S. Finck, and R. Ros, "Real-parameter black-box optimization benchmarking: Experimental setup," Orsay, France: Université Paris Sud, Institut National de Recherche en Informatique et en Automatique (INRIA) Futurs, Équipe TAO, Tech. Rep., Mar. 24, 2012. [Online]. Available: http://coco.lri.fr/BBOB-downloads/download11.05/bbobdocexperiment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

first page of the report in LaTeX for `IEEEtran`

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

first page of the report in LaTeX for `IEEEtran`



first page of the report in LaTeX for `LNCS`

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Evaluation Report on Six Experiments

Anne Anonymous

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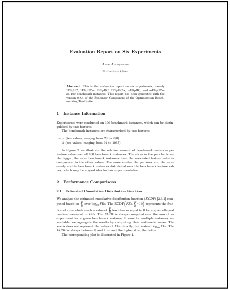
Evaluation Report on Six Experiments

Anne Anonymous

No Institute Given

first page of the report in LaTeX for `LNCS`


Evaluation Report on Six Experiments

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

Result

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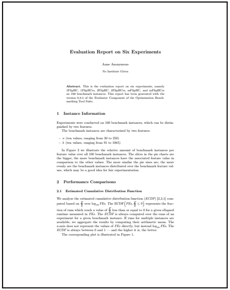
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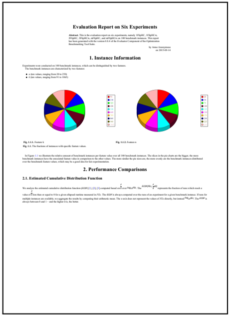
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1. Introduction
2. Example 1: MAX-SAT
3. Example 2: BBOB
4. Conclusions

- Since 2009, the *Black-Box Optimization Benchmarking* (*BBOB*) workshops [71, 80–82] regularly take place at GECCO (now also at CEC)

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

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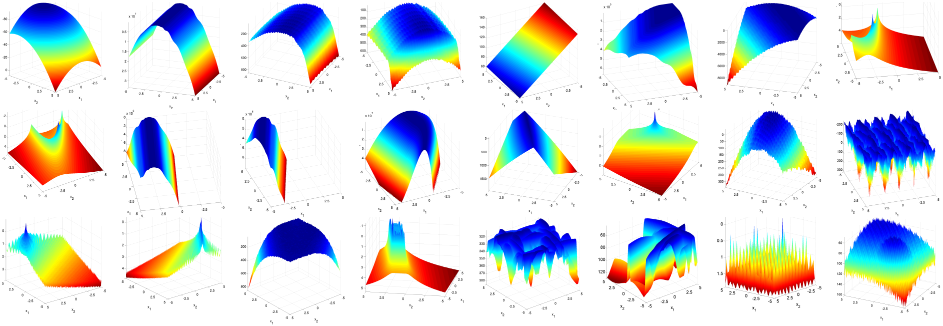
- Researchers can use the *COmparing Continuous Optimisers* (*COCO*) framework to benchmark their *numerical* optimization algorithms
- *COCO*/*BBOB* defines a set of 24 numerical optimization problems



(figures taken from [82])

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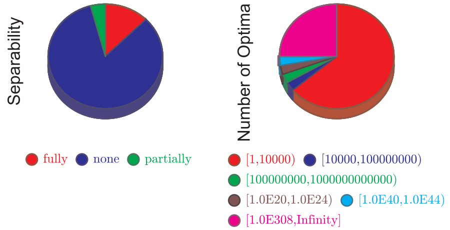

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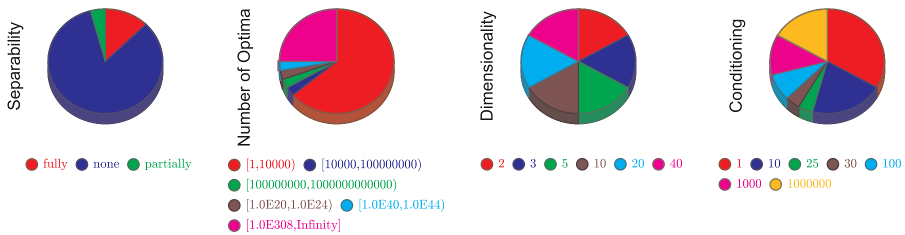

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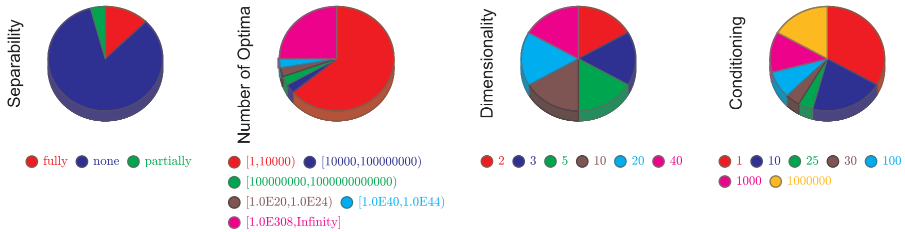

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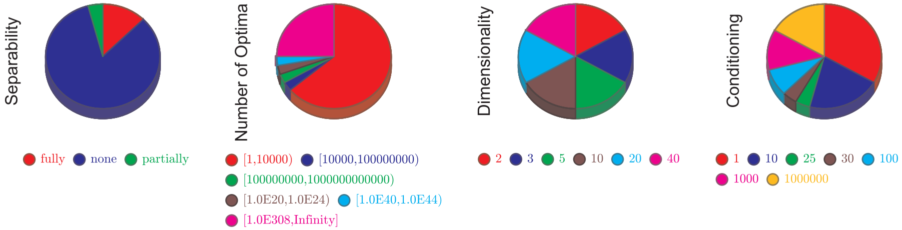

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- The framework and the results of past *BBOB*s are available at `http://coco.gforge.inria.fr`
- `optimizationBenchmarking` has an experimental input driver for *COCO* data
- No need to specify `dimensions.xml` and `instances.xml`, as these are fixed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

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

- 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)

- 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."
```

- 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
  - a filder `reports` with the generated reports

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)
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  - a filder `reports` with the generated reports
- But now, let's continue with the example...

- 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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- All we need to supply to the Evaluator is
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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)

- 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>
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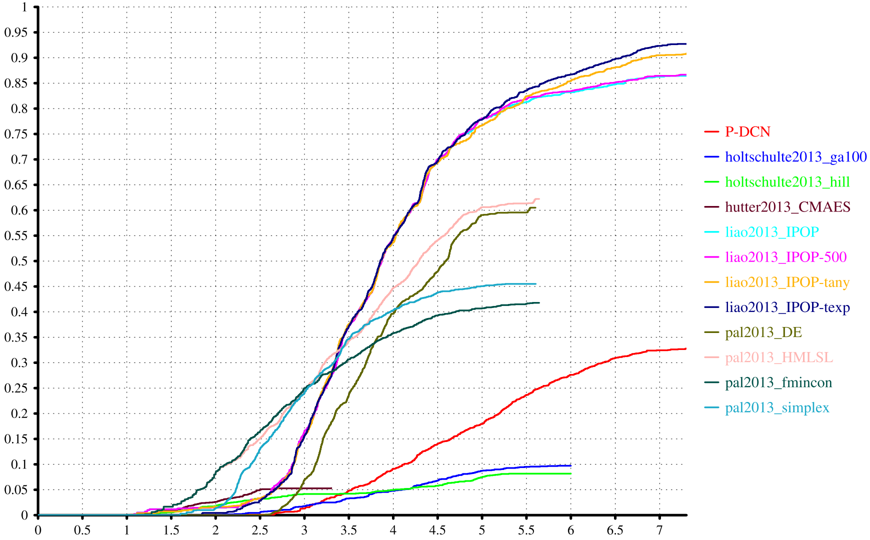
- We set the goal "error" to $1 \cdot 10^{-8}$
- For the time measured in *FEs* and log-scaled, we plot the fraction of runs achieving this goal

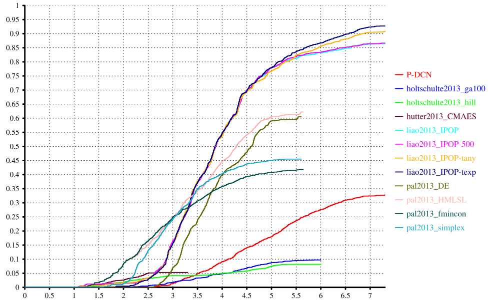
Listing: Part 1 from file evaluation.xml for our *BBOB* example.

