Automated Configuration of MIP solvers

Frank Hutter, Holger Hoos, and Kevin Leyton-Brown

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

CPAIOR 2010, June 16

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)
- Set to optimize empirical performance

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)
- Set to optimize empirical performance

Prominent parameters in MIP solvers

- Preprocessing
- Which type of cuts to apply
- MIP strategy parameters
- Details of underlying linear (or quadratic) programming solver

▶ 76 parameters that affect search trajectory

▶ 76 parameters that affect search trajectory

"Integer programming problems are more sensitive to specific parameter settings, so **you may need to experiment with them.**" [CPLEX 12.1 user manual, page 235]

- ▶ 76 parameters that affect search trajectory
 - "Integer programming problems are more sensitive to specific parameter settings, so **you may need to experiment with them.**" [CPLEX 12.1 user manual, page 235]
- "Experiment with them"
 - Perform manual optimization in 76-dimensional space
 - Complex, unintuitive interactions between parameters

- ▶ 76 parameters that affect search trajectory
 - "Integer programming problems are more sensitive to specific parameter settings, so **you may need to experiment with them.**" [CPLEX 12.1 user manual, page 235]
- "Experiment with them"
 - Perform manual optimization in 76-dimensional space
 - Complex, unintuitive interactions between parameters
 - Humans are not good at that

- 76 parameters that affect search trajectory
 - "Integer programming problems are more sensitive to specific parameter settings, so **you may need to experiment with them.**" [CPLEX 12.1 user manual, page 235]
- "Experiment with them"
 - Perform manual optimization in 76-dimensional space
 - Complex, unintuitive interactions between parameters
 - Humans are not good at that
- ► CPLEX automated tuning tool (since version 11)
 - Saves valuable human time
 - Improves performance

- Given:
 - Runnable algorithm A, its parameters and their domains
 - Benchmark set of instances Π
 - Performance metric *m*

- Given:
 - Runnable algorithm A, its parameters and their domains
 - Benchmark set of instances Π
 - Performance metric m
- ► Find:
 - Parameter setting ("configuration") of A optimizing m on Π

- Given:
 - Runnable algorithm A, its parameters and their domains
 - Benchmark set of instances Π
 - Performance metric m
- ► Find:
 - Parameter setting ("configuration") of A optimizing m on Π
- First to handle this with many categorical parameters
 - E.g. 51/76 CPLEX parameters are categorical
 - -10^{47} possible configurations \rightsquigarrow algorithm configuration

- Given:
 - Runnable algorithm A, its parameters and their domains
 - Benchmark set of instances Π
 - Performance metric m
- ► Find:
 - Parameter setting ("configuration") of A optimizing m on Π
- First to handle this with many categorical parameters
 - E.g. 51/76 CPLEX parameters are categorical
 - -10^{47} possible configurations \rightsquigarrow algorithm configuration

This paper: application study for MIP solvers

- Use existing algorithm configuration tool (PARAMILS)
- ▶ Use different MIP solvers (CPLEX, GUROBI, LPSOLVE)
- Use six different MIP benchmark sets
- Optimize different objectives (runtime to optimality/MIP gap)

Outline

- 1. Related work
- 2. Details about this study
- 3. Results
- 4. Conclusions

Outline

- 1. Related work
- 2. Details about this study
- Results
- 4. Conclusions

Parameter Optimization Tools and Applications

- COMPOSER [Gratch & Dejong, '92; Gratch and Chien, '96]
 - Spacecraft communication scheduling
- CALIBRA [Diaz and Laguna, '06]
 - Optimized various metaheuristics
- ► F-RACE [Birattari et al., '04-present]
 - Iterated Local Search and Ant Colony Optimization
- PARAMILS [Hutter et al, '07-present]
 - SAT (tree & local search), time-tabling, protein folding, ...

