Automating the Configuration of Algorithms for Solving Hard Computational Problems

Ph.D. Thesis Defence

Frank Hutter

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- Prof. Kevin Leyton-Brown (co-supervisor)
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Parameters in Algorithms

Most algorithms have parameters

- Decisions that are left open during algorithm design
  - numerical parameters (*e.g.*, real-valued thresholds)
  - categorical parameters (*e.g.*, which heuristic to use)

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- Set to maximize empirical performance

Real-world example for parameterized algorithms: commercial optimization tool CPLEX

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  $\rightsquigarrow$ developed the first automated tools for this type of problem

Automated Algorithm Configuration

Automate the setting of algorithm parameters

- Eliminate most tedious part of algorithm design and end use
- Save development time
- Improve performance

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Automate the setting of algorithm parameters

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- Save development time
- Improve performance
- First to consider the general problem,
  in particular **many categorical parameters**
  - E.g. 50/63 CPLEX parameters are categorical

$\rightsquigarrow$ Algorithm configuration

Main Contribution of this thesis

Comprehensive study of the algorithm configuration problem

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  - CPLEX: up to 23-fold speedup

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  - CPLEX: up to 23-fold speedup
  - SAT solver: 500-fold speedup for software verification

Outline

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1. Problem Definition & Intuition

2. Model-Free Search for Algorithm Configuration

3. Model-Based Search for Algorithm Configuration

4. Conclusions

Algorithm Configuration as Function Optimization

Deterministic algorithm with continuous parameters

- "Blackbox function" $f : \mathbb{R}^n \rightarrow \mathbb{R}$
- Can query function at arbitrary points $\boldsymbol{\theta} \in \mathbb{R}^n$

$$\text{Find} \quad \min_{\boldsymbol{\theta} \in \mathbb{R}^n} f(\boldsymbol{\theta})$$

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- Can sample from distribution $D_{\boldsymbol{\theta}}$ at arbitrary points $\boldsymbol{\theta} \in \boldsymbol{\Theta}$

$$\text{Find } \min_{\boldsymbol{\theta} \in \mathbb{R}^n} \tau(D_{\boldsymbol{\theta}})$$

Algorithm Configuration: General Case

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- Can *terminate* unsuccessful runs *early*

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   - ParamILS: Iterated Local Search in Configuration Space
   - "Real-World" Applications of ParamILS
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Simple manual approach for configuration

Start with some parameter configuration

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Modify a single parameter

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$\rightsquigarrow$ Manually-executed **local search**

The ParamILS Framework

Iterated Local Serach in parameter configuration space:

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Perform *subsidiary local search* on θ

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Based on *acceptance criterion*,
keep θ or revert to $\theta := \theta'$

With probability $p_{restart}$ randomly pick new θ

$\rightsquigarrow$ Performs **biased random walk over local optima**

Instantiations of ParamILS Framework

How to evaluate each configuration?

- BasicILS(N): perform fixed number of N runs to evaluate a configuration θ
  - Blocking: use same N (instance, seed) pairs for each $\boldsymbol{\theta}$

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  - large $N(\boldsymbol{\theta})$ only for good $\boldsymbol{\theta}$
  - typically outperforms BasicILS

Empirical Comparison to Previous Configuration Procedure

CALIBRA system [Adenso-Diaz & Laguna, '06]

- Based on fractional factorial designs
- Limited to continuous parameters
- Limited to 5 parameters

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Empirical comparison

- FocusedILS typically did better, never worse
- More importantly, much more general

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- Results
  - Provably never hurts
  - Sometimes substantial speedups (factor 10)

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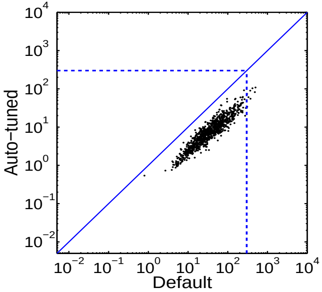

Combinatorial auctions: 7-fold speedup

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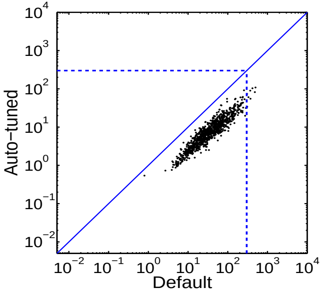

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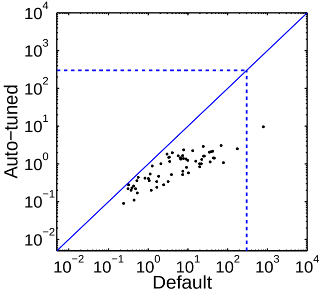

Mixed integer knapsack: 23-fold speedup

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SAT (propositional satisfiability problem)

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Spear, tree search solver for industrial SAT instances

- 26 parameters, 8.34×10^{17} configurations

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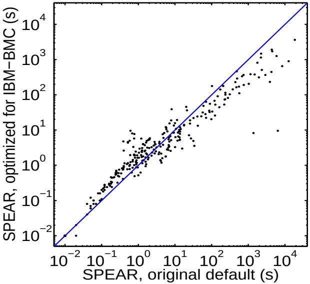