```
<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>
```

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

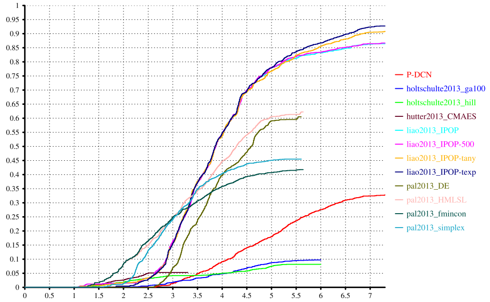


- Let's first plot the ECDF aggregated over all benchmark instances



- It seems that `IPOP-texp` can reach $F \leq 1 \cdot 10^{-8}$ on more instances than the other tested algorithms

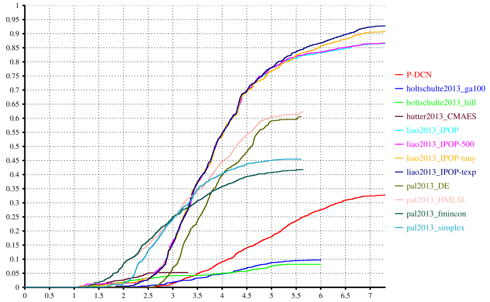
- Let's first plot the ECDF aggregated over all benchmark instances



- It seems that `IPOP-texp` can reach $F \leq 1 \cdot 10^{-8}$ on more instances than the other tested algorithms
- The different `IPOP` variants in general reach this value more often than the other algorithms

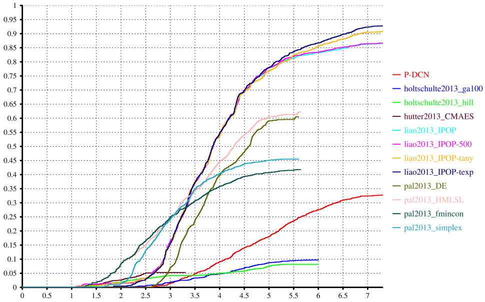
ECDF over Everything

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



- It seems that `IPOP-texp` can reach $F \leq 1 \cdot 10^{-8}$ on more instances than the other tested algorithms
- 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

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



- It seems that `IPOP-texp` can reach $F \leq 1 \cdot 10^{-8}$ on more instances than the other tested algorithms
- 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

- 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>
```

- 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.

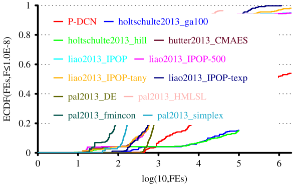
```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
    <cfg:parameter name="yAxis" value="F" />
    <cfg:parameter name="goal" value="1e-8" />
    <cfg:parameter name="groupBy" value="dim" />
  </cfg:configuration>
</e:module>
```

- 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.

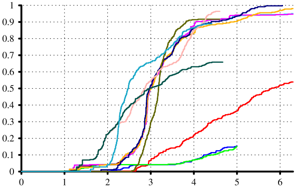
Listing: Part 2 from file `evaluation.xml` for our *BBOB* example.

```
<e:module class="all.ecdf.AllECDF">
  <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>
```

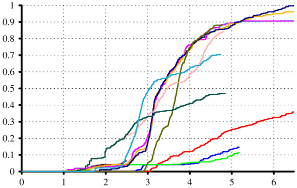
- Let's now plot the ECDF aggregated over each distinct value of the benchmark feature *dimension*



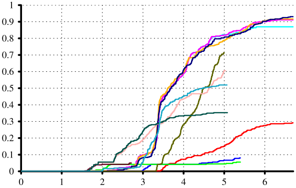
legend



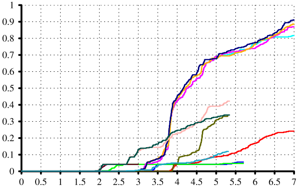
dim = 2



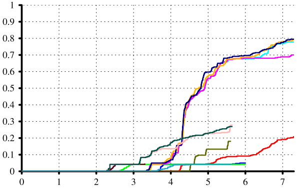
dim = 4



dim = 5



dim = 10



dim = 20

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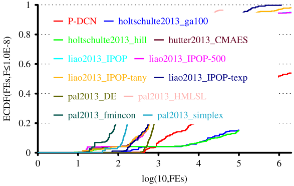
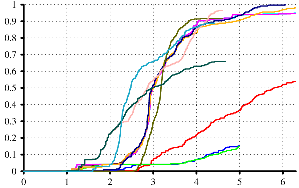
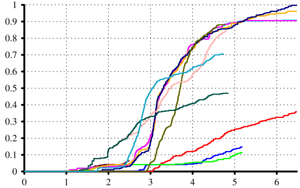
- We find that for larger dimension, fewer problems can be solved



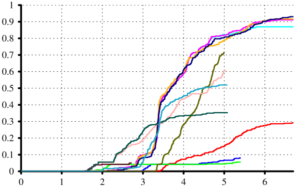
legend



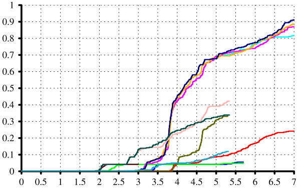
$\mathtt{dim} = 2$



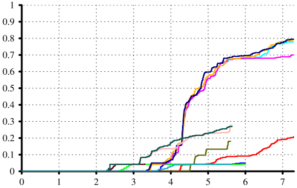
$\mathtt{dim} = 4$



$\mathtt{dim} = 5$

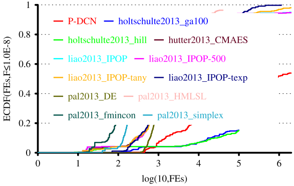


$\mathtt{dim} = 10$

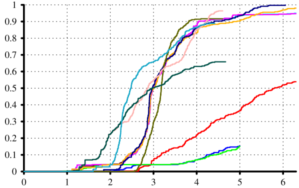


$\mathtt{dim} = 20$

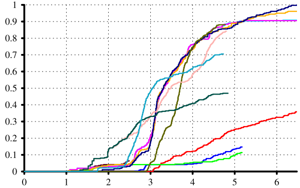
- While the overall performance of `pal2013_fmincon` and `pal2013_simplex` look similar when considering *all* problems, we find that the simplex algorithm is very heavily influenced by the dimension



