The SCIP Optimization Suite 10

https://scipopt.org

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Outline

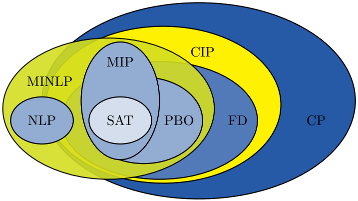
This talk has been split into two parts:

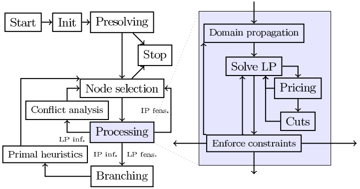
$$\underbrace{\textbf{The SCIP Optimization Suite}}_{\text{Part 1}} \quad \underbrace{\textbf{10}}_{\text{Part 2}}$$

The SCIP Optimization Suite

SCIP: Solving Constraint Integer Programs

- a framework for constraint integer programming, incorporating features from
  - MILP (cutting planes, LP relaxation)
  - CP (domain propagation)
  - SAT (conflict analysis, restarts)
  - MINLP (spatial branch-and-bound, NLPs)
- a branch-cut-and-price framework
- includes full-scale solvers for MILP, MINLP, and Pseudo-Boolean optimization (→ WB-43)





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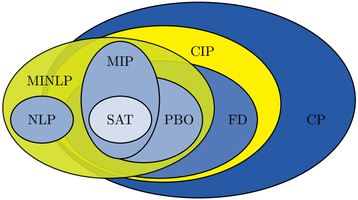
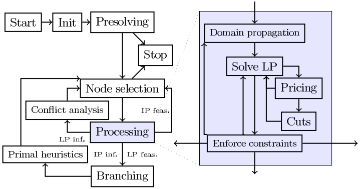
- and much more: Benders decomp., exact MILP, IIS, MILP reoptimization, concurrent solving, cumulative and logical constraints, ...





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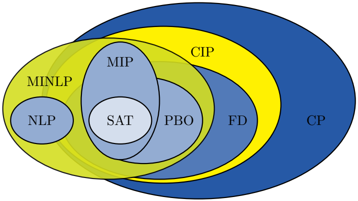
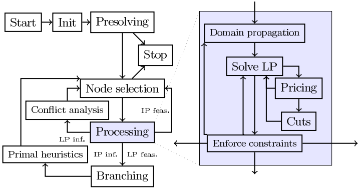
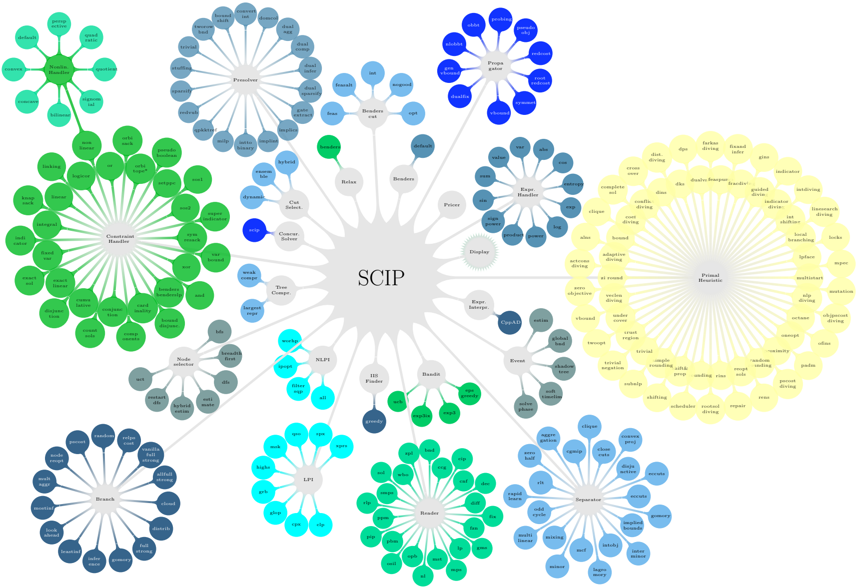
- and much more: Benders decomp., exact MILP, IIS, MILP reoptimization, concurrent solving, cumulative and logical constraints, . . .
- a platform for researchers to implement and test own methods in a general-purpose solver
  - plugin-based structure
  - basis for specialized extensions (GCG, SCIP-SDP, SCIP-Jack, QuBowl, . . .)
  - available open-source (Apache 2.0 license)
  - readable code



