Programming by Optimisation:

Towards a new Paradigm for Developing High-Performance Software

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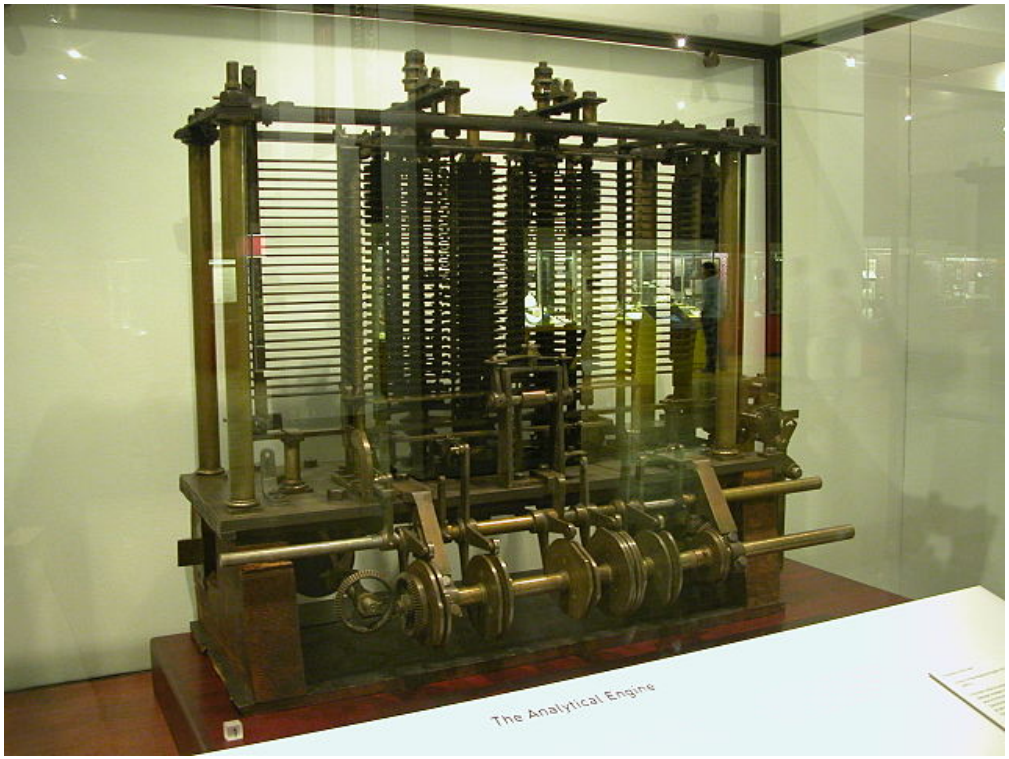
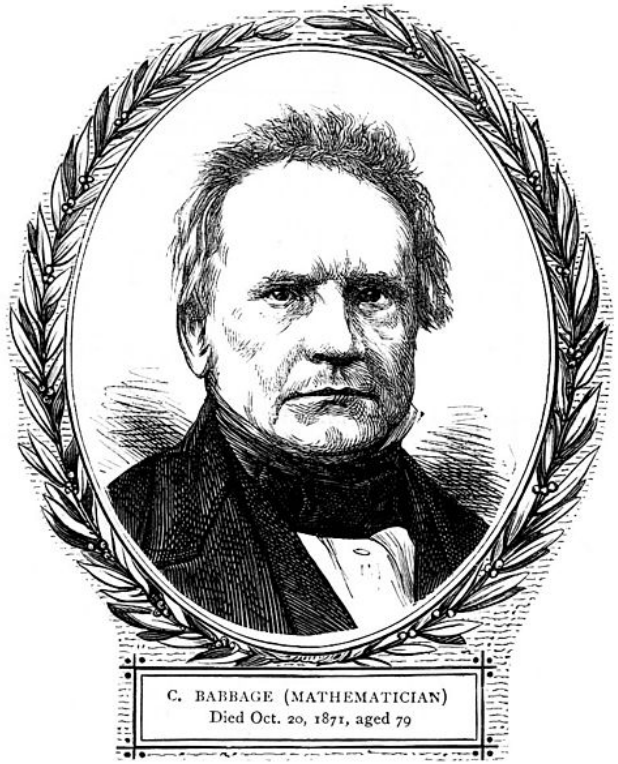
The age of machines





"As soon as an Analytical Engine exists, it will necessarily guide the future course of the science. Whenever any result is sought by its aid, the question will then arise – by what course of calculation can these results be arrived at by the machine in the shortest time?"

(Charles Babbage, 1864)

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When algorithms control the world

By Jane Wakefield
Technology reporter

If you were expecting some kind of warning when computers finally get smarter than us, then think again.

There will be no soothing HAL 9000-type voice informing us that our human services are now surplus to requirements.

In reality, our electronic overlords are already taking control, and they are doing it in a far more subtle way than science fiction would have us believe.

Their weapon of choice - the algorithm.

Behind every smart web service is some even smarter web code. From the web retailers - calculating what books and films we might be interested in, to Facebook's friend finding and image tagging services, to the search engines that guide us around the net.

Algorithms are spreading their influence around the globe

It is these invisible computations that increasingly control how we interact with our electronic world.

At last month's TEDGlobal conference, algorithm expert Kevin Slavin delivered one of the tech show's most "sit up and take notice" speeches where he warned that the "maths that computers use to decide stuff" was infiltrating every aspect of our lives.

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"The maths[!] that computers use to decide stuff [is] infiltrating every aspect of our lives."

- financial markets
- social interactions
- cultural preferences
- artistic production
- ...

Performance matters ...

- computation speed (time is money!)
- energy consumption (battery life, ...)
- quality of results (cost, profit, weight, ...)

... increasingly:

- globalised markets
- just-in-time production & services
- tighter resource constraints

Example: Resource allocation

- resources $>$ demands $\rightsquigarrow$ many solutions, easy to find

  economically wasteful

  $\rightsquigarrow$ reduction of resources / increase of demand

- resources $<$ demands $\rightsquigarrow$ no solution, easy to demonstrate

  lost market opportunity, strain within organisation

  $\rightsquigarrow$ increase of resources / reduction of demand

- resources $\approx$ demands

  $\rightsquigarrow$ difficult to find solution / show infeasibility

This talk:

new approach to software development, leveraging . . .

- human creativity
- optimisation & machine learning
- large amounts of computation / data

Key idea:

- program $\rightsquigarrow$ (large) space of programs
- encourage software developers to
  - avoid premature commitment to design choices
  - seek & maintain design alternatives
- automatically find performance-optimising designs for given use context(s)

$\Rightarrow$ Programming by Optimisation (PbO)

Outline

1. Introduction
2. Vision & promise of PbO
3. Design space specification
4. Design optimisation
5. Cost & concerns
6. The road ahead – towards main-stream use of PbO

DOI:10.1145/2076450.2076468

Avoid premature commitment, seek design alternatives, and automatically generate performance-optimized software.

BY HOLGER H. HOOS

Programming by Optimization

WHEN CREATING SOFTWARE, developers usually explore different ways of achieving certain tasks. These alternatives are often eliminated or abandoned early in the process, based on the idea that the flexibility they afford would be difficult or impossible to exploit later. This article challenges this view, advocating an approach that encourages developers to not only avoid premature commitment to certain design choices but to actively develop promising alternatives for parts of the design. In this approach, dubbed Programming by Optimization, or PbO, developers specify a potentially large design space of programs that accomplish a given task, from which versions of the program optimized for various use contexts are generated automatically, including parallel versions derived from the same sequential sources. We outline a simple, generic programming language extension that supports the specification of such design spaces and discuss ways specific programs that perform well in a given use context can be obtained from these specifications through relatively simple source-code transformations and powerful design-optimization methods. Using PbO, human experts can focus on the creative task of devising possible mechanisms for solving given problems or subproblems, while the tedious task of determining what works best in a given use context is performed automatically, substituting human labor by computation.

The potential of PbO is evident from recent empirical results (see the table here). In the first two use cases—mixed integer programming and planning—existing software exposing many design choices in the form of parameters was automatically optimized for speed. This resulted in, for example, up to 52-fold speedups for the widely used commercial IBM ILOG CPLEX Optimizer software for solving mixed-integer programming problems.[3] In the third use case—verification problems encoded into propositional satisfiability—the proactive development of alternatives for important components of the program were an important part of the design process, enabling even greater performance gains.

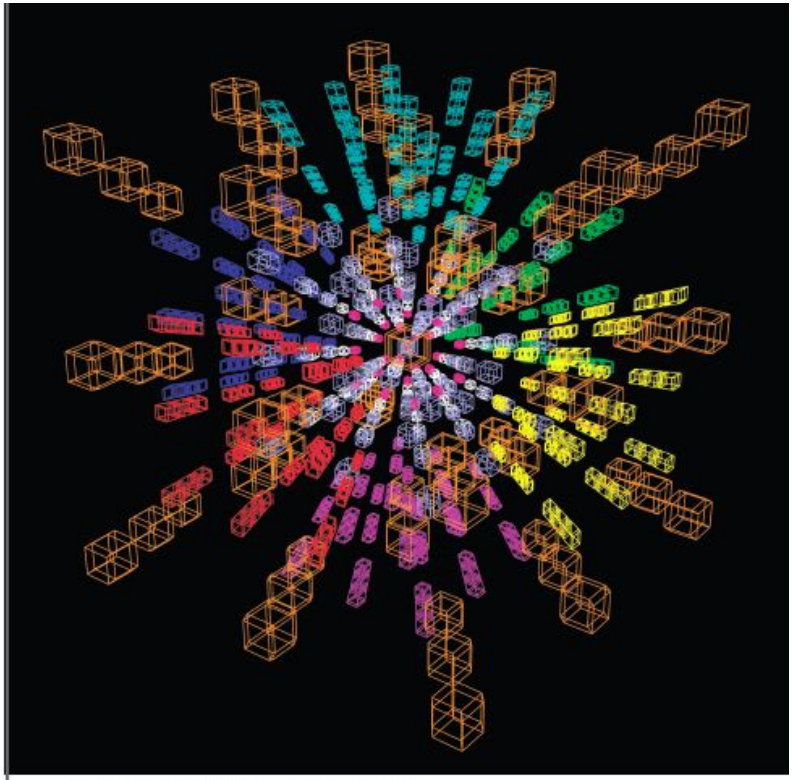
Performance Matters

Computer programs and the algorithms on which they are based frequently involve different ways of getting something done. Sometimes, certain choices are clearly preferable, but it is often unclear a priori which of several design decisions will ultimately give the best results. Such design choices can, and, routinely, do, occur at many levels, from high-level architectural aspects of a software system to low-level implementation details. They are often made based on considerations of maintainability, extensibility, and performance of the system or program under development. This article focuses on this latter aspect of a system's performance, considering only sets of semantically equivalent design choices and situations in which the performance of a program depends on the decisions made for each part of the program for which one or more candidate designs are available, even though these choices do not affect the program's correctness and functionality. Note this premise differs fundamentally from that of program synthesis, in which the primary goal is to come up with a design that satisfies a given functional specification.

It may appear that (partly due to the sustained, exponential improvement in computer hardware over more than five decades) software performance is a relatively minor concern. However, upon closer inspection this is far from

» key insights

- Premature commitment to design choices during software development often leads to loss of performance and limited flexibility.
- PbO aims to avoid premature design choices and actively develop design alternatives, leading to large and rich design spaces of programs that can be specified through simple generic extensions of existing programming languages.
- Advanced optimization and machine-learning techniques make it possible to perform automated performance optimization over the large spaces of programs arising in PbO-based software development; per-instance algorithm selectors and parallel algorithm portfolios can be obtained from the same sequential source.



MagicCube5D, a fully functional five-dimensional analogue of Rubik's Cube.

Communications of the ACM, 55(2), pp. 70–80, February 2012

www.prog-by-opt.net

Example: SAT-based software verification

Hutter, Babić, HH, Hu (2007)

- **Goal:** Solve SAT-encoded software verification problems as fast as possible
- new DPLL-style SAT solver SPEAR (by Domagoj Babić)
  = highly parameterised heuristic algorithm
  (26 parameters, $\approx 8.3 \times 10^{17}$ configurations)
- manual configuration by algorithm designer
- automated configuration using ParamILS, a generic algorithm configuration procedure
  Hutter, HH, Stützle (2007)

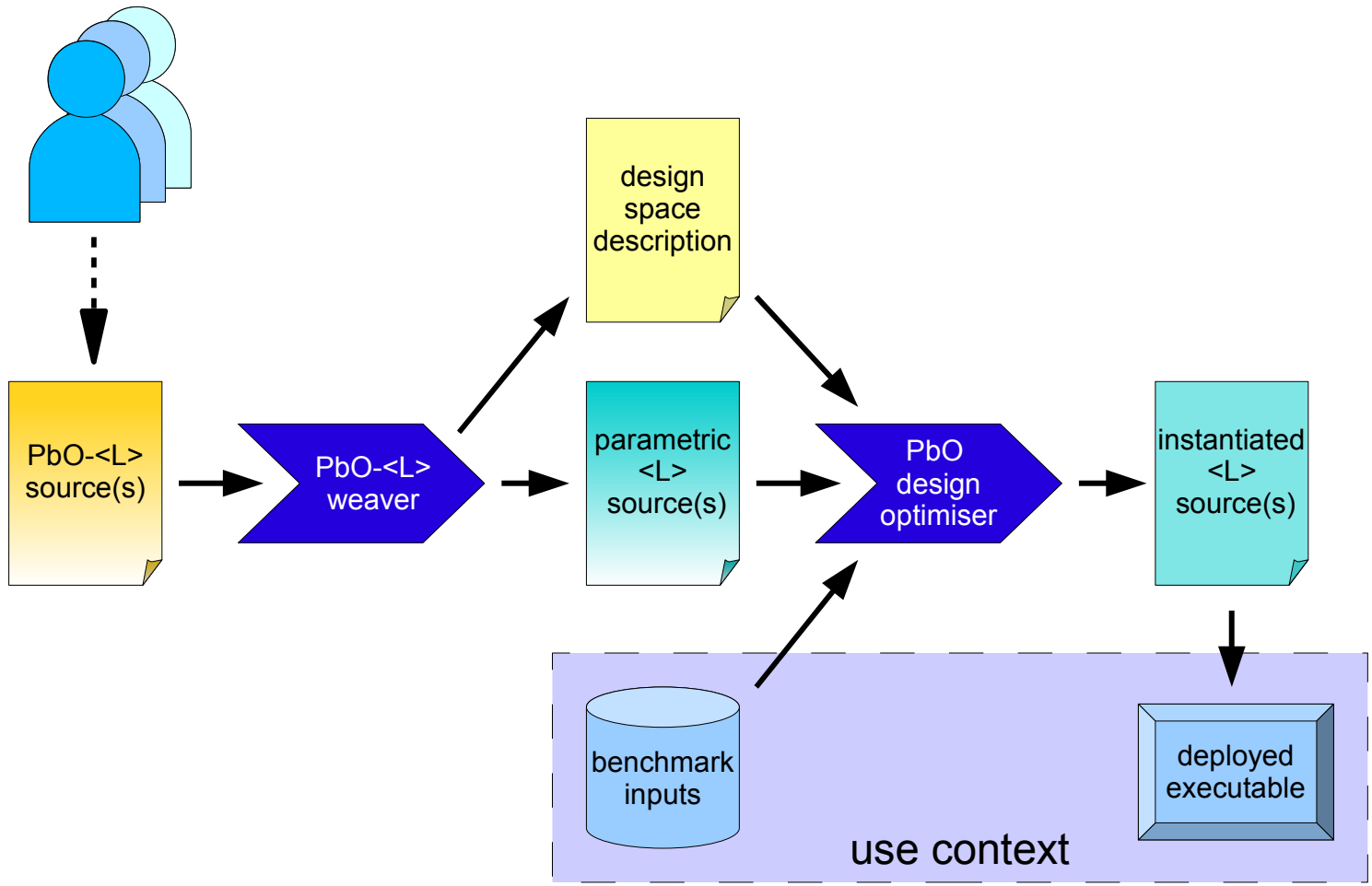
SPEAR: Performance on software verification benchmarks

solver	num. solved	mean run-time
MiniSAT 2.0	302/302	161.3 CPU sec
SPEAR original	298/302	787.1 CPU sec
SPEAR generic. opt. config.	302/302	35.9 CPU sec
SPEAR specific. opt. config.	302/302	1.5 CPU sec

- $\approx$ 500-fold speedup through use automated algorithm configuration procedure (ParamILS)
- new state of the art

  (winner of 2007 SMT Competition, QF_BV category)

Software development in the PbO paradigm



Levels of PbO:

Level 4: Make no design choice prematurely that cannot be justified compellingly.

Level 3: Strive to provide design choices and alternatives.

Level 2: Keep and expose design choices considered during software development.

Level 1: Expose design choices hardwired into existing code (magic constants, hidden parameters, abandoned design alternatives).

Level 0: Optimise settings of parameters exposed by existing software.

Success in optimising speed:

Application, Design choices	Speedup	PbO level
SAT-based software verification (SPEAR), 41 Hutter, Babić, HH, Hu (2007)	4.5–500 ×	2–3
AI Planning (LPG), 62 Vallati, Fawcett, Gerevini, HH, Saetti (2011)	3–118 ×	1
Mixed integer programming (CPLEX), 76 Hutter, HH, Leyton-Brown (2010)	2–52 ×	0

... and solution quality:

University timetabling, 18 design choices, PbO level 2–3
$\rightsquigarrow$ new state of the art; UBC exam scheduling
Fawcett, Chiarandini, HH (2009)

Machine learning / Classification, 803 design choices, PbO level 0–1
$\rightsquigarrow$ outperforms specialised model selection & hyper-parameter optimisation methods from machine learning
Thornton, Hutter, HH, Leyton-Brown (2012)

Mixed Integer Programming (MIP)

Hutter, HH, Leyton-Brown, Stützle (2009); Hutter, HH, Leyton-Brown (2010)

- MIP is widely used for modelling optimisation problems
- MIP solvers play an important role for solving broad range of real-world problems

CPLEX:

- prominent and widely used commercial MIP solver
- exact solver, based on sophisticated branch & cut algorithm and numerous heuristics
- 159 parameters, 81 directly control search process

"A great deal of algorithmic development effort has been devoted to establishing default ILOG CPLEX parameter settings that achieve good performance on a wide variety of MIP models."

[CPLEX 12.1 user manual, p. 478]

Automatically Configuring CPLEX:

- starting point: factory default settings
- 63 parameters (some with 'AUTO' settings)
- 1.38×10^{37} configurations
- configurator: FocusedILS 2.3 (Hutter *et al.* 2009)
- performance objective: minimal mean run-time
- configuration time: 10×2 CPU days

CPLEX on various MIPS benchmarks

Benchmark	Default performance [CPU sec]	Optimised performance [CPU sec]	Speedup factor
BCOL/CONIC.SCH	5.37	2.35 (2.4 ± 0.29)	2.2
BCOL/CLS	712	23.4 (327 ± 860)	30.4
BCOL/MIK	64.8	1.19 (301 ± 948)	54.4
CATS/REGIONS200	72	10.5 (11.4 ± 0.9)	6.8
RNA-QP	969	525 (827 ± 306)	1.8

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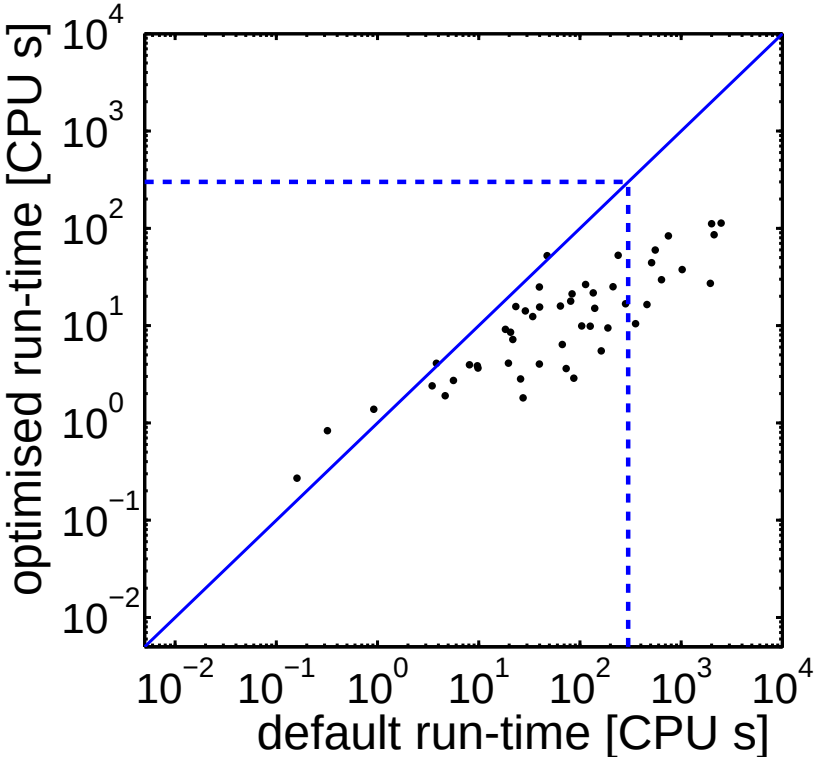
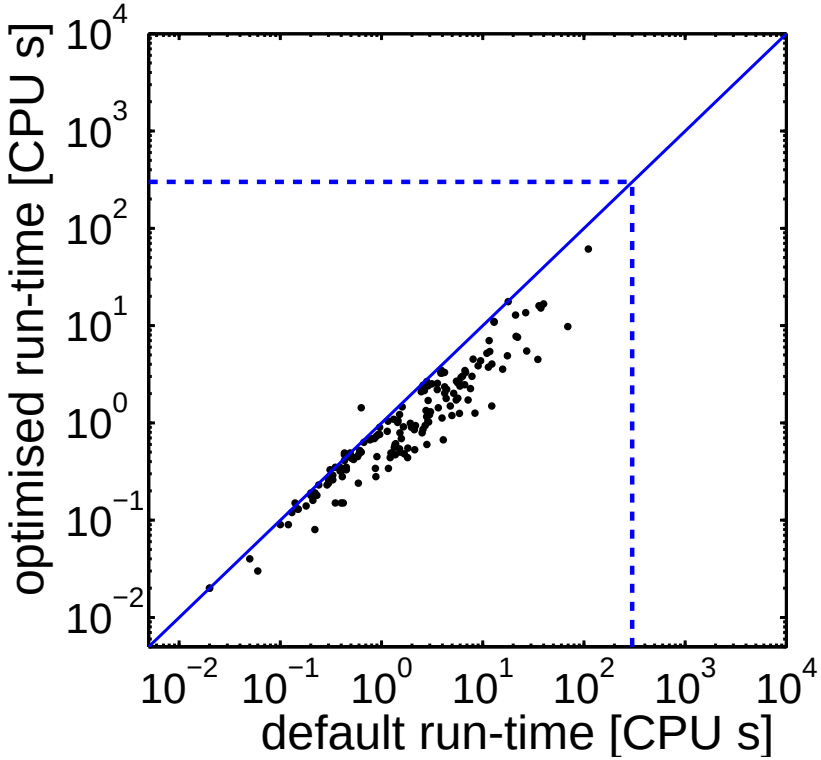
(Timed-out runs are counted as $10 \times$ cutoff time.)

