From Standardized Data Formats to Standardized Tools for Optimization Algorithm Benchmarking

Thomas Weise · 汤卫思

tweise@hfuu.edu.cn · http://iao.hfuu.edu.cn

Hefei University, South Campus	合肥学院 南艳湖校区
Faculty of Computer Science and Technology	计算机科学与技术系
Institute of Applied Optimization	应用优化研究所
230601 Hefei, Anhui, China	中国 安徽省 合肥市 230601
Econ. & Tech. Devel. Zone, Jinxiu Dadao 99	经济技术开发区 锦绣大道99号

Outline

1. Introduction
2. Tools for Research on Optimization
3. Example Experiment and Data
4. Conclusions

website

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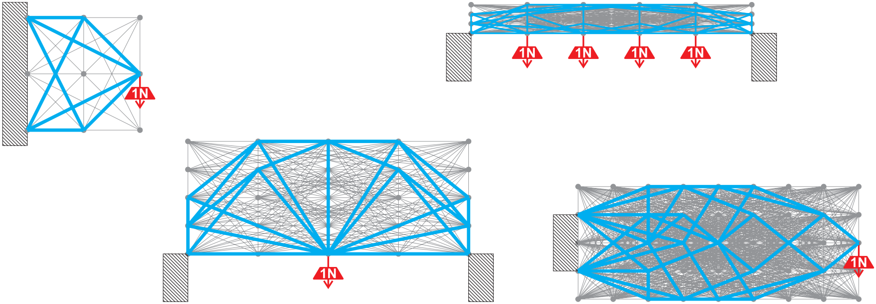
  - How can I construct a truss which can hold a certain weight with at most a certain amount of iron?



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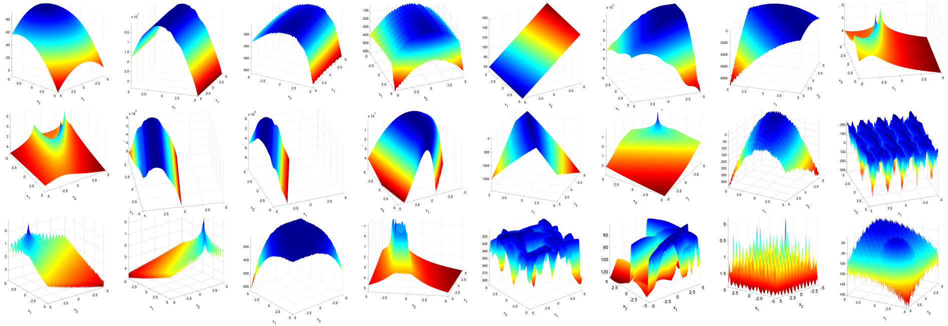

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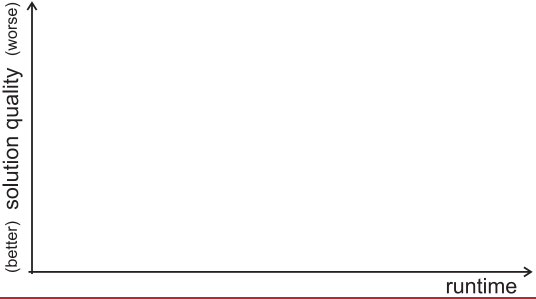

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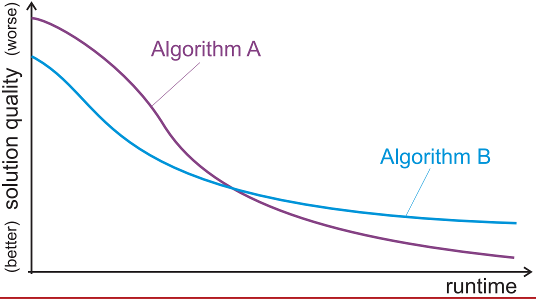

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- Experiments must capture data on the whole runtime behavior!

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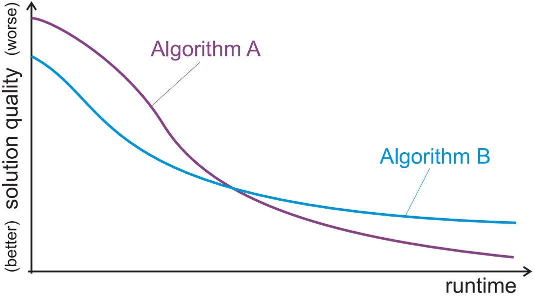

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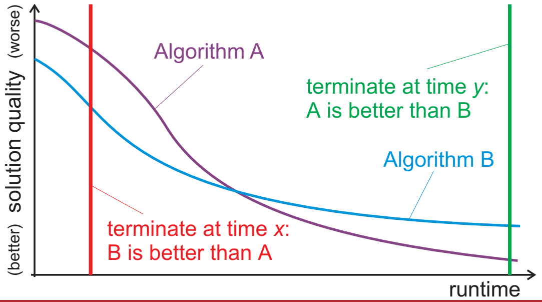