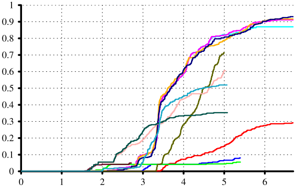
legend



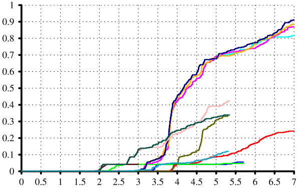
dim = 2



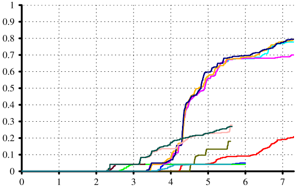
dim = 4



dim = 5

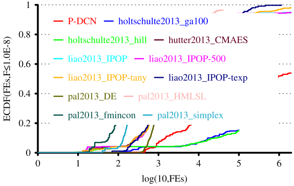


dim = 10

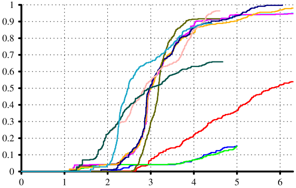


dim = 20

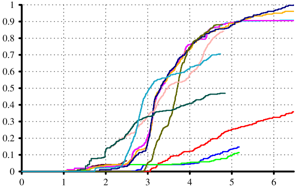
- Similarly, the performance of DE breaks down when the dimension increases



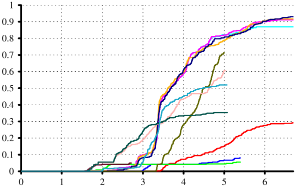
legend



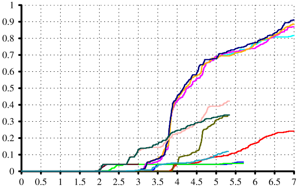
$\mathtt{dim} = 2$



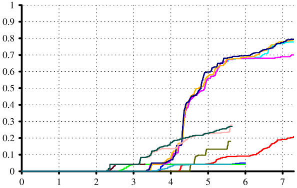
$\mathtt{dim} = 4$



$\mathtt{dim} = 5$



$\mathtt{dim} = 10$



$\mathtt{dim} = 20$

ECDF by Dimension

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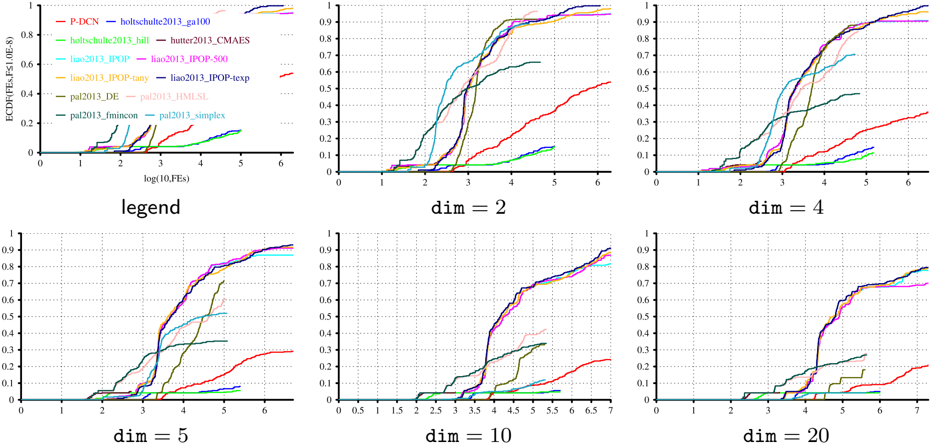
- The performance of the IPOP algorithm family, on the other hand, degenerates gracefully with rising dimension



- 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" />
    <cfg:parameter name="groupBy" value="cond" />
  </cfg:configuration>
</e:module>
```

- 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]

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" />
    <cfg:parameter name="groupBy" value="cond" />
  </cfg:configuration>
</e:module>
```

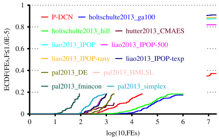
- Let's now plot the ECDF aggregated over the benchmark instances with the same value of feature *condition number*
- *"the condition number corresponds to the square root of the ratio between the largest axis of the ellipsoid and the shortest axis"* [82]
- As goal "error" to achieve, this time we pick $1 \cdot 10^{-5}$

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

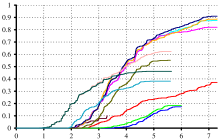
```
<e:module class="all.ecdf.AllECDF">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg FEs" />
    <cfg:parameter name="yAxis" value="F" />
    <cfg:parameter name="goal" value="1e-5" />
    <cfg:parameter name="groupBy" value="cond" />
  </cfg:configuration>
</e:module>
```

ECDF by Condition Number

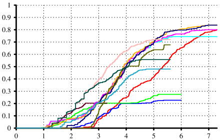
- Let's now plot the ECDF aggregated over the benchmark instances with the same value of feature *condition number*



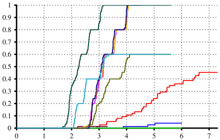
legend



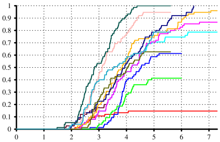
cond $= 1$



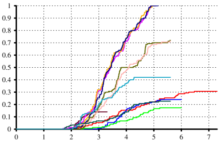
cond $= 10$



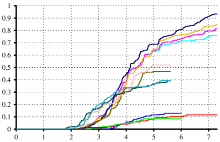
cond $= 25$



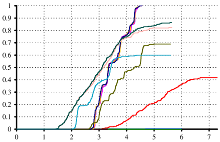
cond $= 30$



cond $= 100$



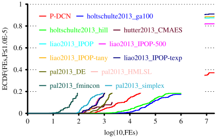
cond $= 1000$



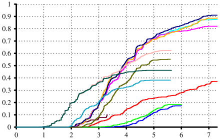
cond $= 1\,000\,000$

ECDF by Condition Number

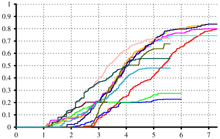
- The influence of the condition number on problem hardness does not seem to obvious at first glance



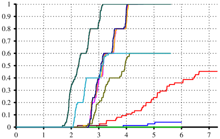
legend



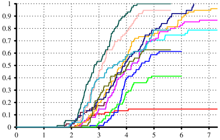
cond $= 1$



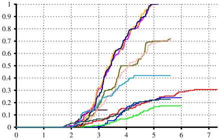
cond $= 10$



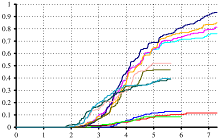
cond $= 25$



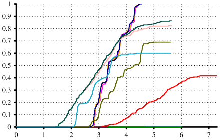
cond $= 30$



cond $= 100$



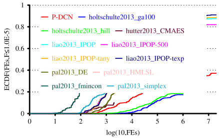
cond $= 1000$



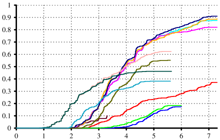
cond $= 1\,000\,000$

ECDF by Condition Number

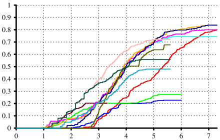
- Some algorithms perform bad on some mediocre condition numbers while performing better on smaller and larger ones (e.g., `P-DCN` on `cond` $= 1000$)