CPLEX on BCOL/CLS



CPLEX on BCOL/CONIC.SCH



Planning

Vallati, Fawcett, HH, Gerevini, Saetti (2011)

- classical, well-studied AI challenge
- many variations, domains (explicitly specified)

LPG:

- state-of-the-art, versatile system for plan generation, plan repair and incremental planning for PDDL2.2 domains
- based on stochastic local search over partial plans
- 62 parameters, over 6.5×10^{17} configurations
  4 of these previously "magic constants",
  50 hidden (= undocumented)
- automated configuration using FocusedILS 2.3 (as for CPLEX)

LPG on various planning domains

Domain	Default performance [CPU sec] (% solved)	Optimised performance [CPU sec] (% solved)
Blocksworld	105.3 (98.8%)	4.29 (100%)
Depots	78.1 (90.3%)	5.7 (98.5%)
Gold-miner	94.4 (90.5%)	1.6 (100%)
Matching-BW	93.8 (15.8%)	5.6 (97.8%)
N-Puzzle	321 (85%)	31.2 (86.8%)
Rovers	72.2 (100%)	21.2 (100%)
Satellite	64 (100%)	1.3 (100%)
Sokoban	24.6 (75.8%)	1.19 (96.5%)
Zenotravel	103.7 (100%)	11.1 (100%)

Run-time cutoff for evaluation: 600 CPU sec

Post-Enrolment Course Timetabling

Chiarandini, Fawcett, HH (2008); Fawcett, HH, Chiarandini (in preparation)

Setting:

- students enroll in courses
- courses are assigned to rooms and time slots, subject to *hard constraints*
- preferences are represented by *soft constraints*

Our solver:

- modular multiphase stochastic local search algorithm
- *hard constraint solver:* finds feasible course schedules
- *soft constraint solver:* optimise schedule (maintaining feasibility)

Solver #1:

- developed over ca. 1 month
- starting point: Chiarandini *et al.* (2003)
- *soft constraint solver* unchanged
- automatically configured *hard constraint solver*

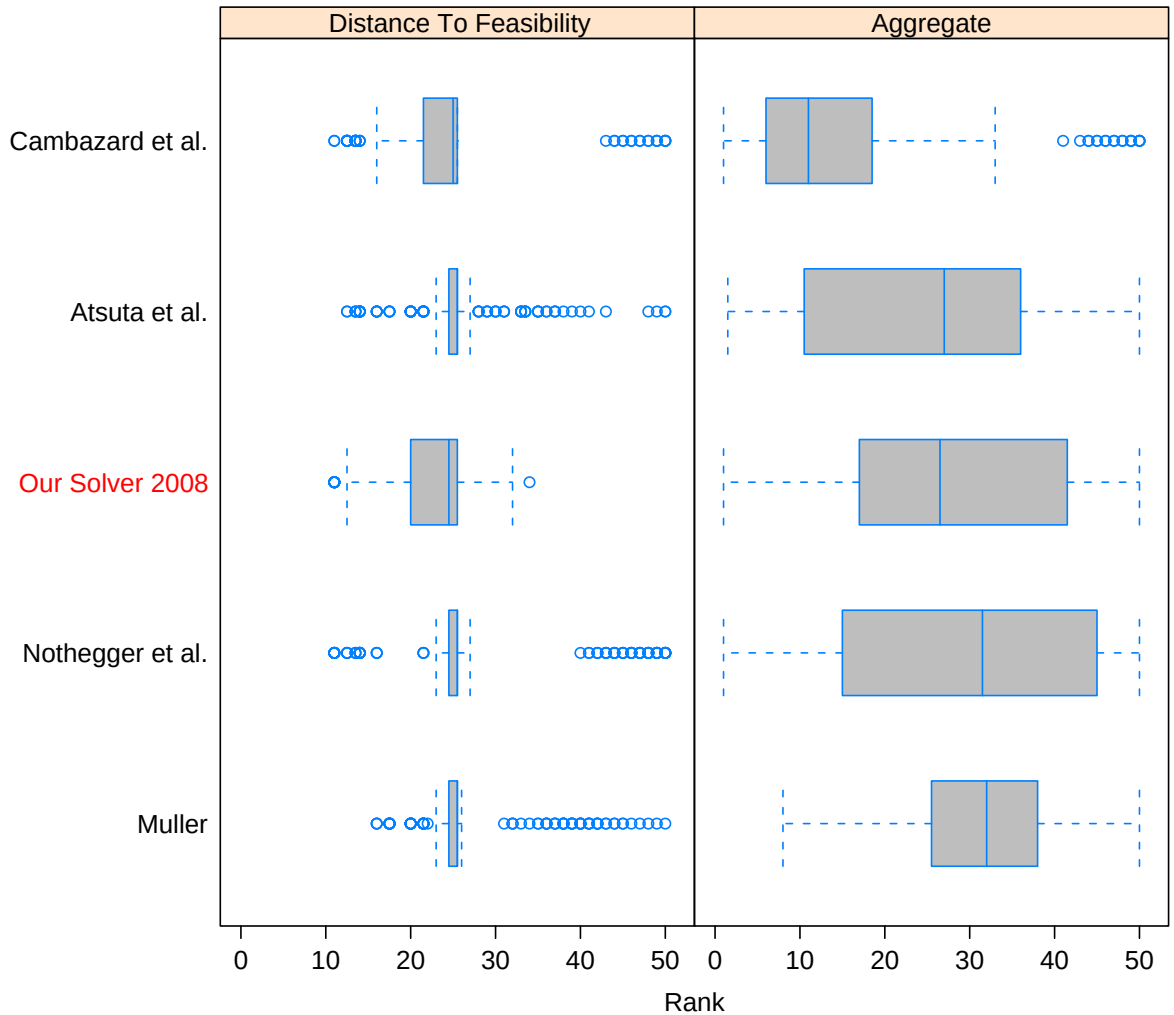
Design space for hard constraint solver:

- parameterised combination of constructive search, tabu search, diversification strategy
- 7 parameters, 50 400 configurations

Automated configuration process:

- configurator: FocusedILS 2.3 (Hutter *et al.* 2009)
- performance objective: solution quality after 300 CPU sec

2nd International Timetabling Competition (ITC), Track 2



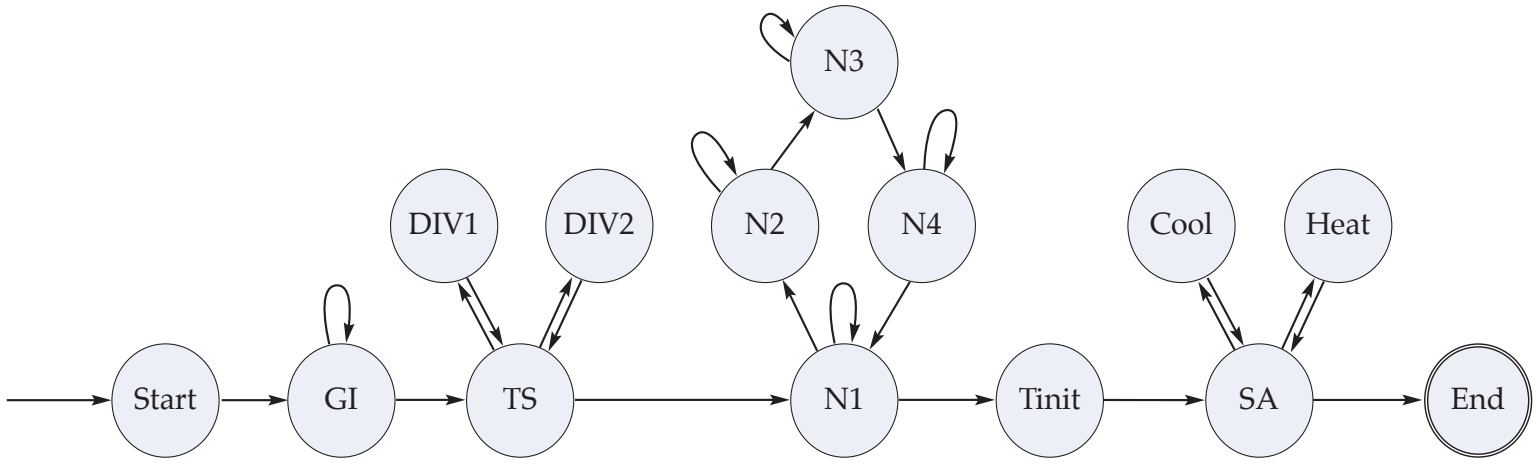
Solver #2:

- developed over ca. 6 months
- starting point: solver #1
- automatically configured *hard & soft constraint* solvers

Design space for soft constraint solver:

- highly parameterised simulated annealing algorithm
- 11 parameters, 2.7×10^9 configurations

High-level structure of timetabling solver



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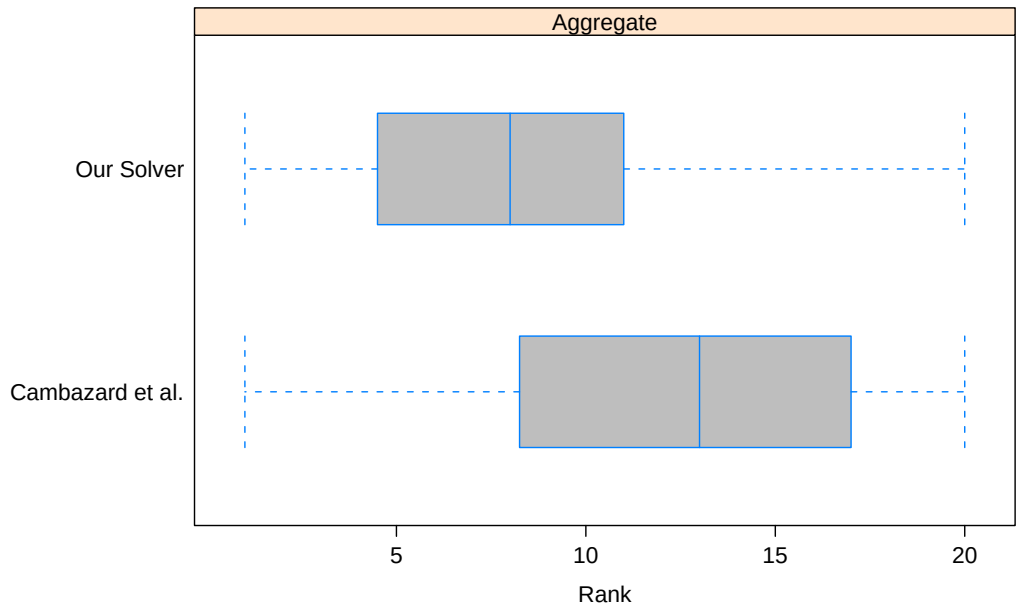
Design space for soft constraint solver:

- highly parameterised simulated annealing algorithm
- 11 parameters, 2.7×10^9 configurations

Automated configuration process:

- configurator: FocusedILS 2.4 (new version, multiple stages)
- multiple performance objectives
  (final stage: solution quality after 600 CPU sec)

2-way race against ITC Track 2 winner



- solver #2 wins beats ITC winner on 20 out of 24 competition instances
- application to university-wide exam scheduling at UBC
  ($\approx$ 1650 exams, 44 000 students)

Automated Selection and Hyper-Parameter Optimization of Classification Algorithms

Thornton, Hutter, HH, Leyton-Brown (2012)

Fundamental problem:

Which of many available algorithms (models) applicable to given machine learning problem to use, and with which hyper-parameter settings?

Example: WEKA contains 47 classification algorithms

Our solution, Auto-WEKA

- select between the 47 algorithms using a top-level categorical choice
- consider hyper-parameters for each algorithm
- solve resulting algorithm configuration problem using general-purpose configurator SMAC
- first time joint algorithm/model selection + hyperparameter-optimisation problem is solved

Automated configuration process:

- configurator: SMAC
- performance objective: cross-validated mean error rate
- time budget: $4 \times 10\,000\,CPUsec$

Selected results (median error rate over 25 runs)

Dataset	#Instances	#Features	#Classes	Best Def.	TPE	Auto-WEKA
WDBC	569	30	2	3.53	3.53	**2.94**
Hill-Valley	606	101	2	7.73	6.08	**0.55**
Arcene	900	10 000	2	8.33	5.00	8.33
Semeion	1593	256	10	8.18	7.87	7.87
Car	1728	6	4	0.77	0.39	**0**
KR-vs-KP	3196	37	2	0.73	0.84	**0.31**
Waveform	5000	40	3	14.33	14.53	**14.20**
Gisette	7000	5000	2	2.81	2.62	**2.29**

Further details: http://arxiv.org/abs/1208.3719

PbO enables . . .

- performance optimisation for different use contexts
  (some details later)
- adaptation to changing use contexts
  (see, *e.g.*, life-long learning – Thrun 1996)
- self-adaptation while solving given problem instance
  (*e.g.*, Battiti *et al.* 2008; Carchrae & Beck 2005; Da Costa *et al.* 2008)
- automated generation of instance-based solver selectors
  (*e.g.*, SATzilla – Leyton-Brown *et al.* 2003, Xu *et al.* 2008;
  Hydra – Xu *et al.* 2010; ISAC – Kadioglu *et al.* 2010)
- automated generation of parallel solver portfolios
  (*e.g.*, Huberman *et al.* 1997; Gomes & Selman 2001;
  Schneider *et al.* 2012)

Design space specification

Option 1: use language-specific mechanisms

- command-line parameters
- conditional execution
- conditional compilation (`ifdef`)

Option 2: generic programming language extension

Dedicated support for ...

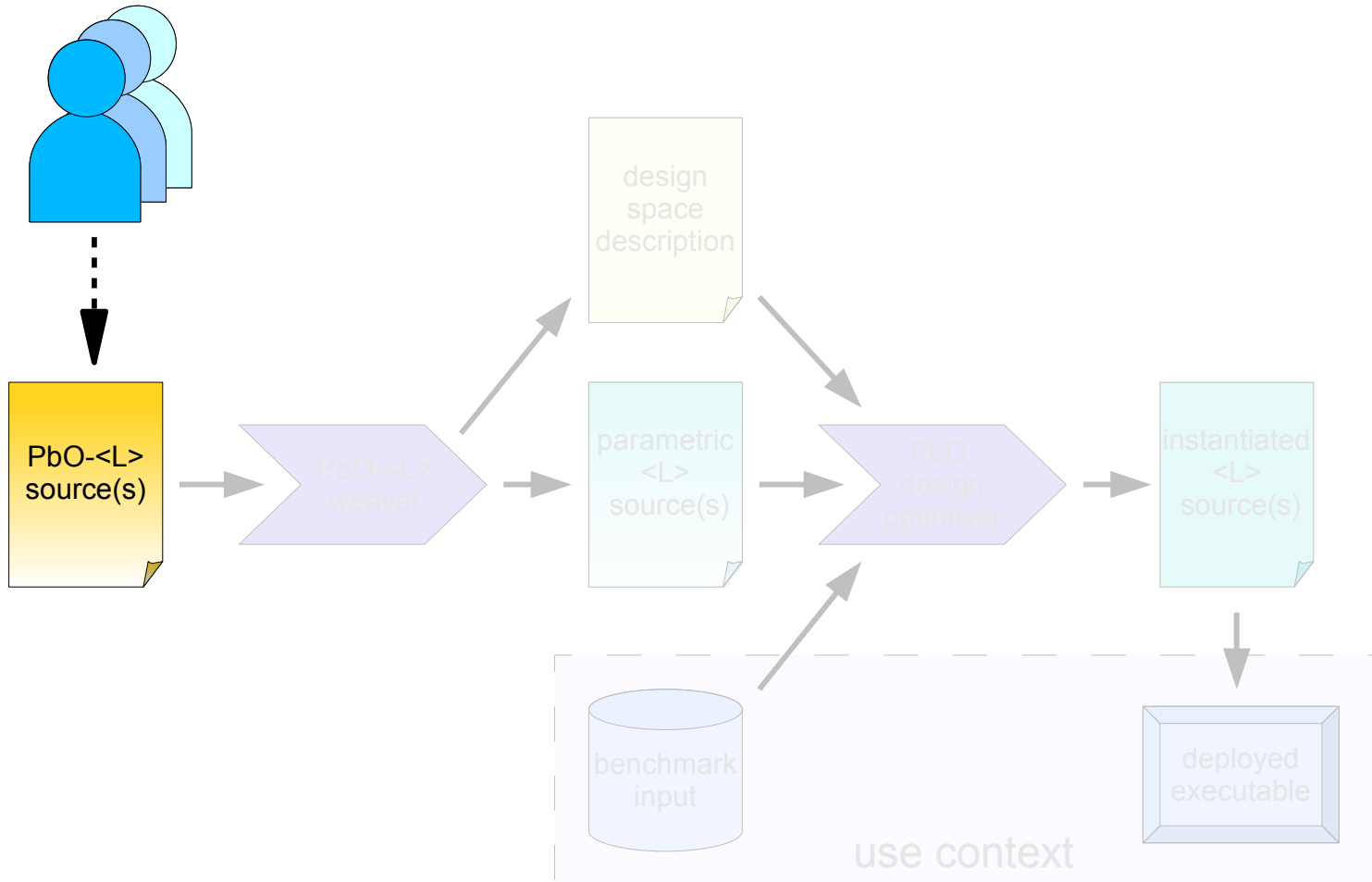
- exposing parameters
- specifying alternative blocks of code

Advantages of generic language extension:

- reduced overhead for programmer
- clean separation of design choices from other code
- dedicated PbO support in software development environments

Key idea:

- augmented sources: *PbO-Java* = Java + PbO constructs, ...
- tool to compile down into target language: *weaver*


PbO-<L>
source(s)
PbO-<L>
weaver
design
space
description
parametric
<L>
source(s)
PbO
design
optimiser
instantiated
<L>
source(s)
benchmark
input
deployed
executable
use context

Exposing parameters

```
...
numerator -= (int) (numerator / (adjfactor+1) * 1.4);
...       ...
##PARAM(float multiplier=1.4)
numerator -= (int) (numerator / (adjfactor+1) * ##multiplier);
...
```

- parameter declarations can appear at arbitrary places (before or after first use of parameter)
- access to parameters is read-only (values can only be set/changed via command-line or config file)

Specifying design alternatives

- **Choice:** set of interchangeable fragments of code that represent design alternatives (**instances of choice**)
- **Choice point:** location in a program at which a choice is available

```
##BEGIN CHOICE preProcessing
<block 1>
##END CHOICE preProcessing
```

Specifying design alternatives

- **Choice:** set of interchangeable fragments of code that represent design alternatives (**instances of choice**)
- **Choice point:** location in a program at which a choice is available

```
##BEGIN CHOICE preProcessing=standard
<block S>
##END CHOICE preProcessing

##BEGIN CHOICE preProcessing=enhanced
<block E>
##END CHOICE preProcessing
```

