An Experimental Investigation of Model-Based Parameter Optimization: SPO and Beyond

Frank Hutter, Holger H. Hoos,
Kevin Leyton-Brown, Kevin P. Murphy

Department of Computer Science
University of British Columbia
Canada
{hutter, hoos, kevinlb, murphyk}@cs.ubc.ca

Motivation for Parameter Optimization

Genetic Algorithms & Evolutionary Strategies are

+ Very flexible frameworks

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– Tedious to configure for a new domain
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Automated parameter optimization can help

- High-dimensional optimization problem
- Automate $\rightsquigarrow$ saves time & improves results

Parameter Optimization Methods

- Numerical parameters
  - See Blackbox optimization workshop (this GECCO)
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  - Genetic algorithms [Terashima-Marín, Ross & Valenzuela-Réndon, '99]
  - Iterated Local Search
    [Hutter, Hoos, Leyton-Brown & Stützle, '07-'09]
    - ⇝ Dozens of parameters (*e.g.*, CPLEX with 63 parameters)
    - ⇝ For many problems: SAT, MIP, time-tabling, protein folding, MPE, ...

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Model-free Parameter Optimization

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Model-based Parameter Optimization

- Methods
  - Fractional factorial designs [*e.g.*, Ridge & Kudenko, '07]
  - Sequential Parameter Optimization (SPO)
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  - Sequential Parameter Optimization (SPO)
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- Can use model for more than optimization
  - Importance of each parameter
  - Interaction between parameters

Outline

1. Sequential Model-Based Optimization (SMBO): Introduction

2. Comparing Two SMBO Methods: SPO *vs* SKO

3. Components of SPO: Model Quality

4. Components of SPO: Sequential Experimental Design

5. Conclusions and Future Work

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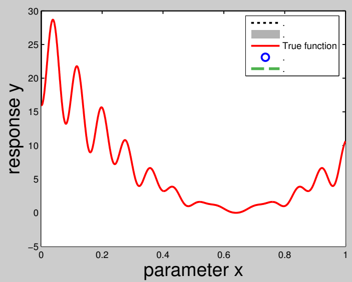
SMBO: Introduction



First step of SMBO

SMBO: Introduction

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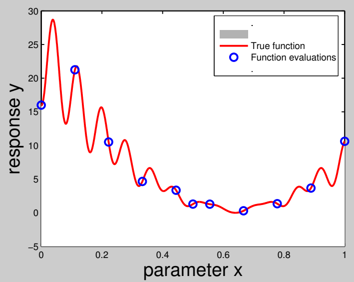

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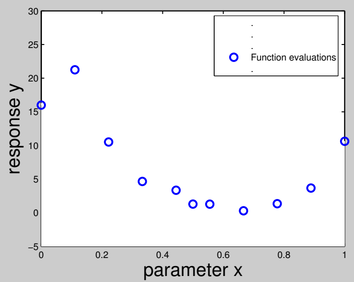

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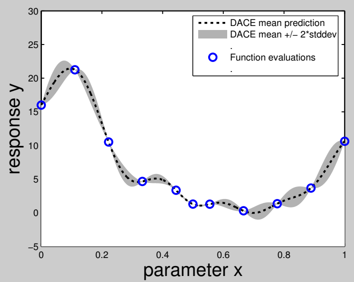

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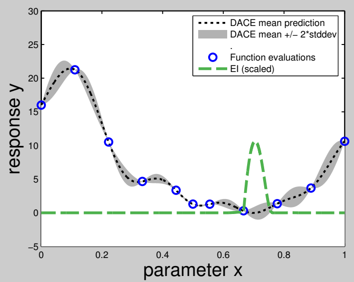

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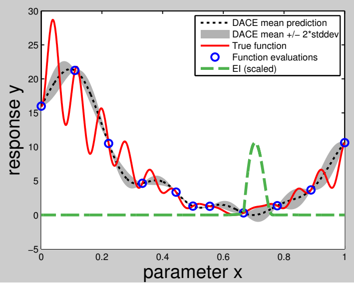

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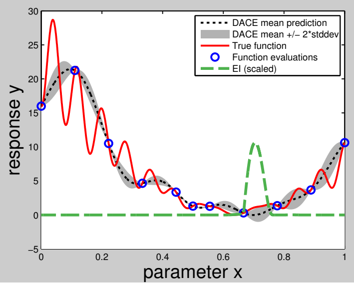
4. Repeat 2. and 3. until time is up