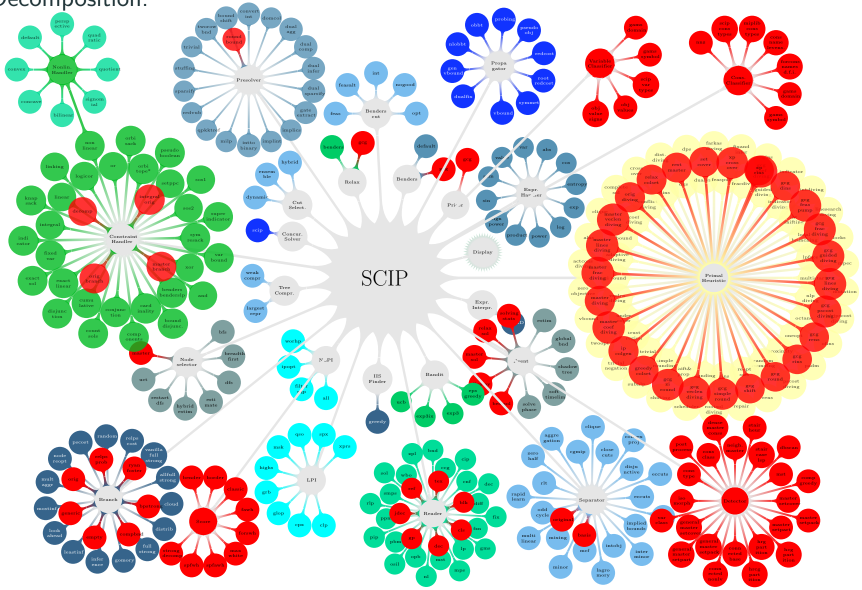


SCIP plugins



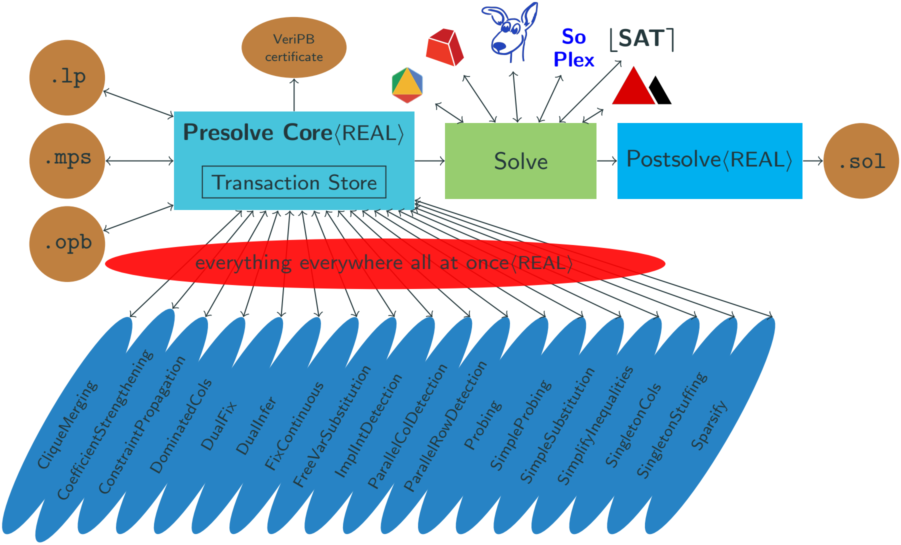
GCG: Generic Column Generation

Generic MILP solver with automatic structure detection, Dantzig-Wolfe, and Benders Decomposition.



PaPILO: Parallel Presolve for Integer and Linear Optimization

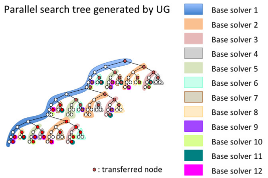
An independent library for presolving MILPs in parallel and with arbitrary precision.