Specifying design alternatives

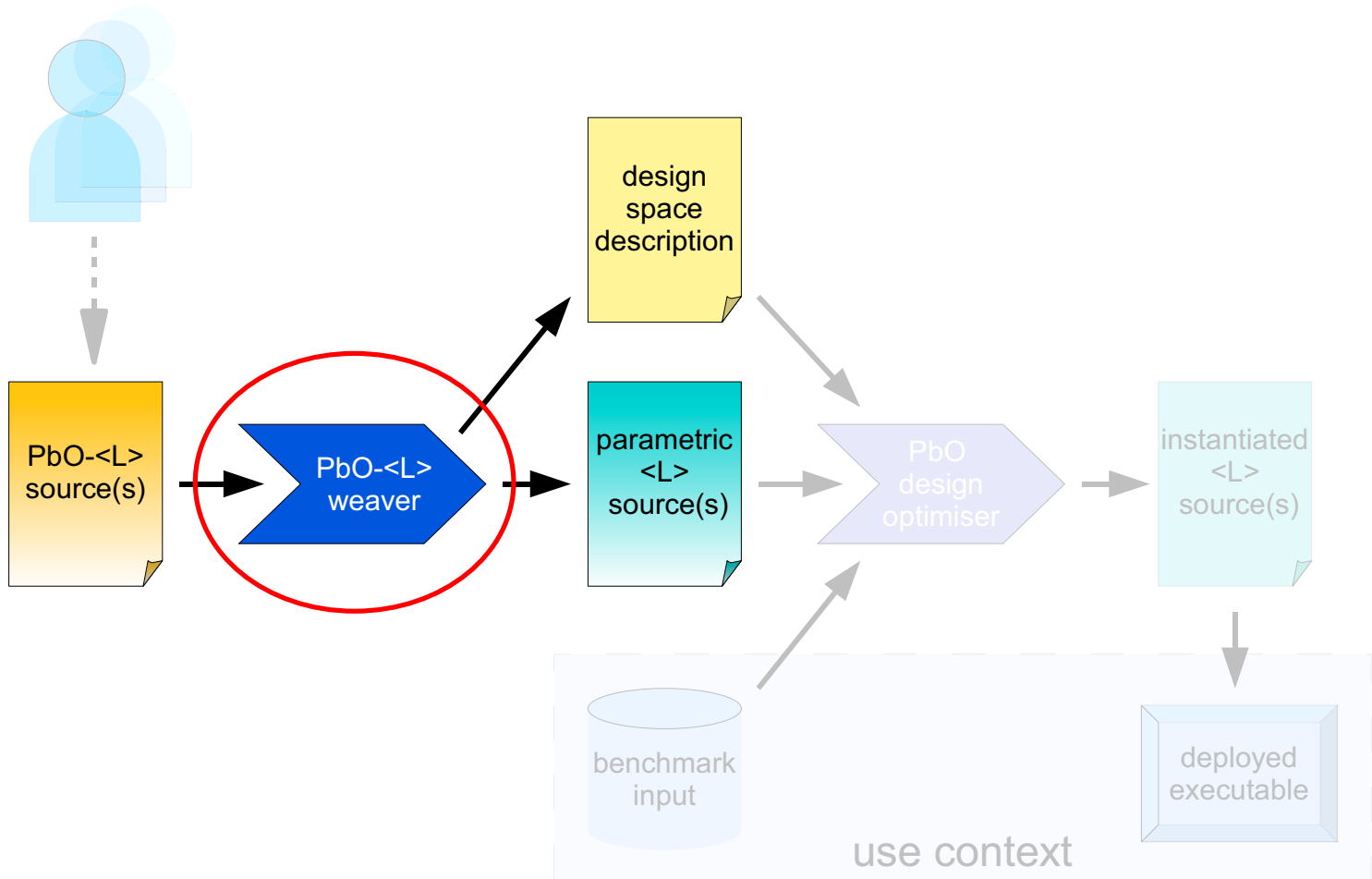
- **Choice:** set of interchangeable fragments of code that represent design alternatives (**instances of choice**)
- **Choice point:** location in a program at which a choice is available

```
##BEGIN CHOICE preProcessing
<block 1>
##END CHOICE preProcessing

...

##BEGIN CHOICE preProcessing
<block 2>
##END CHOICE preProcessing
```

Specifying design alternatives

- **Choice:** set of interchangeable fragments of code that represent design alternatives (**instances of choice**)
- **Choice point:** location in a program at which a choice is available

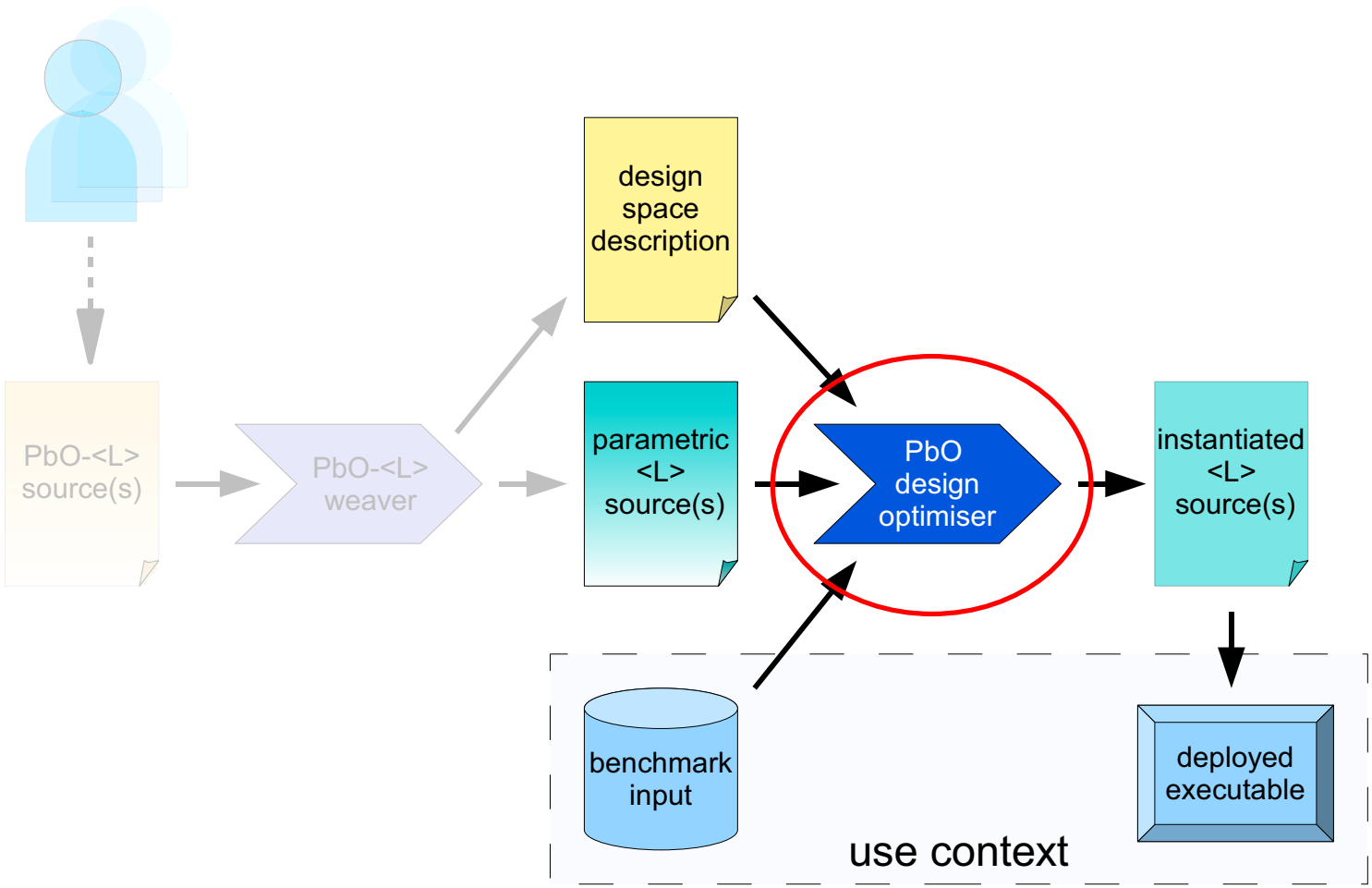
```
##BEGIN CHOICE preProcessing
<block 1a>
  ##BEGIN CHOICE extraPreProcessing
  <block 2>
  ##END CHOICE extraPreProcessing
<block 1b>
##END CHOICE preProcessing
```


design space description
PbO-<L> source(s)
PbO-<L> weaver
parametric <L> source(s)
PbO design optimiser
instantiated <L> source(s)
benchmark input
deployed executable
use context

The Weaver

transforms PbO-<L> code into <L> code
(<L> = Java, C++, . . .)

- parametric mode:
  - expose parameters
  - make choices accessible via (conditional, categorical) parameters
- (partial) instantiation mode:
  - hardwire (some) parameters into code (expose others)
  - hardwire (some) choices into code (make others accessible via parameters)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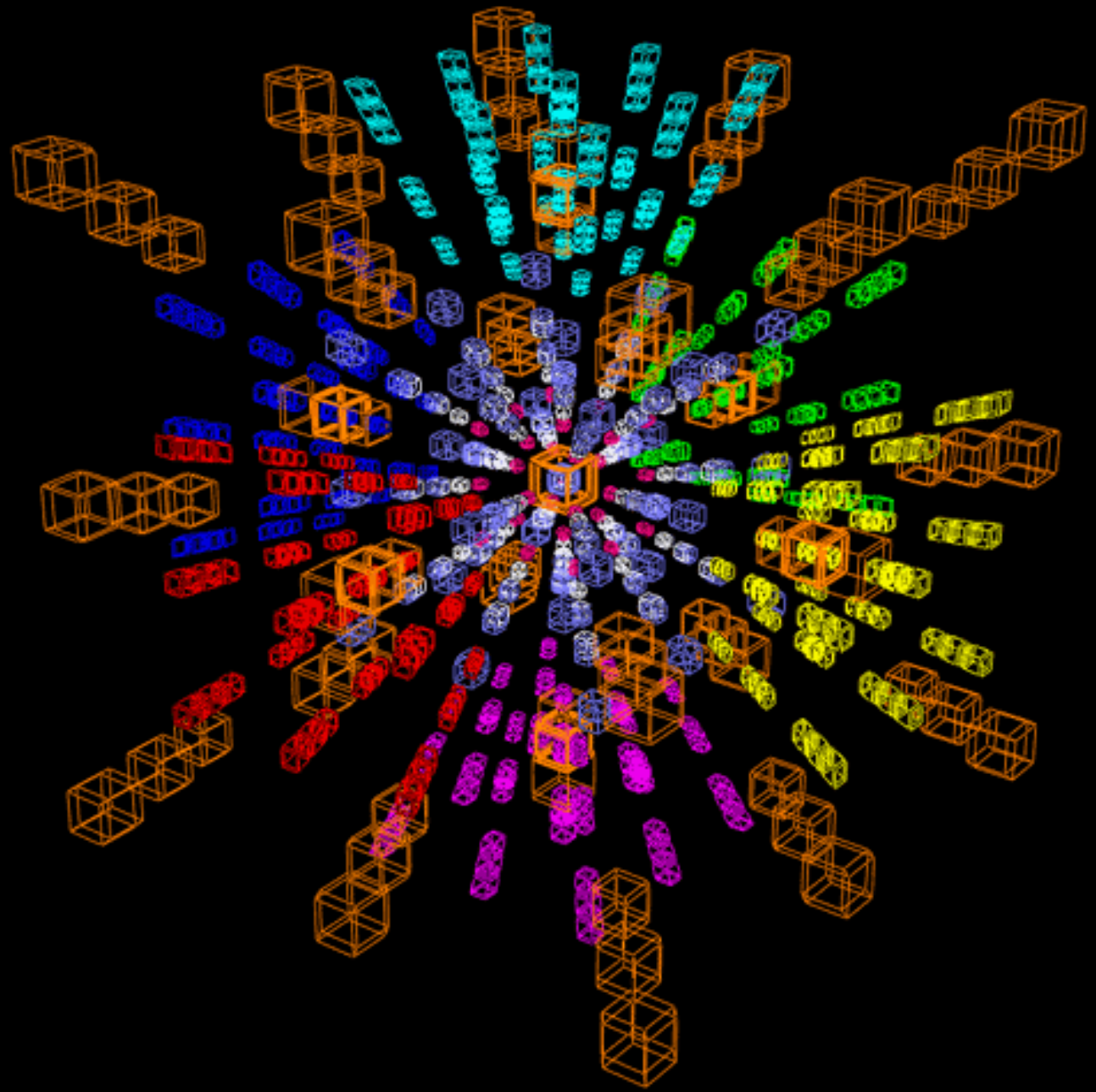


Design optimisation

Simplest case: Configuration / tuning

- Standard optimisation techniques

  (*e.g.*, CMA-ES – Hansen & Ostermeier 01; MADS – Audet & Orban 06)

- Advanced sampling methods

  (*e.g.*, REVAC, REVAC++ – Nannen & Eiben 06–09)

- Racing

  (*e.g.*, F-Race – Birattari, Stützle, Paquete, Varrentrapp 02;

  Iterative F-Race – Balaprakash, Birattari, Stützle 07)

- Model-free search

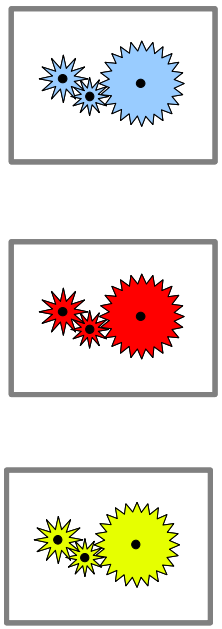
  (*e.g.*, ParamILS – Hutter, HH, Stützle 07;

  Hutter, HH, Leyton-Brown, Stützle 09)

- Sequential model-based optimisation

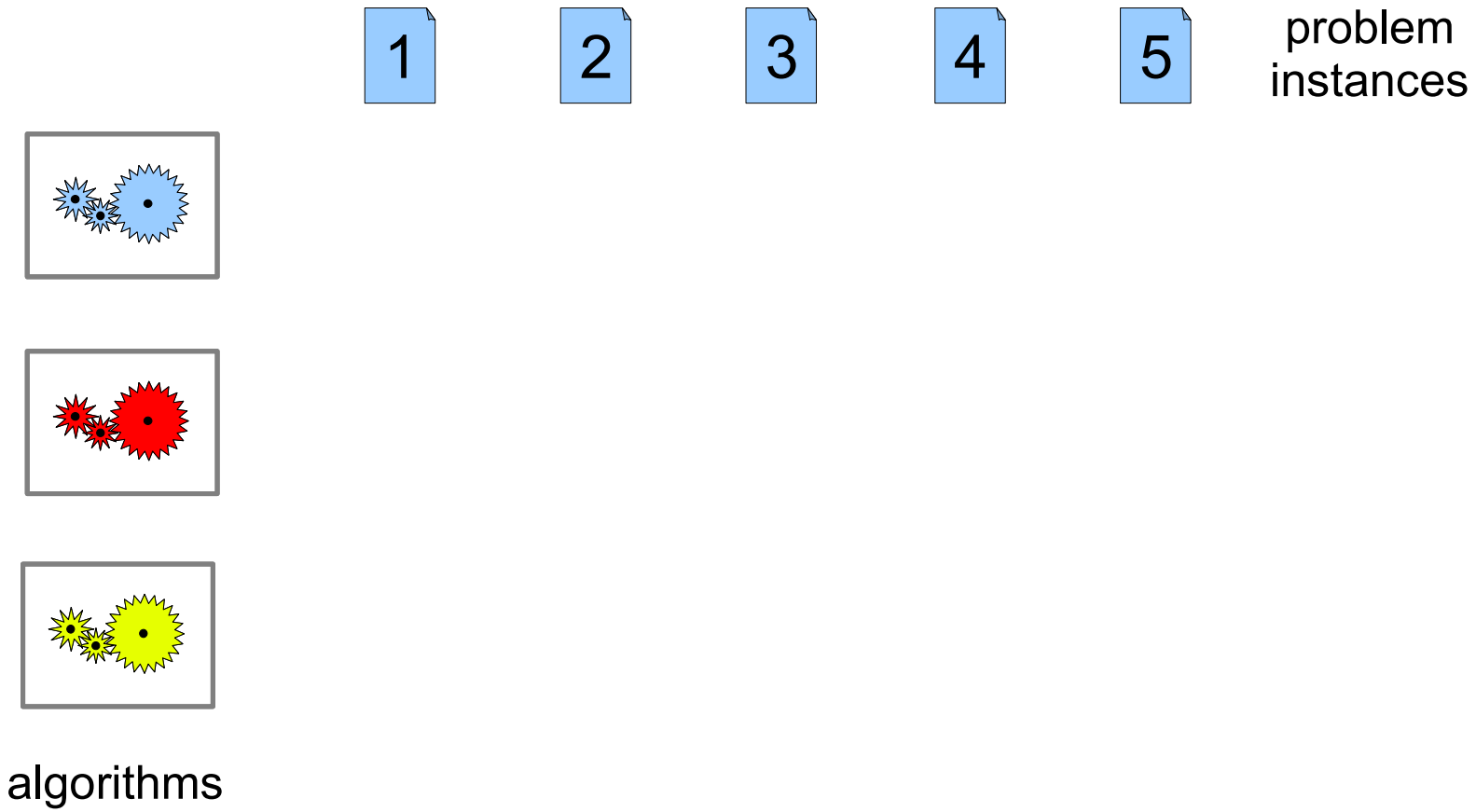
  (*e.g.*, SPO – Bartz-Beielstein 06; SMAC – Hutter, HH, Leyton-Brown 11–12)

Racing (for Algorithm Selection)



algorithms

Racing (for Algorithm Selection)



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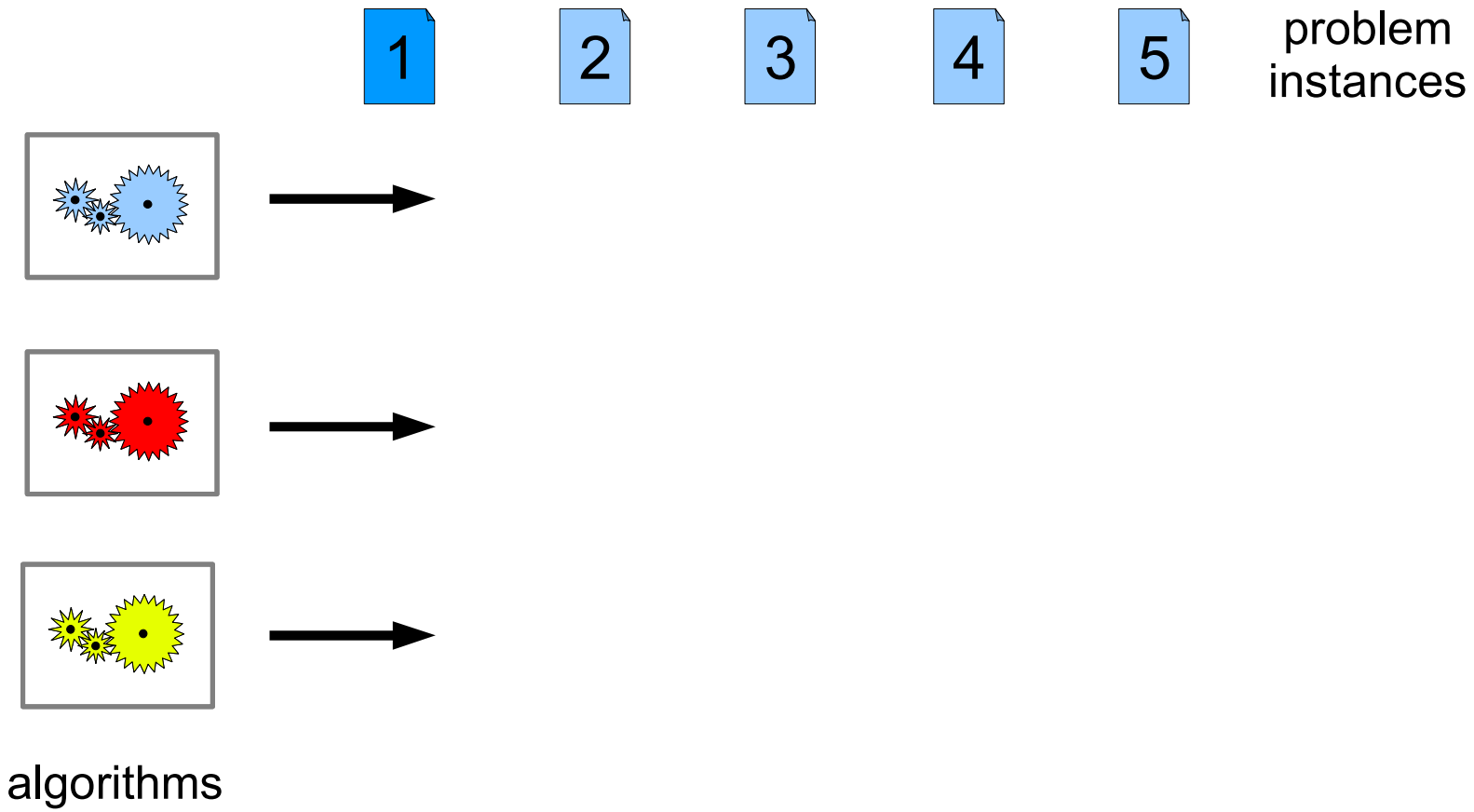