Parameter Optimization Tools and Applications

- COMPOSER [Gratch & Dejong, '92; Gratch and Chien, '96]
 - Spacecraft communication scheduling
- CALIBRA [Diaz and Laguna, '06]
 - Optimized various metaheuristics
- ► F-RACE [Birattari et al., '04-present]
 - Iterated Local Search and Ant Colony Optimization
- ► PARAMILS [Hutter et al, '07-present]
 - SAT (tree & local search), time-tabling, protein folding, ...
- ► STOP [Baz, Hunsaker, Brooks & Gosavi, '07 (Tech report)] [Baz, Hunsaker & Prokopyev, Comput Optim Appl, '09]
 - Optimized MIP solvers, including CPLEX
 - We only found this work pprox 1 month ago

Parameter Optimization Tools and Applications

- COMPOSER [Gratch & Dejong, '92; Gratch and Chien, '96]
 - Spacecraft communication scheduling
- ► CALIBRA [Diaz and Laguna, '06]
 - Optimized various metaheuristics
- ► F-RACE [Birattari et al., '04-present]
 - Iterated Local Search and Ant Colony Optimization
- ► PARAMILS [Hutter et al, '07-present]
 - SAT (tree & local search), time-tabling, protein folding, ...
- ► STOP [Baz, Hunsaker, Brooks & Gosavi, '07 (Tech report)] [Baz, Hunsaker & Prokopyev, Comput Optim Appl, '09]
 - Optimized MIP solvers, including CPLEX
 - We only found this work ≈ 1 month ago
 - Main problem: only optimized performance for single instances
 - Only used small subset of 10 CPLEX parameters

Outline

- 1. Related work
- 2. Details about this study

The automated configuration tool: PARAMILS The MIP solvers: CPLEX, GUROBI & LPSOLVE Experimental Setup

- Results
- 4. Conclusions

Outline

- 1. Related work
- 2. Details about this study

The automated configuration tool: PARAMILS

The MIP solvers: CPLEX, GUROBI & LPSOLVE Experimental Setup

- 3. Results
- 4. Conclusions

Start with some parameter configuration

Start with some parameter configuration

Modify a single parameter

Start with some parameter configuration

Modify a single parameter

if results on benchmark set improve then

keep new configuration

```
Start with some parameter configuration
repeat
```

Modify a single parameter

until no more improvement possible (or "good enough")

```
Start with some parameter configuration

repeat

| Modify a single parameter

if results on benchmark set improve then

| keep new configuration

until no more improvement possible (or "good enough")
```

→ Manually-executed local search

```
Start with some parameter configuration

repeat

Modify a single parameter

if results on benchmark set improve then

keep new configuration

until no more improvement possible (or "good enough")
```

→ Manually-executed local search

PARAMILS [Hutter et al., AAAI'07 & '09]: Iterated local search: 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
 - Variance reduction: use same N instances & seeds for each θ

Instantiations of ParamILS Framework

How to evaluate each configuration?

- ▶ BASICILS(N): perform fixed number of N runs to evaluate a configuration θ
 - Variance reduction: use same N instances & seeds for each θ
- ▶ FOCUSEDILS: choose $N(\theta)$ adaptively
 - small $N(\theta)$ for poor configurations θ
 - large $N(\theta)$ only for good θ

Instantiations of ParamILS Framework

How to evaluate each configuration?

- ▶ BASICILS(N): perform fixed number of N runs to evaluate a configuration θ
 - Variance reduction: use same N instances & seeds for each θ
- ▶ FOCUSEDILS: choose $N(\theta)$ adaptively
 - small $N(\theta)$ for poor configurations θ
 - large $N(\theta)$ only for good θ
 - typically outperforms BASICILS
 - used in this study

Adaptive Choice of Cutoff Time

Evaluation of poor configurations takes especially long

Adaptive Choice of Cutoff Time

- Evaluation of poor configurations takes especially long
- Can terminate evaluations early
 - Incumbent solution provides bound
 - Can stop evaluation once bound is reached