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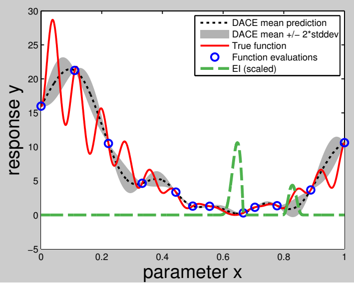

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Dealing with Noise: SKO *vs* SPO

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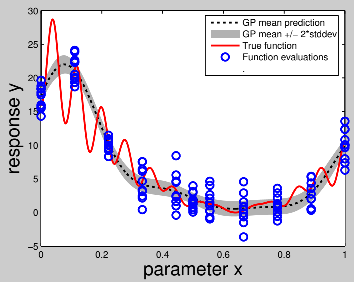
  - Fit standard GP assuming Gaussian observation noise
  - Can only fit the mean of the responses



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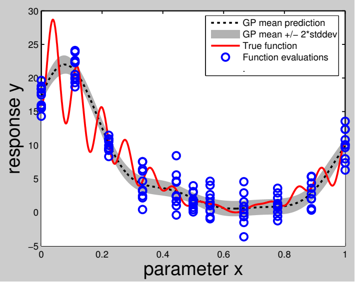
- Method II (used in SPO) [Bartz-Beielstein, Preuss, Lasarczyk, '05-'09]
  - Compute *statistic of empirical distribution of responses* at each design point
  - Fit noise-free GP to that



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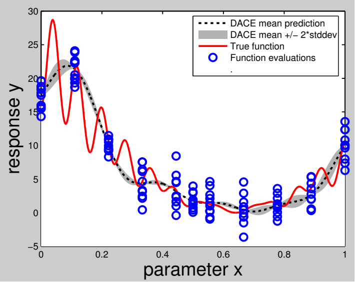

Method II: noise-free fit of cost statistic

Experiment: SPO *vs* SKO for Tuning CMA-ES

- CMA-ES [Hansen et al., '95-'09]
  - Evolutionary strategy for global optimization
  - State-of-the-art (see BBOB workshop this GECCO)
  - Parameters: population size, number of parents, learning rate, damping parameter

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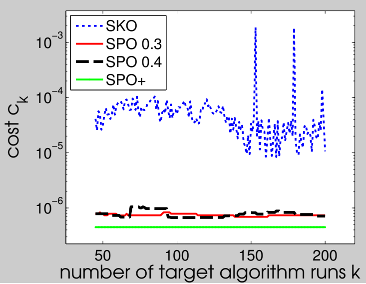

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  - SPO's standard LHD
- Result: no significant difference
  - Initial design not very important
  - Using cheap random LHD from here on

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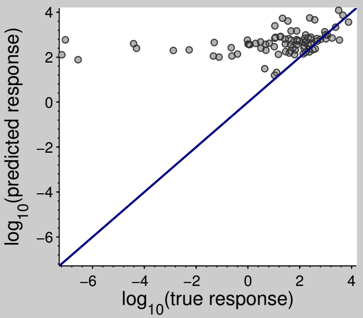

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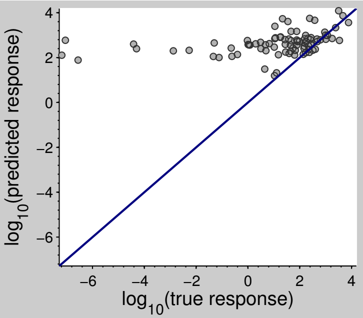

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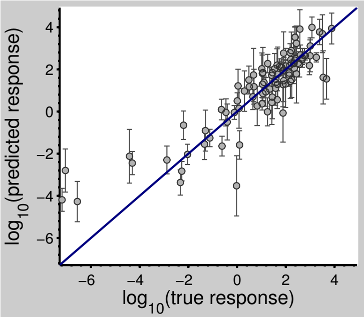

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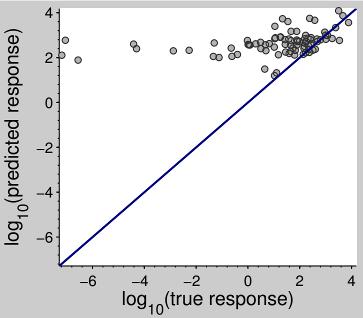

