# SCIP Beyond 8.0

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# The SCIP Optimization Suite

A toolbox for generating and solving MILPs, MINLPs, and CIPs:

- SCIP : MIP solver and CIP framework,
- SoPlex: LP solver,
- PaPILO: parallel presolver for integer and linear optimization,
- ZIMPL: mathematical programming language,
- UG: parallel framework for MIPs,
- GCG: generic branch-cut-and-price solver,
- SCIP-SDP: extension for solving MISDPs,
- SCIP-Jack: extensiion for solving Steiner tree and related problems.

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# SCIP (Solving Constraint Integer Programs)

- Provides a full-scale MILP and MINLP solver,
- is constraint based,
- is a branch-cut-and-price framework,
- incorporates
  - MILP features (cutting planes, LP relaxation),
  - MINLP features (spatial branch-and-bound, OBBT)
  - CP features (domain propagation),
  - SAT-solving features (conflict analysis, restarts),
- has a modular structure via plugins,
- is licensed under Apache 2.0,
- and is available in source-code under https:// scipopt.org !



# **Overview of Recent Developments**

- Primal heuristics:
  - Online learning for scheduling heuristics
  - Feasibility jump
  - Indicator diving
- Cutting planes:
  - Lift-and-project cuts
  - Lagromory cuts
  - Improved implicit product filtering for RLT cuts
  - Monoidal strengthening of intersection cuts for MIQCPs
- Branching via cutting plane selection
- Pseudo-Boolean conflict analysis
- Updates to the exact solving framework for MILPs
- Improvements to symmetry handling
- New and improved interfaces
  - SCIP will be able to call HiGHS (https://highs.dev) as an LP solver
  - New interface: Rust
  - Improvements to the Julia interface

# **Scheduling Primal Heuristics: Motivation**

- MIP solving executes a broad range of primal heuristics for finding good solutions.
- The settings of heuristics are static with strict working limits.



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#### STATIC HEURISTIC HANDLING

## Question

Static settings derived from heterogeneous benchmark test sets might not yield best performance since performance of heuristics is highly instance-dependent.

#### Idea

Make the execution of heuristics adaptive by learning which heuristics perform well for the current instance.

# Scheduling Primal Heuristics: Online Learning

- A Chmiela, A Gleixner, P Lichocki, S Pokutta Online Learning for Scheduling MIP Heuristics
- Online scheduling framework manages (i) selection and (ii) working limits by learning from past observations.
- A novel reward function catches heuristics' impact on the solving process beyond simply finding new solutions.
- General framework enables us to schedule complex heuristics of different types simultaneously.



#### ONLINE SCHEDULING FRAMEWORK

- Consistent node reductions over the MIPLIB 2017 Benchmark set.
- Speedup of 4% for instances that take at least 1000s to solve.

## The Feasibility Jump Heuristic

B. Luteberget, G. Sartor Feasibility Jump: an LP-free Lagrangian MIP heuristic

1st place: MIP 2022 Computational Competition

Computational results on the MIPLIB benchmark:

- High success rate: Finds feasible solutions for over 30% of the instances
- Between 3 and 8% faster to the first feasible solution on average
- On average slightly slower

## The Feasibility Jump Heuristic

It's a Lagrangian heuristic method:  $\min c^T x$  s.t.  $Ax \leq b \rightarrow \min \mathcal{L}(x, \lambda) = \lambda^{\top} (b - Ax)$ 

- Start with an incumbent vector x<sup>\*</sup>
- Choose a single variable
- "Jump" to the value that minimizes the weighted sum of constraint violations (taking integrality into account)
- The neighborhood, defined by scores, is updated after each jump "lazily"
- Score: decrease in total constraint violation

 $\max\{\lambda^{\top}(\boldsymbol{b} - \boldsymbol{A}\boldsymbol{x}), 0\} - \max\{\lambda^{\top}(\boldsymbol{b} - \boldsymbol{A}\boldsymbol{x}^{*}), 0\}$ 

(i.e. violation before the jump - violation after the jump)

Update weights in the Lagrangian function



## **Indicator Diving Heuristic**

- A diving heuristic simulates a depth-first search.
  It alternates between tightening variable bounds and solving LP relaxations.
- Indicatordiving is a diving heuristic with focus on (unbounded) semi-continuous variables.
- Semi-cont. variables  $y \in \{0\} \cup [\ell, u]$  with  $u \in \mathbb{R}_+ \cup \{\infty\}$ are modeled with a binary indicator variable:  $z = 0 \rightarrow y = 0$  $z = 1 \rightarrow y > \ell$
- During the diving process z is fixed depending on the LP solution value  $y^{LP}$  of the semi-cont. variable y:



# Lift-and-project and Lagromory Cuts for MILPs

Lift-and-project cuts:

- Based on Bonami's 2012 work "On optimizing over lift-and-project closures"
- Goal: find cuts for the convex hull of a disjunction (e.g. branching)
- A trivial normalization constraint (NC) accounts for coefficient scaling
- NC  $\rightarrow$  reduce the cut generating LP (CGLP) based on certain inferences
- Dualize the reduced CGLP  $\rightarrow$  membership LP
- Solve membership LP, obtain dual information, and generate a cut

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#### Lagromory cuts:

- Based on Fischetti and Salvagnin's 2011 work "A relax-and-cut framework for Gomory mixed-integer cuts"
- In the root node consider Lagrangian dual problem, add GMI cuts as soft constraints
- GMI cuts 'tilt' the objective  $\rightarrow$  explore nearby bases, add more GMI cuts
- Solve this problem iteratively by updating the Lagrangian multipliers
- Select cuts from the set of all thus generated GMI cuts to add to cut pool

## Branching via Cutting Plane Selection: Motivation

Many cutting planes are derived from disjunctions. Most commonly from split disjunctions.