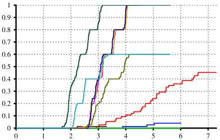
legend



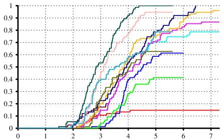
`cond` $= 1$



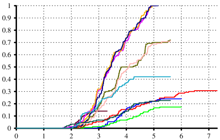
`cond` $= 10$



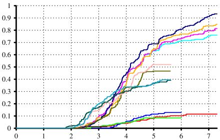
`cond` $= 25$



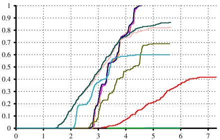
`cond` $= 30$



`cond` $= 100$



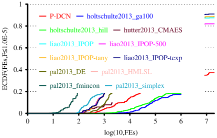
`cond` $= 1000$



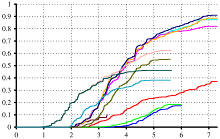
`cond` $= 1\,000\,000$

ECDF by Condition Number

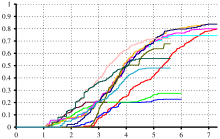
- For some problems, there doesn't seem to be a direct relationship between conditioning and performance (e.g., DE)



legend



cond = 1



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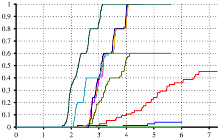

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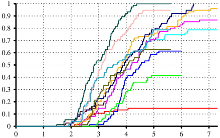

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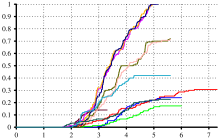

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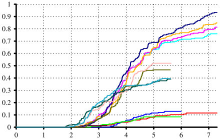

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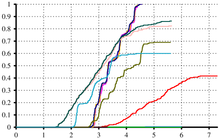
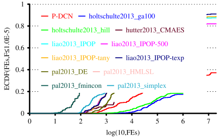


cond = 1 000 000

- 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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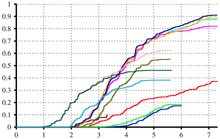
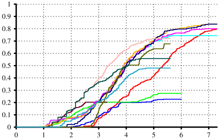
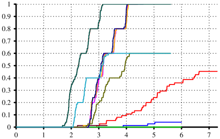


cond = 1



cond = 10



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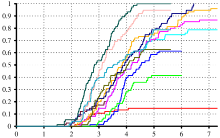

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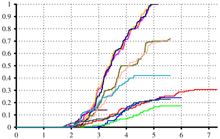
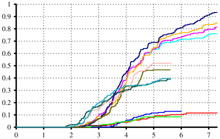
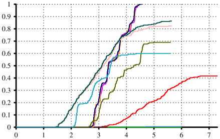


cond = 100

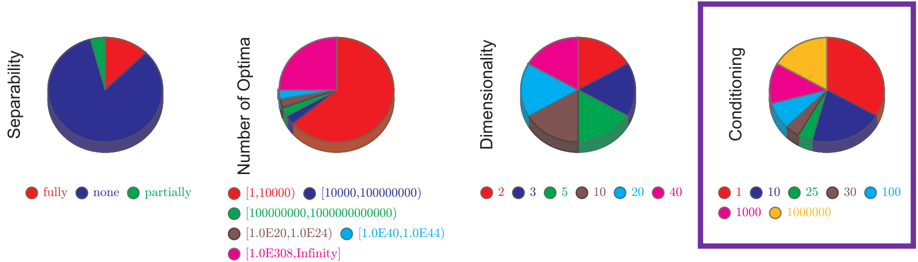


cond = 1000



cond = 1 000 000

- 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

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

Listing: Part 4 from file `evaluation.xml` for our *BBOB* example.

```
<e:module class="all.aggregation2D.AllAggregation2D">
  <cfg:configuration>
    <cfg:parameter name="xAxis" value="lg(FEs/dim²)" />
    <cfg:parameter name="yAxis" value="lg F" />
    <cfg:parameter name="aggregate" value="median" />
    <cfg:parameter name="groupBy" value="sep" />
  </cfg:configuration>
</e:module>
```

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- The x-axis be again the log-scaled *FEs* divided by the square of the benchmark instance dimension[1]