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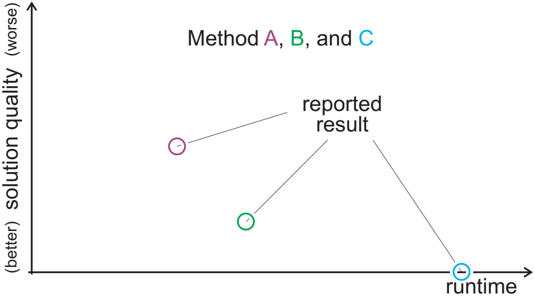

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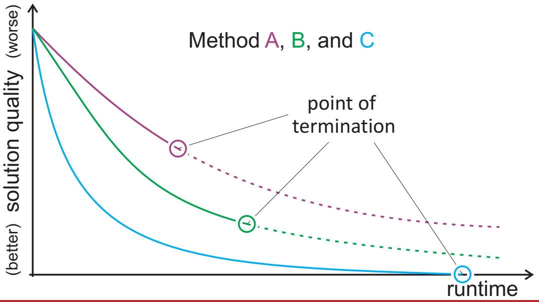

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- The *optimizationBenchmarking.org* is an example for such tools.

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- We prescribe this folder structure of `instance` $\longrightarrow$ `algorithm setup` $\longrightarrow$ `run(s).txt`, as it can be adopted for any kind experiment in optimization.

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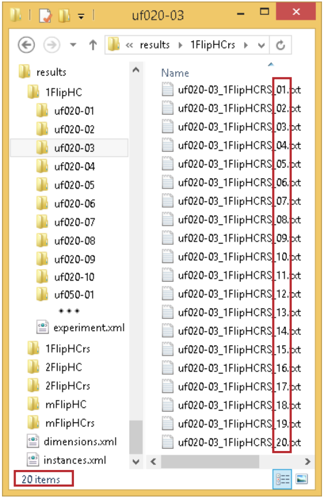

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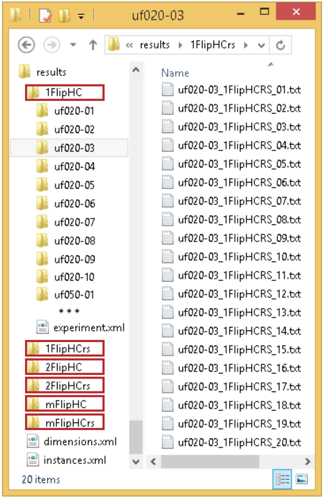

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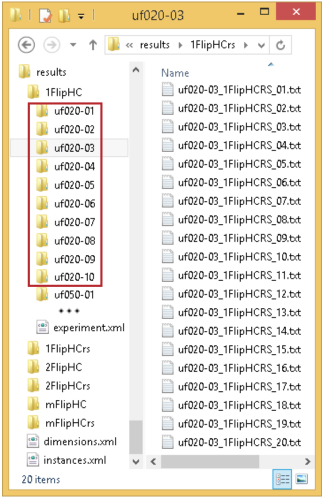

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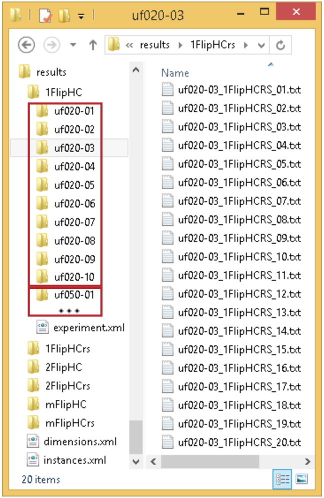

Example of Log File Structure

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

Listing: Log File `uf075-02_2FlipHCrs_01.txt`.

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1         9806       46
3         24643      28
17        106040     25
19        115529     23
20        120373     21
25        144087     18
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solution quality

Metadata

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Metadata

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Listing: The description of the measured dimensions.

