MO-ParamILS

A Multi-objective Framework for Automatic Algorithm Configuration

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Context

Problematic: Parameter Setting

- Algorithms with many parameters
- Default configuration is not necessarily best!

IBM ILOG CPLEX Optimization Studio

- Commercial solver for mixed integer programming problems
- More than 70 performance parameters, $\approx 10^{46}$ configurations!

Automatic Algorithm Configuration

- How to deal with those parameters?
- How to find the best configuration?

Offline Configuration

Algorithm Configuration – Parameter Tuning

Given:

- Problem (*e.g.*, MIP, Knapsack, SAT)
- Set of training instances
- Performance objective
- Parameterised target algorithm (*e.g.*, CPLEX, GA)

Find best configuration, *i.e.*, most adequate set of parameters.

Statistical methods

- F-Race [Birattari *et al.*, 2009]
- irace [López-Ibáñez *et al.*, 2011]

Optimisation methods

- ParamILS [Hutter *et al.*, 2009]
- SMAC [Hutter *et al.*, 2011]
- GGA [Antosegui *et al.*, 2009]

Motivation

Target Algorithm Performance Assessment

Generally with regard to a single performance objective:

- Solution quality
- CPU time

Motivation

May want to use multiple performance objectives for comparing different configurations of the target algorithm.

Outline

ParamILS

Reference

Hutter, Hoos, Leyton-Brown, Stützle (2009)

Why ParamILS?

- Prominent, state-of-the-art, general-purpose automated algorithm configurator
- Many successful applications
- Deals with very large configuration spaces
- Part of ACLib [Hutter *et al.*, 2014]

ParamILS

Principles

- Model-free search procedure
- Iterated local search (ILS) [Louranço *et al.*, 2003]

ParamILS

- Single-objective optimisation
- Input
  - Set of problem instances
  - Target algorithm
  - Configuration space
- Output: best configuration found

ParamILS

General framework

```
best_config ← init();
until termination criterion met do
    config ← perturb(best_config);
    config ← local_search(config);
    best_config ← accept(config, best_config);
return best_config;
```

ParamILS

Initialisation

Best of:

- Default or hand-picked configurations
- $r = 10$ random configurations

Perturbation

- After the first local search descent
- $s = 3$ random one-exchange moves

Neighbourhood: One-exchange

Two configurations are neighbours if and only if they differ by a single parameter value.

ParamILS

Local Search

- Exploration
  - Neutrality-based Hillclimbing
  - Stops on better or equal neighbours
- Tabu list
  - Unbounded
  - All visited configurations
- Stops if all neighbours are worse or tabu

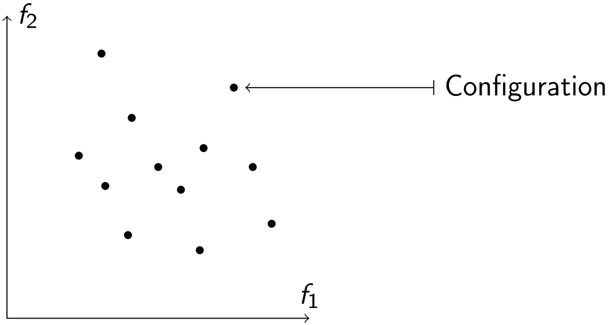
Acceptance Criterion

- Accept better of two given configurations

Multi-objective Optimisation

Pareto Dominance – Minimisation

$$x \prec y \iff \begin{cases} \forall i \in \{1, \ldots, n\} : & c_i(x) \leq c_i(y) \\ \exists i \in \{1, \ldots, n\} : & c_i(x) < c_i(y) \end{cases}$$



Multi-objective Optimisation

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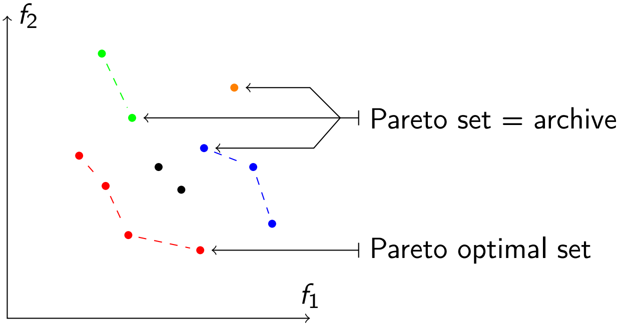