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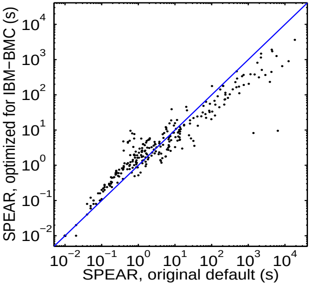

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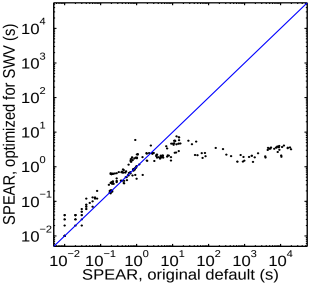

Software verification: 500-fold speedup
$\rightsquigarrow$ won 2007 SMT competition

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  - Time-tabling [Fawcett, Hoos & Chiarandini '09]
  - Local Search for SAT [Khudabukhsh, Xu, Hoos, & Leyton-Brown '09]

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  - $\rightsquigarrow$ demonstrates versatility & maturity

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   - State of the Art
   - Improvements for Stochastic Blackbox Optimization
   - Beyond Stochastic Blackbox Optimization

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- In then end: state-of-the-art configuration tool

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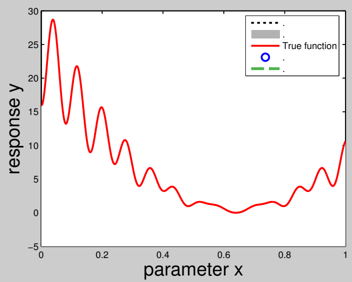
EGO algorithm [Jones, Schonlau & Welch '98]



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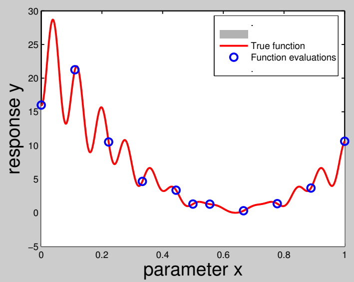

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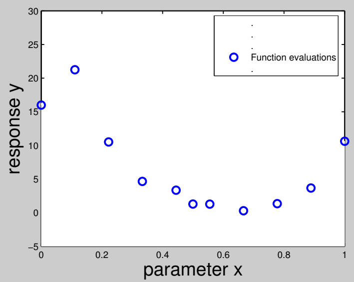

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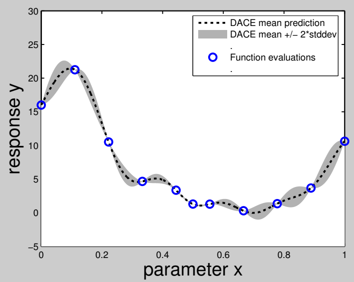

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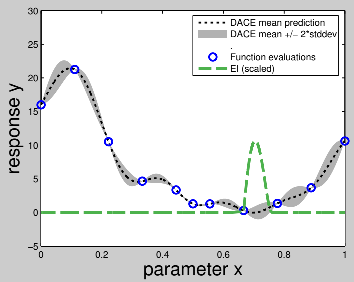

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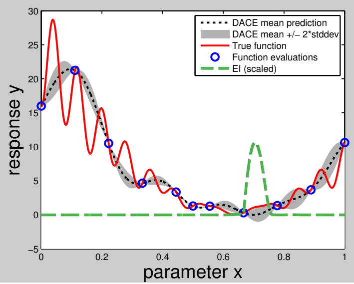

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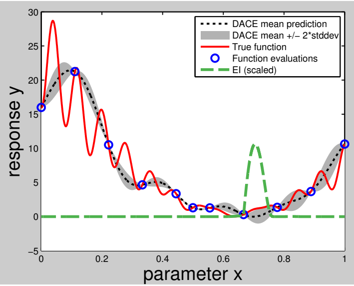
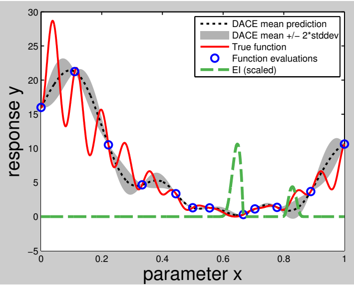


First step



Second step

Stochastic Blackbox Optimization (BBO): State of the Art

Extensions of EGO algorithm for *stochastic* case

- Sequential Parameter Optimization (SPO)
  [Bartz-Beielstein, Preuss, Lasarczyk, '05-'09]
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Empirical Evaluation

- SPO more robust

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  - Resulting configuration procedure: ActiveConfigurator
  - **Improved state of the art** for model-based stochastic BBO

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Empirical evaluation

- **ActiveConfigurator outperformed FocusedILS**

Extension II: Multiple Instances

Models incorporating multiple instances

- Can still learn probabilistic models of algorithm performance
- Model inputs:
  - algorithm parameters
  - instance features

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  - instance features

General algorithm configuration

- Algorithms with categorical parameters
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Empirical evaluation

- ActiveConfigurator never worse than FocusedILS
- Overall: model-based approaches very promising

Outline

Conclusions

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  - Can be solved by automated approaches
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Blackbox approaches

- Very general
- Can be used to optimize *your* parameters

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- Demonstrated practical relevance of algorithm configuration

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- Explore other fields of applications

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