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</e:module>
```

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

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

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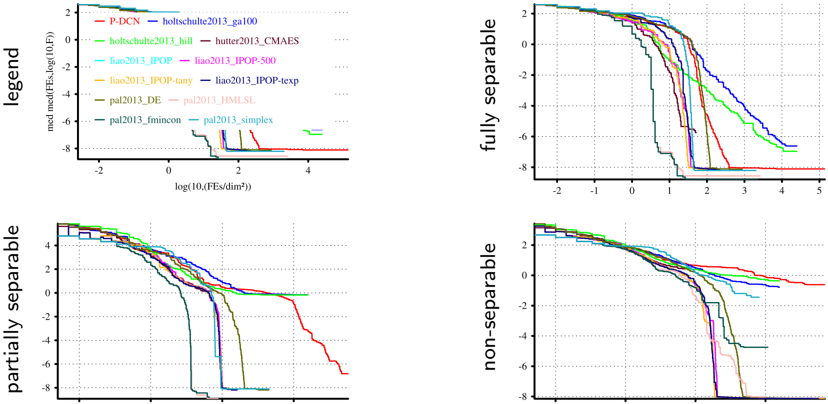
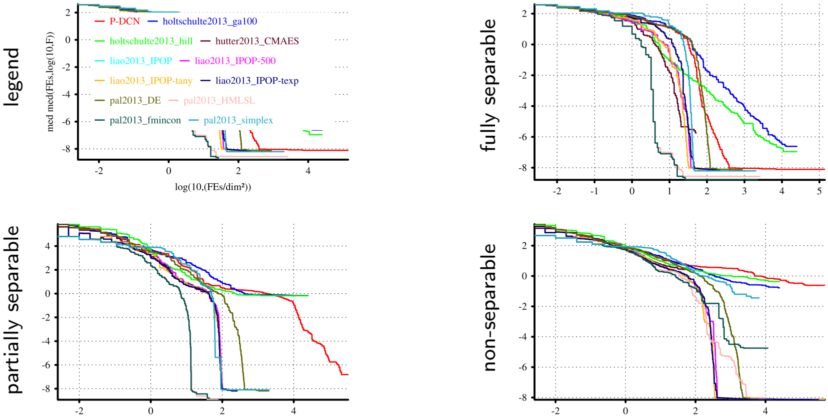
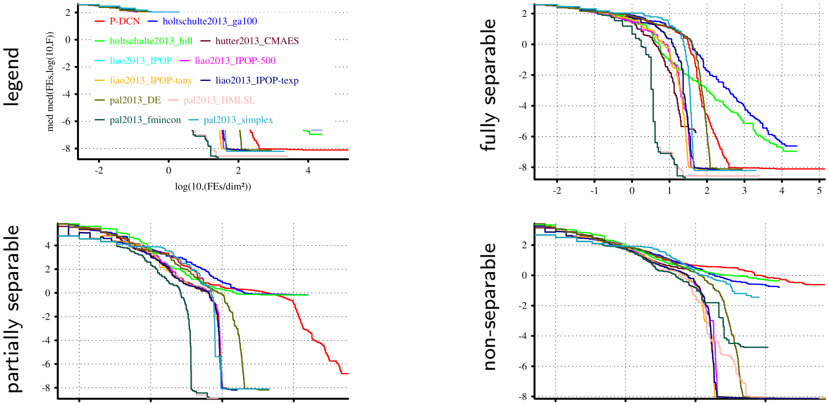


中国科学技术大学
University of Science and Technology of China

- 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



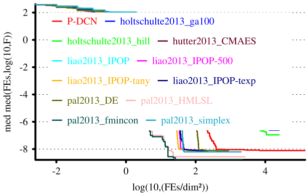
- Here seems to be the strength of the IPOP family of algorithms



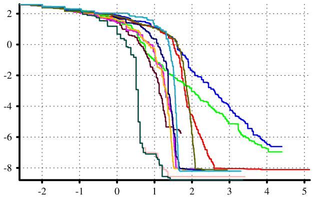
Progress by Separability

- 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

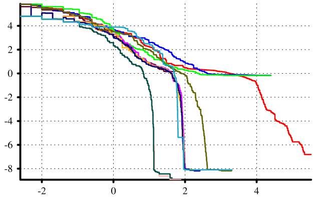
legend



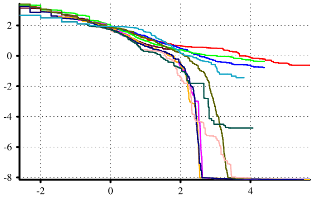
fully separable



partially separable



non-separable



Example Summary

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1

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Anne Anonymous

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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.intellektik.informatik.tu-darmstadt.de/TR/1998/98-02.ps.Z

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1

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- Evaluator modules implemented once can be used for benchmark data from various algorithms and various optimization problems.


1

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Conclusions

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- But it can already load and evaluate performance data from *your* optimization or Machine Learning algorithm
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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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- Write an overview paper about our system to publish it more widely

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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 0.8.4) 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.