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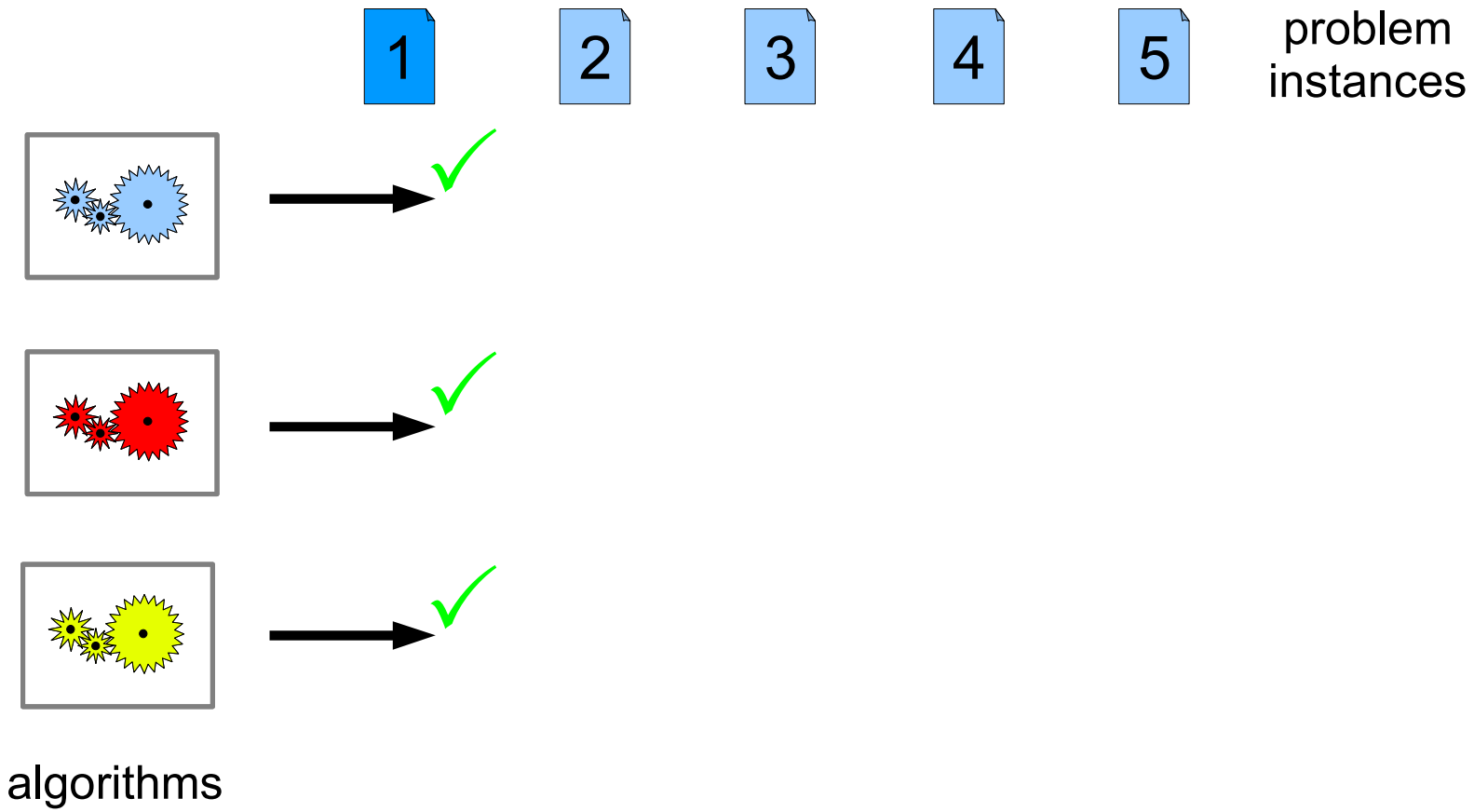

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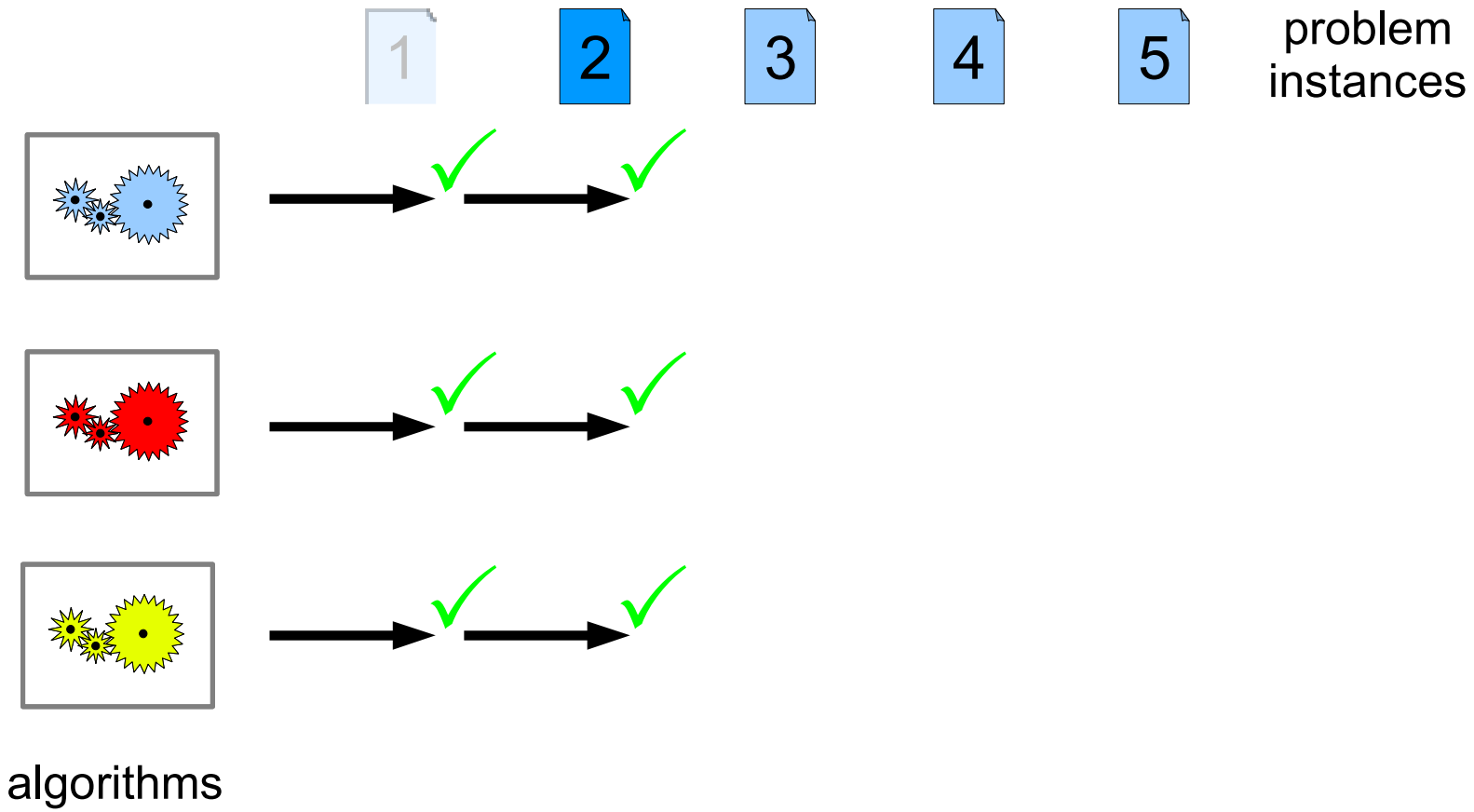

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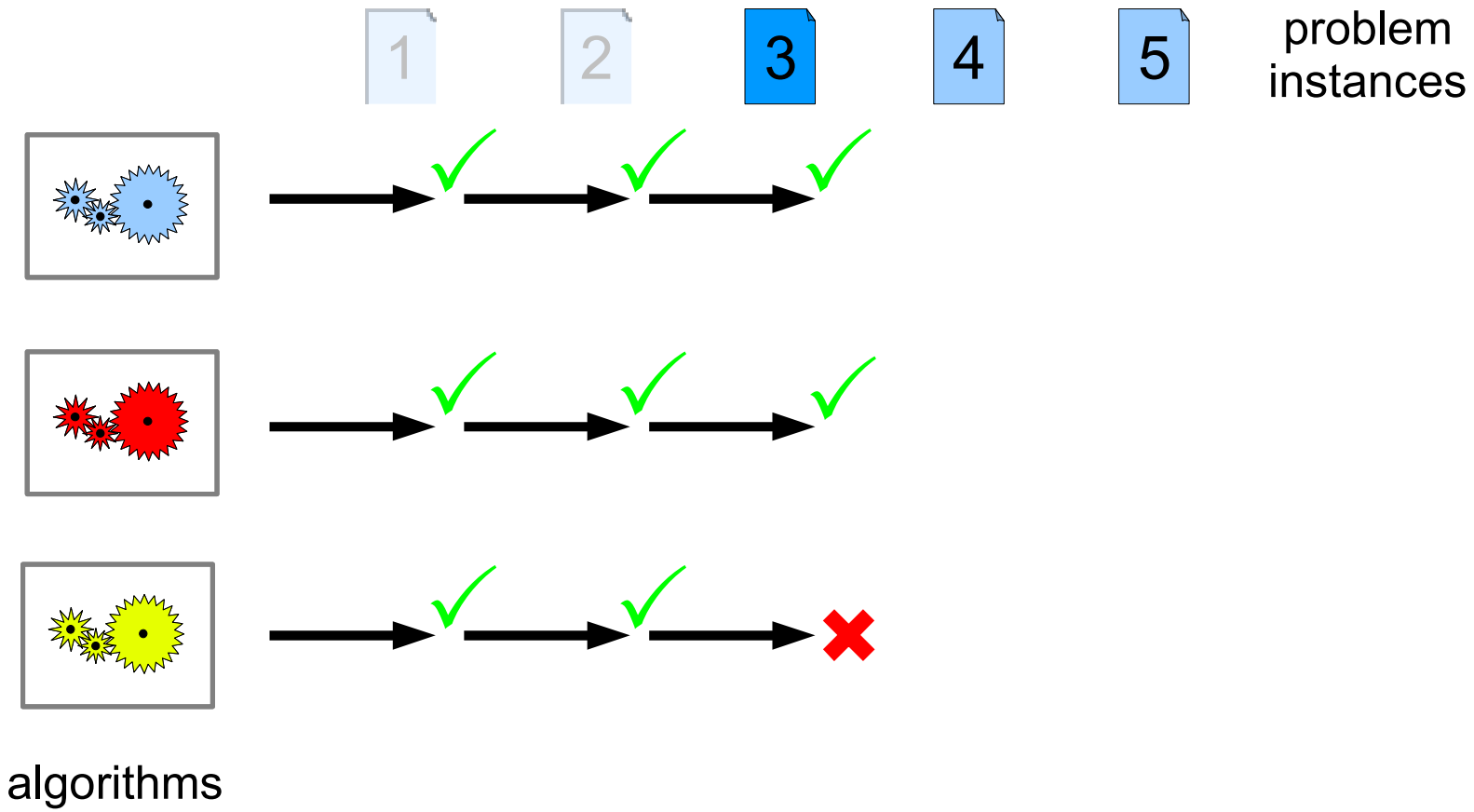

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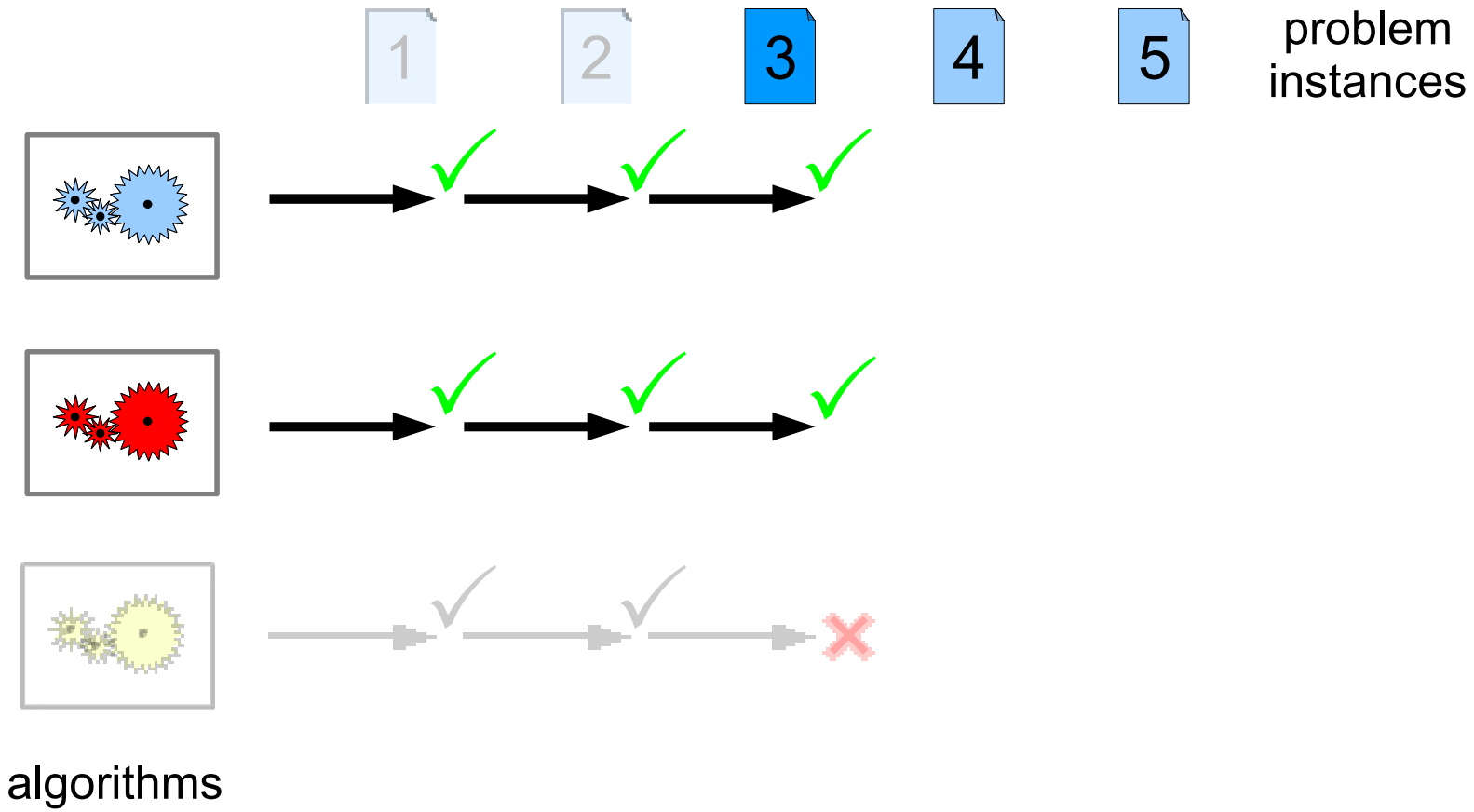

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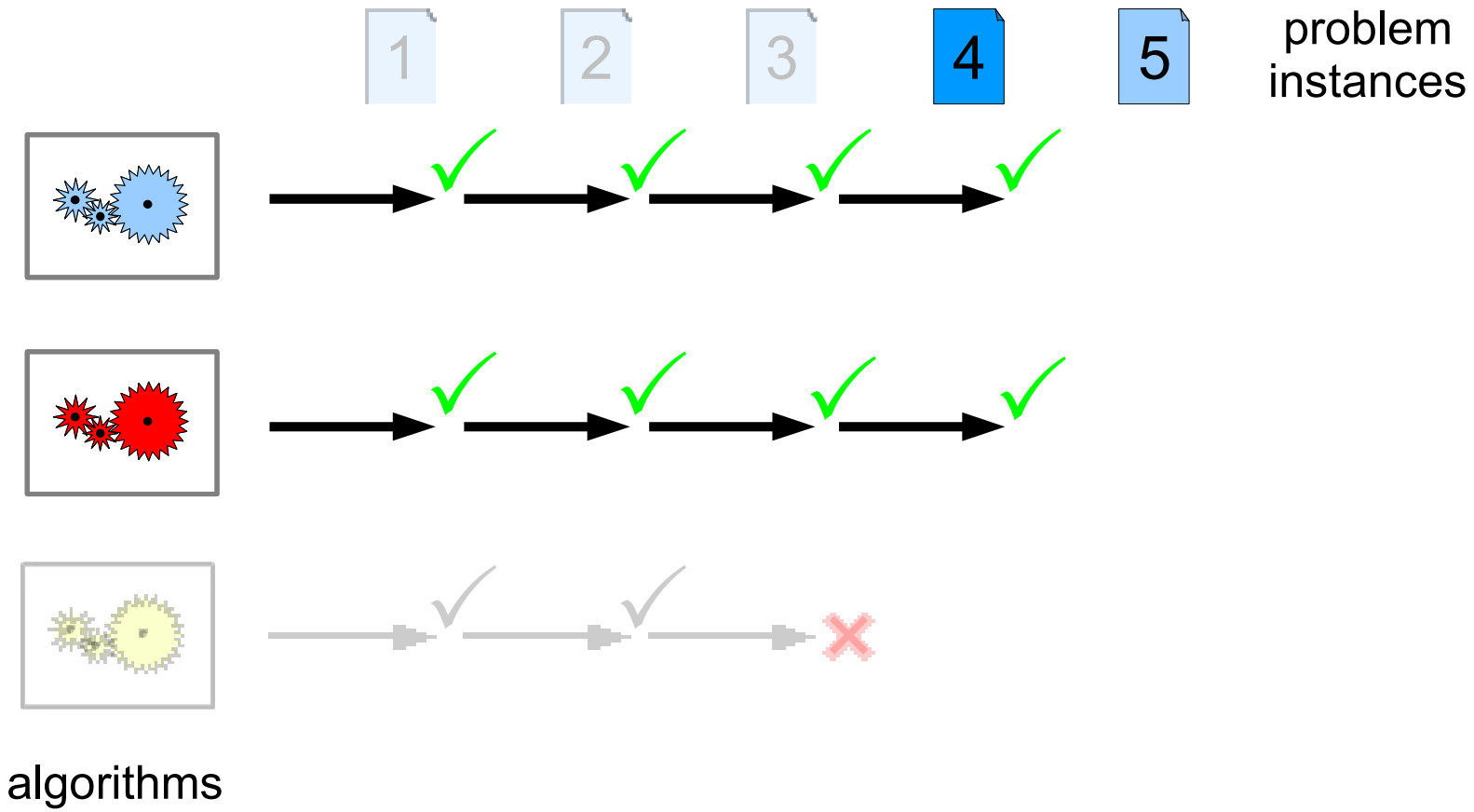