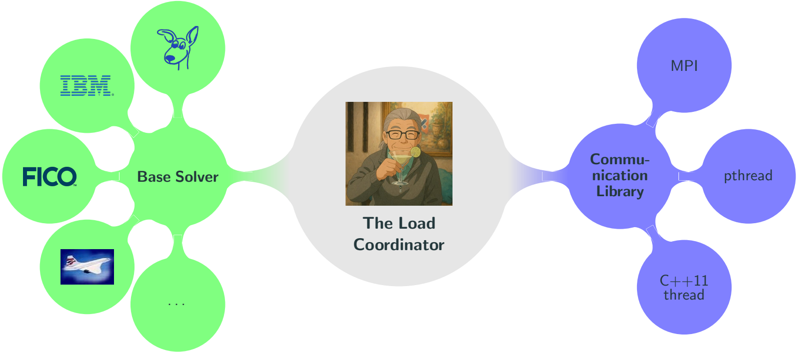


UG: Ubiquity Generator

Parallelization framework for solvers doing tree-search or other parallelizable tasks.

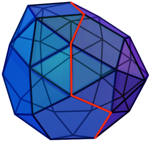
- distributed and shared memory environments
- normal and racing ramp-up, checkpointing
- more from Yuji in WB-43





SoPlex: Sequential object-oriented simPlex

- Simplex LP solver
- high precision and exact solving
- iterative refinement



SoPlex, ZIMPL

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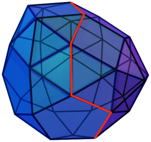

ZIMPL: Zuse Institute Mathematical Programming Language

- Algebraic modeling language in the style of AMPL
- rational arithmetic

ZIB

SCIP Optimization Suite Ecosystem

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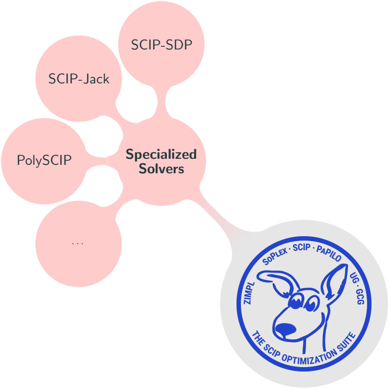

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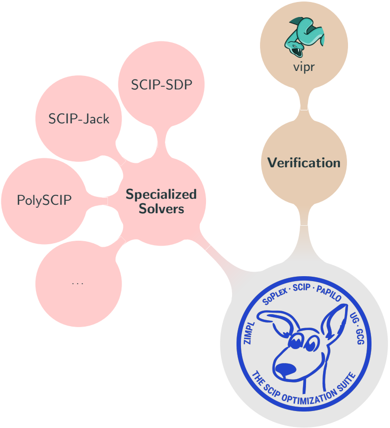

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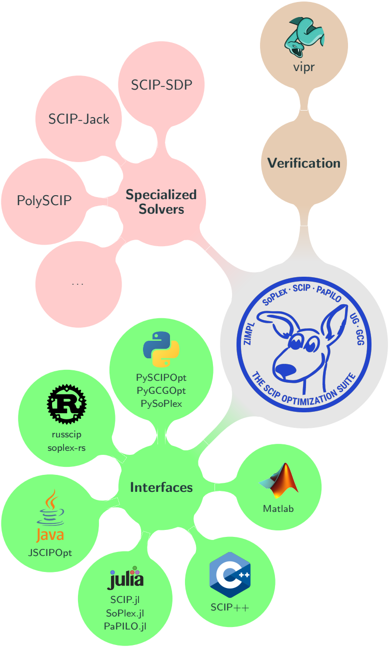

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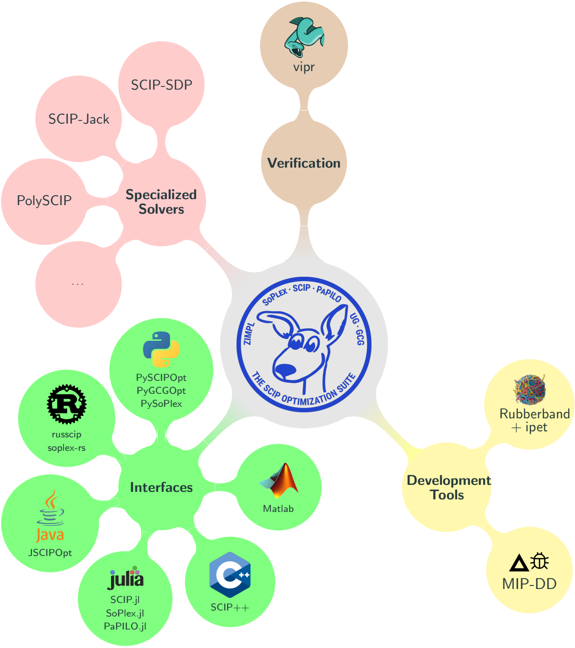