Adaptive Choice of Cutoff Time

- Evaluation of poor configurations takes especially long
- Can terminate evaluations early
 - Incumbent solution provides bound
 - Can stop evaluation once bound is reached
- Results
 - Provably never hurts
 - Sometimes substantial speedups [Hutter et al., JAIR'09]

Outline

- 1. Related work
- 2. Details about this study

The automated configuration tool: PARAMILS
The MIP solvers: CPLEX, GUROBI & LPSOLVE
Experimental Setup

- 3. Results
- 4. Conclusions

▶ Commercial solvers: CPLEX 12.1 & GUROBI 2.0.1

► Commercial solvers: CPLEX 12.1 & GUROBI 2.0.1

Algorithm	Parameter type	# params	# values	Total # configurations
CPLEX	Boolean	6	2	1.90 · 10 ⁴⁷
	Categorical	45	3–7	
	Integer	18	discretized: 5-7	
	Continuous	7	discretized: 5–8	

▶ Commercial solvers: CPLEX 12.1 & GUROBI 2.0.1

Algorithm	Parameter type	# params	# values	Total # configurations
CPLEX	Boolean	6	2	1.90 · 10 ⁴⁷
	Categorical	45	3–7	
	Integer	18	discretized: 5-7	
	Continuous	7	discretized: 5–8	
Gurobi	Boolean	4	2	$3.84 \cdot 10^{14}$
	Categorical	16	3–5	
	Integer	3	discretized: 5	
	Continuous	2	discretized: 5	

▶ Commercial solvers: CPLEX 12.1 & GUROBI 2.0.1

Algorithm	Parameter type	# params	# values	Total # configurations
CPLEX	Boolean	6	2	1.90 · 10 ⁴⁷
	Categorical	45	3–7	
	Integer	18	discretized: 5-7	
	Continuous	7	discretized: 5–8	
Gurobi	Boolean	4	2	$3.84 \cdot 10^{14}$
	Categorical	16	3–5	
	Integer	3	discretized: 5	
	Continuous	2	discretized: 5	
LPSOLVE	Boolean	40	2	$1.22\cdot 10^{15}$
	Categorical	7	3–8	

MIP Solvers & their parameters

▶ Commercial solvers: CPLEX 12.1 & GUROBI 2.0.1

▶ Open-source solver: LPSOLVE 5.5

Algorithm	Parameter type	# params	# values	Total # configurations	
CPLEX	Boolean	6	2	1.90 · 10 ⁴⁷	
	Categorical	45	3–7		
	Integer	18	discretized: 5-7		
	Continuous	7	discretized: 5–8		
Gurobi	Boolean	4	2	3.84 · 10 ¹⁴	
	Categorical	16	3–5		
	Integer	3	discretized: 5		
	Continuous	2	discretized: 5		
LPSOLVE	Boolean	40	2	$1.22 \cdot 10^{15}$	
	Categorical	7	3–8	1.22 · 10-3	

Problems with some parameter configurations

► Segmentation faults & wrong results

MIP Solvers & their parameters

▶ Commercial solvers: CPLEX 12.1 & GUROBI 2.0.1

▶ Open-source solver: LPSOLVE 5.5

Algorithm	Parameter type	# params	# values	Total # configurations	
CPLEX	Boolean	6	2	1.90 · 10 ⁴⁷	
	Categorical	45	3–7		
	Integer	18	discretized: 5-7	1.90 · 10**	
	Continuous	7	discretized: 5–8		
Gurobi	Boolean	4	2		
	Categorical	16	3–5	2.04. 1014	
	Integer	3	discretized: 5	$3.84 \cdot 10^{14}$	
	Continuous	2	discretized: 5		
LPSOLVE	Boolean	40	2	$1.22 \cdot 10^{15}$	
	Categorical	7	3–8	1.22 · 1029	

Problems with some parameter configurations

- ► Segmentation faults & wrong results
- ▶ Detect such runs online, give worst possible score
 - Local search avoids problematic parameter configurations