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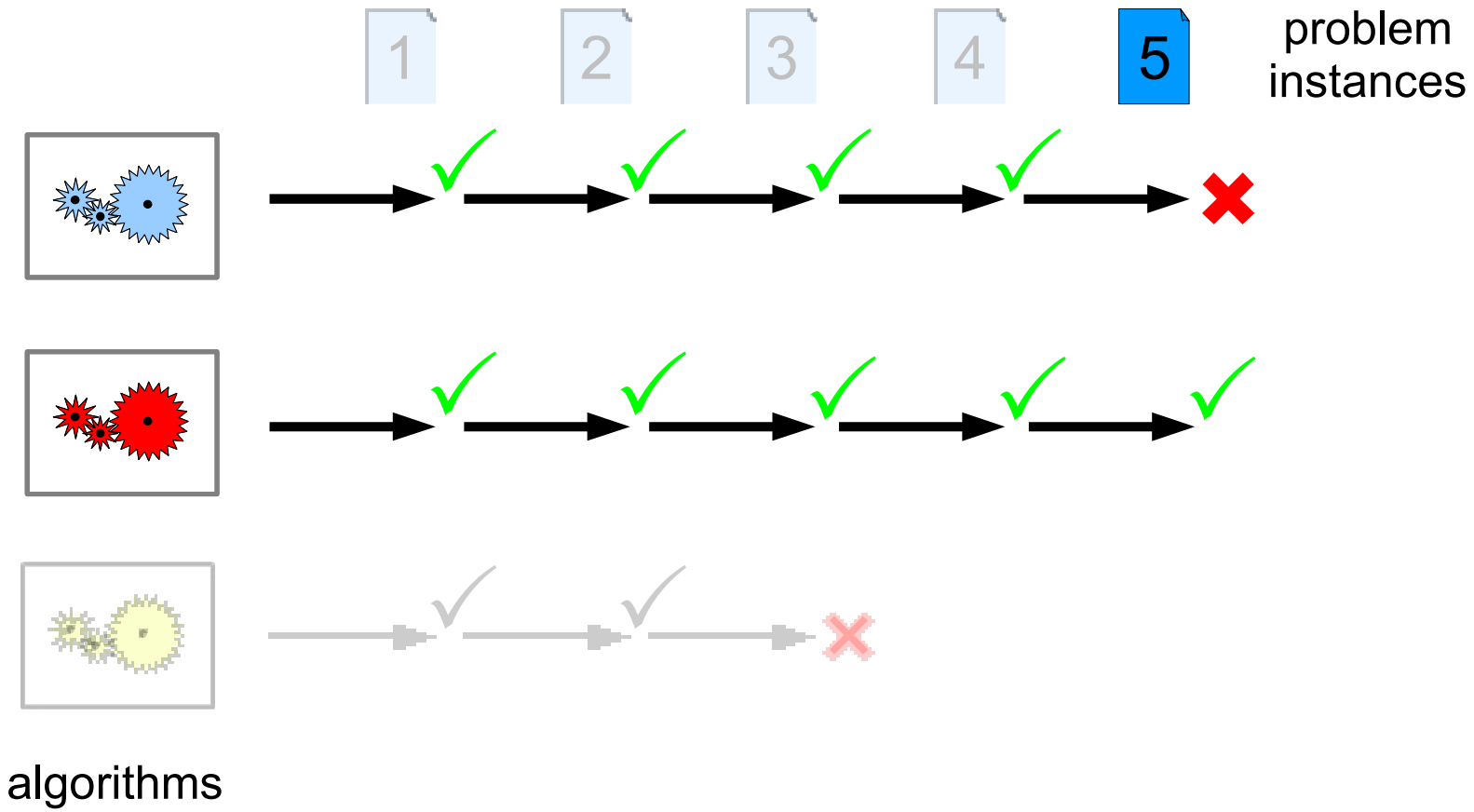

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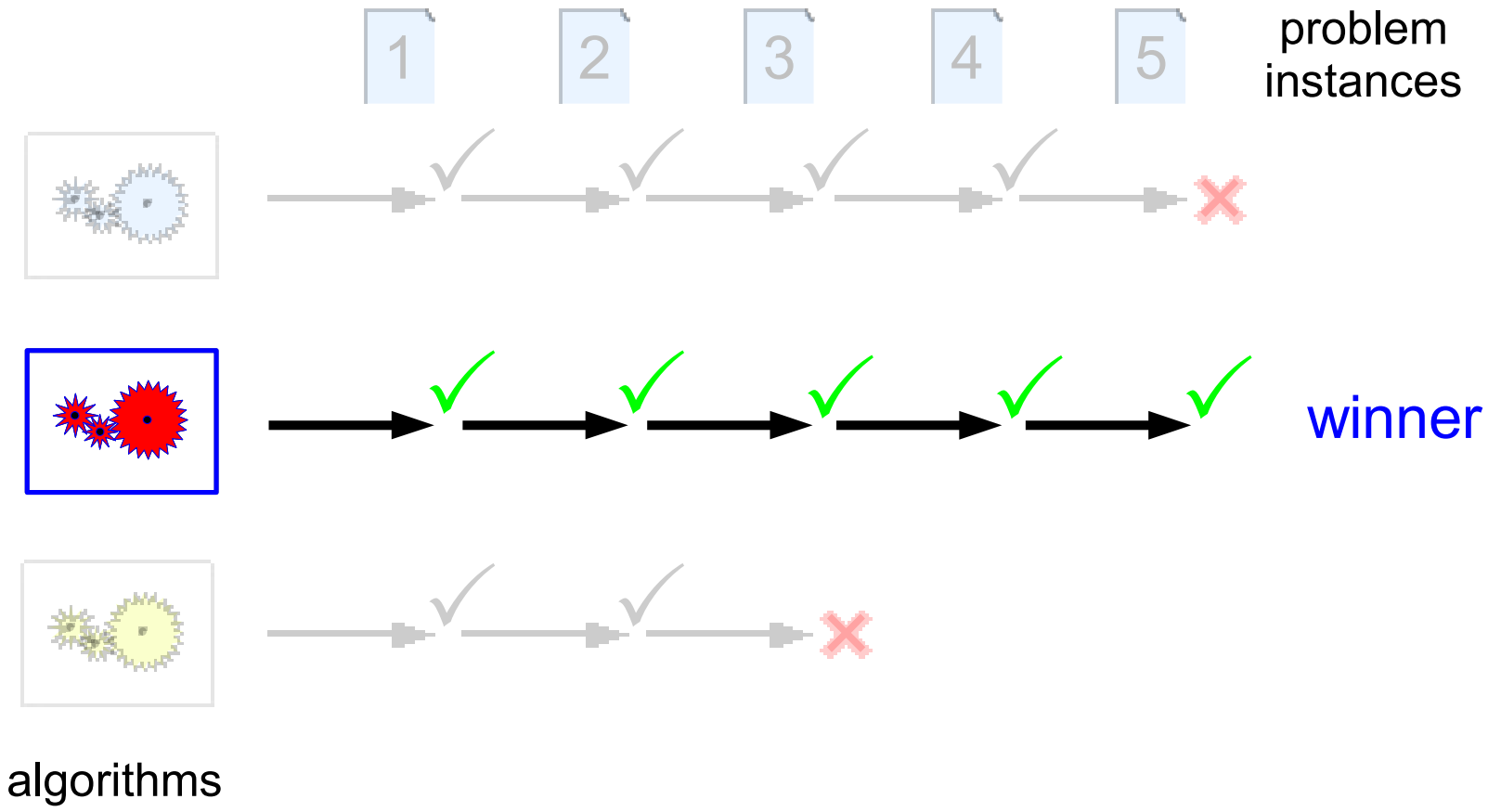


F-Race (Birattari, Stützle, Paquete, Varrentrapp 2002)

- inspired by methods for model selection methods in machine learning

  (Maron & Moore 1994; Moore & Lee 1994)

- sequentially evaluate algorithms/configuration, in each iteration, perform one new run per algorithm/configuration
- eliminate poorly performing algorithms/configurations as soon as sufficient evidence is gathered against them
- use Friedman test to detect poorly performing algorithms/configurations

Iterat{ive,ed} F-Race (Balaprakash, Birattari, Stützle 2007)

Problem: When using F-Race for algorithm configuration, number of initial configurations considered is severely limited.

Solution:

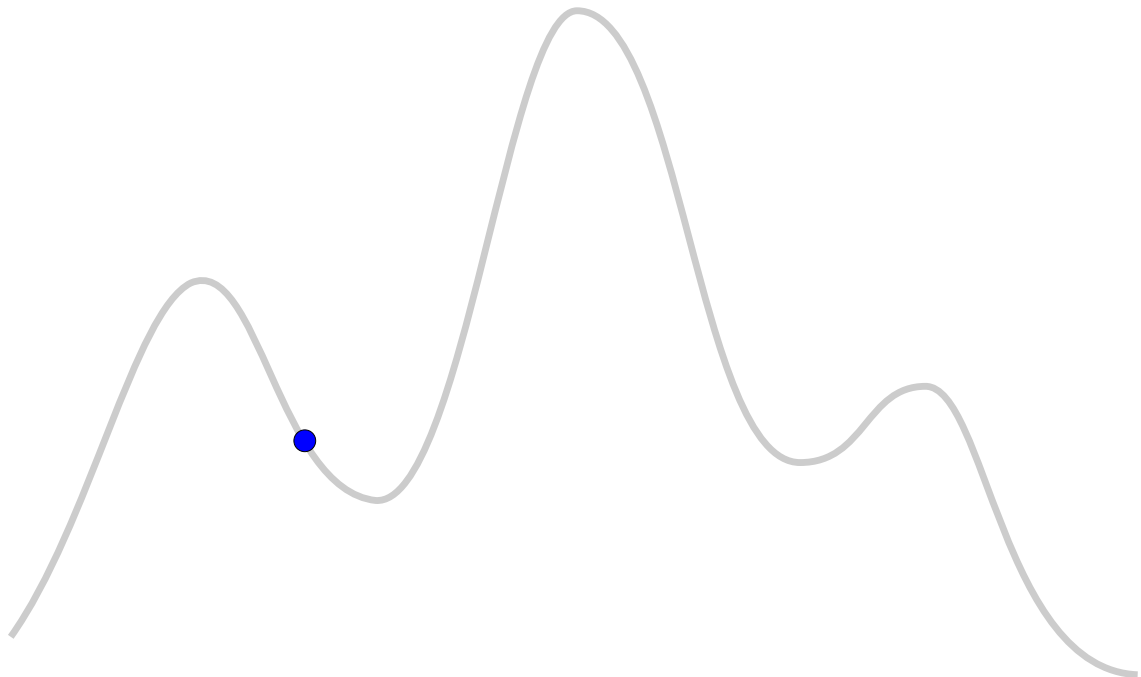
- perform *multiple iterations of F-Race* on *limited set of configurations*
- sample candidate configurations based on *probabilistic model* (independent normal distributions centred on surviving configurations)
- gradually reduce variance over iterations (*volume reduction*)

$\rightsquigarrow$ good results for

- MAX-MIN Ant System for the TSP (6 parameters)
- simulated annealing for stochastic vehicle routing (4 parameters)
- estimation-based local search for PTSP (3 parameters)