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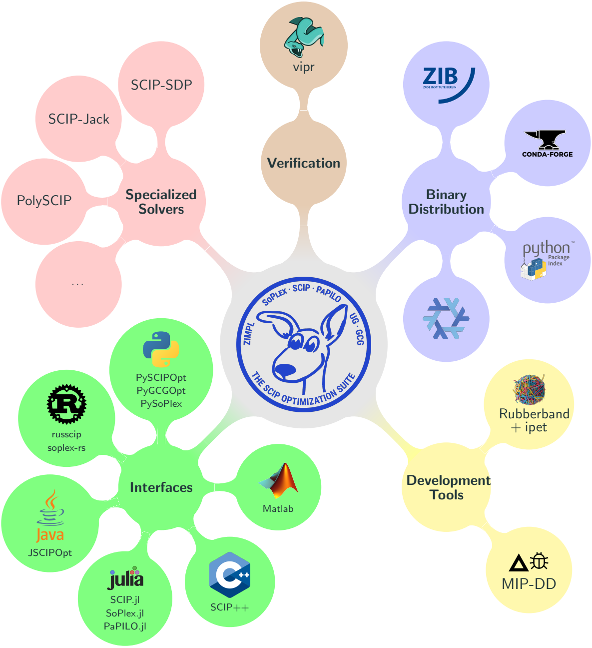

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SCIP can now **solve mixed-integer linear programs over $\mathbb{Q}$ exactly**: no rounding errors, zero tolerances

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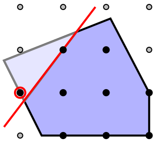

Exact MILP Solving

[Eifler, Gleixner 2023, 2024]

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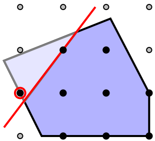

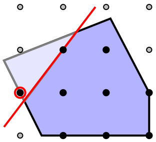

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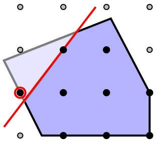

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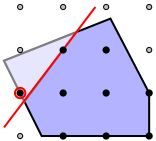

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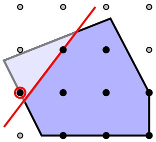

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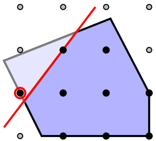

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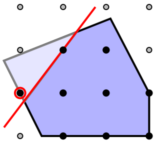

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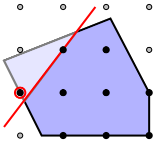

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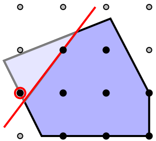

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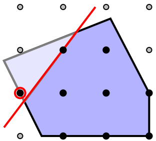

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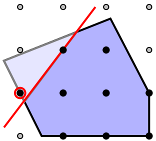

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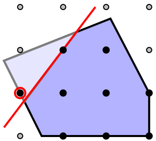

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- log deductions in solving process (without presolve) for verification with VIPR
- MIP-DD supports exact MILP, too

Exact MILP Solving: Performance

MIPLIB 2017 benchmark set, 3 random seeds, 2h time limit

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- default SCIP (floating-point) solves 342 instance+seed combinations

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153 can be solved in any configuration; on these instance+seed:

- disabling SCIP features (floating-point mode) increases mean time by 89% and mean nodes by 161%

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153 can be solved in any configuration; on these instance+seed:

- disabling SCIP features (floating-point mode) increases mean time by 89% and mean nodes by 161%
- switching to exact mode increases time by 258% and nodes by 155% (in addition)

Presolve: Implicit Integral Variables

A variable is implicit integral, if constraints (and objective) imply that it takes an integral value in any feasible (or any optimal, or at least one optimal) solution, e.g.,

- $x + y = 0$, $x \in \mathbb{Z} \quad \Rightarrow \quad y \in \mathbb{Z}$ if feasible
- $\max y$, s.t. $x + y \leq 0$, $x \in \mathbb{Z} \quad \Rightarrow \quad y \in \mathbb{Z}$ if optimal

Useful property for branching, cut strengthening, primal heuristics, domain propagation, ...