Thomas Weise
tweise@ustc.edu.cn ·
tweise@gmx.de ·
http://www.it-weise.de

USTC-Birmingham Joint Res. Inst. in Intelligent Computation and Its Applications (UBRI)
University of Science and Technology of China (USTC), Hefei 230027, Anhui, China

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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 recomment Eclipse [112] (version $\geq$ Luna), as it natively supports git and Maven [113, 114].

1. Prerequisites

1. Prerequisites:
   1. Obtain a `gitHub` account

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Contribution Lifecycle

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    1. Obtain a `gitHub` account
    2. Register a public/private key pair for your account
    3. Join group `optimizationBenchmarking`

Contribution Lifecycle

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

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

1. Prerequisites
2. Fork project
3. Add your code
4. Test your code

1. Prerequisites
2. Fork project
3. Add your code
4. Test your code
    - add `JUnit` [115–117] tests if possible

1. Prerequisites
2. Fork project
3. Add your code
4. Test your code
   - add `JUnit` [115–117] tests if possible
   - provide examples, example data, and expected results

1. Prerequisites
2. Fork project
3. Add your code
4. Test your code
5. Make sure your code is properly documented and that your commits contain sufficient explanations

1. Prerequisites
2. Fork project
3. Add your code
4. Test your code
5. Make sure your code is properly documented
6. Create a `pull request`, i.e., ask me to include your code in the main project

Contribution Lifecycle

1. Prerequisites
2. Fork project
3. Add your code
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

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- After cloning and importing the clone into `Eclipse`, you need to update the project with `Maven` to properly initialize the project structure and dependencies.