MIP Solvers & their parameters

▶ Commercial solvers: CPLEX 12.1 & GUROBI 2.0.1

▶ Open-source solver: LPSOLVE 5.5

Algorithm	Parameter type	# params	# values	Total # configurations	
CPLEX	Boolean	6	2		
	Categorical	45	3–7	1.90 · 10 ⁴⁷	
	Integer	18	discretized: 5-7		
	Continuous	7	discretized: 5–8		
Gurobi	Boolean	4	2		
	Categorical	16	3–5	2.04. 1014	
	Integer	3	discretized: 5	$3.84 \cdot 10^{14}$	
	Continuous	2	discretized: 5		
LPSOLVE	Boolean	40	2	$1.22 \cdot 10^{15}$	
	Categorical	7	3–8	1.22 · 1023	

Problems with some parameter configurations

- Segmentation faults & wrong results
- Detect such runs online, give worst possible score
 - → Local search avoids problematic parameter configurations
- ► Concise bug reports \rightsquigarrow helped to fix 2 bugs in GUROBI (!)

Outline

- 1. Related work
- 2. Details about this study

The automated configuration tool: PARAMILS The MIP solvers: CPLEX, GUROBI & LPSOLVE Experimental Setup

- 3. Results
- 4. Conclusions

Benchmark sets used

Domain	Туре	#instances	Citation
Comp. sustainability (SUST)	MILP	2 000	[Gomes et al, '08]
Combinatorial auctions (WDP)	MILP	2 000	[Leyton-Brown et al., '00]
Mixed integer knapsack (MIK)	MILP	120	[Atamtürk, '03]
and 3 more			

Benchmark sets used

Domain	Туре	#instances	Citation
Comp. sustainability (SUST)	MILP	2 000	[Gomes et al, '08]
Combinatorial auctions (WDP)	MILP	2 000	[Leyton-Brown et al., '00]
Mixed integer knapsack (MIK)	MILP	120	[Atamtürk, '03]
and 3 more			

Split benchmarks 50:50 into training and test sets

- Optimized parameters on the training set
- Reported performance on the test set
- Necessary to check for over-tuning

Setup of configuration experiments

Perform 10 independent runs of PARAMILS

• Select configuration $\hat{\theta^*}$ of run with best *training* performance

Setup of configuration experiments

Perform 10 independent runs of PARAMILS

Select configuration $\hat{\theta}^*$ of run with best *training* performance

Compare test performance of:

- PARAMILS's configuration $\hat{\theta^*}$
- Default algorithm settings
- CPLEX tuning tool
 - GUROBI and LPSOLVE: no tuning tool available

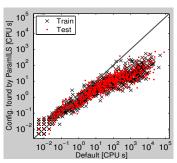
Outline

- 1. Related work
- 2. Details about this study
- 3. Results
- 4. Conclusions

 "Optimal": relative optimality gap of 0.0001 (CPLEX and GUROBI default)

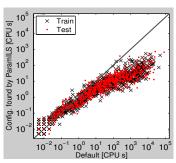
- "Optimal": relative optimality gap of 0.0001 (CPLEX and GUROBI default)
- ► Ran PARAMILS for 2 days on 10 machines

- "Optimal": relative optimality gap of 0.0001 (CPLEX and GUROBI default)
- ► Ran PARAMILS for 2 days on 10 machines
- Mean speedup (on test instances)
 - CPLEX 2x to 50x

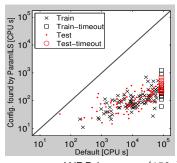


CPLEX on SUST instances (50x)

- "Optimal": relative optimality gap of 0.0001 (CPLEX and GUROBI default)
- ► Ran PARAMILS for 2 days on 10 machines
- Mean speedup (on test instances)
 - CPLEX 2x to 50x
 - LPSOLVE 1x (no speedup) to 150x

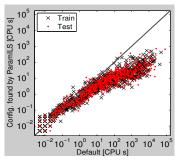


CPLEX on SUST instances (50x)

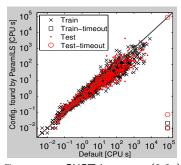


LPSOLVE on WDP instances (150x)