So far, SCIP's presolve could detect implicit integrality for only one variable at a time.

Presolve: Implicit Integrality via TU matrices [van der Hulst, Walter 2024, 2025]

Now, whole sets of implicit integral variables can be detected:

- partition variables into (x, y, z) such that constraints take form

$$\begin{aligned} Ax \quad + By \quad\quad\quad &\leq d \\ Ex \quad\quad\quad + Fz &\leq h \\ x \in \mathbb{Z}^n \end{aligned}$$

with A, d integral, B totally unimodular[1]

[1] every square submatrix has determinant -1, 0, or 1

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- for any fixing $x := \bar{x}$, the polyhedron $\{y : By \le d - A\,\bar{x}\}$ is integral

$\Rightarrow$ y is implicit integral

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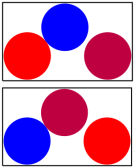
- SCIP very fast detects (transposed) *network matrices* B, a large sub-class of totally unimodular matrices
- implicit integrality now detected on 69% of MIPLIB2017 instances (SCIP 9: 20%)
- mean fraction of implicit integral variables increased from 3% to 19%

[1] every square submatrix has determinant -1, 0, or 1

Presolve: PaPILO updates

- PaPILO now licensed under Apache 2.0
- added clique merging
- faster column domination presolve by topological compression of domination arc sets

SCIP: Reflection Symmetries [Hojny 2024]



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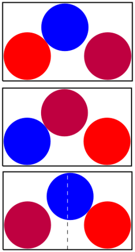

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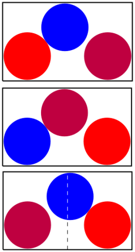

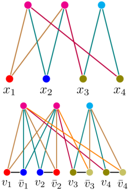

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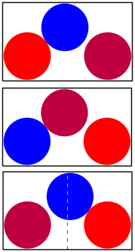

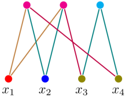

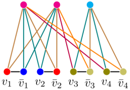

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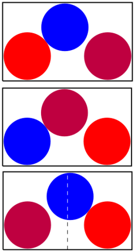

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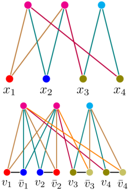

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- symmetry detection now also for pseudo-boolean constraints

Separator: k-flower inequalities

Consider a binary product constraints

$$y_f = \prod_{v \in f} x_v, \qquad x_v \in \{0, 1\},$$

The standard relaxation includes the cut

$$y_f + \sum_{v \in f} (1 - x_v) \geq 1$$

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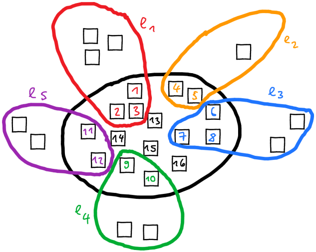

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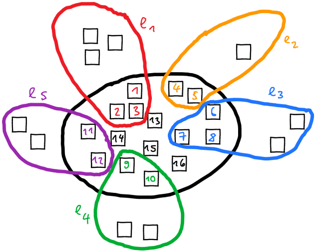

Rewrite the standard cut for f as

$$y_f + \sum_{i=1}^{k} \sum_{v \in f \cap e_i} (1 - x_v) + \sum_{v \in f \setminus \cup_{i=1}^{k} f_i} (1 - x_v) \geq 1$$

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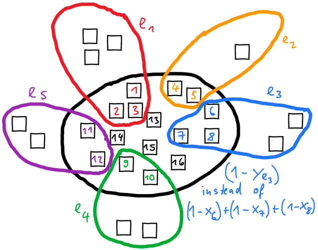

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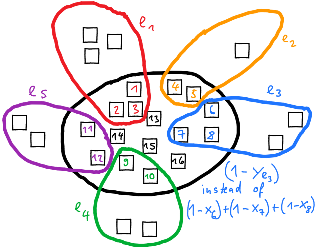

The *k-flower inequality* is

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SCIP separates these inequalities efficiently for $k = 1$ and $k = 2$.