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

  <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>
```

Metadata

- Metadata on the measured dimensions and the benchmark instance features is represented as XML.

Listing: The description of the benchmark instance features.

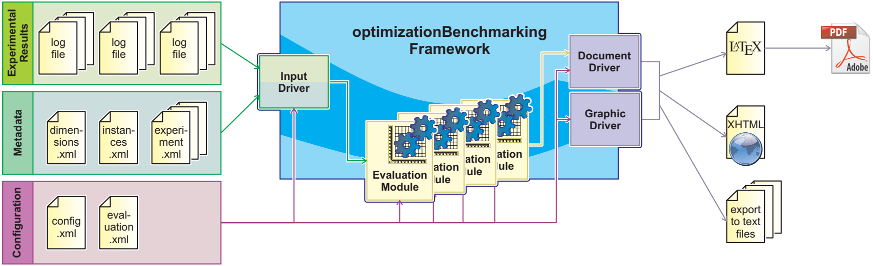
```
<?xml version="1.0" encoding="UTF-8"?>
<instances xmlns="http://www.optimizationBenchmarking.org/formats/...">
  <instance name="uf020-01"
    description="A uniformly randomly generated satisfiable 3-SAT instance with 20 variables and 91 clauses.">
    <feature name="n" value="20" />
    <feature name="k" value="91" />
  </instance>
...
  <instance name="uf050-01"
    description="A uniformly randomly generated satisfiable 3-SAT instance with 50 variables and 218 clauses.">
    <feature name="n" value="50" />
    <feature name="k" value="218" />
  </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>
...
</instances>
```

Metadata

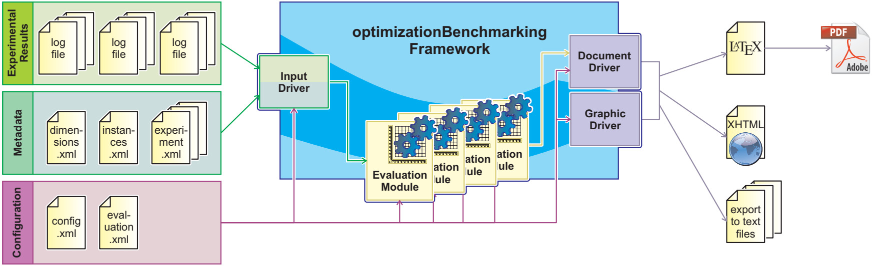
- Metadata on the measured dimensions, the benchmark instance features, and the algorithm setups is represented as XML.

Listing: The description of the parameters of one specific experiment setup.

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



- The *optimizationBenchmarking.org* framework is an example for software accepting data in such common formats.

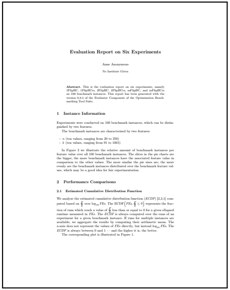


- The *optimizationBenchmarking.org* framework is an example for software accepting data in such common formats.
- It can be configured and launched via a web-based GUI and researchers can select, transform, and group data based on the meta-information.


Evaluation Report on Six Experiments

Anne Anonymous

first page of the report in LaTeX for IEEEtran


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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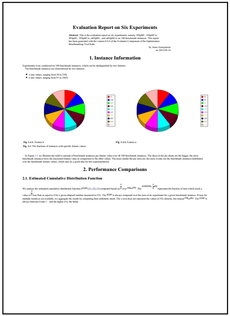
first page of the report in LaTeX for sig-alternate


Evaluation Report on Six Experiments

1. Instance Information

first page of the report in XHTML

- As result, it can produce human-readable reports with high-level conclusions and publication-ready diagrams from this data.

Conclusions

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Conclusions

- Experimentation with optimization algorithms is complicated and involves much data if we want to do it right.
- We therefore need tool support.
- The existing tool support is limited to specific problems, i.e., there is 1:1 relationship between tool and problem.
- A general data format would lift this boundary, general tools could evolve.
- We define such a format and give an example for a tool using it (*optimizationBenchmarking.org*).

谢谢
Thank you

Thomas Weise [汤卫思]
tweise@hfuu.edu.cn
http://iao.hfuu.edu.cn

Hefei University, South Campus
Institute of Applied Optimization
Hefei, Anhui, China

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

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Heuristic Optimization

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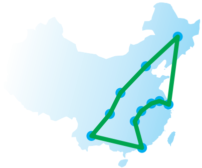

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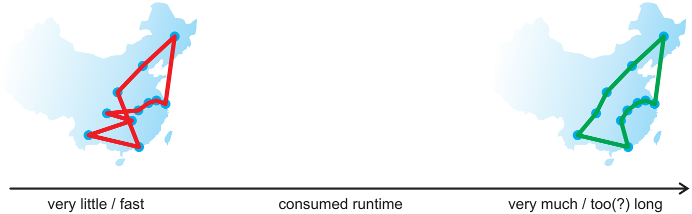

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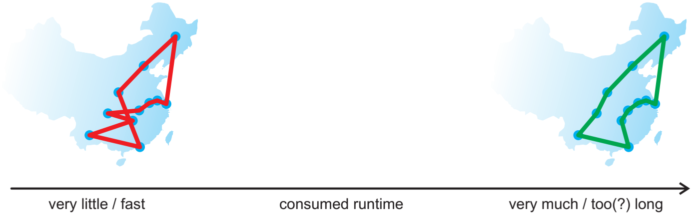

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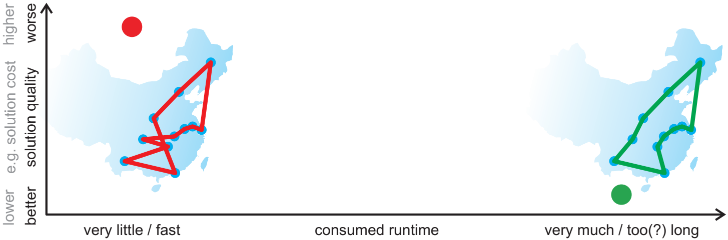

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  - (Meta-)Heuristic optimization algorithms try to find solutions which are as good as possible as fast as possible.