- "Optimal": relative optimality gap of 0.0001 (CPLEX and GUROBI default)
- ► Ran PARAMILS for 2 days on 10 machines
- Mean speedup (on test instances)
 - CPLEX 2x to 50x
 - LPSOLVE 1x (no speedup) to 150x
 - GUROBI 1.2x to 2.3x

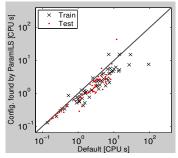


CPLEX on SUST instances (50x)

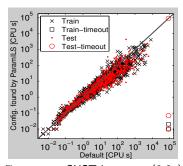


GUROBI on SUST instances (2.3x)

- "Optimal": relative optimality gap of 0.0001 (CPLEX and GUROBI default)
- ▶ Ran PARAMILS for 2 days on 10 machines
- Mean speedup (on test instances)
 - CPLEX 2x to 50x
 - LPSOLVE 1x (no speedup) to 150x
 - GUROBI 1.2x to 2.3x



GUROBI on MIK instances (1.2x)

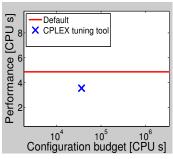


GUROBI on SUST instances (2.3x)

- CPLEX tuning tool
 - Evaluates predefined good configurations, returns best one
 - Required runtime varies (from < 1h to weeks)

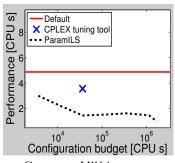
- CPLEX tuning tool
 - Evaluates predefined good configurations, returns best one
 - Required runtime varies (from < 1h to weeks)
- ► PARAMILS: anytime algorithm
 - At each time step, keeps track of its incumbent

- CPLEX tuning tool
 - Evaluates predefined good configurations, returns best one
 - Required runtime varies (from < 1h to weeks)
- ► PARAMILS: anytime algorithm
 - At each time step, keeps track of its incumbent



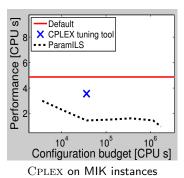
CPLEX on MIK instances

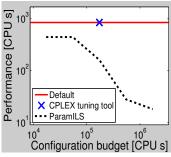
- CPLEX tuning tool
 - Evaluates predefined good configurations, returns best one
 - Required runtime varies (from < 1h to weeks)
- ► PARAMILS: anytime algorithm
 - At each time step, keeps track of its incumbent



CPLEX on MIK instances

- CPLEX tuning tool
 - Evaluates predefined good configurations, returns best one
 - Required runtime varies (from < 1h to weeks)
- ► PARAMILS: anytime algorithm
 - At each time step, keeps track of its incumbent





CPLEX on SUST instances

Minimization of Optimality Gap

▶ Objective: minimal optimality gap within 10 seconds runtime

Minimization of Optimality Gap

- ▶ Objective: minimal optimality gap within 10 seconds runtime
- ▶ Ran PARAMILS for 5 hours on 10 machines

Minimization of Optimality Gap

- ▶ Objective: minimal optimality gap within 10 seconds runtime
- ▶ Ran PARAMILS for 5 hours on 10 machines
- Reduction factors of average optimality gap (on test set)
 - CPLEX 1.3x to 8.6x
 - LPSOLVE 1x (no reduction) to 46x
 - Gurobi 1.1x to 2.2x

Outline

- 1. Related work
- 2. Details about this study
- 3. Results
- 4. Conclusions

Conclusions

MIP solvers can be configured automatically

- ► Configuration tool PARAMILS available online:
 - http://www.cs.ubc.ca/labs/beta/Projects/ParamILS/
 - off-the-shelf tool (knows nothing about MIP or MIP solvers!)
- Sometimes substantial improvements
- Saves valuable human time

Conclusions

MIP solvers can be configured automatically

- ► Configuration tool PARAMILS available online:
 - http://www.cs.ubc.ca/labs/beta/Projects/ParamILS/
 - off-the-shelf tool (knows nothing about MIP or MIP solvers!)
- Sometimes substantial improvements
- Saves valuable human time

Requirements

- ► Representative instance set
 - 100 instances sometimes not enough
 - If you generate instances, please make more (e.g., 2000)!