Figure: (Left) An example (simple) split. (Right) An example (simple) split cut.

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#### Idea

Make branching decisions based on history of cut strength from similar disjunctions.

# Branching via Cutting Plane Selection: Details

- Branching rule-1
  - Generate Gomori Mixed-Integer cuts from tableau rows corresponding to fractional basic variables.
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  - Generate Gomori Mixed-Integer cuts from tableau rows corresponding to fractional basic variables.
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- Branching rule-2
  - Similar to above, but based on weak-GMI cuts.
- Branching rule-3
  - Generate GMI cuts similar to above.
  - Calculate the average cut strength.
  - Incorporate this as an additional metric into SCIP's default branching scoring function.
  - Select a branching candidate based on the cut with largest score.

## Results on MIPLIB 2017 benchmark:

- Rule 3 affects 67% of instances
- 4% reduction in mean time on affected instances

## **Conflict Analysis: Brief Introduction**

When MIP solving reaches an infeasible subproblem, analyze the infeasibility to

- extract a shorter reason
- that prunes other parts of the tree
- and also helps in backtracking



- Generate a bound disjunction explaining the infeasibility similar to SAT solving.
  - · Operates on clauses and not on the more expressive linear constraints
- Generate the Farkas constraint  $(y^T A)x \ge y^T b$  for infeasible LPs.
  - May be dense with bad numerics

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## **Generalized Resolution Conflict Analysis**

Goal: Given the infeasible system

```
\begin{cases} a^{\top} x \ge a_o \quad (\text{reason: for propagating } x_i \ge \alpha) \\ b^{\top} x \ge b_o \quad (\text{conflict: infeasible for } x_i \ge \alpha) \\ x \in [\ell', u'] \subset [\ell, u]. \end{cases}
```

Can we find a single constraint that proves the infeasibility?

- G Mexi, T Berthold, A Gleixner, J Nordstroem Improving Conflict Analysis in MIP Solvers by Pseudo-Boolean Reasoning
- Applicable to pure binary constraints
- "massage" reason constraint until it propagates x<sub>i</sub> tightly.
  - Weakening: Set variables at global bounds and
  - Stengthening: MIR, CG, Coef. Tightening
- "Resolve" x<sub>i</sub> (add the two constraints so that x<sub>i</sub> disappears)

## Exact MILP Solving: Hybrid Branch-and-Bound



Implemented in SCIP: more details in Cook, Koch, Steffy, Wolter 2013.

Uses floating-point + directed rounding + rational arithmetic.

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## Exact MILP Solving: New Exact SCIP Features

## Eifler, Gleixner 2021 & 2022:

- thorough revision of hybrid-precision branch and bound
- integrate SoPlex as exact LP solver (Gleixner, Steffy 2019 & 2020)
- addition of rational presolving (Gleixner, Gottwald, Hoen 2023)
- addition of primal heuristics
- output of VIPR certificates (Cheung, Gleixner, Steffy 2017)

#### Eifler, Gleixner 2023 (preprint available)

safe, verified generation of Gomory mixed-integer cuts

#### Published soon:

- domain propagation + conflict analysis (Borst, Eifler, Gleixner)
- precision boosting + iterative refinement in exact LP (Eifler, Gleixner, Thouvenin)

## Symmetries in MIPs

Symmetries of a MIP

 $\max\{c^T x : Ax \le b, x \in \mathbb{Z}^n\}$ 

are bijections  $f: \mathbb{R}^n \to \mathbb{R}^n$  such that  $x \in \mathbb{R}^n$  is feasible iff f(x) is feasible and both have the same objective value.

**Issue** Branch-and-bound trees become unnecessarily large since symmetric subproblems are explored multiple times.

 $\max x_1 + x_2$  $x_1 + 2x_3 \le 3$  $x_2 + 2x_3 \le 3$ 

# **SCIP's Symmetry Handling Tools**

## Tools in SCIP 8.0

- automatic symmetry detection
- symmetry handling constraints (orbitopes, orbisacks, symresacks, SST cuts)
- propagation algorithms (orbital fixing)

Issue: Constraint-based and propagation-based methods can not be combined.

## Latest Symmetry Handling Changes

- completely revised symmetry handling framework that allows to combine constraints and propagation algorithms.
- at the time of merging, the new framework improves on the old framework by 5.9% (25.4% on instances running at least 1000s).
- interface to graph automorphims code sassy to accelerate symmetry detection

# Thank you!