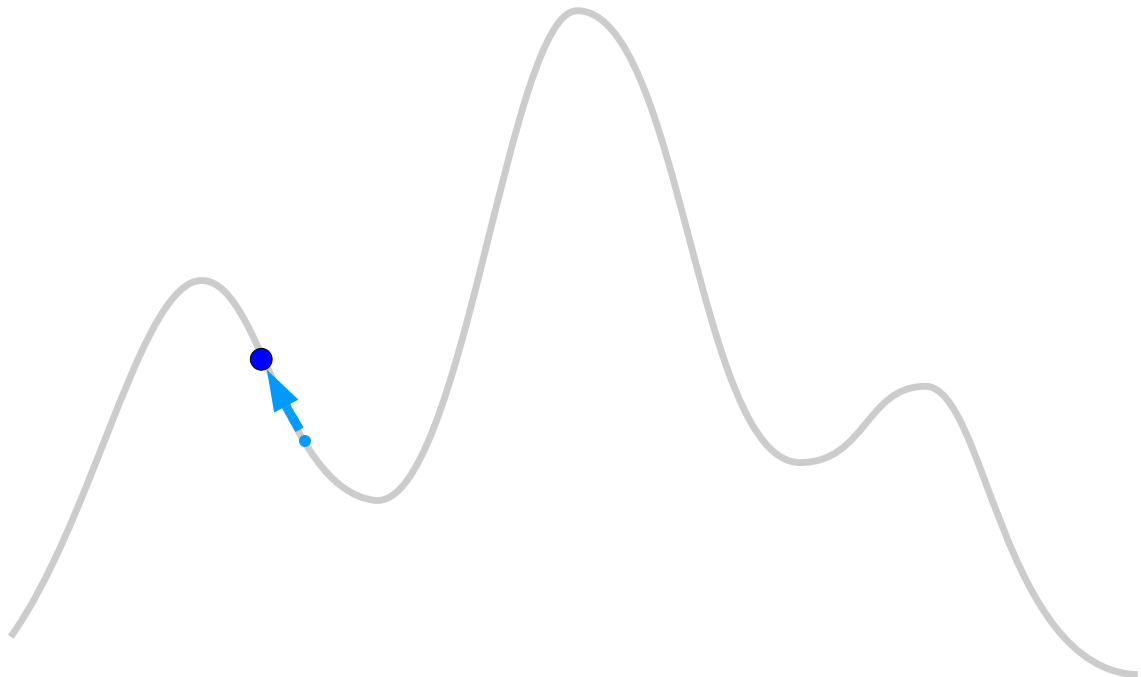
Iterated Local Search

Iterated Local Search



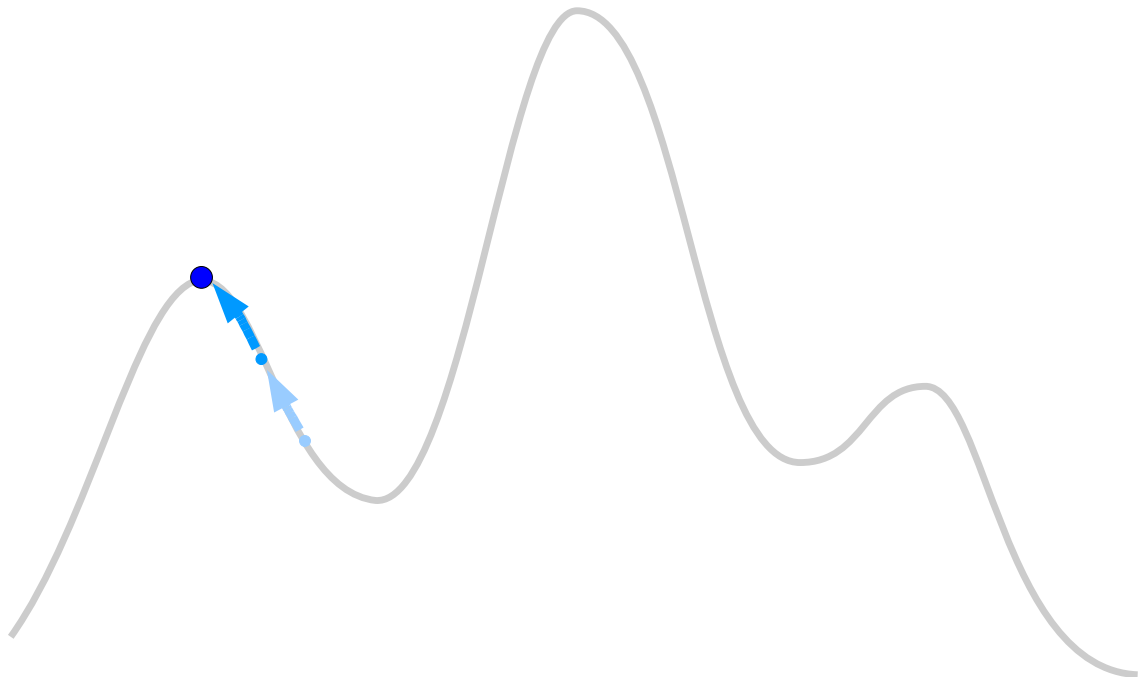
Initialisation

Iterated Local Search



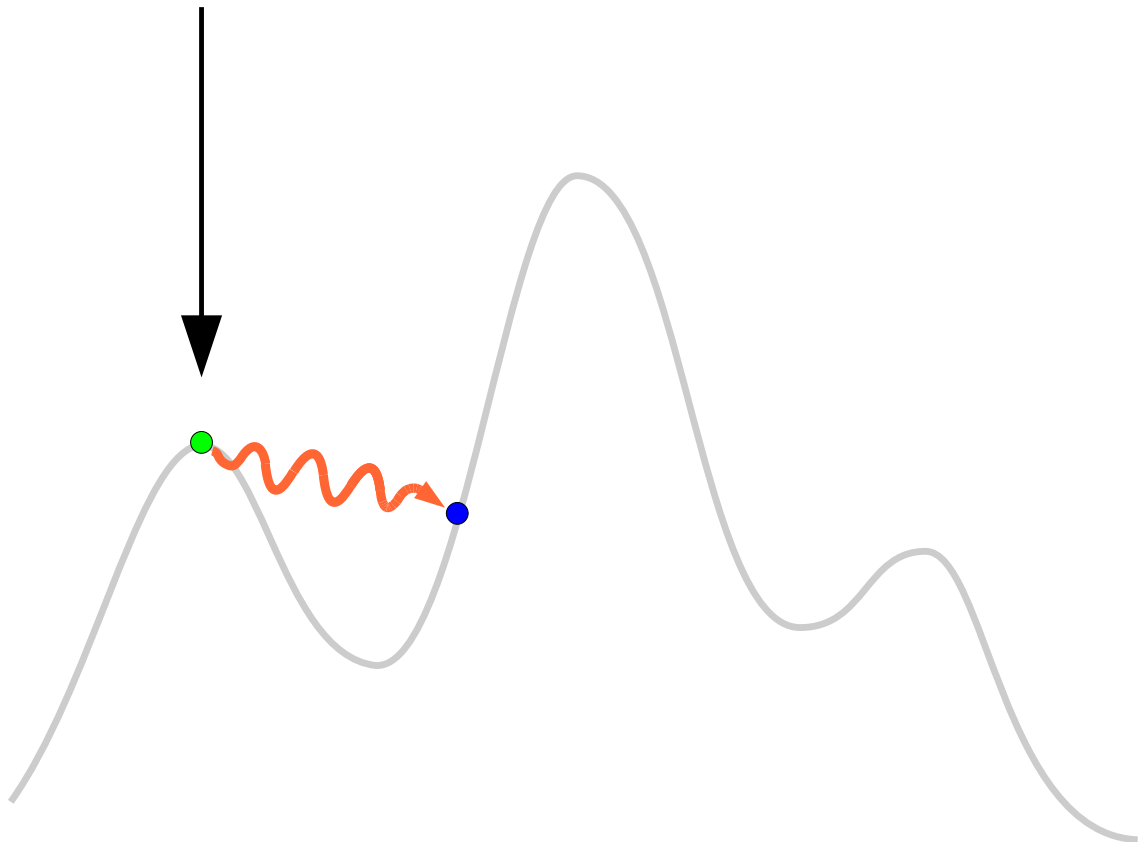
Local Search

Iterated Local Search



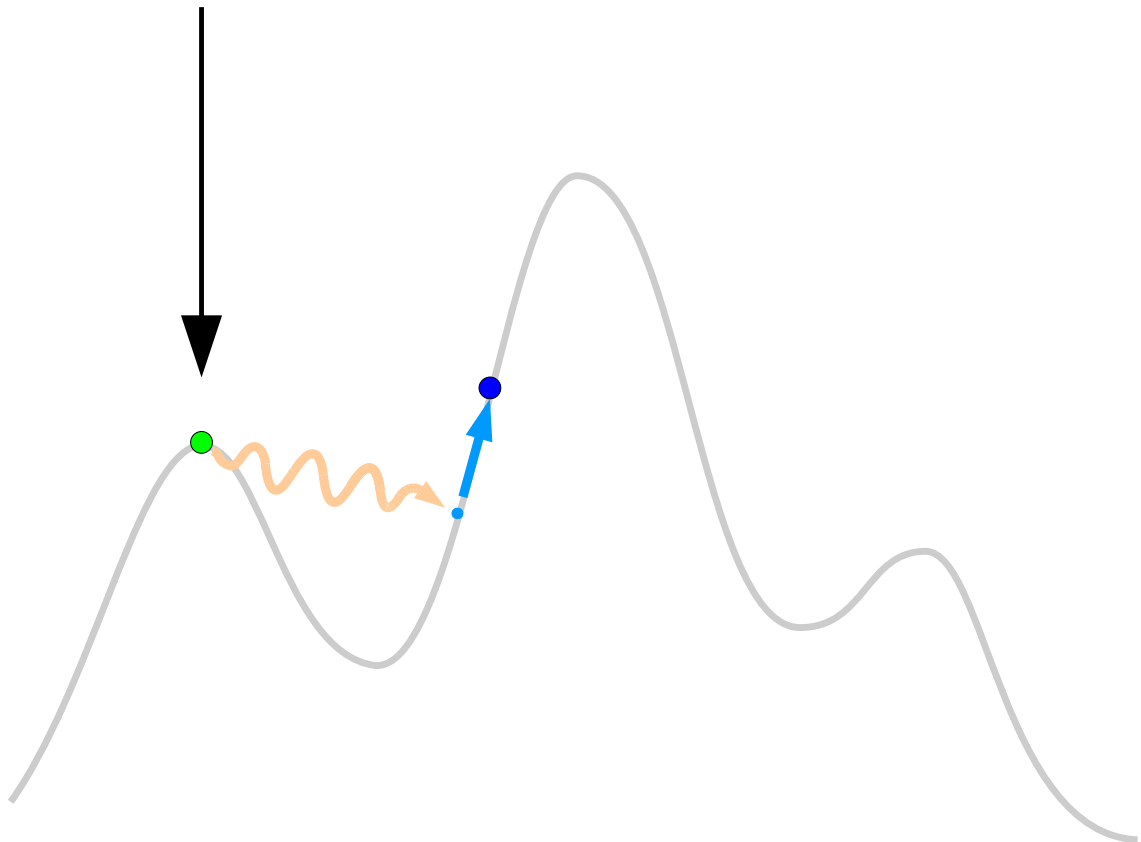
Local Search

Iterated Local Search



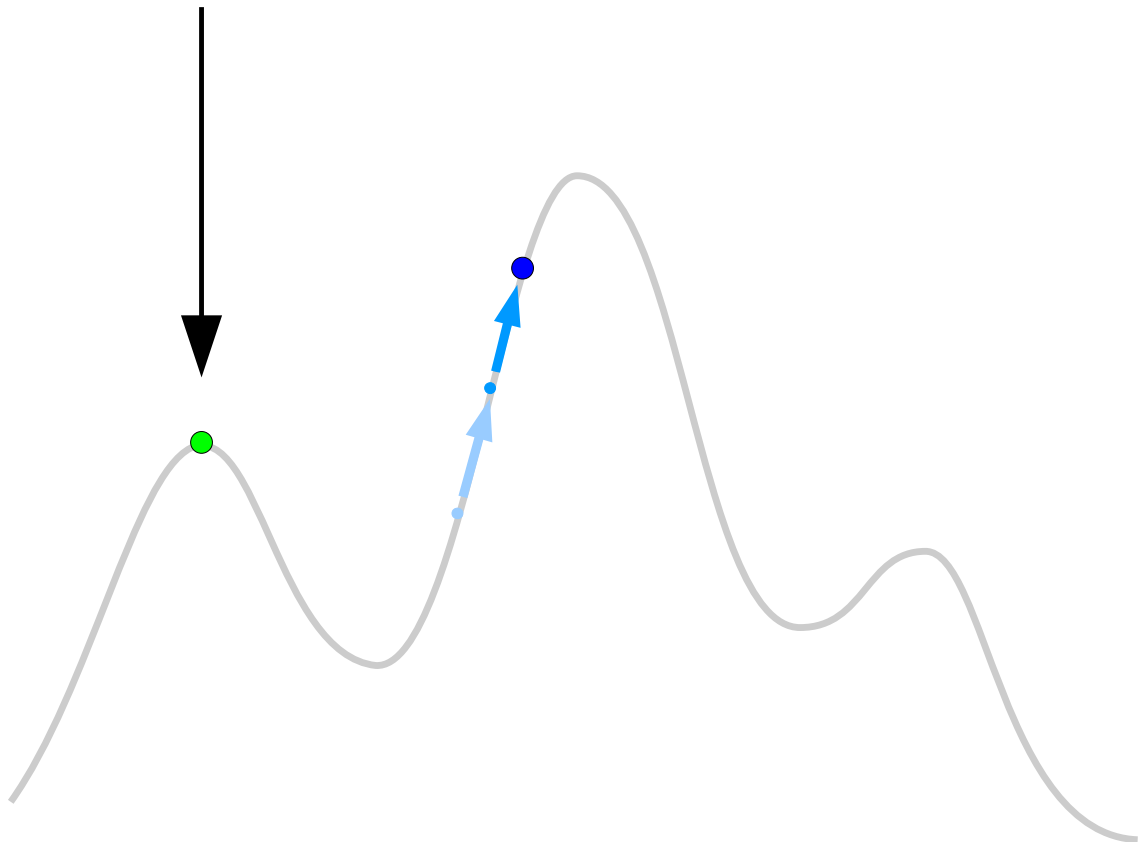
Perturbation

Iterated Local Search



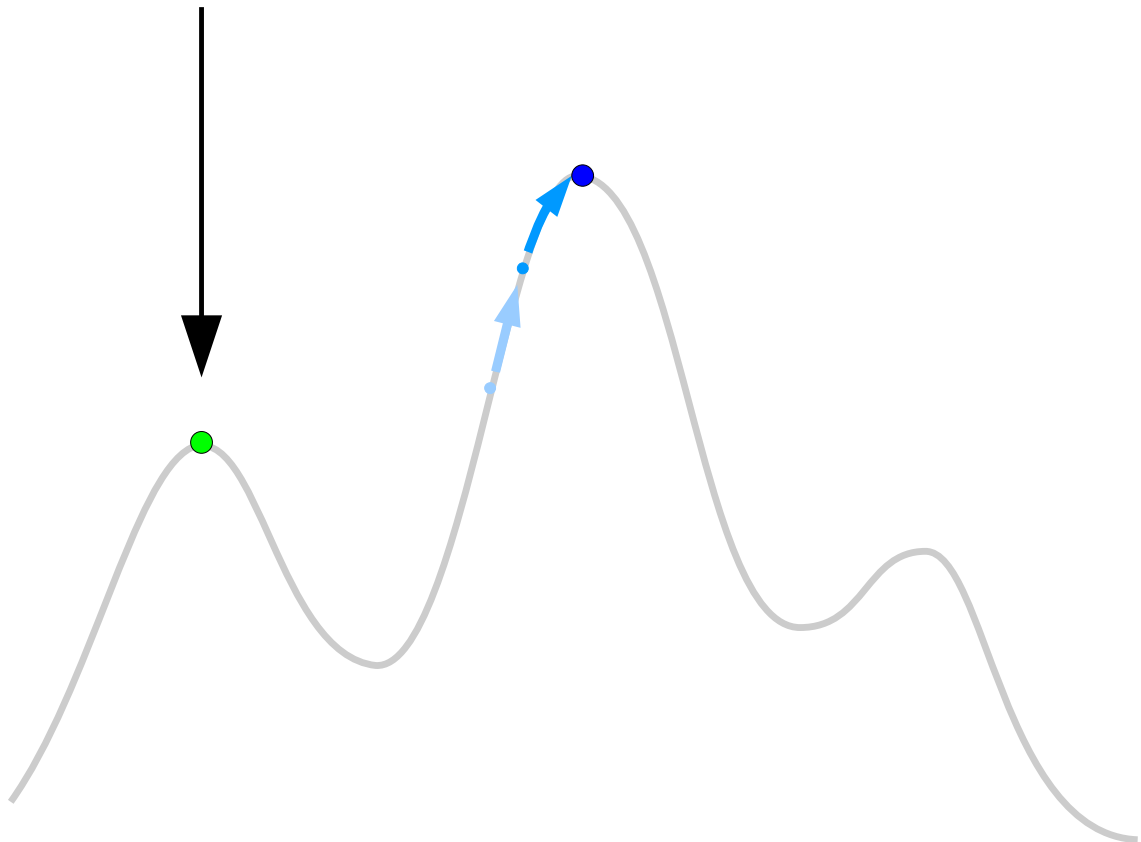
Local Search

Iterated Local Search



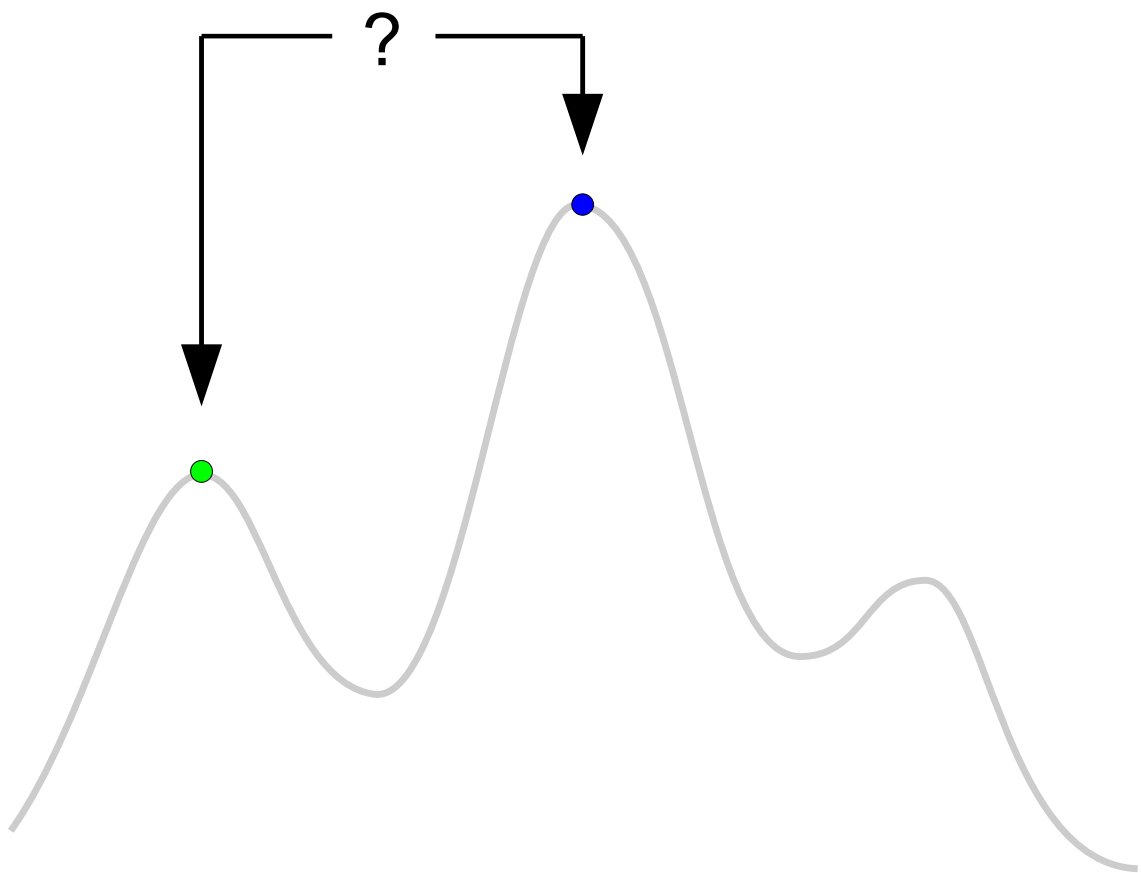
Local Search

Iterated Local Search



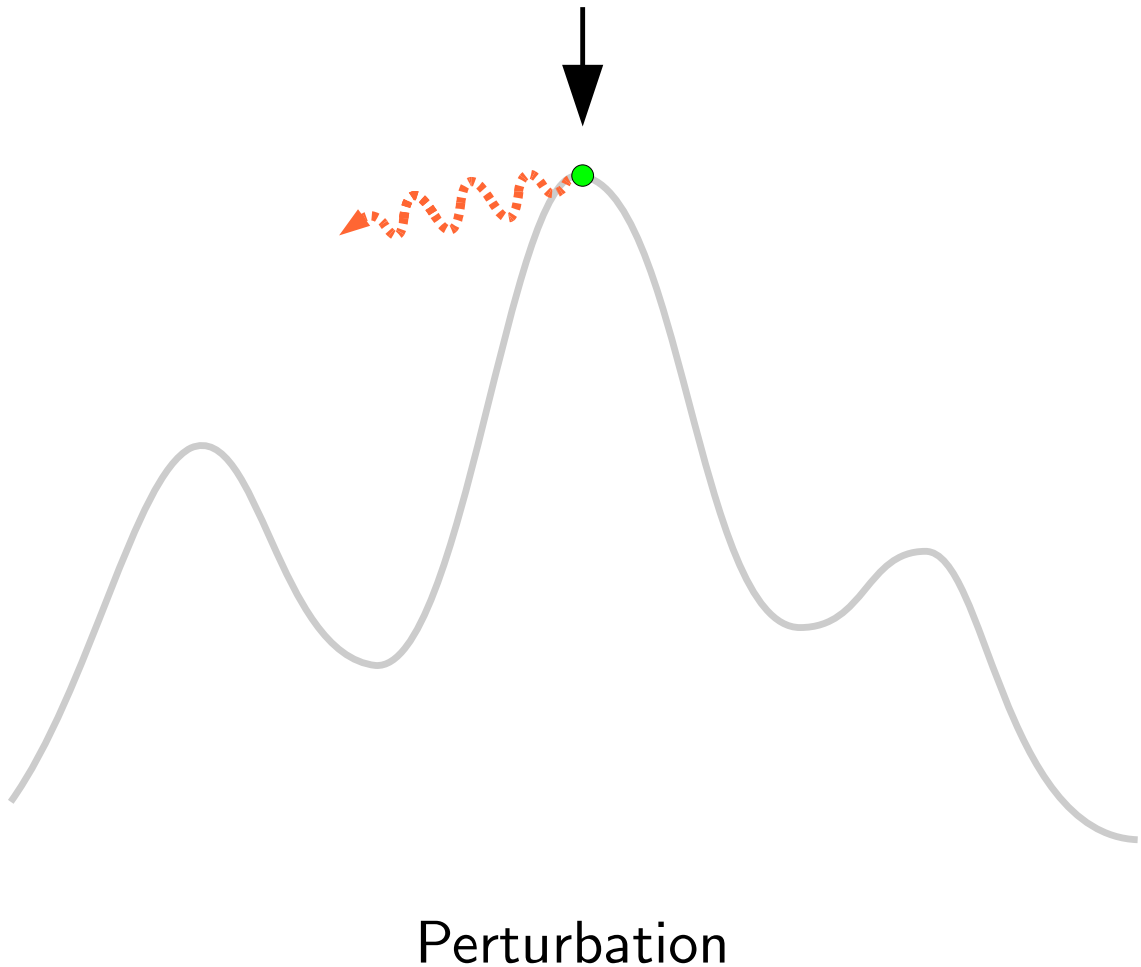
Local Search

Iterated Local Search



Selection (using Acceptance Criterion)

Iterated Local Search



Perturbation

ParamILS

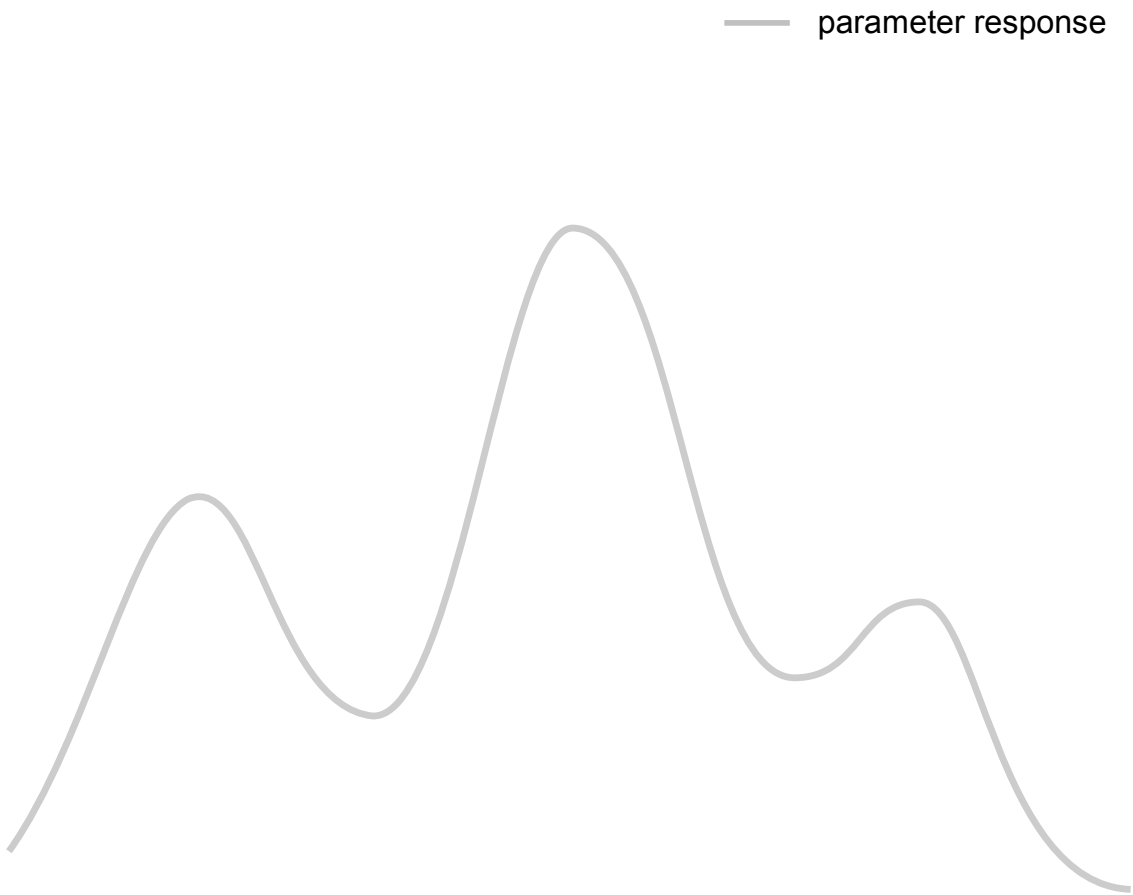
- iterated local search in configuration space
- initialisation: pick *best* of default + R random configurations
- subsidiary local search: iterative first improvement, change one parameter in each step
- perturbation: change s randomly chosen parameters
- acceptance criterion: always select *better* configuration
- number of runs per configuration increases over time; ensure that incumbent always has same number of runs as challengers

Sequential Model-based Optimisation

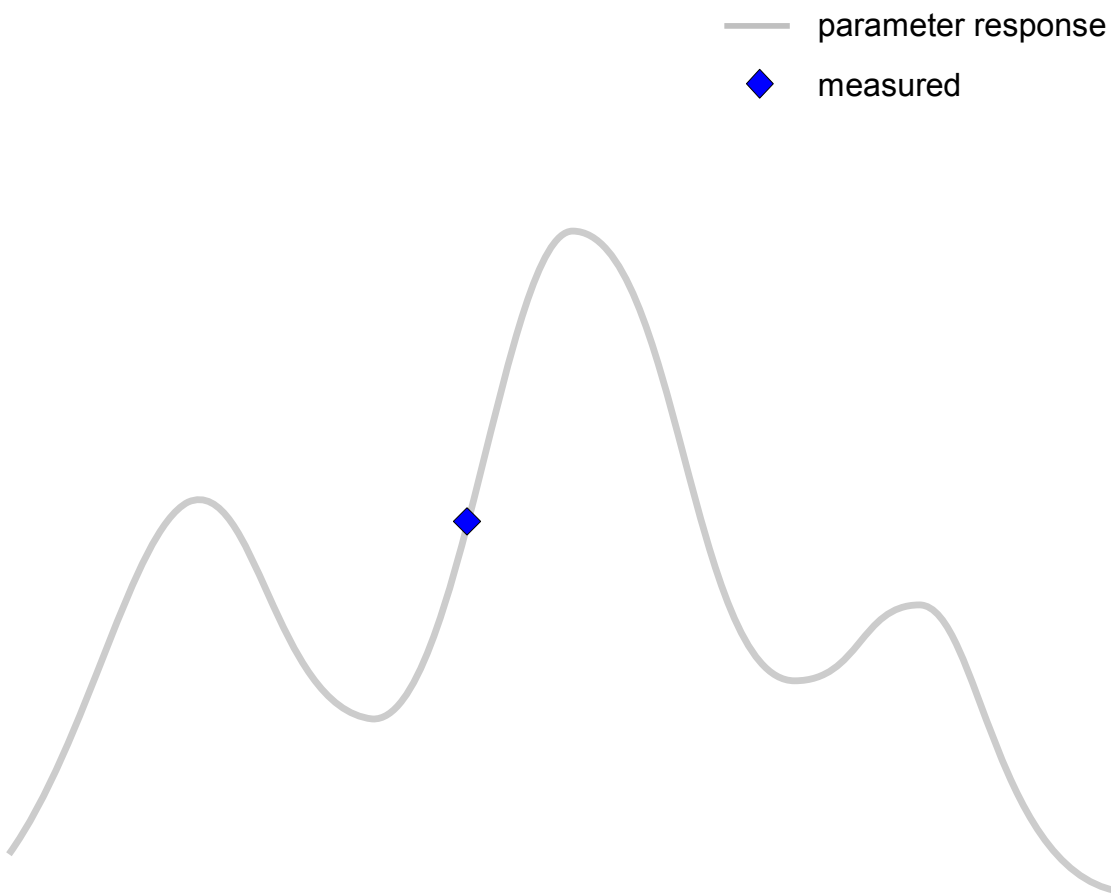
e.g., Jones (1998), Bartz-Beielstein (2006)

- **Key idea:**
  use predictive performance model (response surface model) to find good configurations
- perform runs for selected configurations (initial design) and fit model (*e.g.*, noise-free Gaussian process model)
- iteratively select promising configuration, perform run and update model