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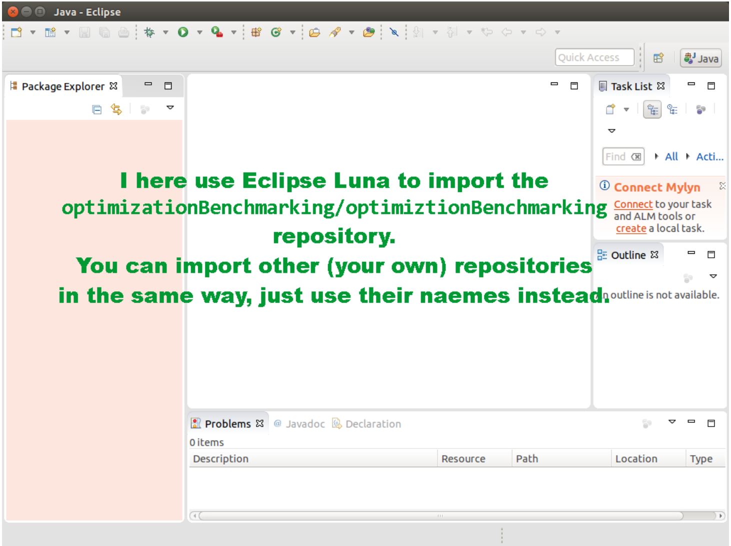
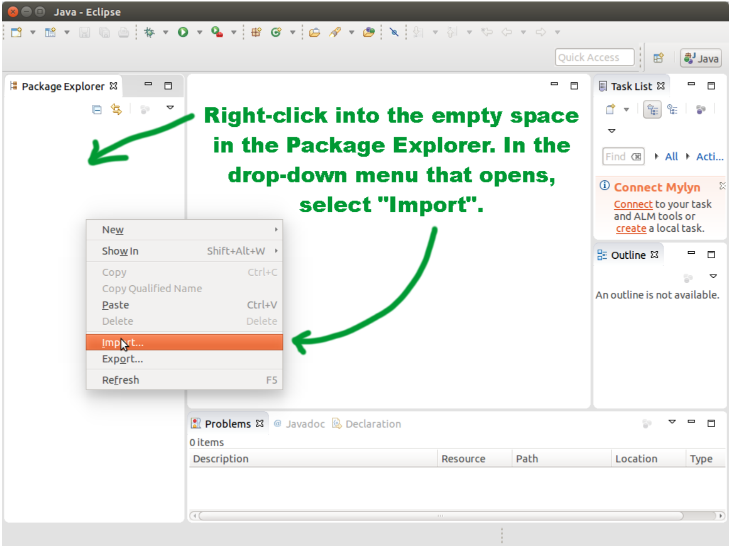
- Although `gitHub` offers cloning via HTTPS as the default, for me it worked better with SSH.
- After cloning and importing the clone into `Eclipse`, you need to update the project with `Maven` to properly initialize the project structure and dependencies.
- In the following, I provide a step-by-step 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.


Java - Eclipse
Quick Access
Java
Package Explorer
Task List
Find
All
Acti...
Connect Mylyn
Connect to your task and ALM tools or create a local task.
Outline
An outline is not available.
Right-click into the empty space in the Package Explorer. In the drop-down menu that opens, select "Import".
New
Show In Shift+Alt+W
Copy Ctrl+C
Copy Qualified Name
Paste Ctrl+V
Delete Delete
Import...
Export...
Refresh F5
Problems
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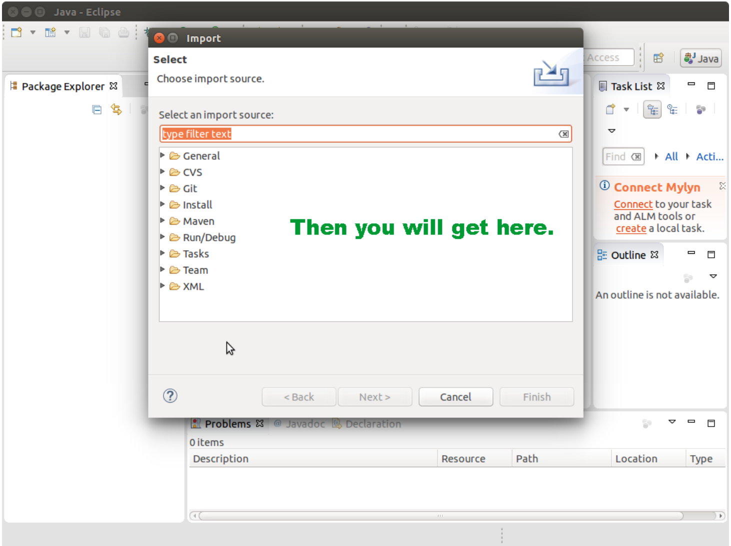
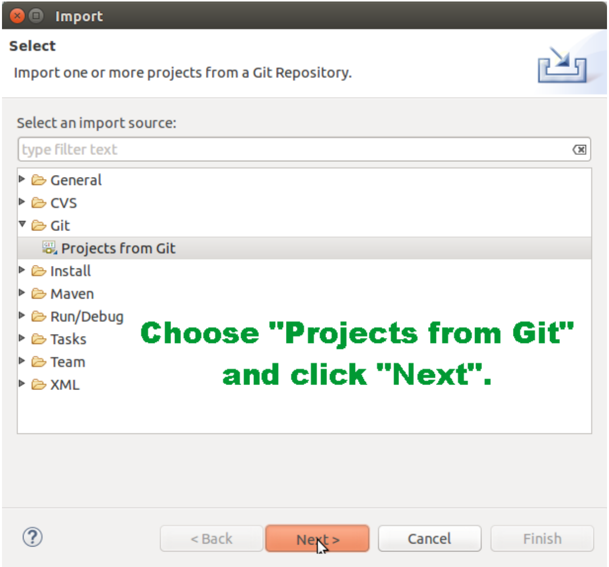
Description
Resource
Path
Location
Type

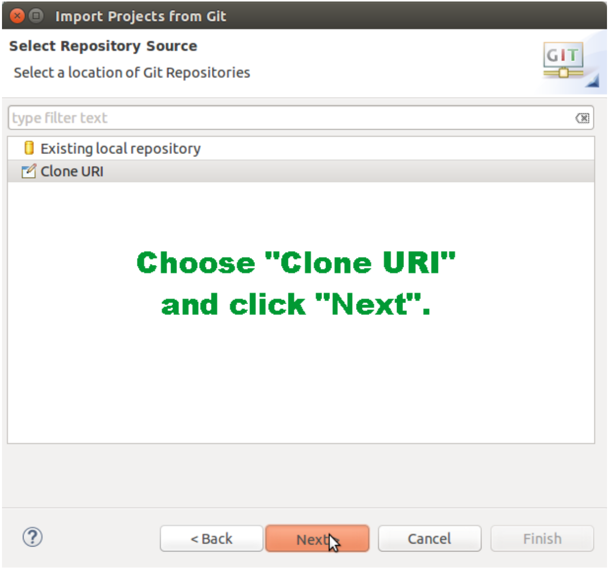
Import Fork into Eclipse

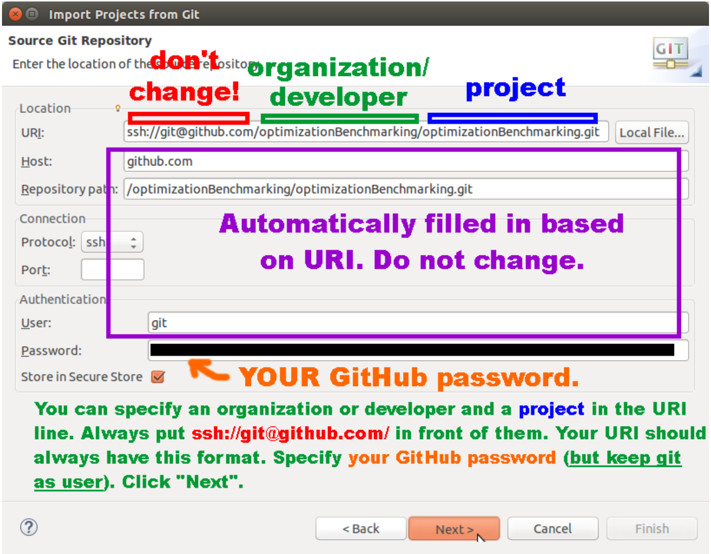


Import Fork into Eclipse



Import Fork into Eclipse

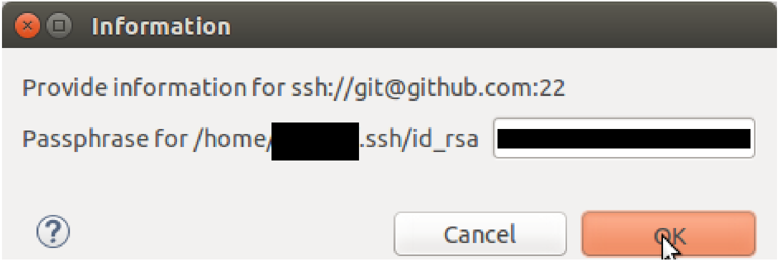




You can specify an organization or developer and a project in the URI line. Always put ssh://git@github.com/ in front of them. Your URI should always have this format. Specify your GitHub password (but keep git as user). Click "Next".

Import Fork into Eclipse

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



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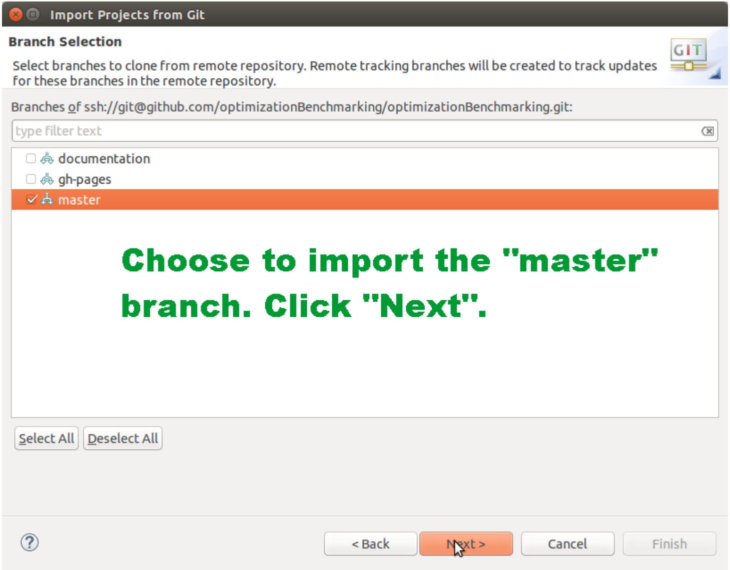

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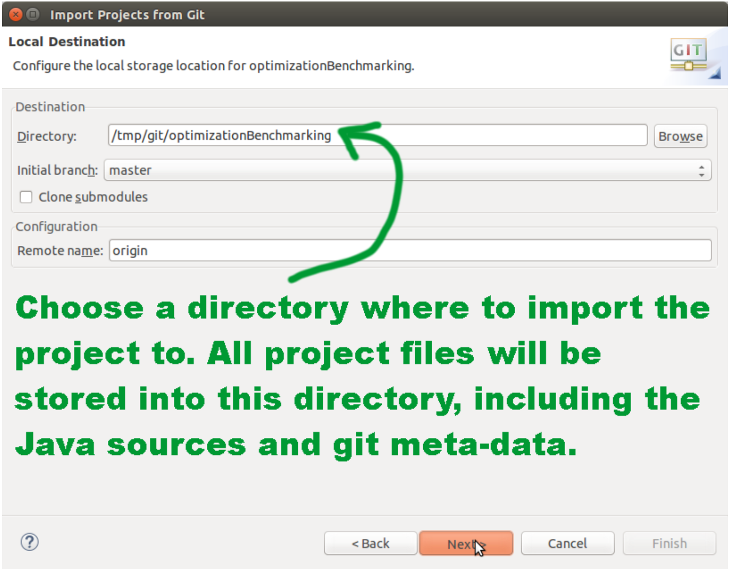

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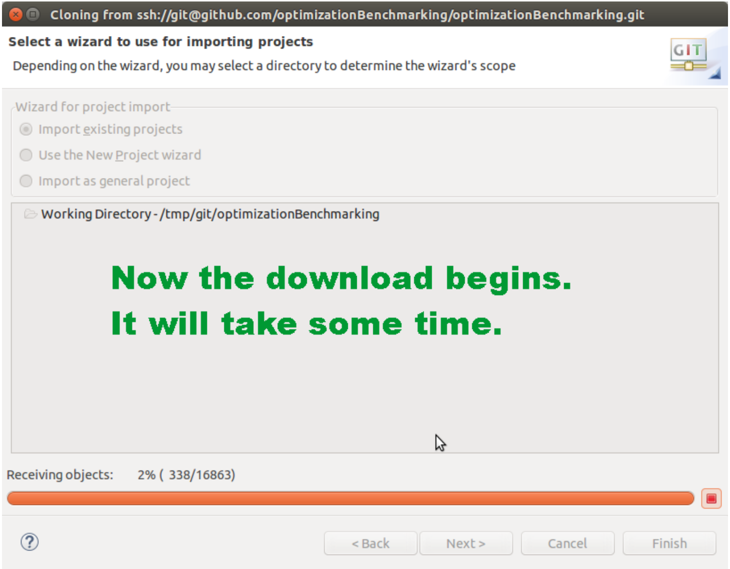

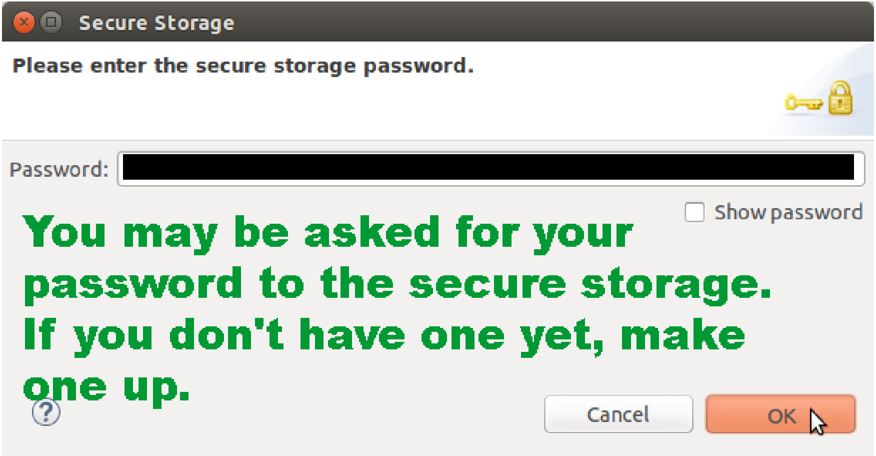