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increase β_i when column with $a_i = 1$ found

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- on 160 suitable MIPLIB2017 instances: 5% improvement in gap between optimal value and primal bound

Based on Guastaroba, Savelsbergh, and Speranza (2017): Adaptive Kernel Search – A heuristic for solving Mixed Integer linear Programs

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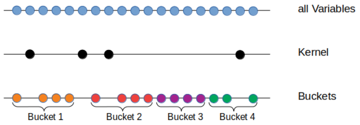
- split remaining variables into buckets, e.g., by logarithm of reduced costs



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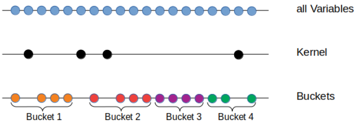

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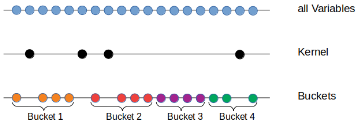

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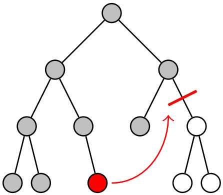
- additional adjustments if problem decomposition is available: ensure each bucket contains variables from all blocks

SCIP: Cut-based Conflict Analysis

[Mexi, Serrano, Berthold, Gleixner, Nordström 2024]

Encountering an infeasible branch-and-bound node, **conflict analysis** is about obtaining a constraint that would have identified the infeasibility earlier.



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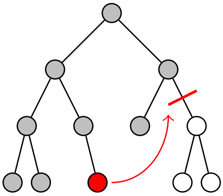
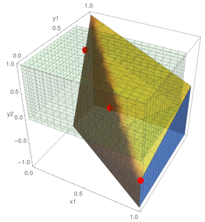


- so far, SCIP could derive bound disjunctions $\bigvee_i \{x_i \lesseqgtr b_i\}$ (SAT-based approach) or use Farkas proof from infeasible LP
- now, directly use the linear constraints that were responsible for the bound tightenings that lead to infeasibility
- a sequence of linear combinations, integer roundings, and MIR cut generation to derive a cut that separates the infeasible local domain
- more details in WB-43



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GCG: Component Bound Branching

- branch entirely in reformulated problem, similar to Vanderbeck's generic branching scheme (2011), but less complex

Decomposition

More News from GCG:

- now licensed under Apache 2.0
- new JSON-based file format for decomposition: allows for nested decompositions and symmetry info
- new pricing solvers: GCG (nested decomp.) and HiGHS
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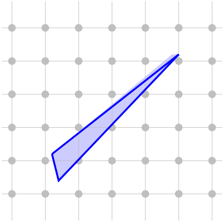
Benders in SCIP:

- full solution can now be obtained if decomposition happens in SCIP
- allow for $\max_i \theta_i$ instead of $\sum_i \theta_i$ objective function
- distinguish master and linking variables

Irreducible Infeasible Subsystem

- a subset of the problem's constraints and variable bounds that cannot be satisfied jointly and that becomes feasible if reducing further



Irreducible Infeasible Subsystem

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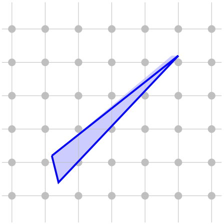
- SCIP and MIP-DD can now compute IIS by greedy algorithms, either building up from an empty problem or reducing from the full problem



Interfaces

PySCIPOpt:

- Matrix variables are now available, e.g.,

```
x = scip.addMatrixVar((2,2), vtype='C', name='x', ub=8)
scip.addMatrixCons(x + y <= z)
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SCIP.jl:

- event handler access
- MinUC computation

SCIP solving statistics

SCIP can prints hundreds of line of statistics on the solving process.