From ParamILS to MO-ParamILS

ParamILS

- Single-objective optimisation
- Input
  - Set of problem instances
  - Target algorithm
  - Configuration space
- Output: best configuration found

MO-ParamILS

- Multi-objective optimisation
- Input
- Output: Pareto set of the best configurations found

MO-ParamILS

General framework

```
best_arch ← init();
until termination criterion met do
    arch ← mo_perturb(best_arch);
    arch ← mo_local_search(arch);
    best_arch ← archive(arch, best_arch);
return best_arch;
```

MO-ParamILS

Initialisation

Best of:

- Default or hand-picked configurations
- $r = 10$ random configurations

Perturbation

- After the first local search descent
- Select a single configuration from the current archive
- $s = 3$ random one-exchange moves

Neighbourhood: One-exchange

Two configurations are neighbours if and only if they differ by a single parameter value.

MO-ParamILS

Multi-objective Local Search

- Selection
  - All current configurations are explored
- Exploration
  - Dominance-based Hillclimbing
  - Stops on dominating neighbours
  - Keeps non-dominated neighbours
- Tabu list
- Stops if all neighbours are worse or tabu

Acceptance Criterion

- Archive new configurations

MO-BasicILS, MO-FocusedILS

BasicILS – MO-BasicILS

- Evaluate on fixed subset of N random training instances

Issues of BasicILS

- Need to fix N
  - N too high: wasted time on poor configurations
  - N too low: imprecise evaluation on good configurations

FocusedILS – MO-FocusedILS

- Evaluate on increasingly large parts of training set
- Domination and intensification mechanisms

Experimental Protocol

Algorithms

- Default configuration
- FocusedILS (aggregation)
- MO-BasicILS
- MO-FocusedILS

Machine learning

- Training set
- Disjoint validation set

Scenarios

	Dataset	Algorithm	Training	Performance objectives
S1	Regions200	CPLEX (MIP)	1 day	[Quality, Cutoff]
S2	Regions200	CPLEX	1 day	[Quality, CPU time]
S3	CORLAT	CPLEX	1 day	[Quality, Cutoff]
S4	CORLAT	CPLEX	1 day	[Quality, CPU time]
S5	QUEENS	CLASP (SAT)	1 day	[CPU time, Memory usage]

Results

Minimisation of hypervolume (top) and ε-indicator values (bottom)

Approach	S1	S2	S3	S4	S5
Default	2.43e-01	3.57e-01	2.70e-01	5.30e-01	1.08e+00
FocusedILS	3.82e-02	5.82e-02	3.35e-01	1.72e-01	3.04e-02
MO-BasicILS	2.46e-03	5.41e-02	5.53e-02	1.02e-01	5.49e-02
MO-FocusedILS	9.02e-03	2.07e-03	2.37e-02	7.63e-04	1.57e-02
Default	2.22e-01	2.69e-01	2.33e-01	3.90e-01	1.00e+00
FocusedILS	5.77e-02	1.38e-02	3.33e-01	1.42e-01	6.52e-02
MO-BasicILS	1.80e-02	1.71e-01	1.11e-01	1.48e-01	8.35e-02
MO-FocusedILS	1.44e-02	9.05e-03	9.00e-02	8.06e-04	2.64e-02

MO-ParamILS > FocusedILS > Default

MO-FocusedILS > MO-BasicILS

Conclusion and Future Work

MO-ParamILS

- Efficient, general-purpose, *multi-objective* algorithm configurator

Future Work

- Compare to other multi-objective configurators
  - SPRINT-Race [Zhang *et al.*, 2015]
  - SMAC [Hutter *et al.*, 2011] $\rightarrow$ MO-SMAC
- Test MO-ParamILS on multi-objective target algorithms
- Distinguish symbolical and numerical parameters in ParamILS