Secure Storage
Please enter the secure storage password.
Password:
Show password
You may be asked for your password to the secure storage. If you don't have one yet, make one up.
Cancel
OK

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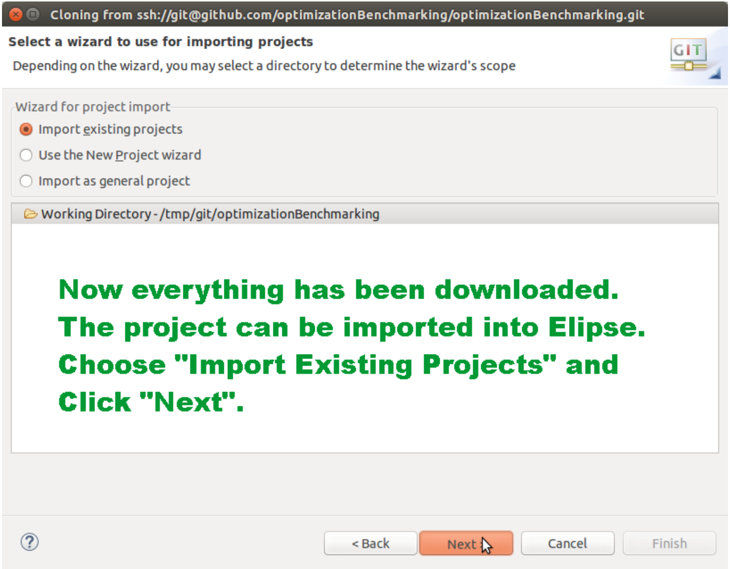

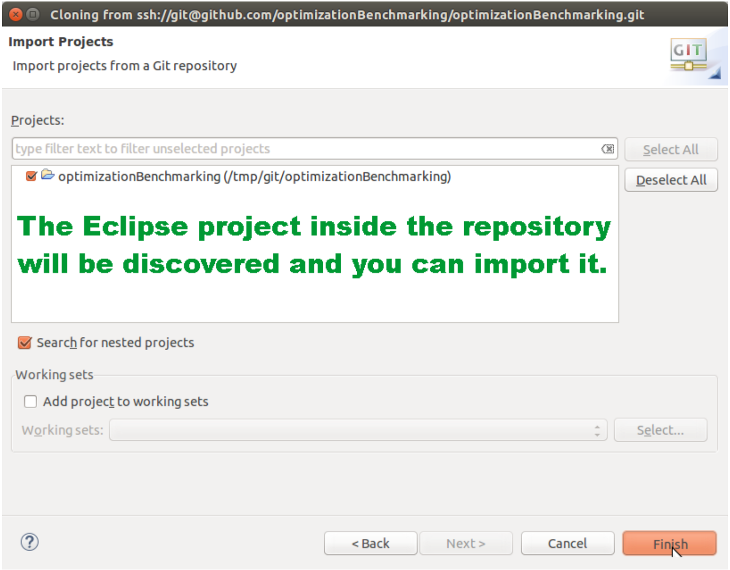
Cloning from ssh://git@github.com/optimizationBenchmarking/optimizationBenchmarking.git
Import Projects
Import projects from a Git repository
Projects:
type filter text to filter unselected projects
Select All
Deselect All
optimizationBenchmarking (/tmp/git/optimizationBenchmarking)
The Eclipse project 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

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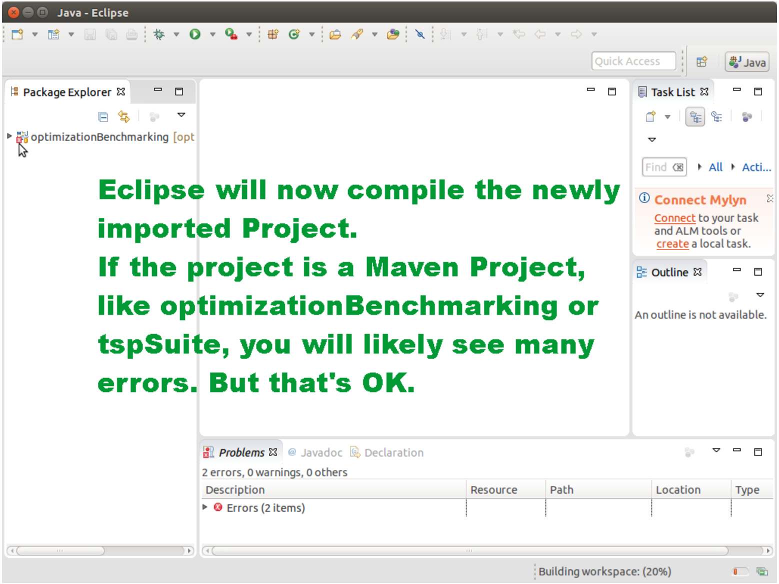
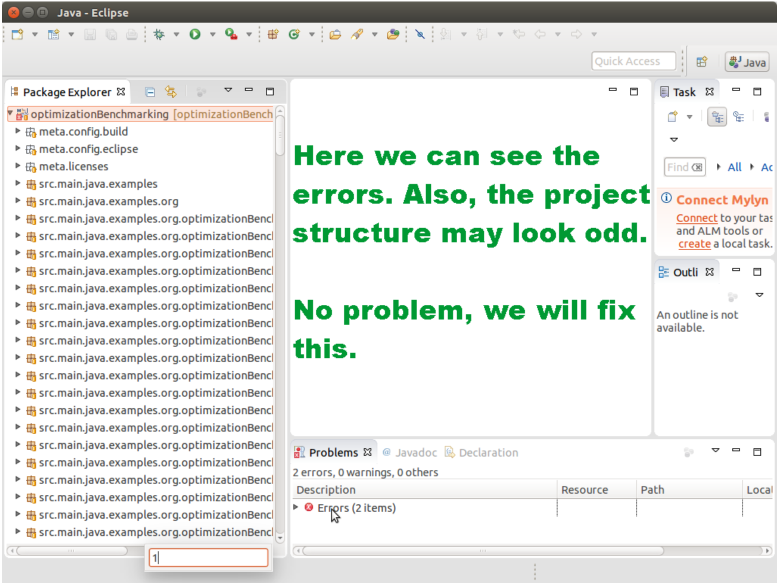
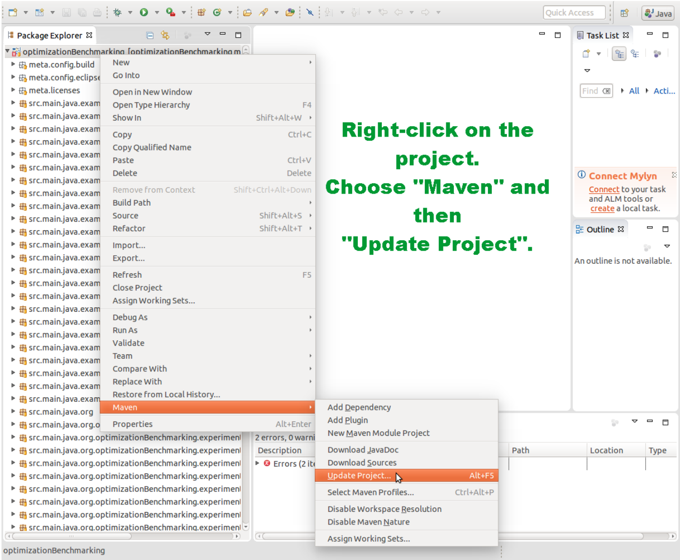


Eclipse will now compile the newly imported Project.
If the project is a Maven Project, like optimizationBenchmarking or tspSuite, you will likely see many errors. But that's OK.



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

No problem, we will fix this.



Right-click on the project. Choose "Maven" and then "Update Project".

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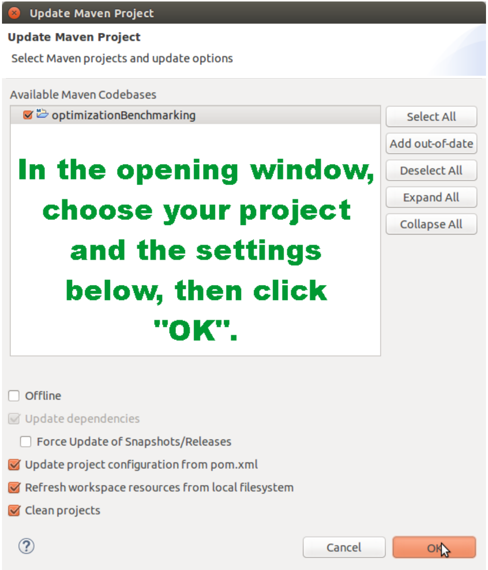

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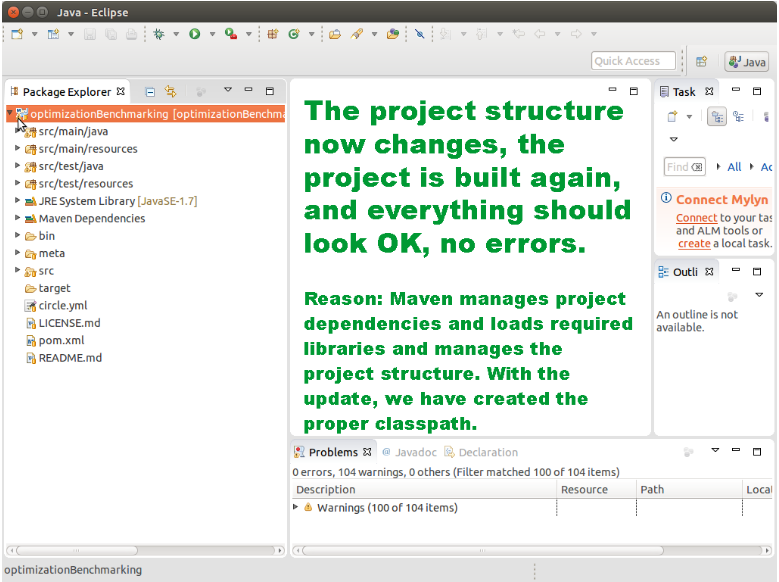

The project structure now changes, the project is built again, and everything should look OK, no errors.

Reason: Maven manages project dependencies and loads required libraries and manages the project structure. With the update, we have created the proper classpath.

Log Points and Termination

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Visit our website

http://www.optimizationBenchmarking.org

or

http://optimizationbenchmarking.github.io/optimizationBenchmarking

for downloading the software (version 0.8.4) 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)