Conclusions

MIP solvers can be configured automatically

- ► Configuration tool PARAMILS available online:
 - http://www.cs.ubc.ca/labs/beta/Projects/ParamILS/
 - off-the-shelf tool (knows nothing about MIP or MIP solvers!)
- Sometimes substantial improvements
- Saves valuable human time

Requirements

- Representative instance set
 - 100 instances sometimes not enough
 - If you generate instances, please make more (e.g., 2000)!
- ► CPU time (here: 10 × 2 days per domain)

Future Work

- Model-based techniques
 - Fit a model that predicts performance of a given configuration on a given instance

Future Work

- Model-based techniques
 - Fit a model that predicts performance of a given configuration on a given instance
 - Use that model to quantify
 - + Importance of each parameter
 - + Interaction of parameters
 - + Interaction of parameters and instance characteristics

Future Work

- Model-based techniques
 - Fit a model that predicts performance of a given configuration on a given instance
 - Use that model to quantify
 - + Importance of each parameter
 - + Interaction of parameters
 - + Interaction of parameters and instance characteristics
- Per-instance approaches for heterogeneous benchmarks
 - Given a new unseen instance:
 - + Compute instance characteristics (fast)
 - + Use parameter config. predicted to be best for the instance

Thanks to:

- Providers of instance benchmark sets
 - Louis-Martin Rousseau
 - Bistra Dilkina
 - Berkeley Computational Optimization Lab
- Commercial MIP solvers for free full academic license
 - IBM (CPLEX)
 - Gurobi
- ▶ LPSOLVE developers for their solver
- Compute clusters
 - Westgrid
 - CFI-funded arrow cluster
- Funding agencies
 - Postdoc fellowship from CBIE
 - MITACS
 - NSFRC

Backup slides

Differences to STOP [Baz et al, '09]

Baz et al optimized for single instances

"In practice, users would typically be tuning for a family of related instances rather than for an individual instance"

- Generalization to sets of instances is nontrivial
 - Cannot afford to run all instances for each configuration
 - → FocusedILS adapts # runs per configuration

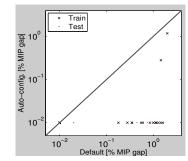
Further differences

- ▶ Baz et al used older CPLEX version (9.0)
 - defaults improved in newer CPLEX versions
- ▶ Baz et al considered (only) 10 CPLEX parameters
 - and also not all possible values for each parameter
 - in order to improve STOP's performance
 - requires domain knowledge

▶ Objective: minimal optimality gap within 10 seconds runtime

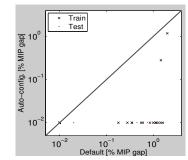
- ▶ Objective: minimal optimality gap within 10 seconds runtime
- ▶ Ran PARAMILS for 5 hours on 10 machines

- ▶ Objective: minimal optimality gap within 10 seconds runtime
- ▶ Ran PARAMILS for 5 hours on 10 machines
- Reduction factors of average optimality gap (on test inst.)
 - CPLEX 1.3x to 8.6x
 - LPSOLVE 1x (no reduction) to 46x
 - GUROBI 1.1x to 2.2x

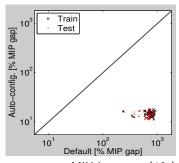


CPLEX on MIK instances (8.6x)

- ▶ Objective: minimal optimality gap within 10 seconds runtime
- ▶ Ran PARAMILS for 5 hours on 10 machines
- Reduction factors of average optimality gap (on test inst.)
 - CPLEX 1.3x to 8.6x
 - LPSOLVE 1x (no reduction) to 46x
 - Gurobi 1.1x to 2.2x



CPLEX on MIK instances (8.6x)



LPSOLVE on MIK instances (46x)