```
SCIP Status        : solving was interrupted [gap limit reached]
Total Time         :       0.64
  solving          :       0.63
  presolving       :       0.03 (included in solving)
  reading          :       0.01
  copying          :       0.01 (5 #copies) (minimal 0.00, maximal 0.00, average 0.00)
Original Problem   :
  Problem name     : BELL5
  Variables        : 104 (30 binary, 28 integer, 46 continuous)
  implied integral : 0 (0 binary, 0 integer, 0 continuous)
  Constraints      : 91 initial, 91 maximal
  Objective        : minimize, 74 non-zeros (abs.min = 0.1825, abs.max = 60000)
Presolved Problem  :
  Problem name     : t_BELL5
  Variables        : 30 (2 binary, 11 integer, 17 continuous)
  implied integral : 0 (0 binary, 0 integer, 0 continuous)
  Constraints      : 61 initial, 62 maximal
  Objective        : minimize, 28 non-zeros (abs.min = 1.41693, abs.max = 59000)
  Nonzeros         : 553 constraint, 0 clique table
Presolvers         :   ExecTime  SetupTime  Calls  FixedVars   AggrVars   ChgTypes  ChgBounds   AddHoles    DelCons    AddCons   Chg
  boundshift       :       0.00       0.00      0          0          0          0          0          0          0          0
  convertinttobin  :       0.00       0.00      0          0          0          0          0          0          0          0
  domcol           :       0.00       0.00      5          1          0          0          0          0          0          0
  dualagg          :       0.00       0.00      0          0          0          0          0          0          0          0
  dualcomp         :       0.00       0.00      5          0          0          0          0          0          0          0
  dualinfer        :       0.00       0.00      0          0          0          0          0          0          0          0
  dualsparsify     :       0.00       0.00      1          0          0          0          0          0          0          0
  gateextraction   :       0.00       0.00      0          0          0          0          0          0          0          0
  implics          :       0.00       0.00     12          0          0          0          0          0          0          0
  implint          :       0.00       0.00      0          0          0          0          0          0          0          0
  inttobinary      :       0.00       0.00     49          0          2          2          0          0          0          0
  milp             :       0.00       0.00      4          4          2          0         15          0          0          0
```

SCIP solving statistics

SCIP can prints hundreds of line of statistics on the solving process.

```
SCIP Status        : solving was interrupted [gap limit reached]
Total Time         :       0.64
  solving          :       0.63
  presolving
  reading
  copying
Original Problem
  Problem name
  Variables
  implied integral
  Constraints
  Objective
Presolved Problem
  Problem name
  Variables
  implied integral
  Constraints
  Objective
  Nonzeros
Presolvers                                      elCons    AddCons    Chg
  boundshift                                         0          0
  convertinttobin                                    0          0
  domcol                                             0          0
  dualagg                                            0          0
  dualcomp                                           0          0
  dualinfer                                          0          0
  dualsparsify                                       0          0
  gateextraction                                     0          0
  implics                                            0          0
  implint                                            0          0
  inttobinary                                        0          0
  milp                                               0          0
```

Now this information is available via an API and JSON.


```
"origprob" : {
   "description" : "original problem statistics table",
   "num_binary_variables" : 30,
   "num_continuous_variables" : 46,
   "num_implied_binary_variables" : 0,
   "num_implied_continuous_variables" : 0,
   "num_implied_integer_variables" : 0,
   "num_initial_constraints" : 91,
   "num_integer_variables" : 28,
   "num_maximal_constraints" : 91,
   "num_variables" : 104,
   "objective_abs_max" : 60000,
   "objective_abs_min" : 0.1825,
   "objective_non_zeros" : 74,
   "objective_sense" : "minimize",
   "problem_name" : "BELL5"
},
"presolvedprob" : {
   "clique_table_nonzeros" : 0,
   "constraint_nonzeros" : 539,
   "description" : "presolved problem statistics table",
   "num_binary_variables" : 2,
   "num_continuous_variables" : 17,
   "num_implied_binary_variables" : 0,
   "num_implied_continuous_variables" : 0,
   "num_implied_integer_variables" : 0,
   "num_initial_constraints" : 60,
```

Availability

- SCIP Optimization Suite 10 should be released in the next months.
- Everything is already publicly available in the development branches (master or develop) on `https://github.com/scipopt`.

Availability

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- A release report with many details will be available again.

The SCIP Optimization Suite 10.0

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Abstract

Keywords Constraint integer programming · linear programming · mixed-integer linear programming · mixed-integer nonlinear programming · optimization solver · branch-and-cut · branch-and-price · column generation · parallelization · mixed-integer semidefinite programming

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