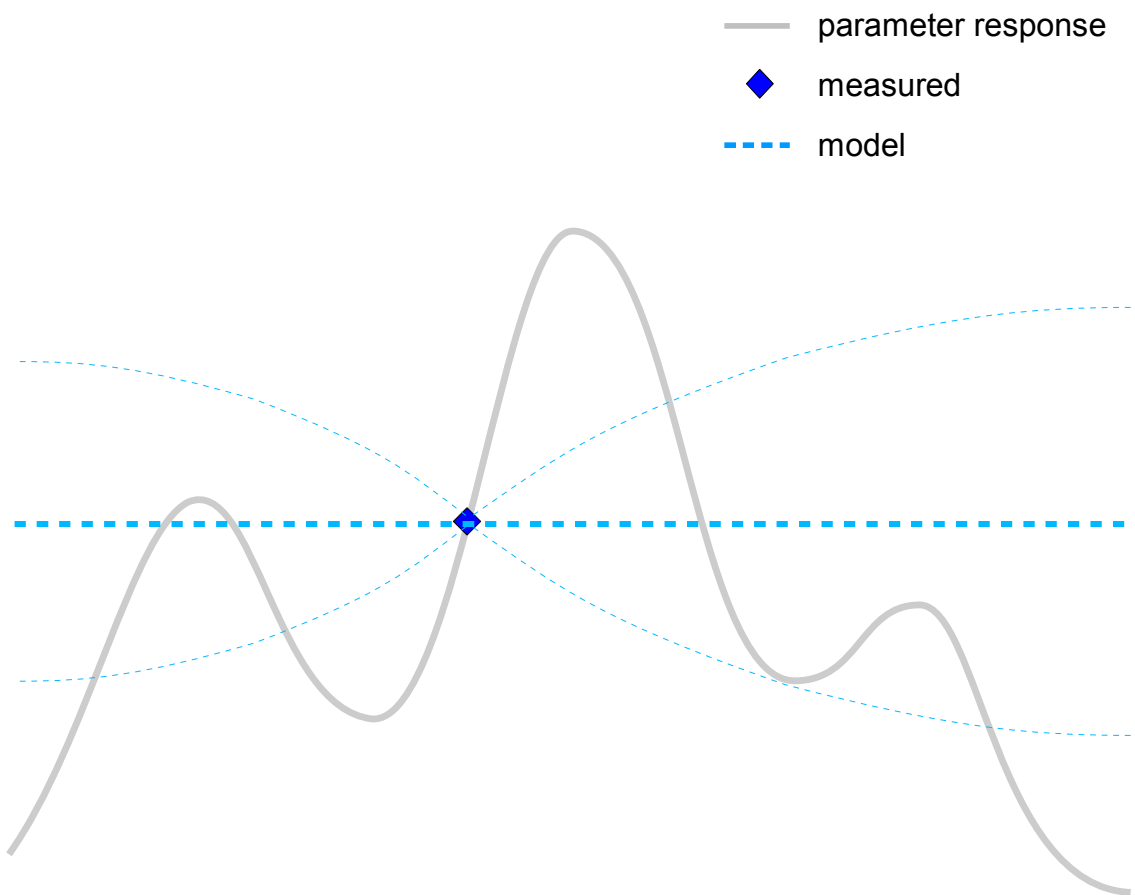
Sequential Model-based Optimisation



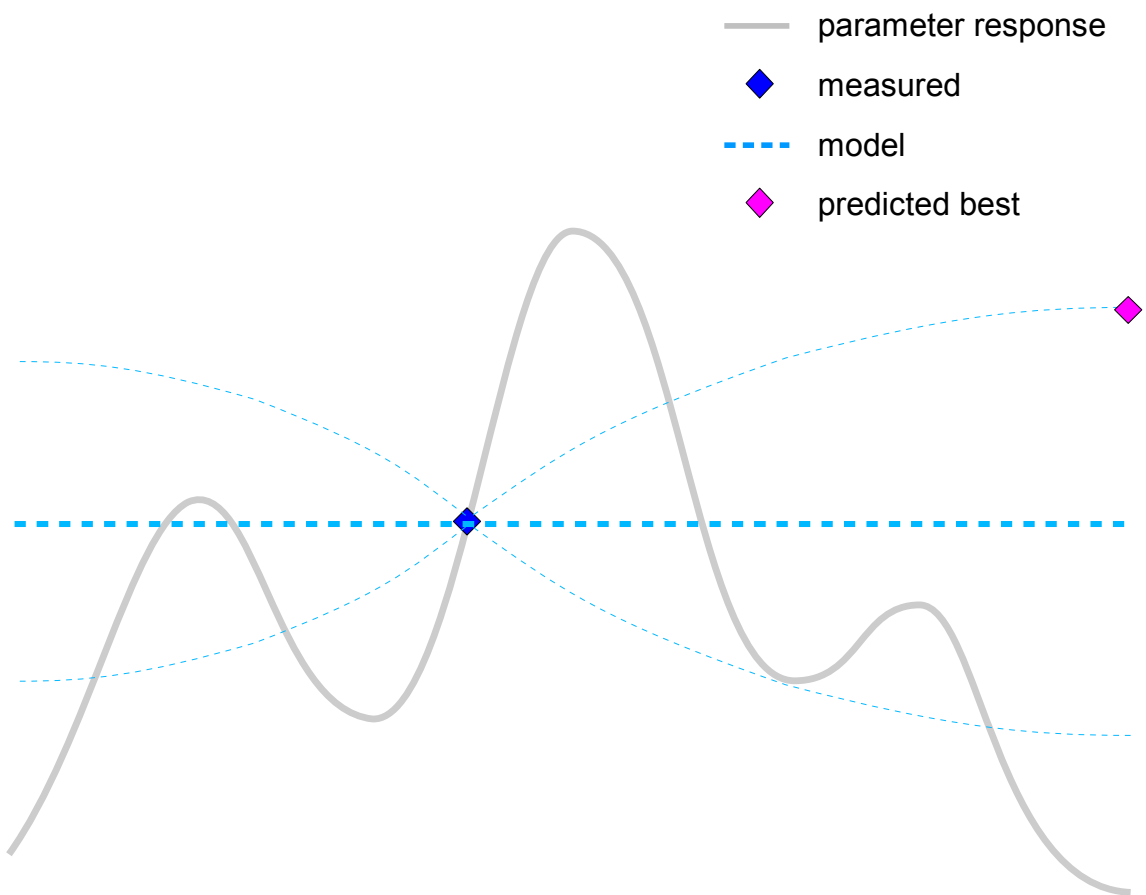
Sequential Model-based Optimisation



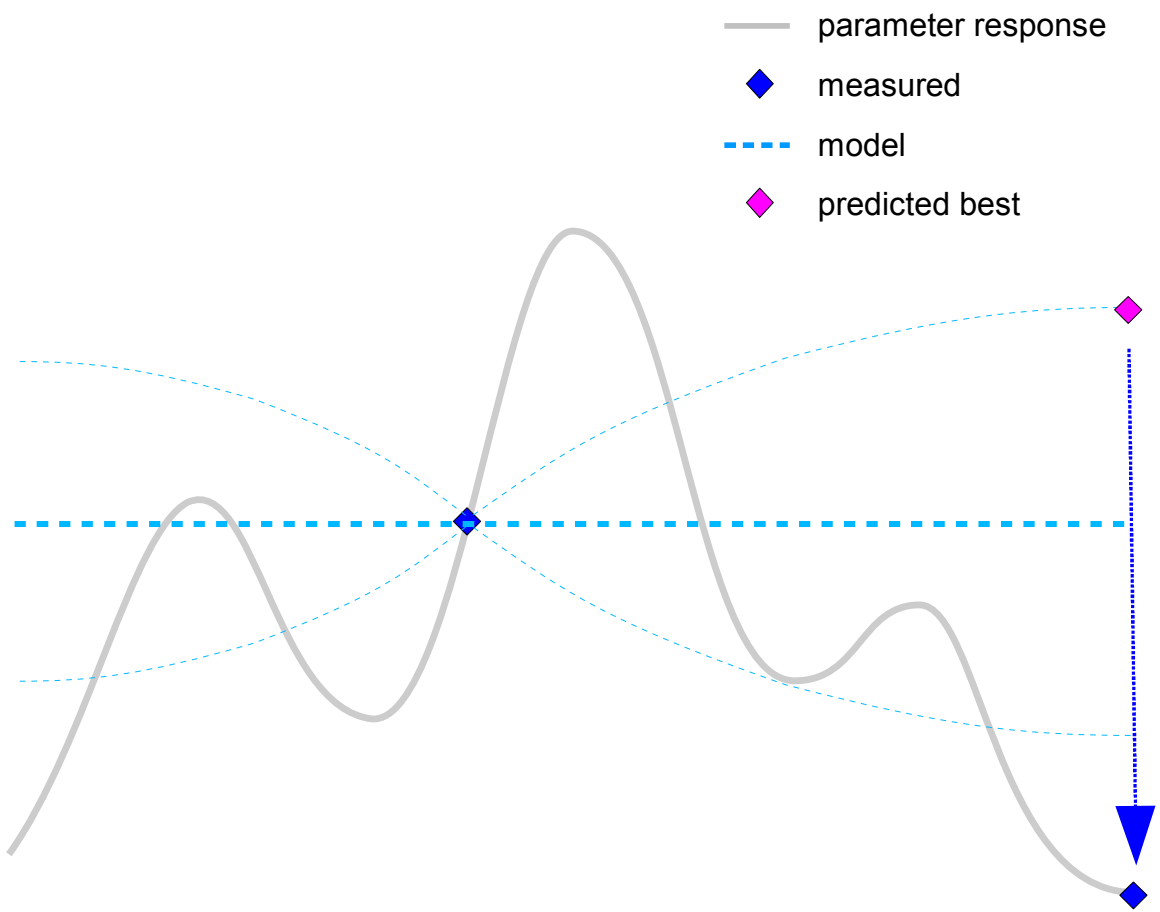
Sequential Model-based Optimisation



Sequential Model-based Optimisation



Sequential Model-based Optimisation



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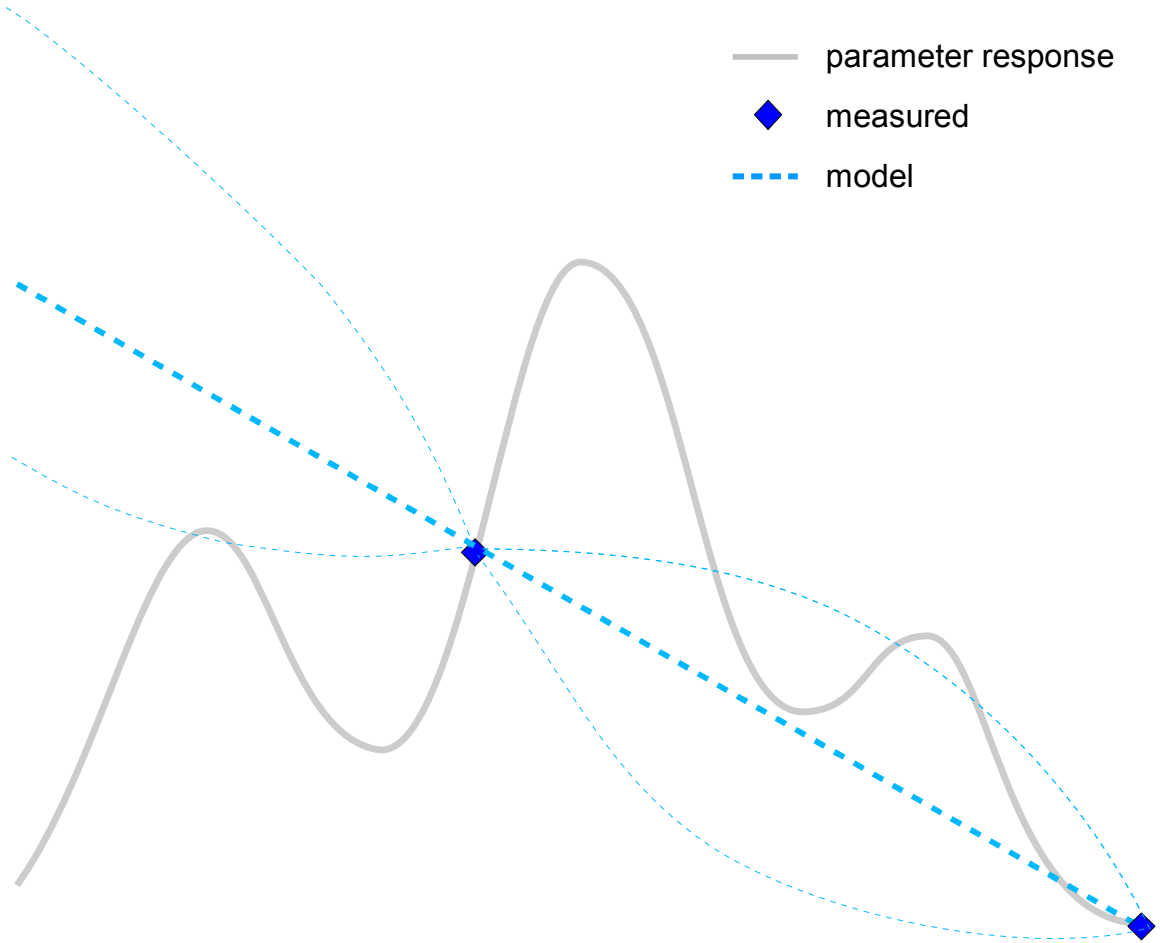

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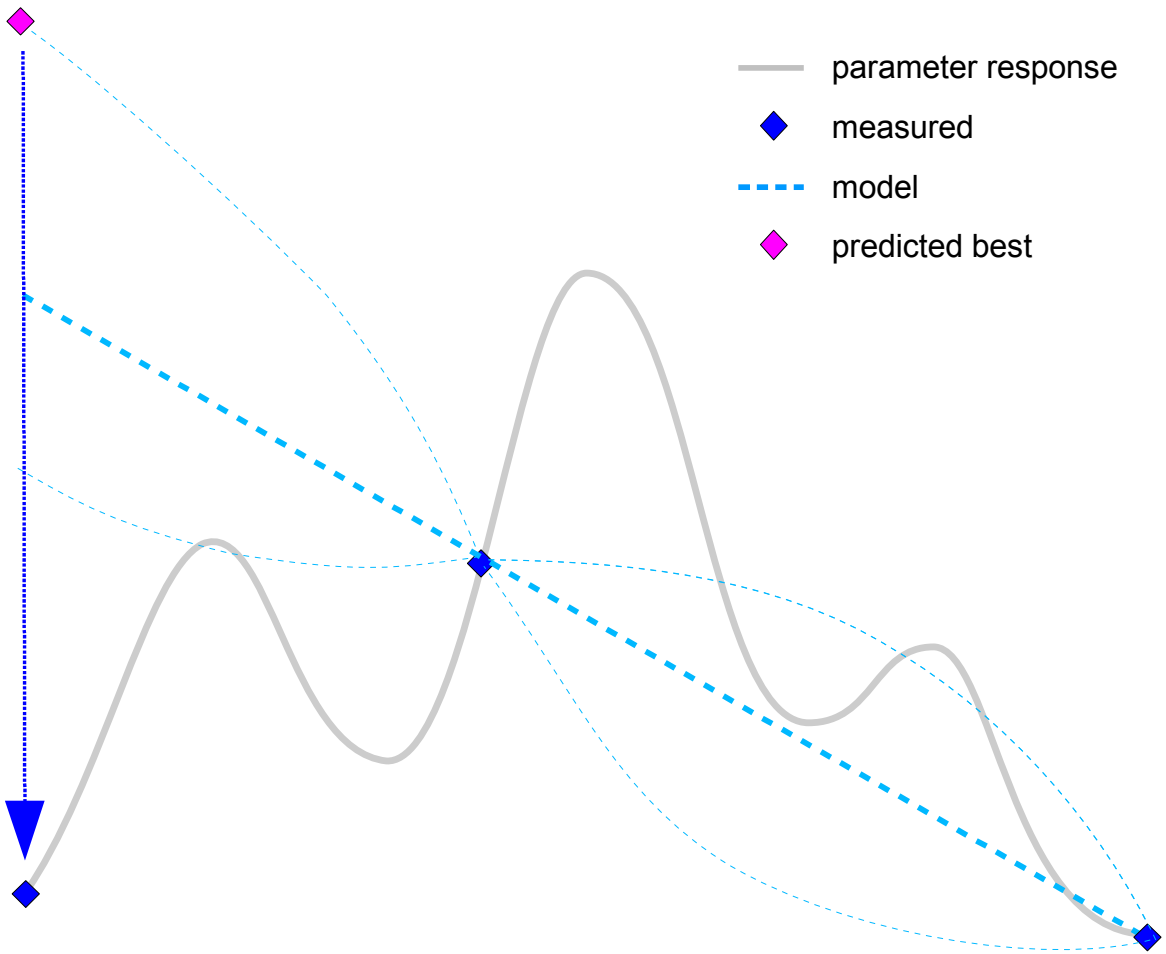
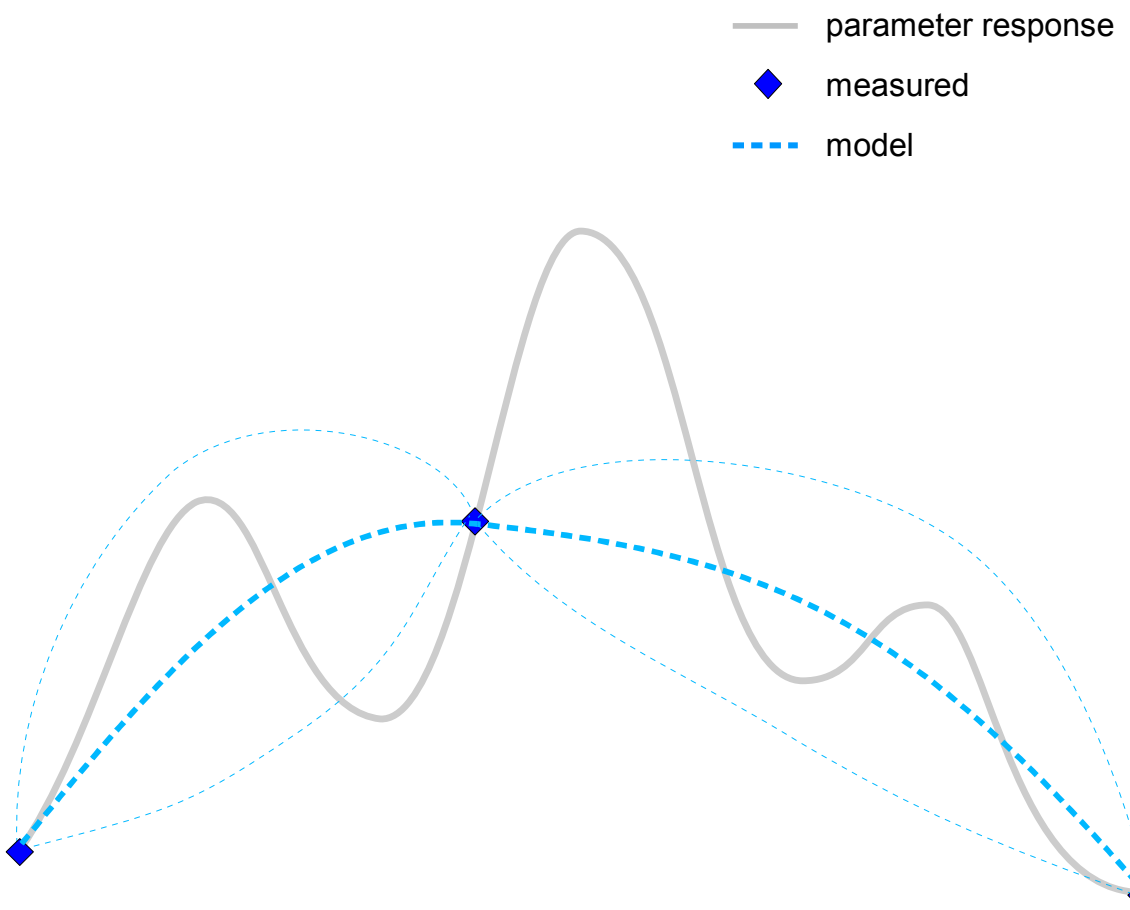
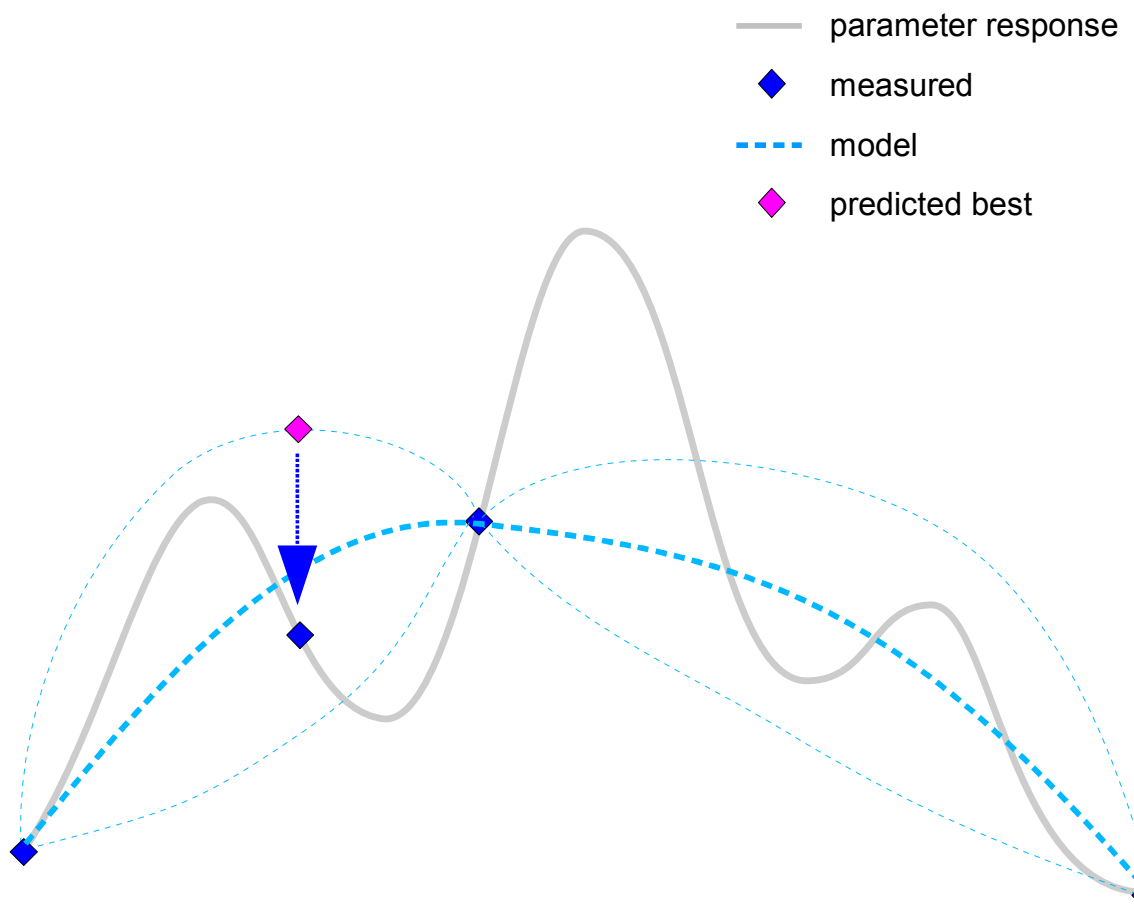