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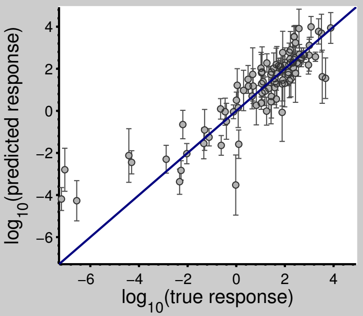

Log transformation

Note: In newer experiments, SKO with log models was competitive

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- However: no significant improvement in our experiments

Components of SPO: choosing the incumbent parameter setting in presence of noise

Some algorithm runs can be lucky

- $\rightsquigarrow$ need extra mechanism to ensure incumbent is really good
- $\rightsquigarrow$ SPO increases number of repeats over time

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- But what if it doesn't perform well?
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  - That might also turn out not to be good...

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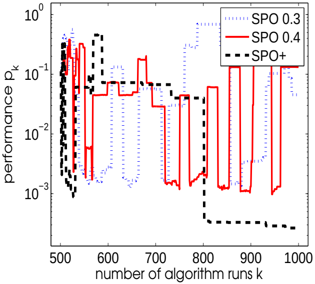

Tuning CMA-ES on Griewangk

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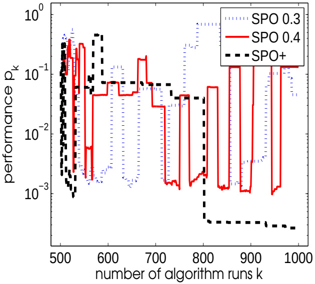

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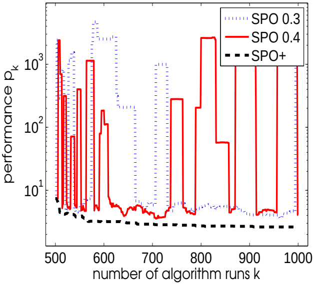

Tuning CMA-ES on Rastrigin

Summary of Study of SPO components & Definition of SPO$^+$

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Sequential Experimental Design

- Expected improvement criterion
  - $\leadsto$ New one that's better in theory but not in practice
  - $\leadsto$ Use original one in SPO$^+$
- New mechanism for increasing #runs & selecting incumbent
  - $\leadsto$ substantially improves robustness
  - $\leadsto$ Use it in SPO$^+$

Comparison to State of the Art for tuning SAPS

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  - Stochastic local search algorithm for SAT
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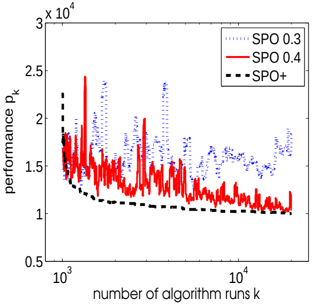

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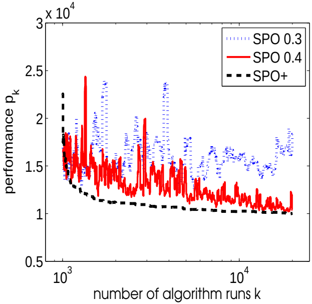

Comparison to SPO variants, with varying budget

Procedure	SAPS median run-time/10^3
SAPS default	85.5
CALIBRA(100)	10.7 ± 1.1
BasicILS(100)	10.9 ± 0.6
FocusedILS	10.6 ± 0.5
SPO 0.3	18.3 ± 13.7
SPO 0.4	10.4 ± 0.7
SPO$^+$	$\mathbf{10.0} \pm \mathbf{0.4}$

With budget of 20000 runs of SAPS

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  - More principled, saves development time
  - Can exploit full potential of flexible algorithms
- Our contribution
  - Insights: what makes a popular SMBO algorithm, SPO, work
  - Improved version, SPO^+, often performs better than SPO

Ongoing & Future Work

Ongoing Extensions of Model-Based Framework

- Use of different models in SPO^{+} framework
- Dealing with categorical parameters
- Optimization for Sets/Distributions of Instances

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Use of models for scientific understanding

- Interactions of instance features and parameter values
- Can help understand and hopefully improve algorithms

Thanks to

- Thomas Bartz-Beielstein
  - SPO implementation & CMA-ES wrapper
- Theodore Allen
  - SKO implementation