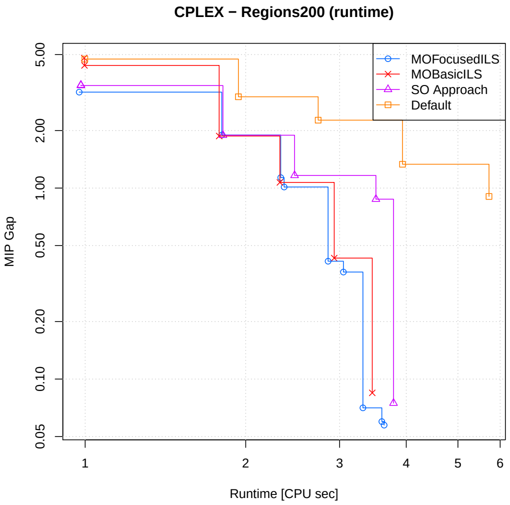
Example

CPLEX

- MIP solver
- 74 params

Regions200

- Actions
- 200 goods
- 1000 bids



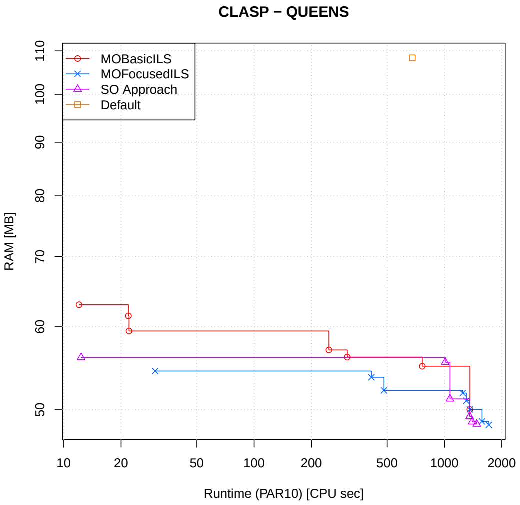
Example

CLASP

- ASP/SAT solver
- 73 params

QUEENS

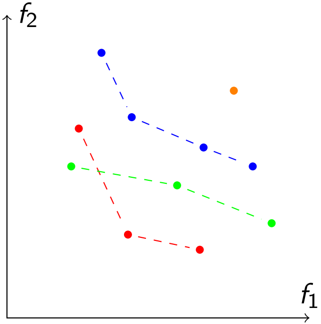
- n-queens
- $n \in \{10 \ldots 50\}$



Methodology

Suggested protocol

1. Train multiple times
2. Select everything
3. Validate on the training set
4. Select the Pareto set
5. Validate on the validation set



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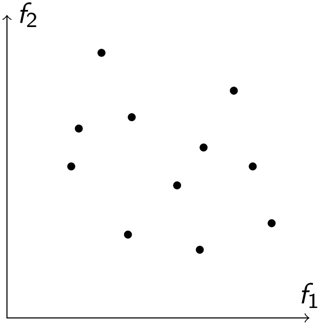

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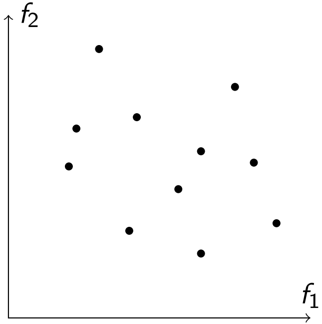

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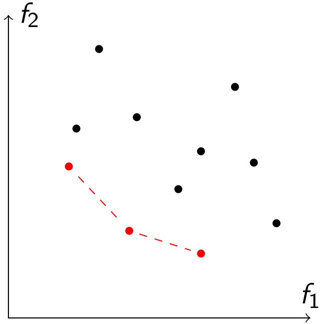

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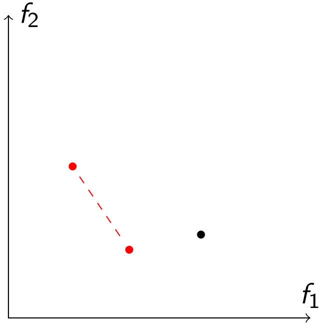

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