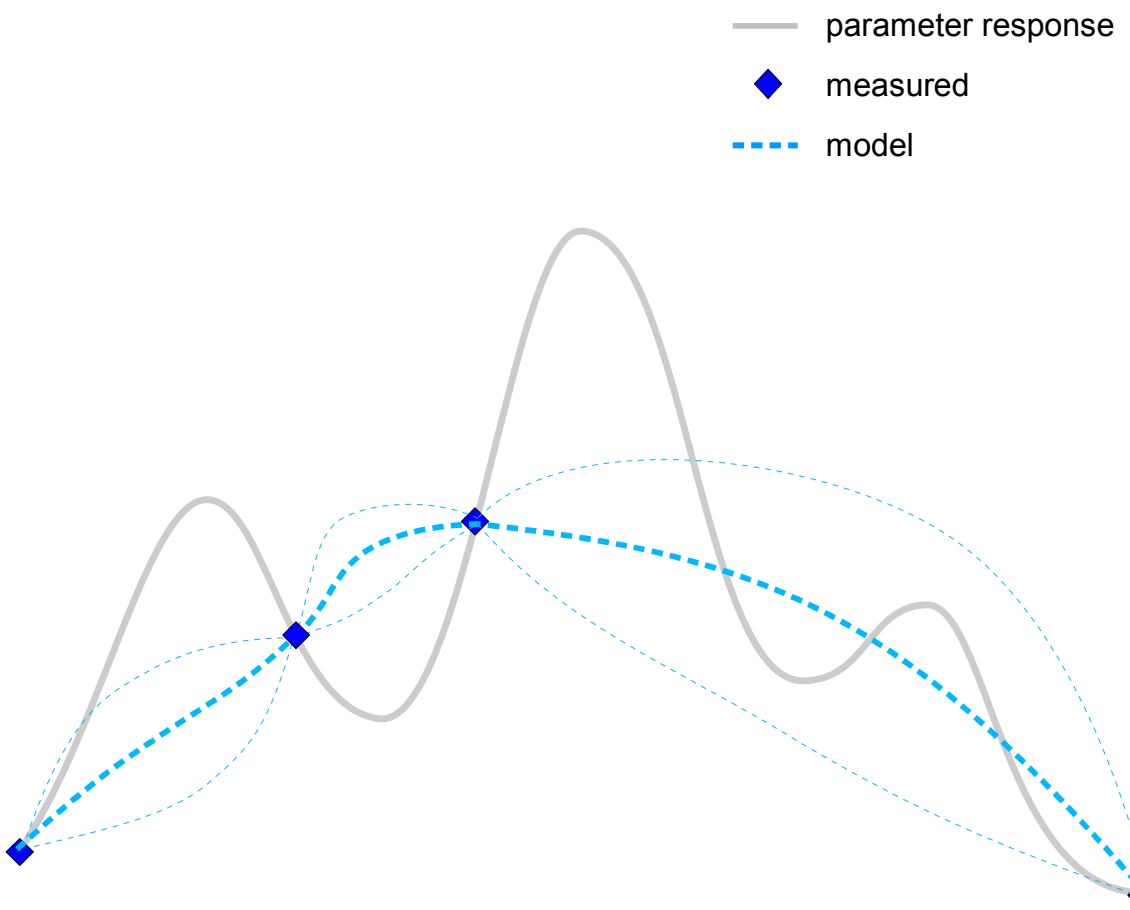
Sequential Model-based Optimisation



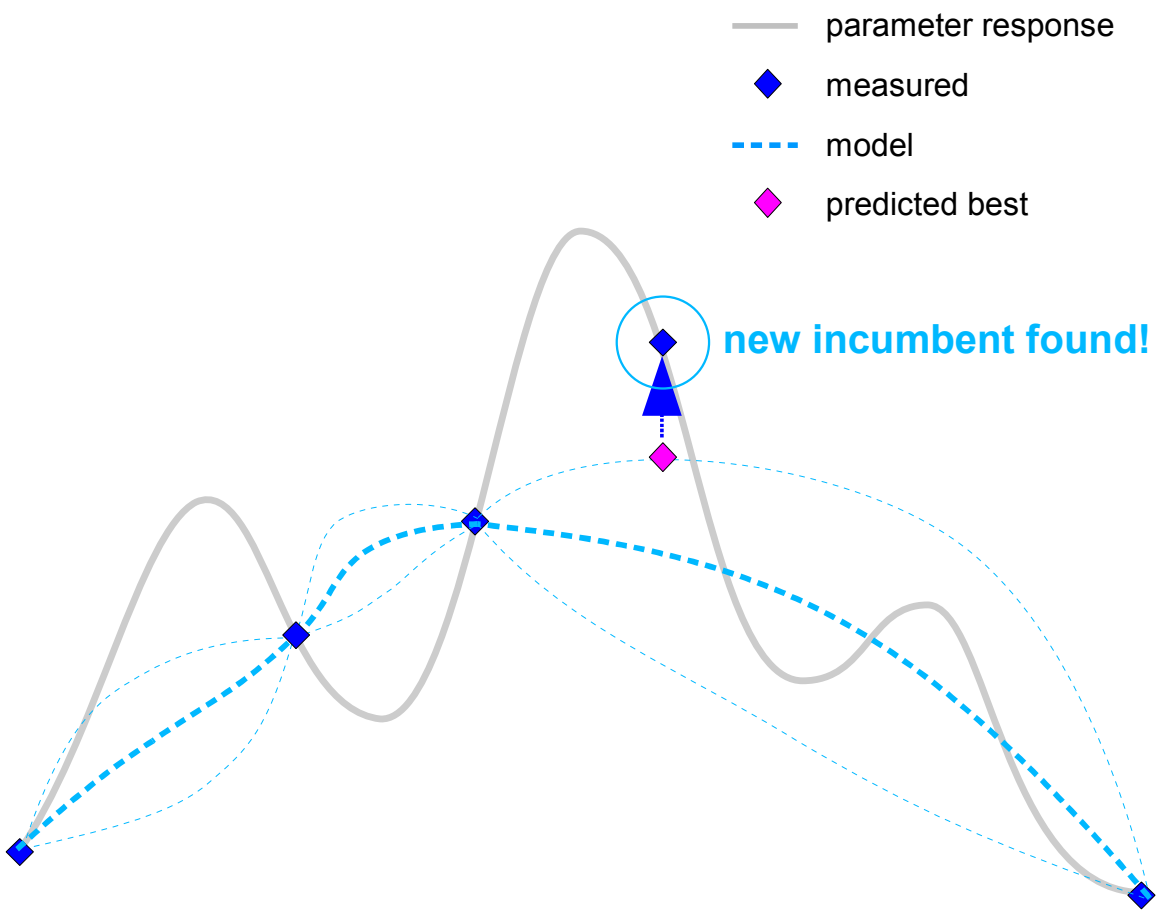
Sequential Model-based Optimisation



Sequential Model-based Optimisation



Sequential Model-based Optimisation



Sequential Model-based Algorithm Configuration (SMAC)

Hutter, HH, Leyton-Brown (2011)

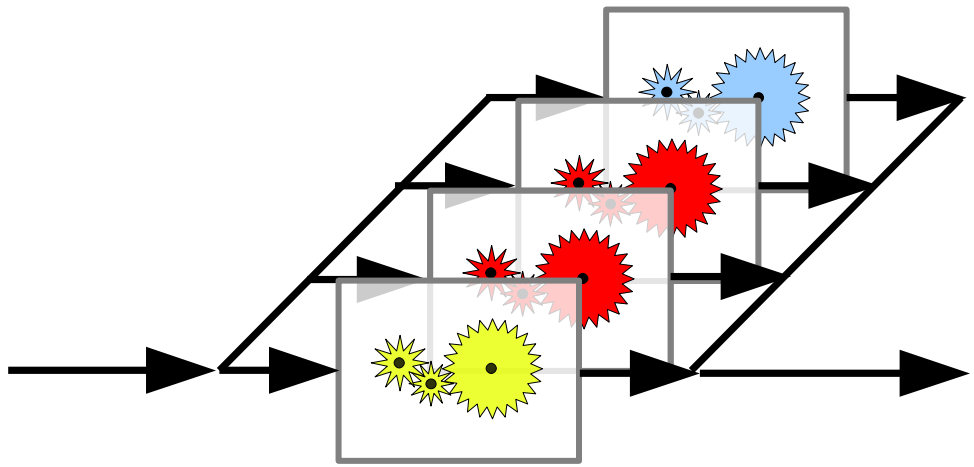
- uses *random forest model* to predict performance of parameter configurations
- predictions based on algorithm parameters and instance features, aggregated across instances
- finds promising configurations based on *expected improvement criterion*, using multi-start local search and random sampling
- initialisation with single configuration (algorithm default or randomly chosen)

Parallel algorithm portfolios

Key idea:

Exploit complementary strengths by running multiple algorithms (or instances of a randomised algorithm) concurrently.

Parallel Algorithm Portfolios



Parallel algorithm portfolios

Key idea:

Exploit complementary strengths by running multiple algorithms (or instances of a randomised algorithm) concurrently.

$\rightsquigarrow$ risk *vs* reward (expected running time) tradeoff,
robust performance on a wide range of instances

Huberman, Lukose, Hogg (1997); Gomes & Selman (1997,2000)

Note:

- can be realised through time-sharing / multi-tasking
- particularly attractive for multi-core / multi-processor architectures

Application to decision problems (like SAT, SMT):

Concurrently run given component solvers until the first of them solves the instance.

$\rightsquigarrow$ running time on instance π =
(# solvers) $\times$ (running time of VBS on π)

Examples:

- ManySAT (Hamadi, Jabbour, Sais 2009; Guo, Hamadi, Jabbour, Sais 2010)
- Plingeling (Biere 2010–11)
- ppfolio (Roussel 2011)

$\rightsquigarrow$ excellent performance (see 2009, 2011 SAT competitions)

Constructing portfolios from a single parametric solver

HH, Leyton-Brown, Schaub, Schneider (2012)

Key idea: Take single parametric solver, find configurations that make an effective parallel portfolio

Note: This allows to automatically obtain parallel solvers from sequential sources *(automatic parallisation)*

Ingredients for parallel solver

based on competitive parallel portfolio

- Parametric solver A
- Configuration space C
- Instance set I
- Algorithm configurator AC

That's all!

Recipe for parallel solver

based on competitive parallel portfolio

1. Use algorithm configurator to produce multiple configurations of given solver that work well together
2. Run configurations in parallel until one solves given instance

Fully automatic method!

Recipe: GLOBAL

for parallel solver based on competitive parallel portfolio

- For k portfolio components (= processors/threads), consider combined configuration space C^k of k copies of given parametric solver
- Use configurator AC to find good joint configuration in C^k (standard protocol for current configurators: pick best result from multiple independent runs)
- Configurations are assessed using (training) instance set I

Challenge: Large configuration spaces (exponential in k)

Recipe: GREEDY

for parallel solver based on competitive parallel portfolio

- Add portfolio components, one at a time,
  starting from single solver
- *Iteration 1:* Configure given solver A using configurator AC
  $\rightsquigarrow$ single-component portfolio A^1
- *Iteration* $j = 2 \ldots k$*:* Configure given solver A using AC
  to achieve optimised performance of
  extended portfolio $A^j := A^{j-1} \,||\, A$
  i.e., optimise improvement in A^j over A^{j-1}

Note: Similar idea to many greedy constructive algorithms
(including `Hydra`, Xu *et al.* 2010)

Product: parallel *Lingeling* (v.276)

on *SAT Comp. Application* instances

	PAR10	Overall Speedup *vs* Configured-SP	Avg. Speedup *vs* Configured-SP
Default-SP	3747	0.93	1.44
Configured-SP	3499	1.00	1.00
Plingeling	3066	1.14	7.39
Global-MP4	2734	1.27	10.47
Greedy-MP4	1341	2.61	3.52

Cost & concerns

But what about ...

- Computational complexity?
- Cost of development?
- Limitations of scope?

Computationally too expensive?

SPEAR revisited:

- total configuration time on software verification benchmarks:
  $\approx$ 30 CPU days
- wall-clock time on 10 CPU cluster:
  $\approx$ 3 days
- cost on Amazon Elastic Compute Cloud (EC2):
  61.20 USD (= 42.58 EUR)
- 61.20 USD pays for ...
  - 1:45 hours of average software engineer
  - 8:26 hours at minimum wage

Too expensive in terms of development?

Design and coding:

- tradeoff between performance/flexibility and overhead
- overhead depends on level of PbO
- traditional approach: cost from manual exploration of design choices!

Testing and debugging:

- design alternatives for individual mechanisms and components can be tested separately

$\rightsquigarrow$ effort linear (rather than exponential) in the number of design choices

Limited to the "niche" of NP-hard problem solving?

Some PbO-flavoured work in the literature:

- computing-platform-specific performance optimisation of linear algebra routines

  (Whaley *et al.* 2001)

- optimisation of sorting algorithms using genetic programming

  (Li *et al.* 2005)

- compiler optimisation

  (Pan & Eigenmann 2006, Cavazos *et al.* 2007)

- database server configuration

  (Diao *et al.* 2003)

The road ahead

- Support for PbO-based software development
  - Weavers for PbO-C, PbO-C++, PbO-Java
  - PbO-aware development platforms
  - Improved / integrated PbO design optimiser
- Best practices
- Many further applications
- Scientific insights

Leveraging parallelism

- design choices in parallel programs

  (Hamadi, Jabhour, Sais 2009)

- deriving parallel programs from sequential sources
  $\rightsquigarrow$ concurrent execution of optimised designs
  (parallel portfolios)

  (Schneider, HH, Leyton-Brown, Schaub *in progress*)

- parallel design optimisers

  (*e.g.*, Hutter, Hoos, Leyton-Brown 2012)

Programming by Optimisation ...

- leverages computational power to construct better software
- enables creative thinking about design alternatives
- produces better performing, more flexible software
- facilitates scientific insights into
  - efficacy of algorithms and their components
  - empirical complexity of computational problems

... changes how we build and use high-performance software

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- Arrow, BETA, ICICS clusters
- Compute Canada / WestGrid

Gli uomini hanno idee [...]
– Le idee, se sono allo stato puro, sono belle.
Ma sono un meraviglioso casino.
Sono apparizioni provvisorie di infinito.

People have ideas [...]
– Ideas, in their pure state, are beautiful.
But they are an amazing mess.
They are fleeting apparitions of the infinite.

(Prof. Mondrian Kilroy *in Alessandro Baricco: City*)

DOI:10.1145/2076450.2076468

Avoid premature commitment, seek design alternatives, and automatically generate performance-optimized software.

BY HOLGER H. HOOS

Programming by Optimization

WHEN CREATING SOFTWARE, developers usually explore different ways of achieving certain tasks. These alternatives are often eliminated or abandoned early in the process, based on the idea that the flexibility they afford would be difficult or impossible to exploit later. This article challenges this view, advocating an approach that encourages developers to not only avoid premature commitment to certain design choices but to actively develop promising alternatives for parts of the design. In this approach, dubbed Programming by Optimization, or PbO, developers specify a potentially large design space of programs that accomplish a given task, from which versions of the program optimized for various use contexts are generated automatically, including parallel versions derived from the same sequential sources. We outline a simple, generic programming language extension that supports the specification of such design spaces and discuss ways specific programs that perform well in a given use context can be obtained from these specifications through relatively simple source-code transformations and powerful design-optimization methods. Using PbO, human experts can focus on the creative task of devising possible mechanisms for solving given problems or subproblems, while the tedious task of determining what works best in a given use context is performed automatically, substituting human labor by computation.

The potential of PbO is evident from recent empirical results (see the table here). In the first two use cases—mixed integer programming and planning—existing software exposing many design choices in the form of parameters was automatically optimized for speed. This resulted in, for example, up to 52-fold speedups for the widely used commercial IBM ILOG CPLEX Optimizer software for solving mixed-integer programming problems.[3] In the third use case—verification problems encoded into propositional satisfiability—the proactive development of alternatives for important components of the program were an important part of the design process, enabling even greater performance gains.

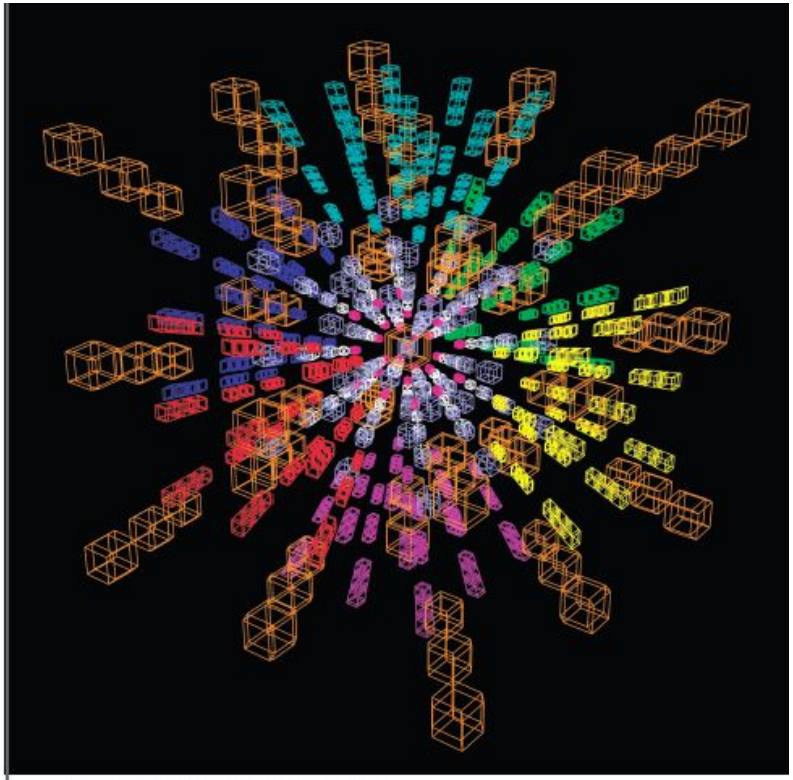
Performance Matters

Computer programs and the algorithms on which they are based frequently involve different ways of getting something done. Sometimes, certain choices are clearly preferable, but it is often unclear a priori which of several design decisions will ultimately give the best results. Such design choices can, and, routinely, do, occur at many levels, from high-level architectural aspects of a software system to low-level implementation details. They are often made based on considerations of maintainability, extensibility, and performance of the system or program under development. This article focuses on this latter aspect of a system's performance, considering only sets of semantically equivalent design choices and situations in which the performance of a program depends on the decisions made for each part of the program for which one or more candidate designs are available, even though these choices do not affect the program's correctness and functionality. Note this premise differs fundamentally from that of program synthesis, in which the primary goal is to come up with a design that satisfies a given functional specification.

It may appear that (partly due to the sustained, exponential improvement in computer hardware over more than five decades) software performance is a relatively minor concern. However, upon closer inspection this is far from

» key insights

- Premature commitment to design choices during software development often leads to loss of performance and limited flexibility.
- PbO aims to avoid premature design choices and actively develop design alternatives, leading to large and rich design spaces of programs that can be specified through simple generic extensions of existing programming languages.
- Advanced optimization and machine-learning techniques make it possible to perform automated performance optimization over the large spaces of programs arising in PbO-based software development; per-instance algorithm selectors and parallel algorithm portfolios can be obtained from the same sequential source.



MagicCube5D, a fully functional five-dimensional analogue of Rubik's Cube.

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